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Optimization Framework for Infrastructure Management Considering Traffic Safety Costs

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16. Abstract

This project developed a multi-objective optimization for infrastructure management system that can optimize maintenance, repair, and rehabilitation (MR&R) decisions while simultaneously considering agency costs, total vehicle operating costs, and costs associated with safety performance. To do so, models that relate safety (e.g., crash outcomes) to the roadway condition (e.g., IRI) were developed for Pennsylvania and then used as input into a multi-objective optimization framework. The results suggest that considering safety impacts in infrastructure maintenance decision making can significantly change the decisions and their timing.

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Infrastructure management, safety, multi-objective optimization

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Table of Contents

List of Figures

List of Tables

CHAPTER 1

Introduction

BACKGROUND

Infrastructure management systems (IMS) help agencies develop the most effective maintenance, repair, and rehabilitation (MR&R) strategic plans to extend the lifetime of a set of infrastructure facilities. Identifying these optimal policies is not trivial due to the large number of possible actions over the lifetime of a facility, the probabilistic nature of infrastructure deterioration and impacts of MR&R activities, and the (tight) budget constraints that limit the decisions that can be made. However, systematic methodological approaches to infrastructure management that account for these issues have proven to both save DOTs money and extend the life of pavement and other facilities (e.g., bridges, pipelines, etc.). For example, Arizona's initial pavement management system in the 1980s (*11*) was found to save the Arizona DOT $14 million in the year it was implemented (*15*). Such savings allow for more MR&R activities to be performed, maximizing the impact of a fixed budget at preserving infrastructure.

Existing methodological IMS approaches consider multiple measures when identifying optimal MR&R decisions and treat these in different ways. The simplest IMS methods identify the optimal MR&R decisions that minimize the total sum of costs experienced over the lifetime of the infrastructure facilities being considered. These costs are typically made up of costs to the agency managing the infrastructure and costs to users. More advanced IMS frameworks employ bi-objective optimization models that consider agency cost and user cost independently. Both approaches generally take into consideration the costs that are simple to quantify based on previous experience, data and/or model availability. For example, agency costs included in IMS consist of costs for individual MR&R decisions based on historical agency data. User costs typically include vehicle operating costs (*3*) and travel delay costs (*10*) for which cost quantification methods as a function of the pavement conditions have been developed.

However, these existing approaches neglect the impact of infrastructure condition on safety performance, even though crashes can damage the transportation infrastructure and prematurely reduce its life and serviceability. This is perhaps because very few studies have quantified the impact of infrastructure condition on safety performance (*1, 2, 7, 20, 23*), and this relationship is a necessary component to incorporate into IMS. The few studies that have attempted to quantify this relationship do not utilize state-of-the-art statistical methods for modeling safety performance. For instance, earlier studies aggregated crashes of all severity levels and developed a single statistical model that assumes homogenous impact of infrastructure conditions for different severity levels. In reality, infrastructure conditions can have different impacts on crashes of different severity levels (e.g., roads with lower friction levels might lead to more severe crashes). Also, earlier studies that focused on pavement conditions ignore spatial and temporal dependencies in crash patterns (*5*). For these reasons, a multi-objective optimization methodology including safety for optimizing MR&R decisions has yet to be developed. However, incorporating safety into MR&R decision-making can directly consider how infrastructure deterioration might influence safety performance, potentially reducing crashes and the associated damage to the infrastructure that they cause. This can help increase the serviceable lifetime of pavements or bridge decks. It can also expand an agency's potential funding pool for MR&R activities. For example, if an MR&R activity can also improve safety performance, an agency can use safety funds to support this project.

OBJECTIVE

The goal of this project is to develop a multi-objective optimization for IMS that can optimize MR&R decisions while simultaneously considering agency costs, total vehicle operating costs, and costs associated with safety performance. To do so, models that relate safety (e.g., crash outcomes) to the roadway condition (e.g., IRI) will be developed for Pennsylvania, and then used as input into a multi-objective optimization framework. The results of this project can optimize how DOTs can utilize existing budgets for infrastructure management, as well as potentially expand the budget for MR&R activities.

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CHAPTER 2

Integrating pavement roughness into safety performance

INTRODUCTION

Highway safety is a critical aspect of the transportation system. In 2019, there were approximately 6.76 million police-reported crashes, resulting in 33,244 fatalities and more than 1.91 million injuries on highways and streets in the United States (1). Although fatalities and injured persons per 100 million vehicle miles traveled had been decreasing for four consecutive years since 2016, highway safety remains a large problem. Therefore, significant research efforts are needed to identify safety problems and identify solutions to make roadways safer.

The *Highway Safety Manual* (HSM) provides a set of methods to help quantitatively analyze the safety performance of individual roadway facilities (2). One set of tools currently available in the HSM are safety performance functions (SPFs), which relate the expected crash frequency of a roadway segment or intersection to traffic volumes, geometric characteristics (horizontal curvature, vertical curvature, cross-sectional characteristics), roadside features, and presence of safety countermeasures. The development of SPFs can help analysts understand how changing/improving these features influences the expected number and severity of crashes at individual locations.

The HSM provides a set of national level SPFs for various roadway facility types, but agencies are encouraged to develop their own jurisdiction-specific SPFs to improve the accuracy of the predictions (3-7). One aspect that is known to influence safety but generally missing from HSM SPFs and many jurisdiction-specific SPFs is the influence of roadway (or pavement) condition. For example, pavement friction directly impacts how well vehicles are able to maneuver on a roadway section (8-10). Wet pavements also do not offer the same level of maneuverability/stopping distance as dry pavements and thus are less safe (11, 12). For these reasons, pavement condition is likely a critical contributing factor to safety performance. Moreover, incorporating pavement condition into SPFs might not only improve estimates of safety performance but might also help both safety and pavement engineers make better decisions on when and where to apply maintenance activities to improve pavement condition—especially when limited resources are available.

Several indicators have been defined to measure the pavement performance, such as International Roughness Index (IRI, a measure of pavement roughness), Pavement Condition Rating (PCR, a measure of pavement distress), Present Serviceability Index (PSI), and rutting depth (13). Researchers have used various data sources to model how pavement condition changes over time as roadways are used. For example, several studies (14,15) developed friction degradation models as a function of volumes, geometric characteristics, and speed. Perera et al. (16) performed a linear regression analysis between time sequence IRI values and pavement age to identify sections for which a linear relationship exists between those two variables. The study also developed models to predict IRI values at different General Pavement Study

(GPS) sections with variables such as precipitation, water/cement ratios, and traffic volume. A review of IRI prediction models can be found in (17).

Studies on the effects of such pavement condition measures on safety performance exist since the late 1990s. For example, many studies show that increasing IRI increases the total crash frequency (18-20). Chan et al. (21) found that crash frequencies generally increase as IRI increases or as PSI decreases, regardless of time of day and weather conditions. Chen et al., (22) concluded that high IRI values increase the injury crash frequency on multi-lane highways in Indiana. The relationship between pavement condition and the frequencies of different crash types has been investigated as well. For example, (23) found that an increase in IRI value would decrease the likelihood of single-vehicle crashes. One possible explanation is that rough roads affect driving quality, forcing drivers to decrease speeds and likely pay more attention to the driving task. On the other hand, the rate of multi-vehicle crashes tends to increase as IRI value increases.

Research has analyzed the safety effects of pavement resurfacing activities on different crash types. Abdel-Aty et al. (24) found that resurfacing projects reduced total, severe, and rear-end crashes on multilane arterials with partially limited access. Zeng et al. (25) found that pavement resurfacing in Virginia reduced fatal and injury crash frequency by 26% but did not significantly change total crash frequency. Park et al. (26) applied a comparison group method and found that in the first year after pavement resurfacing projects, total crash frequency reduced by 23.4% and fatal and injury crash frequency reduced by 31.2% in Florida. The results indicate that pavement resurfacing was more effective to reduce severe crashes.

This present study seeks to provide more understanding on the relationship between pavement condition and safety performance on two-lane rural roadway segments in Pennsylvania and use this information to understand the safety impacts of pavement maintenance activities. Negative binomial regression is used to estimate SPFs for three types of crash frequencies: total, fatal+injury, and rear-end crashes. Furthermore, a pavement deterioration model is developed using linear regression to describe how pavements would deteriorate with use. The deterioration model is then combined with the SPFs to demonstrate how pavement maintenance activities may influence safety performance. The results of the work can be used to demonstrate how regular maintenance can be considered as another means to improve safety performance and make roadways safer.

The remainder of this report is organized as follows. First, the data used to develop the SPFs and pavement deterioration model are described. Then, the statistical modeling methodologies and metrics to assess the goodness of fit of those proposed models are presented. Next, the results of the SPFs and pavement deterioration model are provided. This is followed by a discussion of deterioration impacts on safety. Finally, concluding remarks and potential directions for future work are offered.

DATA

This section describes the individual data sources used to develop the analysis databases for this study. These include roadway inventory, crash, and pavement condition data. Two unique analysis databases were developed: the first was used to estimate an SPF that relates safety performance with other roadway features (including pavement condition), and the second was used to estimate a model of pavement deterioration (i.e., how pavement condition changes over time).

Data description and compilation

Roadway and crash data used in this study were obtained from previous studies performed to estimate SPFs for two-lane, two-way rural roadway segments in Pennsylvania (27, 28). Roadway information was originally obtained from the Pennsylvania Department of Transportation (PennDOT) Roadway Management System (RMS) database, which provided information such as annual traffic volume (i.e., AADT) and composition (i.e., truck percentage), cross-sectional information, segment lengths, and posted speed limits for PennDOT-defined roadway segments. These data elements were supplemented by manual data collection via Google Earth and PennDOT's online video photolog system. The manually collected data elements included roadside condition measured using the roadside hazard rating (RHR), presence of passing zones, presence of low-cost safety improvements (e.g., shoulder and centerline rumble strips), horizontal curvature, number of access points, and number of intersections. Note that RHR was incorporated using indicator variables for different RHR groupings with similar safety performance as identified in (28).

Roadway information was merged with crash data available from PennDOT's Pennsylvania Crash Information Tool (PCIT). Crashes were matched to individual roadway segments using PennDOT's linear referencing system, which provides the location of crashes on state-owned roadways based on the county, state road number, segment ID, and offset along the segment. Three crash frequency metrics were considered in this study: total crashes, fatal and injury crashes, and rear-end crashes.
The pavement condition considered in this paper was pavement roughness, measured using the International Roughness Index. The IRI information was obtained for the individual roadway segments from PennDOT's RMS database and appended to the existing datasets. Up to four unique IRI observations were available for a given segment per year. As part of the data compilation process, these repeated observations for a given year were aggregated to provide a single IRI estimate for every segment per year. The most straightforward way to do so was to simply average all non-zero values for a particular segment within a given year. However, for some segments, the IRI jumps up to a larger number (or jumps down to a smaller number) and then returns within the same year; an example of this is shown in Figure 2.1.

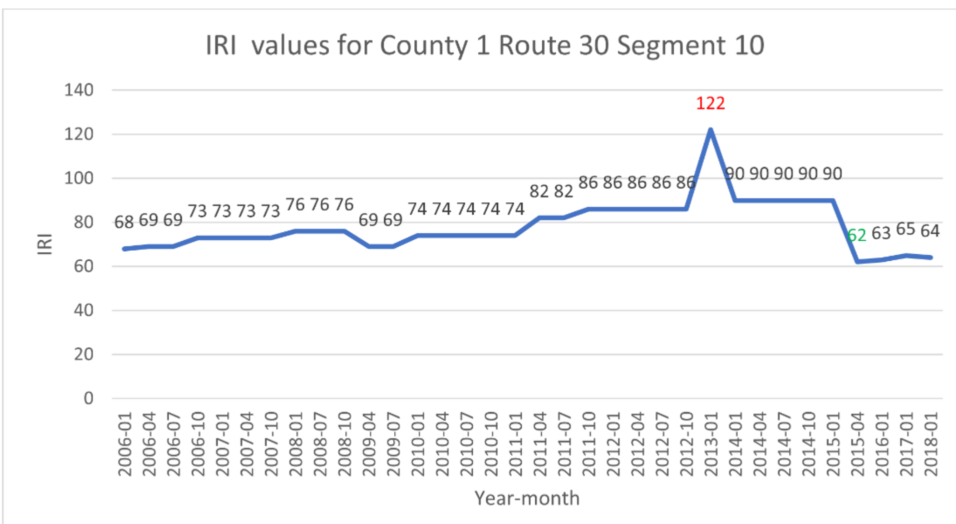


Fig 2.1 IRI values for County 1 Route 30, Segment 10,

Such abnormal IRI values are likely to be erroneous. A simple rule was proposed to identify these errors: The maximum IRI value for a segment was assumed to be an error if the difference between the maximum value and the second-largest value was larger than 20. Likewise, the minimum IRI value was assumed to be an error if the difference between the second-smallest value and the minimum value was larger than 20. These errors were updated depending on the position of the error within the database. If the error appeared in the first (last) record, it was filled backward (forward). Otherwise, the error was replaced by the average of two adjacent non-zero values. After processing the data as described, the proposed criteria were applied to re-check for errors. If additional errors were observed, the updating procedures were performed again.

After cleaning the errors, the IRI value for a segment-year combination was then set to be the average of all non-zero values for that year. For cases in which all IRI values were zero for a given year, these segments were removed from the database.

Table 2.1. Crash, traffic volume, and site characteristic data summary for two-lane rural roadway segments in 2015-2018.

	Mean	SD	Minimum	Maximum
Total crashes per year	0.611	1.065	0	22
Fatal+injury crashes per year	0.281	0.635	0	12
Rear-end crashes per year	0.097	0.397	0	12
AADT	3014.6	2749.9	55	25,535
Segment length	0.475	0.126	0.013	1.267
Horizontal curve density	2.318	2.522	0	42.581
Degree of curvature per mile	19.089	44.148	0	1,263.475
Access density	119.055	52.154	29	863
IRI	119.055	52.154	29	863
Categorical Variables	**Category**		**Proportion**	
Roadside hazard rating	1, 2, 3		5.4	
	4, 5		74.7	
	6, 7		19.9	
Presence of passing zone	Yes		28.5	
	No		71.5	
Presence of shoulder rumble strips	Yes		8.0	
	No		92.0	
Engineering District	1		11.1	
	2		16.3	
	3		13.9	
	4		9.2	
	5		5.7	
	6		1.8	
	8		13.0	
	9		10.5	
	10		8.8	
	11		2.4	
	12		7.3	

SPF development database

Crash data for the last four available years (2015-2018) were selected for the SPF development database to consider only the most recent conditions when modeling safety performance. The SPF development database contained a total of 48,099 crashes across the four-year period observed across 19,691 unique segments. Among these crashes, 15.9% were rear-end crashes. Table 2.1 provides summary statistics of total crashes, fatal+injury crashes, rear-end crashes, traffic volume, and the roadway and roadside characteristics included in the SPF development database.

Pavement deterioration database

A separate analysis database was developed to estimate a model of pavement deterioration. For this database, segments-year combinations only with increasing IRI values over time were considered to avoid the impacts of possible maintenance activities, which were not available from PennDOT. For each segment, the longest and most recent period of increasing IRI values across the years 2006 through 2018 were identified and included in the database. The minimum and maximum periods of time with increasing IRI are 2 and 12 years, respectively. The result was a final pavement deterioration modeling database that included 71,351 records from years 2006 through 2018. Potential explanatory variables in this database included traffic volume (split between car volume and truck volume, to evaluate the effect of different vehicle types on pavement deterioration), pavement condition in the previous year, and access density. A summary of the database used for the deterioration model is provided in Table 2.2.

Table 2.2. Summary of database used for the deterioration model for 2006-2008.

	Mean	SD	Minimum	Maximum
IRI for year *i*+1	117.022	47.286	30	472
IRI for year *i*	111.760	44.773	27	472
AADT of car	2,918.348	2,602.665	51	24,258
AADT of truck	277.767	315.193	0	6,391
Access density	16.330	13.919	0	240

METHODOLOGY

This section describes the methods used in this section. The first subsection provides details on the statistical modeling methodologies that were applied to estimate the SPF and pavement deterioration models, while the second describes the metrics used to assess the goodness of fit of those proposed models.

Statistical modeling approaches

Negative Binomial (NB) regression

NB regression was used to estimate the safety performance function that relates observed crash frequencies with traffic volumes, geometric features, and pavement condition. NB regression is a count regression modeling approach that addresses over-dispersion commonly found in crash data, in which the variance of the reported crash frequency exceeds the mean (29-31). A variety of cross-sectional extensions have been proposed to estimate SPFs that take advantage of the panel nature of most safety analysis databases (i.e., the presence of repeated observations from the same segment across multiple years). Examples include mixed or random effects, NB regressions, and models with random parameters (18, 32-35). However, NB regression was chosen in this study to be consistent with the model development approach used to estimate SPFs in the first edition of the *Highway Safety Manual*. Furthermore, recent studies have shown that the performance of these more advanced approaches is consistent with traditional NB regression when applied to segments not used to directly estimate the models, as would be with HSM-type SPFs (36). The output of the NB model has the following general form:

$$\ln \boldsymbol{\lambda_i} = \boldsymbol{\beta X_i} + \boldsymbol{\varepsilon_i} \tag{2.1}$$

where λ_i is the expected number of crashes at segment i; X_i is a set of J independent variables including geometric design, traffic volume, and other site-specific data for segment i (such as IRI, access density and horizontal curve density); β is a vector of $(J+1)$ estimable regression parameters; and ε_i is a gamma-distributed error term. In this study, we assume the SPF can be estimated using the following model specification:

$$\ln \lambda_i = \beta_0 + \beta_1 L_i + \beta_2 AADT_i + \beta_3 (IRI \times AADT_i) + \beta_4 X_{4i} + \cdots + \beta_j X_{ji} \tag{2.2}$$

where L_i is the roadway segment length for segment i; $AADT_i$ is the average annual daily traffic for segment i; $IRI \times AADT_i$ is the product of IRI and AADT for segment i and is calculated by $IRI \times AADT_i/10^6$. The probability function that described the NB model is:

$$\Pr(y_i = y) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i+1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\alpha\lambda_i}{1+\lambda_i\alpha}\right)^{y_i} \left(\frac{1}{1+\lambda_i\alpha}\right)^{\frac{1}{\alpha}} \tag{2.3}$$

where $\Gamma(\cdot)$is the gamma function, y_i is the observed crash outcome for segment i, and α is the overdispersion parameter. The maximum likelihood method is applied to estimate the model parameters. Since the product of probability is usually too small to work with, the objective function is reformulated as maximizing the following quantity, commonly referred to as the log-likelihood function:

$$LL = \sum_n ln\Gamma\left(y_i + \frac{1}{\alpha}\right) - ln\Gamma\left(\frac{1}{\alpha}\right) - ln\Gamma(y_i+1) + y_i \ln(\alpha\lambda_i) - (y_i + \frac{1}{\alpha}\ln(1+\lambda_i\alpha) \tag{2.4}$$

Linear regression

The pavement deterioration model was developed using linear regression. The output of the linear regression model has the following general form:

$$y_i = \beta X_i + \varepsilon_i \tag{2.5}$$

where y_i is the dependent variable being modeled, X_i is a set of J independent variables, and β is a vector of $(J+1)$ estimable regression parameters.

In this study, a log-linear model is used where the dependent variable is incorporated using a log transformation. This is a common transformation for cases in which the dependent variable can only take positive values. The final model specification considered is:

$$\ln(IRI_i) = \beta_0 + \beta_1 \ln(IRI_{i-1}) + \beta_2 lnAADT_{car} + \beta_3 lnAADT_{truck} + \beta_4 AD \tag{2.6}$$

where IRI_i and IRI_{i-1} represent the pavement conditions in year i and $i-1$, respectively; $AADT_{car}$ and $AADT_{truck}$ represent the annual car and truck volumes, respectively, and AD is the access density along the roadway segment. Note that modeling the pavement condition in the current year as a function of the pavement condition in the previous year is common and helps account for the fact that pavement condition declines more rapidly as it gets worse (37). The model parameters are estimated using the ordinary least squares method.

Goodness of fit

Root-mean-square-error and mean absolute error

We use the following two metrics to assess the prediction accuracy of the proposed SPFs: root mean square error (RMSE) and mean absolute error (MAE). As shown in (7) and (8), both metrics quantify the difference between reported and predicted crash frequencies. In general, RMSE tends to emphasize outliers more strongly than MAE.

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(N_{pred,i} - N_{obs,i})^2}{n}} \tag{2.7}$$

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n}|N_{pred,i} - N_{obs,i}|}{n} \tag{2.8}$$

where $N_{pred,i}$ is the predicted number of crashes for observation i; $N_{obs,i}$ is the reported number of crashes for observation i, n is the number of observations. A smaller RMSE indicates that the predicted crash is closer to the reported value, and the same applies for MAE.

We also use RMSE and MAE to present the accuracy of the proposed deterioration model. Similar to (2.7) and (2.8), these metrics are calculated as shown in (2.9) and (2.10).

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(IRI_{pred,i} - IRI_{obs,i})^2}{n}} \tag{2.7}$$

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n}|IRI_{pred,i} - IRI_{obs,i}|}{n} \tag{2.8}$$

where $IRI_{pred,i}$ and $IRI_{obs,i}$ are the predicted and reported IRIs for the succeeding year for observation i.

Normalized root mean square error

We also apply normalized root mean square error (NRMSE) to evaluate the performance of multi-year predictions. There are different types of NRMSE out there that fall into two main camps: (1) normalization to a central moment of the data such as mean or median; and (2) normalization to the variance of the data (standard deviation, range, interquartile range). In this study, we normalize RMSE to its mean and standard deviation. They are denoted as $NRMSE_m$ and $NRMSE_{sd}$

$NRMSE_m$ is calculated by dividing RMSE with the average of IRI values. According to (38), model accuracy is considered excellent when $NRMSE_m$ < 0.1, good if 0.1 < $NRMSE_m$< 0.2, fair if 0.2 < $NRMSE_m$ < 0.3, and poor if $NRMSE_m$> 0.3. And $NRMSE_{sd}$ is calculated by dividing RMSE with the standard deviation of the IRI values.

Cumulative Residual (CURE) plots

CURE plots are recommended by various researchers to assess the overall fit of an SPF (5, 39, 40). CURE plots can visually depict how good a model fits the observed data and help identify areas where values are consistently over- or under-predicted. These plots illustrate the relationship between cumulative residuals (i.e., differences between reported and predicted crash frequencies) and another metric, such as the explanatory variables (segment length and AADT), and the crash frequencies. In this paper, we use CURE plots that show the cumulative residuals as a function of predicted crash frequency to assess the goodness-of-fit of the proposed SPF functional form with respect to predicted values. In general, CURE plot values that are close to and oscillate around zero represent better-fitting models. By treating the cumulative residual process as a random walk, confidence intervals can be estimated to determine if a specific CURE plot represents a good-fitting model, as described in (40).

MODEL RESULTS

In this section, we present the results of the estimated SPFs and pavement deterioration model.

SPFs

Model estimation results

Two SPFs are estimated for each crash type considered. For comparison, the first model considers the effect of IRI, while the second does not. Different from the SPFs in (28), indicators for PennDOT engineering district are included to account for the differences in safety performance across the entire state of Pennsylvania, which was found significant in previous studies (6). Table 2.3 provides the model estimation results. The two models estimated include the same explanatory variables, except for the IRI term. Similar to the previous SPFs developed for two-lane rural roadway segments in Pennsylvania, the coefficient estimates are in line with engineering expectations. Total crash frequency decreases with the presence of passing zones and shoulder rumble strips, but increases with segment length, AADT, horizontal curve density, degree of curvature per mile, and access density. Furthermore, we find that the estimated coefficients related to districts 5, 6 and 8 are positive. This suggests that the total crash frequency is higher in those districts. The over-dispersion parameter of both models is statistically greater than 0, suggesting that the NB model is more appropriate than a Poisson model to account for over-dispersion. The model with IRI has a larger value of log-likelihood, a smaller RMSE and similar MAE, which suggests that incorporating IRI into the SPF improves fit to the observed data.

Table 2.4 provides the results for the estimated SPFs for the fatal+injury crash frequency. Similar to the SPFs for total crash frequency, the presence of passing zones and shoulder rumble strips reduces the frequency of fatal+injury crashes, while fatal+injury crash frequency increases with segment length, AADT, horizontal curve density, degree of curvature per mile and access density. A new explanatory variable is included in this model, i.e., the indicator for District 1. The estimated coefficient indicates that fatal+injury crash frequency is lower in District 1 in both models. Again, the over-dispersion parameter of both models is different than 0. The model with IRI has a lower RMSE and MAE compared to the model without IRI.

Table 2.3. Proposed SPFs for total crash frequency for years 2015 through 2018.

	With IRI	*With IRI*	*With IRI*	*Without IRI*	*Without IRI*	*Without IRI*
	Estimate	Standard Error	*Pr* > |*z*|	Estimate	Standard Error	*Pr* > |*z*|
Constant	-5.6910	0.0789	< 0.001	-6.0118	0.0638	< 0.001
Natural logarithm of segment length	0.8729	0.0192	< 0.001	0.8624	0.0192	< 0.001
Natural logarithm of AADT	0.6985	0.0099	< 0.001	0.7440	0.0072	< 0.001
IRI×AADT	1.290E-07	0.0192	< 0.001	-	-	-
Presence of a passing zone	-0.1256	0.0129	< 0.001	-0.1356	0.0128	< 0.001
Presence of shoulder rumble strips	-0.0989	0.0202	< 0.001	-0.1066	0.0201	< 0.001
Roadside hazard rating of 6 or 7	0.1389	0.0267	< 0.001	0.1429	0.0267	< 0.001
Roadside hazard rating of 4 or 5	0.1037	0.0240	< 0.001	0.1057	0.0240	< 0.001
Horizontal curve density	0.0222	0.0028	< 0.001	0.0223	0.0028	< 0.001
Degree of curvature per mile	0.0017	0.0001	< 0.001	0.0018	0.0001	< 0.001
Access density	0.0062	0.0004	< 0.001	0.0064	0.0004	< 0.001
Indicator for District 2	-0.1072	0.0189	< 0.001	-0.1086	0.0189	< 0.001
Indicator for District 3	-0.1397	0.0194	< 0.001	-0.1466	0.0193	< 0.001
Indicator for District 5	0.2990	0.0207	< 0.001	0.3214	0.0205	< 0.001
Indicator for District 6	0.2265	0.0322	< 0.001	0.2631	0.0317	< 0.001
Indicator for District 8	0.1683	0.0165	< 0.001	0.1727	0.0166	< 0.001
Indicator for District 9	-0.0512	0.0211	0.016	-0.0524	0.0212	0.013
Indicator for District 10	-0.1002	0.0211	< 0.001	-0.1065	0.0211	< 0.001
Indicator for District 11	-0.1321	0.0357	< 0.001	-0.1396	0.0357	< 0.001
Over-dispersion parameter	0.3837			0.3873		
Log-likelihood	-75035.404			-75058.160		
RMSE	0.9282			0.9300		
MAE	0.6350			0.6349		

Table 2.4. Proposed SPFs for total crash frequency for years 2015 through 2018.

	With IRI	*With IRI*	*With IRI*	*Without IRI*	*Without IRI*	*Without IRI*
	Estimate	Standard Error	*Pr* > |*z*|	Estimate	Standard Error	*Pr* > |*z*|
Constant	-6.3385	0.1109	< 0.001	-6.7220	0.0913	< 0.001
Natural logarithm of segment length	0.8541	0.0269	< 0.001	0.8410	0.0268	< 0.001
Natural logarithm of AADT	0.6800	0.0136	< 0.001	0.7349	0.0101	< 0.001
IRI×AADT	1.513E-07	0.0255	< 0.001	-	-	-
Presence of a passing zone	-0.1282	0.0185	< 0.001	-0.1383	0.0184	< 0.001
Presence of shoulder rumble strips	-0.0913	0.0282	0.001	-0.0998	0.0282	< 0.001
Roadside hazard rating of 6 or 7	0.1493	0.0371	< 0.001	0.1537	0.0372	< 0.001
Roadside hazard rating of 4 or 5	0.1025	0.0334	< 0.001	0.1048	0.0335	0.002
Horizontal curve density	0.0233	0.0039	< 0.001	0.0232	0.0039	< 0.001
Degree of curvature per mile	0.0017	0.0002	< 0.001	0.0017	0.0002	< 0.001
Access density	0.0069	0.0005	< 0.001	0.0071	0.0005	< 0.001
Indicator for District 1	-0.0534	0.0321	0.097	-0.0684	0.0320	0.033
Indicator for District 2	-0.1183	0.0290	< 0.001	-0.1259	0.0290	< 0.001
Indicator for District 3	-0.1786	0.0296	< 0.001	-0.1925	0.0296	< 0.001
Indicator for District 5	0.2857	0.0298	< 0.001	0.3088	0.0295	< 0.001
Indicator for District 6	0.1506	0.0452	< 0.001	0.1910	0.0446	< 0.001
Indicator for District 8	0.1570	0.0249	< 0.001	0.1565	0.0249	< 0.001
Indicator for District 9	-0.0681	0.0317	0.032	-0.0748	0.0317	0.018
Indicator for District 10	-0.1126	0.0315	< 0.001	0.1258	0.0315	< 0.001
Indicator for District 11	-0.2353	0.0527	< 0.001	0.2502	0.0527	< 0.001
Over-dispersion parameter	0.4536			0.4596		
Log-likelihood	-48039.732			-48057.468		
RMSE	0.5872			0.5881		
MAE	0.3836			0.3838		

Table 2.5. Proposed SPFs for rear-end crash frequency for year 2015 to 2018.

	With IRI	*With IRI*	*With IRI*	*Without IRI*	*Without IRI*	*Without IRI*
	Estimate	Standard Error	*Pr > |z|*	Estimate	Standard Error	*Pr > |z|*
Constant	-13.8301	0.2350	< 0.001	-14.6422	0.1838	< 0.001
Natural logarithm of segment length	0.9145	0.0448	< 0.001	0.8870	0.0446	< 0.001
Natural logarithm of AADT	1.4542	0.0283	< 0.001	1.5605	0.0206	< 0.001
IRI×AADT	1.906E-07	0.0353	< 0.001	-	-	-
Presence of a passing zone	-0.1832	0.0319	< 0.001	-0.1959	0.0318	< 0.001
Roadside hazard rating of 4 or 5	0.0560	0.0316	0.076	0.0556	0.0316	0.079
Horizontal curve density	-0.0271	0.0072	< 0.001	-0.0268	0.0072	< 0.001
Degree of curvature per mile	0.0015	0.0004	0.001	0.0016	0.0004	< 0.001
Access density	0.0163	0.0007	< 0.001	0.0166	0.0007	< 0.001
Indicator for District 1	-0.3554	0.0571	< 0.001	-0.3650	0.0571	< 0.001
Indicator for District 2	-0.2606	0.0480	< 0.001	0.2700	0.0571	< 0.001
Indicator for District 3	-0.2238	0.0470	< 0.001	-0.2370	0.0470	< 0.001
Indicator for District 4	-0.1928	0.0516	< 0.001	-0.1593	0.0511	0.002
Indicator for District 5	0.1049	0.0435	0.016	0.1529	0.0424	< 0.001
Indicator for District 6	-0.2407	0.0666	< 0.001	-0.1798	0.0655	0.006
Indicator for District 9	-0.2771	0.0560	< 0.001	-0.2751	0.0560	< 0.001
Indicator for District 10	-0.2656	0.0493	< 0.001	-0.2788	0.0493	< 0.001
Indicator for District 11	-0.1736	0.0826	0.036	-0.1966	0.0827	0.017
Over-dispersion parameter	0.6023			0.6106		
Log-likelihood	-19888.532			-19902.738		
RMSE	0.3522			0.3521		
MAE	0.1438			0.1440		

Table 2.5 summarizes the results for SPFs for rear-end crash frequency. The variables related to road characteristics are the same, and their coefficients have the same sign compared to the previous two models. As for indicators for districts, only the one for District 8 is excluded from both models, and only the indicator for District 5 is positive. Like the other estimated SPFs, the model with IRI has a smaller RMSE and MAE, as well as a larger value of log-likelihood.

Cure Plots

In this section, we present the CURE plots for the six SPFs introduced above; see Figure 2.2 through Figure 2.4. In each figure, the blue line represents the cumulative residual for the model with IRI included, the red line represents the cumulative residual not accounting for IRI, the black lines are the confidence intervals associated with a random walk process when IRI is included, and the green lines are the confidence intervals without considering IRI.

The CURE plots for total crash frequency (Figure 2.2) reveal that the model with IRI fits the observed data better than the one without IRI. Specifically, the cumulative residuals for the proposed model considering the effect of IRI almost all fall within the 95% confidence intervals and only leave this range for a small proportion of the observations (when the predicted total crash is around 2.5 and over 7.8). Thus, considering the metrics and CURE plot, the proposed SPF form with IRI provides a good fit to the observed total crash frequency data in years 2015-2018.

The CURE plots for fatal+injury crash frequency (Figure 2.3) illustrate the same findings. The cumulative residuals for the proposed model only exceed the bounds for a small proportion of the observations (when the predicted fatal+injury crash is around 1.5 and over 3.9) when IRI is considered. Overall, these goodness-of-fit measures suggest that the proposed model with IRI provides a better fit to the fatal+injury crash data in years 2015-2018.

Figure 2.4 shows the CURE plots for two SPFs for rear-end crash frequency. Different from the two models above, the bounds are narrower if IRI is not included. For both models, the cumulative residuals mostly fall within the 95% confidence intervals when the predicted rear-end crash is less than 2. When the predicted value is higher than 2, the cumulative residuals for a large proportion of the observations fall outside the 95% confidence interval bounds if IRI is not considered in the model. So, the proposed SPF functional form with IRI provides a better fit to the rear-end crash data.

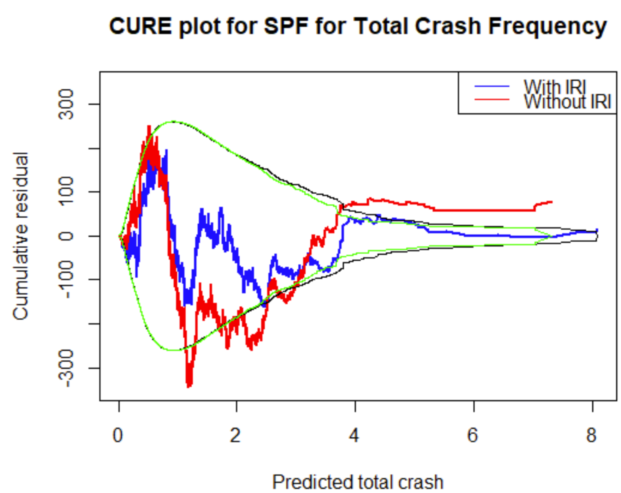


Figure 2.2 CURE plots for SPF for total crash frequency.

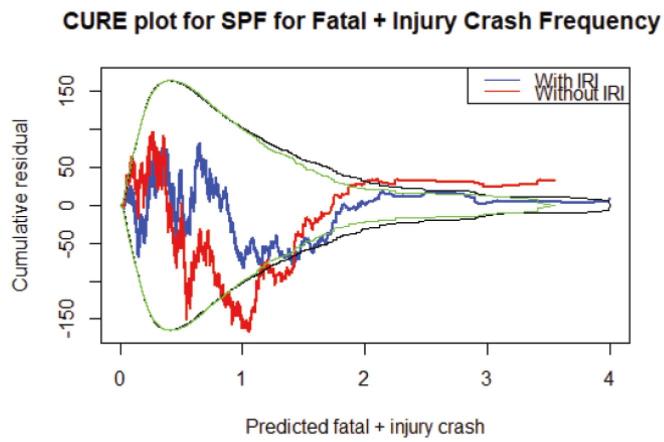


Figure 2.3 CURE plots for SPF for fatal+injury crash frequency.

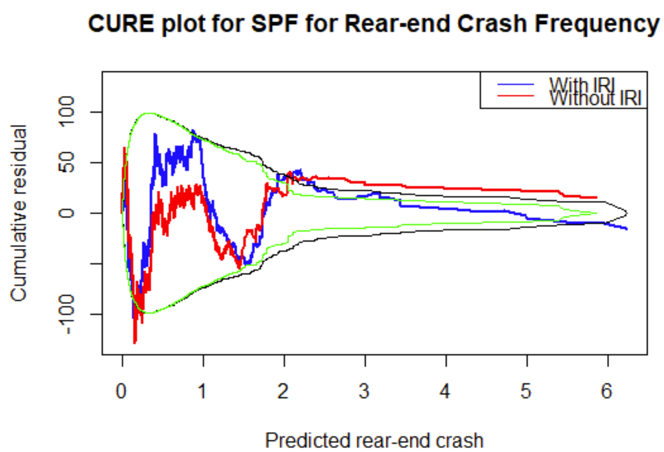


Figure 2.4 CURE plots for SPF for rear-end crash frequency.

Deterioration model

Results for the model estimation

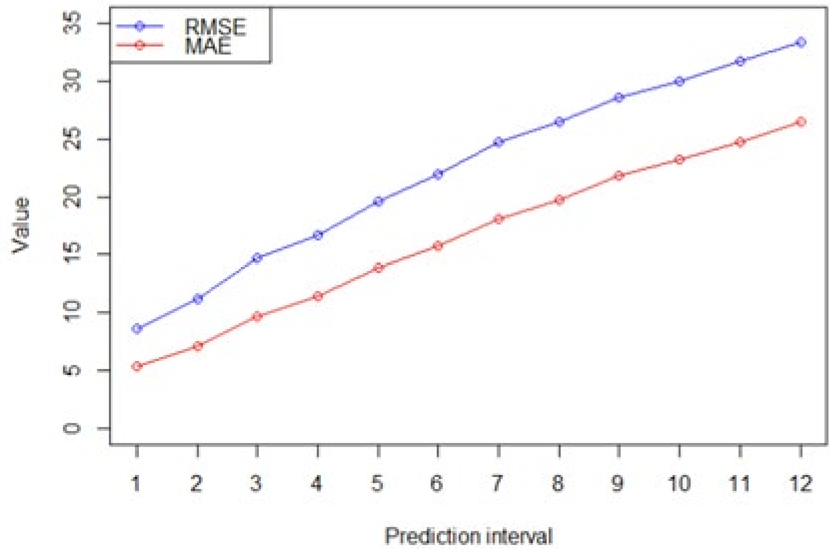
In this section, we provide information on the estimated deterioration model. We choose the natural logarithm of AADT of car and truck as separate independent variables because: (1) increasing traffic demand results in degradation of overall highway service capacity, and (2) the amount of damage imparted on the highway by cars and trucks is likely to be different (41). The other two explanatory variables are IRI in the current year and access density. The results are summarized in Table 2.6. The model fits the data well, with a very high R-squared value of 0.9998. All coefficients are positive, which suggests that IRI increases with car traffic, truck traffic, previous year IRI and access density. The coefficient for truck AADT (2.256e-03) is larger than that for car AADT (1.376e-03). This suggests that a unit increase in truck volume per day has a larger impact on IRI than the unit increase in car volune, which is reasonable and expected.

Table 2.6 Results for deterioration model.

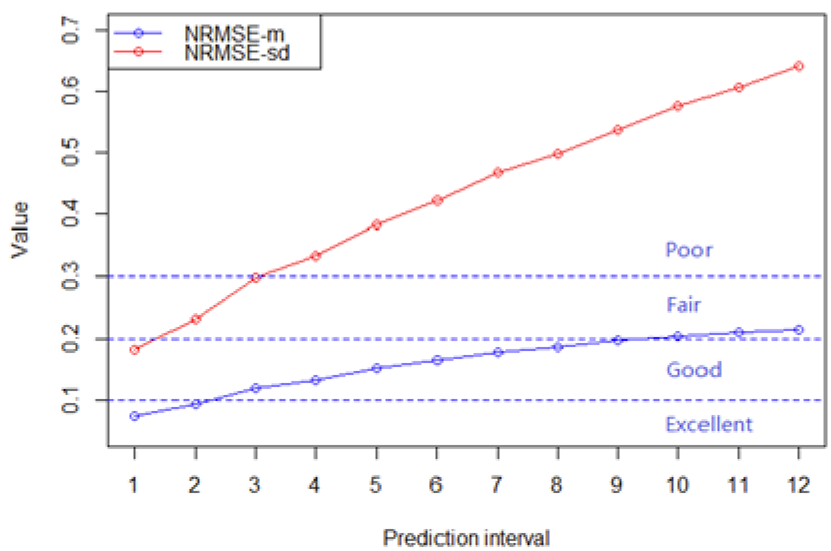
	Estimate	Standard Error	t-value	*Pr*(> |*t*|)
log(IRI1)	1.0046	3.2357E-04	3104.8191	< 0.001
log(caraadt)	1.3760E-03	3.8417E-04	3.5818	< 0.001
log(truckaadt)	2.2557E-03	3.8129E-04	5.9158	< 0.001
Access density	6.5611E-05	1.7560E-05	3.7363	< 0.001
Multiple R-squared: 0.9998				
Adjusted R-squared: 0.9998				
RMSE: 8.6344				
MAE: 5.3563				

Performance of multiyear prediction

In this section, we examine how well the estimated model performs for multiyear prediction. In this case, the predicted IRI in year i is used as an input into the model as the current year IRI to make predictions of IRI in future years (i.e., year $i + 1$ and beyond). Figure 2.5a shows how RMSE and MAE change as the prediction interval increases. When the prediction interval is 1, the corresponding RMSE and MAE are 8.6343 and 5.3566. The values of these error metrics increase as the prediction interval becomes longer. This is expected, as errors in the prediction would grow with time and lead to decreased predictive ability in the future. When the prediction interval reaches the maximum value (12), the RMSE is 33.3551 and the MAE becomes 26.5215. Figure 2.5b shows the trend for two NRMSE values. When the prediction interval is 1, the prediction is excellent, since $NRMSE_m$=0.0738$. The prediction is good for prediction intervals up to 9 years. When the prediction interval is longer than 9 years, the predictive ability becomes only fair. On the other hand, $NRMSE_{sd}$ increases faster than $NRMSE_m$. $NRMSE_{sd}$ is 0.1826 when the interval is 1, and it reaches 0.6408 when the prediction interval is 12. So, the estimated model performs well when the prediction interval is no longer than 9 years.



(a) RMSE and MAE



(b) NRMSE

Figure 2.5 Performance of multiyear prediction.

DISCUSSION OF DETERIORATION IMPACTS ON SAFETY

In this section, we will show how the safety performance for a given site is expected to change over time with and without considering the effects of pavement condition. The models developed in Section 4 show that crash frequency increases with the product of IRI and AADT (see Tables 2.3 and 2.4), and that IRI increases with AADT and access density if no maintenance activities are performed to improve the pavement condition.

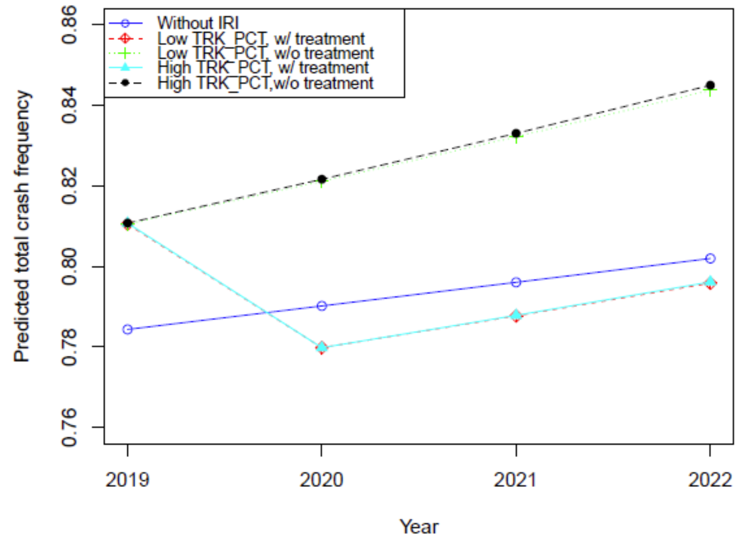
One segment was randomly selected to illustrate how expected safety performance would change when considering pavement condition compared to when it is ignored. The road characteristics were taken from Segment 180 on State Route 255 in Clearfield County. These characteristics are:

- Segment length: 0.4837 mile.
- Horizontal curve density: 4.1347.
- Degree of curvature of per mile: 11.9644.
- Access density: 2.0673.
- Shoulder rumble strips: yes.
- Roadside hazard rating: 6.
- Demand profile: 15,000 veh/day for high AADT scenario, and 4,600 veh/day for low AADT scenario.
- Truck percentage: 40% for high scenario, and 8% for low scenario.

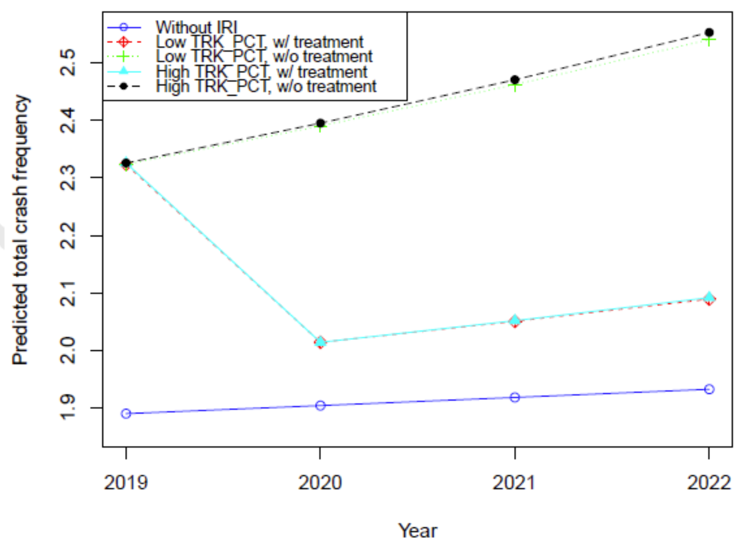
In addition, scenarios are considered with no maintenance activities in which the pavement condition is assumed to continuously deteriorate according to the model developed above and where maintenance (specifically, a resurfacing activity that reduces IRI to 90 as per records from PennDOT) is performed in year 2020. In all cases, traffic volumes are assumed to grow 1% per year.

Figure 2.6a provides a comparison of safety performance over time for the scenarios with low traffic volume, while Figure 2.6b provides a comparison of safety performance over time for the scenarios with high traffic volume. Notice in both cases that when pavement condition is not considered in the prediction of safety performance, crash frequency increases nearly linearly over time as traffic volumes increase. Also notice that when pavement condition is considered, the predictions differ significantly from the predictions when pavement condition is not considered, and the differences are more substantial for roadway segments with higher traffic volumes. Furthermore, when pavement condition is considered, the rate of increase in predicted crash frequency is much higher than when pavement condition is not considered.

Additionally, the two figures visually illustrate that maintenance actions can result in substantial improvements in safety performance by improving the pavement condition that persists over time. For the low-volume scenario, the resurfacing activity reduces predicted crash frequency in 2020 from 0.811 to 0.780, which represents a 3.9% reduction. This improvement lasts—and actually grows—in subsequent years. In the high-volume scenario, the benefits are more pronounced and represent a 15.7% reduction in predicted crash frequency. This suggests that incorporating pavement condition into safety prediction models can not only improve prediction accuracy but also provides safety engineers with additional mechanisms they can use to improve safety performance (i.e., via maintenance activities).



(a) Predicted total crash frequency in year 2019-2022 with low AADT



(b) Predicted total crash frequency in year 2019-2022 with high AADT

Figure 2.6 Predicted total crash frequency.

CONCLUSIONS AND DISCUSSION

Existing approaches to infrastructure management neglect the impact of infrastructure condition on safety performance, even though poorly maintained roadways can contribute to increased crash frequencies. This is perhaps because very few studies have quantified the impact of infrastructure condition on safety performance. Hence, this work developed models that relate safety (e.g., crash outcomes) to the roadway condition (e.g., IRI) for Pennsylvania. To do so, the PennDOT Roadway Management System database, the Pennsylvania Crash Information Tool, and some manually collected data from GoogleEarth and PennDOT's online video photolog system were used. SPFs that consider IRI were developed, considering previous SPFs that were developed using similar data for Pennsylvania. The results showed that including the IRI in the models improves model fit, shown through the use of CURE plots, and that IRI has a significant and positive impact on crash outcomes. In other words, as IRI increases, the possibility of a crash occurring increases. The results further suggest that the IRI has a different impact on total crash frequency as compared to fatal and injury crash frequency, and rear-end crashes. This is likely due to how roughness of the roadway can impact travel speeds. Further, to determine the impact of potential maintenance activities on safety, a deterioration model was developed that predicts future IRI as a function of current IRI, car and truck AADT, and access density. The results of this modeling show that truck AADT has a larger impact on future IRI than car AADT, which is expected. The one-year prediction model fits the data very well (R^2=0.9998). Further tests on multi-year predictions suggest that predictions of IRI up to 9 years can be considered good based on the $NRMSE_m$.

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CHAPTER 3

Including safety cost in the pavement maintenance, rehabilitation, and reconstruction decision making

INTRODUCTION

Background

Implementing an efficient pavement maintenance, rehabilitation, and reconstruction strategy is an important part of infrastructure asset management. Well-timed preservation activities can help extend pavement life, maintain the pavement at a higher performance level, and lower the total lifecycle cost. Typically, MR&R activities are planned by considering agency cost, user cost, and salvage value at the end of service life. However, the safety impact of MR&R plans is usually not specifically considered. Previous statistical studies have shown that pavement condition, specifically roughness of the roadway, has a relationship with crash frequency. Therefore, it is necessary to consider the safety cost when planning MR&R activities.

Literature

Pavement MR&R planning aims at allocating a limited budget to maintain a road network within the service period to achieve the maximum performance of the pavement while controlling the negative impact on the environment. Based on the scope, it can be divided into project-level planning and network-level planning. A project-level planning tries to schedule a series of appropriate maintenance activities across the analysis window for one segment, while network-level planning considers a pavement network's MR&R plan at the same time, which requires adding a spatial dimension to the schedule. A well-designed network-level planning can take advantage of the scale of economies by combining maintenance activities for adjacent segments when possible (Gao and Zhang, 2013).

Successful MR&R planning requires taking multiple goals into consideration. A simple method to address these goals in the model is selecting a principal goal as the objective function; the remaining goals are considered as constraints, such as minimum pavement condition level or budget limitation (Gao and Zhang, 2013). Another way to incorporate multiple goals in the model simultaneously is to assume the main objective function by weighting sub-objectives up, such as converging the different goals to the economic cost (Guo et al., 2020). However, the reliability of the weighted function is highly dependent on the selection of weight coefficients, and some of the objectives are unconvertable to the economic cost, such as safety impact and distraction. Even if the weight coefficients can be well-determined, studies show that the solution based on the weighted function is only a sub-optimal solution under certain circumstances (Chen and Zheng, 2021; Marler and Arora, 2004). Therefore, multi-objective optimization (MOO), which considers multiple goals at the same time without converting them into the same unit, has gained more and more reputation over the past decades. The solution of a MOO model is usually expressed with a Pareto frontier, which consists of a set of optimal solution points instead of a single point. Thereby, the operators can retrieve their desired final solution from the frontier surface in different ways, such as absolute optimal solution method, weight method, deviation function, or knee point method (Chen and Zheng, 2021; Marler and Arora, 2004; Meneses and Ferreira, 2013). Due to the complexity of the MR&R planning, the heuristic methods, such as genetic algorithm, and particle swarm algorithm are usually adopted to solve the MOO model (Chen and Zheng, 2021; Xiong et al., 2012; Yu et al., 2015).

The decision-making objectives in MOO models mainly consist of agency cost, user cost, performance level, environmental impact, and so on. The agency cost is the main goal that needs to be minimized in the planning, which is usually constrained by a fixed budget limitation (Torres-Machi et al., 2017). It is determined by the number of activities required in the analysis window and the expected unit cost of each activity (Guo et al., 2020). The user cost is hard to measure in practice, since it might not only include monetary costs like fuel consumption and traffic delay due to the roadwork or detour, but also needs to account for unmeasurable factors such as distraction to the driver, comfort level when driving on the road, and so on. Studies show that the user cost is the dominant factor in the MR&R planning, overweighting the other costs (Huang et al., 2021). Despite this, the additional fuel consumption result from the pavement roughness is widely used in the literature to account for the user cost (Ziyadi et al., 2018). Since the traffic sector is the second large contributor to greenhouse gas emissions, in which road construction and maintenance lead to high carbon dioxide emissions, there are more and more researchers taking the environmental impact into consideration in the MR&R planning process to achieve sustainable development. The environmental impact was mainly addressed in the construction and usage phases of a segment (Santos et al., 2015; Torres-Machi et al., 2018), but researchers also suggested that the impacts from raw materials extraction and the recycling phase also should be considered (Chen and Zheng, 2021). Other than these commonly considered objectives in MR&R planning, social equity, maintenance mileage, and work production are sometimes incorporated into consideration as well (France-Mensah et al., 2019; Xiong et al., 2012).

Studies show that the pavement condition can significantly influence the crash frequency on the road (Justo-Silva and Ferreira, 2018; Wang et al., 2022); however, the safety cost of MR&R planning is not studied in the literature yet. Yan concluded that the International Roughness Index or Present Serviceability Index are significant predictor variables in all types of accident models, and if IRI increased from 0-100 in/mi to 101-200 in/mi, the crash frequency would increase by 1.64 times for all types of accidents (Chan et al., 2010). Yu suggests that pavement with IRI around 95 in/mi seems to suggest a safer roadway but a pavement with IRI higher than 143 in/mi looks susceptible to much higher crash frequencies (Elghriany et al., 2016). Despite the clear evidence that the pavement condition is tightly correlated to the safety cost, only a few studies considered the impact of safety cost in the MR&R planning process. Zaniewski considered the safety cost in the MR&R planning but only took the skid resistance into account for safety, which ignored the relationship between pavement condition and different types of crashes (Reigle and Zaniewski, 2002). Zheng suggests that safety indicators such as accident rate are missing from the current pavement MR&R planning, which will cause the user cost to be underestimated in the MOO system (Chen and Zheng, 2021).

DATA DESCRIPTION

To determine the MR&R planning activities, agency cost, user cost, and safety cost need to be estimated as a function of pavement condition. The pavement condition considered in this report is the International Roughness Index, since it has an impact on both user and safety costs. Further, the IRI measures the difference in elevation of the road surface along with the longitudinal profiles and hence is thought to have less stochasticity and subjectivity in comparison to other indicators.

IRI data, in units of in/mi, are obtained from PennDOT's Roadway Management System database. The RMS database includes information for every roadway segment within Pennsylvania and records the annual traffic volume (i.e., AADT) and composition (i.e., truck percentage), cross-sectional information, number of access points, presence of a horizontal curve, and IRI value. Each segment has up to four IRI values recorded per year. The IRI values between 2006 to 2018 are cleaned and processed according to the literature (Wang et al., 2022).

Next, the IRI is divided into eight categories as shown in Table 3.1. This categorization is chosen to aid in the development of a stochastic deterioration model. To develop these deterioration models, discrete categories are needed, since the models determine how long a given pavement can spend in any given category of IRI before failing. The categories are chosen as described next. The National Performance Management Measure divides IRI into three categories: 1) good condition for IRI less than 95.04 in/mi, 2) fair condition for IRI between 95.04 and 169.80 in/mi, and 3) bad condition when IRI is greater than 169.80 in/mi. Hence, to stay relatively consistent with these criteria while obtaining even sizes of categories, first, a discretization at every 25 in/mi is adopted. Then, to achieve enough data in each group, IRIs from 25 to 75 and from 225 to 300 are combined as one group, respectively. This resulted in eight unique categories. Finally, using the IRI data from the RMS data, the time each pavement spends in these IRI categories is extracted as the sojourn time. If the beginning or end time of a pavement being in a certain category is unknown, this is marked as a censored data (Lu et al., 2022). A brief statistical summary of the extracted sojourn time is shown in Table 3.1.

Table 3.1. Correspondence between actual IRI and categorized IRI in this study.

Actual IRI (in/mi)	Categorized IRI	Sojourn Count	Average Sojourn (years)	Sojourn Standard Deviation (years)
25-75	IRI 2	2,819	3.82	2.25
75-100	IRI 3	5,204	3.70	2.14
100-125	IRI 4	5,126	3.29	1.89
125-150	IRI 5	3,831	2.85	1.65
150-175	IRI 6	2,376	2.47	1.38
175-200	IRI 7	1,448	2.27	1.27
200-225	IRI 8	807	2.25	1.26
225-300	IRI 9	694	3.14	1.96

METHODOLOGY

The goal of this study was to include safety impacts in MR&R decision-making. To do so, crash frequency predicted as a function of pavement condition is included in pavement-level planning of MR&R. A multi-objective optimization approach is used between the agency cost, user cost, and safety costs, since it is difficult to assign a cost to safety. The goal of multi-objective optimization is to determine the series of actions and their timing that can minimize the objectives. Hence, the decision variable is the MR&R activity to be done (including do-nothing) every year. The objective function can be defined as:

$$f = \sum_{i=1}^{N} C_{Ai} + C_{Ui} + C_{Si} \tag{3.1}$$

where N is the length of the analysis window, C_{Ai} is the associated agency cost in year i, C_{Ui} is the associated user cost in year i, and C_{Si} is the associated safety cost in year i.

The overall process of how to evaluate the objective function is as follows. To determine the impact of the MR&R activity schedule on each of the cost components, a general deterioration model to describe the deterioration of IRI without an MR&R activity is developed. Further, assumptions based on the literature about the impact of different MR&R activities on IRI are considered. The deterioration model, combined with the impact of the MR&R activity, is then used to predict the IRI over years for a given set of MR&R actions and their timings. Next, the user cost, agency cost, and safety cost are calculated as a function of IRI.

A genetic algorithm is used to evaluate different decision variables and calculate the expected total cost based on the given action series. This allows taking into consideration dynamic transition probabilities that are history dependent. A gene is designed to represent a series of actions over the analysis window, where each action is represented with a number, e.g., do-nothing is 0, the minor repair is 1, the major repair is 2, and rehabilitation is 3. The length of the gene represents the analysis window, and the sequence of numbers represents the sequence of actions to be taken each year. However, if every action is allowed every year, the total population of genes becomes very large. For example, when the analysis window is 50 years, the possible gene combination is up to 4^{50}, which significantly reduces the algorithm efficiency. Hence, in this paper, it is assumed that over the lifetime of infrastructure, assumed to be 50 years, at most 10 maintenance actions can be taken. It is assumed that in the remaining years no MR&R actions are taken.

To further get the information about sub-costs so that the tradeoff between different sub-objectives can be explored, a Monte Carlo simulation is employed based on the best gene, e.g., best action series, from the genetic algorithm. A pavement condition pathway, which is sampled based on the transition probabilities after conducting the best action of each year, is acquired during each simulation, and the associated sub-costs are calculated based on the specific sampled pathway. After 10,000 simulations, the average agency cost, user costs, safety cost, and salvage value are derived associated with the best gene. Note, as the number of Monte Carlo simulations increases, the sampled total cost converges to the corresponding objective function value of the best gene.

Finally, to analyze the impact of safety costs on the MR&R planning, the Pareto optimality is drawn, which is defined as a situation in which no individual objects can be improved without compromising the other objectives in the multi-objective optimization problem. It is usually calculated by setting different weights to each objective and getting the optimal solution under each weight combination. The slope of the Pareto frontier represents the tradeoff ratio between objectives. In this study, a range of weights is set to the safety cost to explore the tradeoff between safety and maintenance actions when putting a different value on crash frequency.

The deterioration model and the calculation of individual costs are presented next.

Deterioration model

While different statistical distributions can be used to estimate the deterioration of an infrastructure element, a commonly used model is the accelerated failure time (AFT) Weibull model. The AFT-Weibull model has been shown to be better than most other candidates in terms of predictive accuracy and simplicity (Manafpour et al., 2018; Ashraf-Ul-Alam and Khan, 2021). The semi-Markov chain process, estimated based on the AFT-Weibull model, assumes the deterioration probability of an asset follows a Weibull distribution instead of the traditional exponential model, thus overcoming the memoryless drawback of the classical Markov chain process. The impact of covariates is incorporated into the model through the accelerated failure time (AFT) approach. Considering these advantages, the AFT-Weibull model is used in this study. The details about the AFT-Weibull model can be found in the previous study (Manafpour et al., 2018). An AFT-Weibull model is estimated for each category of IRI using a maximum likelihood function. The details of the deterioration models are shown in Table 3.2.

Table 3.2 Deterioration model coefficients.

Model	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
Dist_2	-0.10*	0.52**	0.42**	0.22**	-	-	-	-
Dist_3	0.19**	0.67**	0.34**	-	-0.12*	0.20*	-	-
Dist_4	-0.73**	0.66**	0.15**	-0.20**	-0.34**	-0.33**	-0.33**	-0.36**
Dist_5	-0.58**	1.16**	0.57**	0.34**	-	-	-	-
Dist_6	-0.72**	0.90**	0.94**	0.34**	0.27**	-	-	-
Dist_8	0.23**	1.43**	1.12**	0.61**	0.27**	0.23**	0.29**	-
Dist_9	-	1.59**	1.14**	0.74**	0.59**	0.60**	0.46**	-
Dist_10	-	0.61**	0.45**	-	-	-	-	-
Dist_11	0.73**	-	0.92**	0.43**	0.26**	0.24*	0.48**	-
Dist_12	-0.39**	1.18**	0.73**	0.22**	-0.16**	-	-	-
Access point density	-0.003**	-	-	-	-	-	-	-0.005
Degree of curvature per mile	-	0.006**	0.002**	0.002**	-	-	-	-
AADT of truck	0.00 036**	0.00 006	-0.00 023**	-0.00 020**	-0.00 019**	-0.00 022**	-0.00 024**	-0.00 093**
Intercept	1.63**	2.08**	1.63**	1.69**	1.70**	1.59**	1.50**	2.86**
k	0.39**	0.70**	0.68**	0.67**	0.71**	0.73**	0.73**	0.70**
C-index	0.60	0.74	0.68	0.65	0.63	0.63	0.61	0.64

Note: ** denotes 95% confident level, * denotes 90% confident level

The models for IRI 3 and IRI 4 had the highest accuracy in terms of C-index, since these two categories had the most available data. The results suggest that the district plays an important role in the deterioration model, since the natural and human environment as well as the available budget impact deterioration. The average annual daily truck traffic is negatively correlated to most of the IRI groups, indicating that higher truck traffic leads to lower expected life, which is consistent with expectation.

The output of the AFT-Weibull model is the probability of a pavement deteriorating from one IRI level to the next level within a time increment Δt. A semi-Markov chain model is used to determine the probability of a pavement segment deteriorating to any lower IRI in any given year. The probability of a pavement remaining in its original IRI, i, at time t, $P_{ii}(t)$, can be calculated as:

$$P_{ii}(t) = S_i(t) = 1 - F_i(t) = 1 - \int_0^t f_i(t')\,dt' \tag{3.2}$$

where $S_i(t)$ is the survival function of $IRI\ i$, which represents the probability of pavement not failing by time t; $F_i(t)$ is the cumulative density function of the AFT-Weibull model of $IRI\ i$; $f_i(t)$ is the PDF of AFT-Weibull model of $IRI\ i$. Next, the PDF of a pavement segment deteriorating from IRI i to j, $f_{ij}(t)$, is calculated as in Equation 3.3. Note, it is assumed that a pavement segment deteriorates from a small i to a large j incrementally, i.e., all intermediate IRI levels are visited.

$$f_{ij}(t) = \begin{cases} f_i(t) & if\ j = i+1 \\ \int_0^t f_{i(j-1)}(t')f_{j-1}(t-t')\,dt' & if\ j > i+1 \end{cases} \tag{3.3}$$

Note, calculating the value of $f_{ij}(t)$ requires considering all possible transition combinations; therefore a multi-layer integral emerges and can be very complicated. Hence, a numerical calculation is recommended to get those values. Finally, the probability of a pavement segment deteriorating from $IRI\ i$ to j or higher, $P_{ij\ldots}(t)$, is calculated as in Equation 3.4. This is used to determine the probability of a bridge deck deteriorating from $IRI\ i$ to j, $P_{ij}(t)$ as in Equation 3.5.

$$P_{ij\ldots}(t) = \int_0^t f_{i(j-1)}(t')F_{j-1}(t-t')\,dt' \tag{3.4}$$

$$P_{ij}(t) = P_{ij\ldots}(t) - P_{i(j+1)\ldots}(t) \quad (3.5$$

Based on these equations, the transition matrix can be calculated. Figure 3.1 shows the transition probabilities when no preservation activities are performed.

Further, three preservation actions are considered to maintain the pavement condition (i.e., minor rehabilitation, major rehabilitation, and reconstruction). These are assumed to have deterministic impacts. The minor rehabilitation is assumed to improve the pavement condition by one IRI level compared to do-nothing; the major rehabilitation is assumed to improve the pavement condition by three IRI levels compared to do-nothing, and the reconstruction is assumed to be able to reset the all the pavement conditions to IRI 2. The transition metric after applying preservation actions is derived based on the transition probability of do-nothing in the first year as shown in Table 3.3 (e.g., the value of transition probabilities in Figure 3.1 when time $t = 1$).

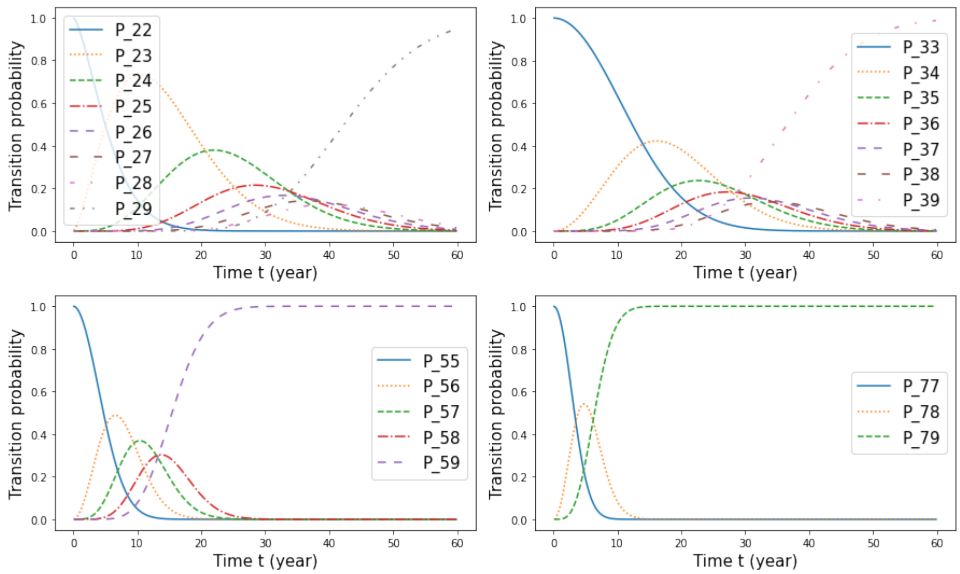


Figure 3.1. Transition probability calculations (only transition probability from IRI 2, IRI 3, IRI 5, and IRI 7 is demonstrated here for conciseness).

Table 3.3 Transition matrix from AFT-Weibull of do-nothing in the first year.

	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
IRI 2	0.9104	0.0895	0.0001	0	0	0	0	0
IRI 3	0	0.9955	0.0045	0	0	0	0	0
IRI 4	0	0	0.9854	0.0146	0.0001	0	0	0
IRI 5	0	0	0	0.975	0.0249	0.0001	0	0
IRI 6	0	0	0	0	0.9655	0.0343	0.0002	0
IRI 7	0	0	0	0	0	0.9577	0.042	0.0003
IRI 8	0	0	0	0	0	0	0.9487	0.0513
IRI 9	0	0	0	0	0	0	0	1

Cost Estimation

Three costs are considered to design an MR&R schedule that improves the general performance of a pavement: 1) agency cost, 2) user cost, and 3) safety cost. The agency cost represents the operating cost of the pavement agency for the regular maintenance, rehabilitation, and necessary reconstruction activities expenses, along with the salvage value that represents the recoverable cost or leftover benefit of an asset at the end of its lifecycle. The user cost estimates the travel cost of drivers in terms of fuel consumption under different pavement conditions. Finally, the safety cost predicts the crash frequency during the service life of a segment.

The scope of this study is to demonstrate project-level MR&R planning for a specific pavement segment. Hence, an example segment is considered, with properties shown in Table 3.4.

Table 3.4 Segment attributes of the assumed study case.

Attribute	Value
Segment length	1 mile
AADT	3,196.11 vehicles/day
Truck percentage	8.96 %
Presence of a passing zone	no
Presence of shoulder rumble strips	no
Horizontal curve density	2.24 degrees/mile
Degree of curvature per mile	17.25 degrees/mile
Access point density	16.33
Roadside hazard rating	4 or 5
Distract	2

Agency cost

According to the Ontario *Pavement Design and Rehabilitation Manual*, there are three categories of pavement improvement activities: routine maintenance, rehabilitation, and reconstruction (Ontario Ministry of Transportation, 2013). Routine maintenance is a reactive, timed activity employed to ensure the basic function of pavement, such as cleaning of roadside ditches and structures, or maintenance of pavement markings and crack filling. These activities usually do not disturb traffic and costs are negligible compared to rehabilitation and reconstruction. Therefore, routine maintenance is treated as do-nothing in this study, and the associated agency cost is assumed to be zero. Rehabilitation is a series of activities that need to be employed when the pavement condition deteriorates to an unacceptable level. Based on the severity, it includes minor rehabilitation and major rehabilitation. Two types of minor rehabilitation activities are considered in this study: diamond grinding for the concrete top layer, and 2 inches of mill and fill for the asphalt top layer. Similarly, two types of major rehabilitation activities are considered: 4 inches of asphalt or concrete overlay based on the top layer type. Reconstruction is needed when the pavement becomes functionally useless. A typical reconstruction activity would be an 8- or 12-inch new asphalt or jointed plain concrete pavement (JPCP). The reconstruction cost is usually significantly higher than rehabilitation and is typically performed after two or three rehabilitation cycles. The expected costs of different activities are estimated based on an analysis of one year of publicly available bid data for highway projects, as shown in Table 3.5 (Guo et al., 2020; Swei et al., 2019).

On the other hand, there is still some value to an asset at the end of its lifetime, which is its salvage value. The salvage value of the top layers and base layers can be determined independently. For the top layers, the remaining lifetime is estimated using the deterioration models and the salvage value is assigned proportionally to the remaining lifespan since the last reconstruction. For example, a brand-new top layer, e.g., in condition IRI 2, has an expected lifespan of 44.1 years. The salvage value of a pavement in IRI 2 is assumed to be the major rehabilitation cost, which is $261,501, while the salvage value of a top layer in condition IRI 4, which has an expected lifespan of 24.7 years, is proportional to the expected lifespan and equals $146,464. The salvage value of base layers is assumed to be a constant value and is determined as the difference between major rehabilitation cost and reconstruction cost. These are included in the agency cost as negative numbers, since they actually represent a benefit. The salvage values are estimated as shown in Table 3.5.

User cost

The user cost reflects the satisfaction and comfort of drivers when driving on the road. Here, the fuel consumption per unit distance is assumed to be the main driver of user cost. An energy consumption regression model from the literature is adopted and formulated as Equation 3.6 (Ziyadi et al., 2018).

$$E(v, IRI) = \frac{p}{v} + (k_a * IRI + d_a) + b * v + (k_c * IRI + d_c) * v^2 \tag{3.6}$$

where $E(v, IRI)$ is the expected energy consumption in units of kj/mi when driving at average speed $v\ mph$ on a pavement condition of $IRI\ in/mi$. The average speed is assumed to be 40 mph. The other variables are the model coefficients, which are provided in the literature. For a passenger car, $k_a = 0.67$, $d_a = 2175.7$, $k_c = 0.000281$, $d_c = 0.2186$, $p = 33753$, and $b = -16.931$; for a medium truck, $k_a = 0.918$, $d_a = 9299.3$, $k_c = 0.000133$, $d_c = 0.9742$, $p = 109380$, and $b = -264.32$.

The expected energy consumption, $E(v, IRI)$, is first converged to gallon gasoline according to the U.S. Environmental Protection Agency. Then, the expected economic user cost in terms of fuel consumption can be derived as shown in Table 3.5 with the national average gasoline price of $3.853 per gallon.

Safety cost

The safety cost of a segment can be represented by the expected crash frequency. The negative binomial model for estimating crash frequency as a function of IRI developed in the previous section is used here. The expected fatal or injury crash frequencies for the case study presented in Table 3.5 under different pavement conditions are predicted using the estimated models. Note that the real impact of a traffic crash is profound and cannot be simply measured with a monetary number, and the recommended transfer rate between crash frequency and economic cost varies significantly from criterion to criterion; therefore, the converged fatal or injury crash frequencies will be used as one of the subobjectives in the multi-objective optimization, as shown in Table 3.5. Nevertheless, a basic reference of economic cost associated with one crash or injury crash frequency is adopted according to the *Pennsylvania Crash Facts & Statistics* in this study, but multiply by a weight w, varies from 0 to 5 when incorporating the safety cost in the objective function. The average economic loss of fatal and injury crashes is about $7,071,403, and is denoted as E_S (Pennsylvania Department of Transportation, 2020).

Table 3.5. Subjective costs calculations for different pavement conditions.

	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
Do-nothing ($)	0	0	0	0	0	0	0	0
Minor rehabilitation ($)	48,365	48,365	48,365	48,365	48,365	48,365	48,365	48,365
Major rehabilitation ($)	87,014	87,014	87,014	87,014	87,014	87,014	87,014	87,014
Reconstruction ($)	261,501	261,501	261,501	261,501	261,501	261,501	261,501	261,501
Car energy consumption (MJ)	7,996	8,118	8,199	8,281	8,362	8,444	8,525	8,688
Truck energy consumption (MJ)	2,311	2,323	2,331	2,339	2,347	2,355	2,363	2,379
Total energy consumption (MJ)	10,306	10,441	10,530	10,620	10,709	10,799	10,888	11,067
Gas consumption (Gallon)	85	86	87	88	88	89	90	91
User cost ($)	**119,490**	**121,048**	**122,086**	**123,124**	**124,162**	**125,200**	**126,238**	**128,314**
Safety cost	**0.0626**	**0.0637**	**0.0645**	**0.0653**	**0.0661**	**0.0669**	**0.0677**	**0.0694**
Lifespan (years)	44.1	39.1	24.7	16.5	10.3	5.6	0	0
Lifespan value ($)	261,501	231,852	146,464	97,840	61,076	33,206	0	0
Base value ($)	174,486	174,486	174,486	174,486	174,486	174,486	174,486	174,486
Salvage value ($)	435,987	406,339	320,951	272,327	235,563	207,693	174,486	174,486

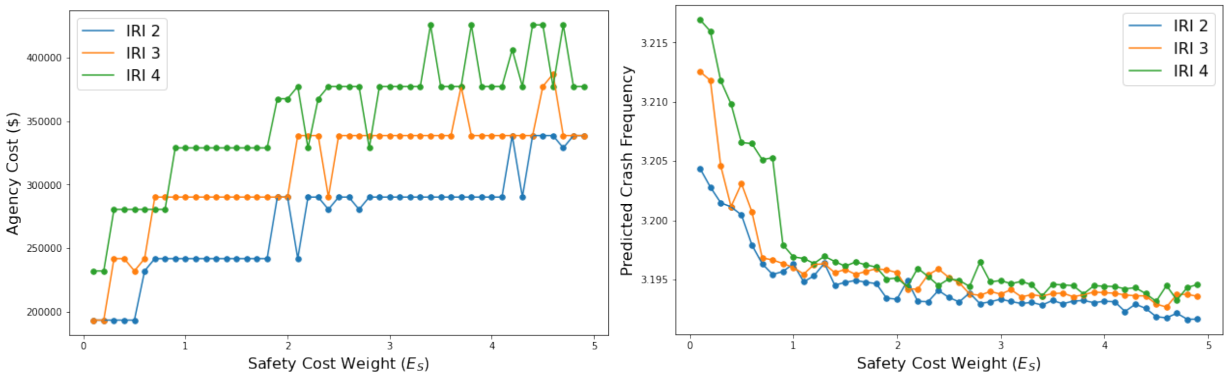
Note: All costs are calculated based on per lane per mile; an average gas price of $3.853 per gallon in 2021 is used in this table.

RESULTS AND DISCUSSION

A set of experiments were performed to explore the impact of safety costs on MR&R planning. The safety cost is incorporated into the model in the unit of converged fatal or injury crash number. A range of weights from 0 to $5E_S$ are set to the safety cost to explore the relationship between agency cost and safety cost when putting different values on crash frequency. E_S is the estimated economic cost of a fatal crash based on the *Pennsylvania Crash Facts & Statistics.* The other sub-costs, including agency cost, user cost, and salvage value are included as the economic cost as Table 3.4 in the model directly. A 50-year time window is considered in this study. The agency cost, user cost, and crash frequency are estimated per mile per lane during the 50 years.

Sensitivity to the starting condition

When the pavements start under different conditions, the required action varies as we put different weights on the safety cost. In this study, the pavements are set to deteriorate starting from a relatively good condition, e.g., IRI 2 to IRI 4. As the safety cost weights increase from 0 to $5E_S$, the change of agency cost and safety cost varies as shown in **Figure 3.2**. From **Figure 3.2**, it can be found that as we put more value on predicted crash frequency, the necessary agency cost increased to maintain the pavement in a higher condition and reduced the predicted crash frequency. A pavement that starts from a worse condition requires both higher agency costs and has a larger crash frequency, as expected. Note that the benefits to safety are diminishing after a safety cost weight of $2E_S$. After this point, the crash frequency can no longer be reduced even with more MR&R activities.



a. Agency cost

b. Predicted crash frequency

Figure 3.2. Impact of safety cost weight on agency cost as safety cost

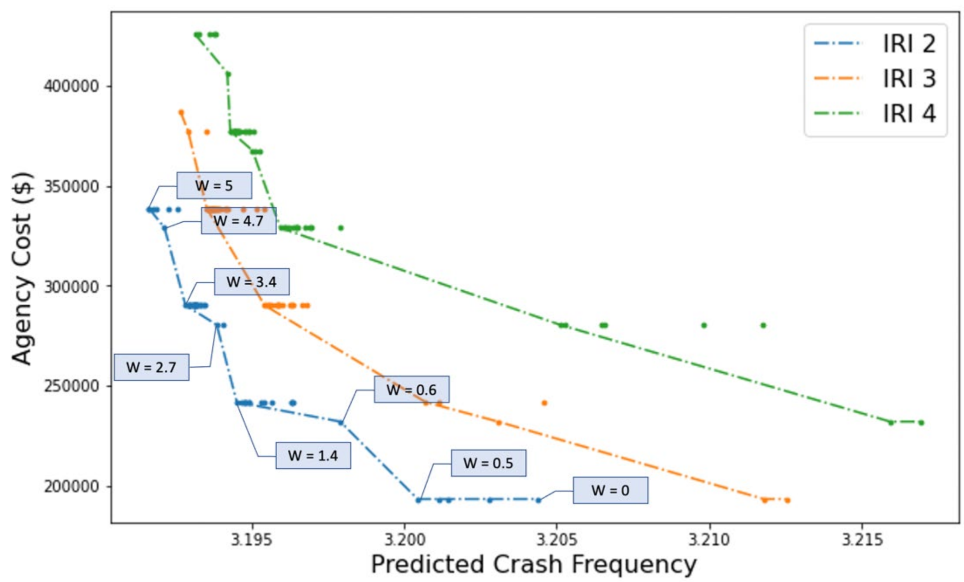


Figure 3.3. Pareto frontiers for pavements start from different conditions (Pareto optimal solutions of pavement starting from IRI 2 are marked in this plot)

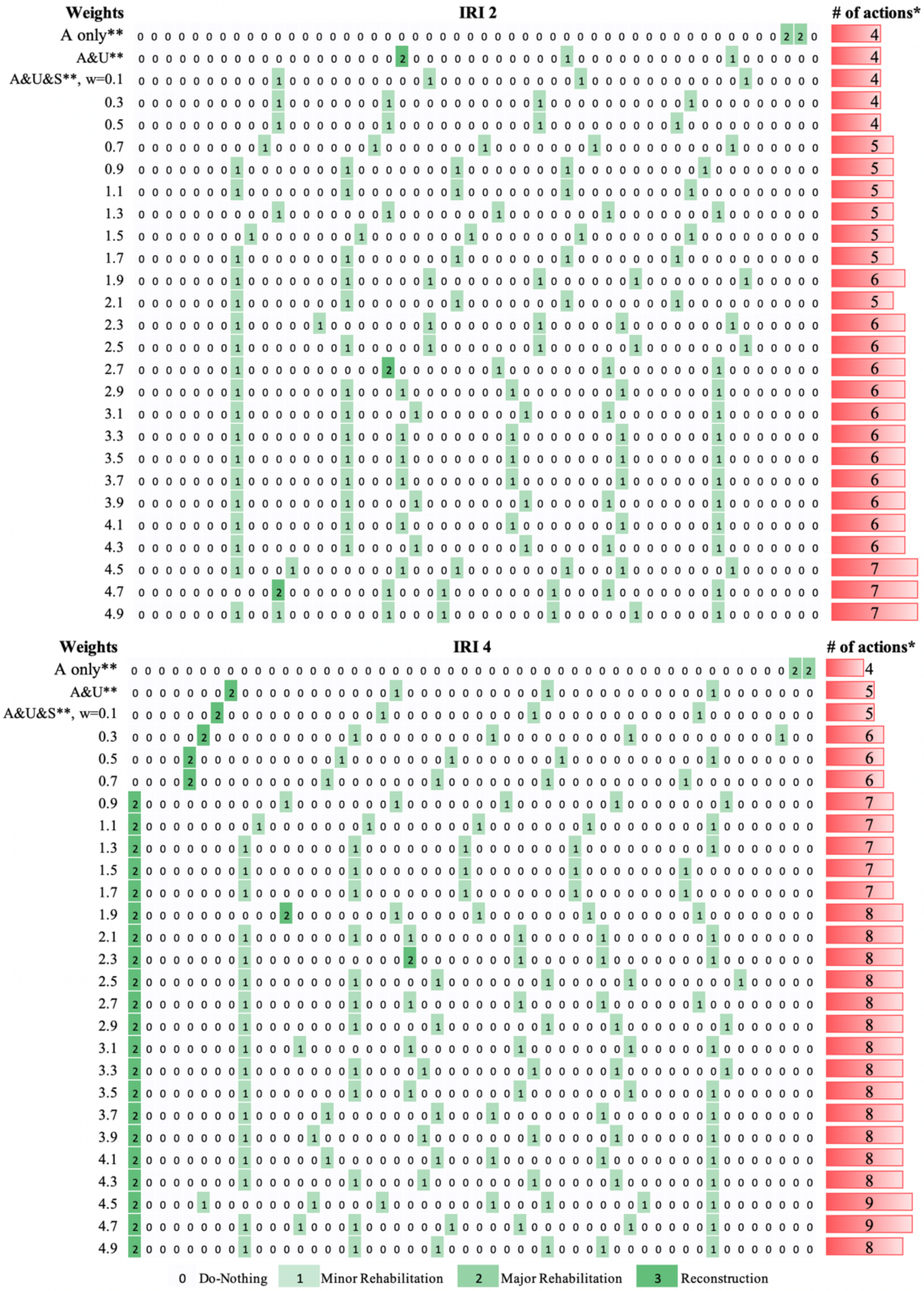
Pareto frontiers to show the tradeoff between agency cost and safety cost are shown in Figure 3.3 as dashed lines. The corresponding safety weights for pavement starting from IRI 2 are marked in the plot for illustration. From this plot, it can be seen that as the safety cost weight increases, the predicted crash frequencies reduce and agency costs increase. Further, it can be noted that if safety is not considered in MR&R planning (w=0), the predicted crash frequency is highest, as expected. As the safety cost is considered more, initially the crash frequency can be decreased without much increase in agency cost. However, as the safety cost is weighed more, the agency cost needs to increase significantly more to reduce the crash frequency further.

How the agency, user, and safety costs change as the weight of safety cost changes is shown in Table 3.6. From Table 3.6, it can be found that when only taking the agency cost into the objective function, the associated user cost and expected crash frequency are very high, since the optimal MR&R plan only adopts preservation activities in the end of the lifespan to achieve a higher salvage value. As the user cost is taken into consideration, the user cost and expected crash frequency decreased significantly. When adding the safety cost into the objective function with a weight of E_S, the predicted crash frequency decreased by 0.0098 fatal or injury crashes, which led to the agency cost increasing to $241,825 for pavement deteriorated from IRI 2. In other words, when the safety cost is considered in the MR&R planning with an economic cost suggested by *Pennsylvania Crash Facts & Statistics*, the agency cost increased 32% for the pavement starting from IRI 2. The user costs also slightly decreased as the pavement condition increased. As more weight is put on crash frequency, the tradeoff between agency cost and crash frequency becomes more obvious. When the safety cost weight increases to $5E_S$, the reduction of predicted crash frequency is minor but leads to a significant agency cost increase. This proved that the safety cost will have a significant impact on the MR&R planning depending on the available budget and the expected total cost associated with crashes.

Table 3.6. Subobjective costs of pavement start from IRI 2.

Objective Function	Agency Cost	User Cost	Crash Frequency	Safety Cost
Agency cost only	$174,028	$6,139,113	3.3054	-
Agency cost, User cost	$183,744	$6,008,371	3.2051	-
Agency cost, User cost, Safety cost (w = 1 E_S)	$241,825	$5,991,380	3.1963	$22,602,467
Agency cost, User cost, Safety cost (w = 2 E_S)	$290,190	$5,987,283	3.1933	$45,162,878
Agency cost, User cost, Safety cost (w = 3 E_S)	$290,190	$5,987,281	3.1933	$67,744,287
Agency cost, User cost, Safety cost (w = 4 E_S)	$290,190	$5,987,041	3.1932	$90,320,788
Agency cost, User cost, Safety cost (w = 5 E_S)	$338,555	$5,984,872	3.1916	$112,845,445

To further explore the change in MR&R plans as the safety cost and starting condition vary, **Figure 3.4** visualizes the best MR&R plans with different safety cost weights for pavements starting from IRI 2 and IRI 4. For comparison, the case where user cost is excluded is also shown. It can be seen that ignoring the user cost leads to all the MR&R activities being scheduled at the end to improve salvage value. Further, as the safety weight increases, the maintenance schedule becomes more frequent and tends to use a series of minor rehabilitations regularly to maintain the pavement in a better condition. The safety cost has a similar impact to the user cost, which forces the MR&R plans to be more detailed and regular. As the safety cost weight increases, the necessary actions keep increasing.



* For visualization, minor rehabilitation, major rehabilitation, and reconstruction are counted as 1, 2, and 3 actions, respectively. ** "*A only*" denotes the best MR&R plan when only considering the agency cost and salvage value; "*A&U*" denotes considering the agency cost and user cost; "*A&U&S*" denotes considering the agency cost, user cost, and safety cost in the objective function but safety costs are considered in a weight of wE_S.

Figure 3.4. MR&R plans for different safety weights when starting at IRI 2 and IRI 8.

Sensitivity to the transition probability matrix

The MR&R planning is determined by two major components, objective functions and transition probability. The safety impact on the MR&R plan is sensitive to the transition probability matrix as well. The transition probabilities are derived from the AFT-Weibull model. Based on this transition probability, the dominating action in the MR&R plan is minor rehabilitation. To explore the transition probability's impact on these patterns, a made-up transition probability matrix is used as a comparison shown in Table 3.7. The average deterioration rates of pavement to deteriorate to the worse condition are the same for the AFT-Weibull model-based transition matrix and the comparison case. The major difference is that the comparison removed the variation deteriorating to worse conditions by setting the probabilities of remaining the same IRI, deteriorating to one lower level, and deteriorating to two lower levels as 0.9, 0.07, and 0.03, respectively.

Table 3.7. Comparison case of transition matrix of do-nothing in the first year.

	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
IRI 2	0.9	0.07	0.03	0	0	0	0	0
IRI 3	0	0.9	0.07	0.03	0	0	0	0
IRI 4	0	0	0.9	0.07	0.03	0	0	0
IRI 5	0	0	0	0.9	0.07	0.03	0	0
IRI 6	0	0	0	0	0.9	0.07	0.03	0
IRI 7	0	0	0	0	0	0.9	0.07	0.03
IRI 8	0	0	0	0	0	0	0.9	0.1
IRI 9	0	0	0	0	0	0	0	1

The corresponding transition matrix for minor, major rehabilitation, and reconstruction is derived in the same way, e.g., the minor rehabilitation is assumed to improve the pavement condition by one IRI level compared to do-nothing; the major rehabilitation is assumed to improve the pavement condition by three IRI levels compared to do-nothing, and the reconstruction is assumed to be able to reset all the pavement conditions to IRI 2. When the assumed comparison case in Table 3.7 is adopted, the best MR&R plan for pavement starting from IRI 2 is shown in Figure 3.5.

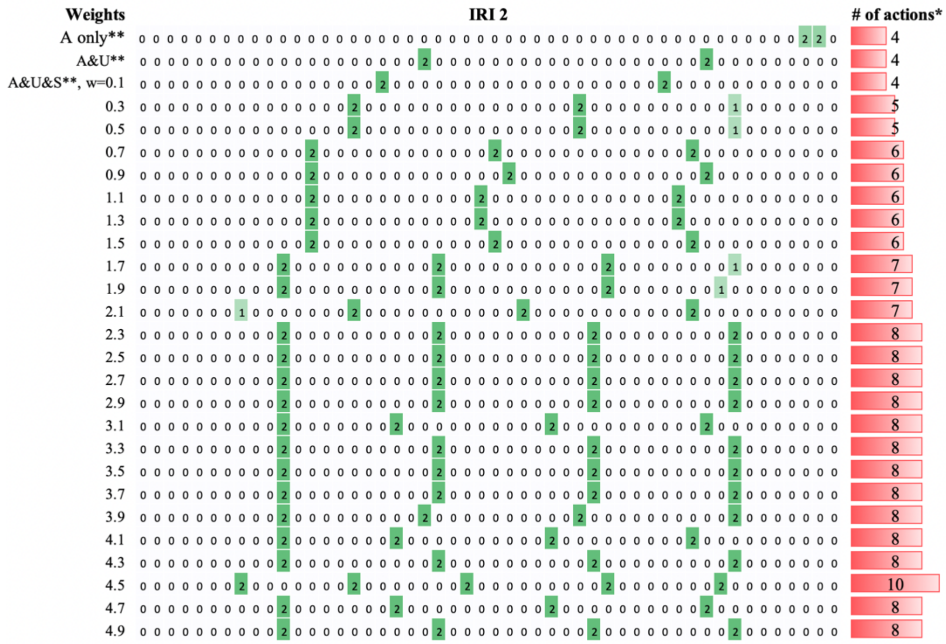


Figure 3.5. Best MR&R plans using assumed transition probability matrix.

From **Figure 3.5**, it can be observed that the most frequent activity is major rehabilitation instead of minor rehabilitation, shown in **Figure 3.4**. The reason is that for the transition matrix from the AFT-Weibull model, the probability of a bridge starting from IRI 3 staying at IRI 3 in the first year is 0.9955. Based on the way we derive the transition matrix for minor reconstruction, there is 99.55% change for a pavement at IRI 3 improving to IRI 2 after conducting minor rehabilitation. Correspondingly, the probability of a pavement improving to IRI 2 in the comparison case is only 90%, while a major rehabilitation is able to improve this probability to 100%. Therefore, the AFT-Weibull model derived transition matrix has more benefits from minor rehabilitation, and the comparison case is more economically efficient when adopting major rehabilitation.

The slight variation of the transition matrix from the AFT-Weibull model leads to a totally different MR&R planning and the safety impact on the best MR&R plan changed as well. Even though the AFT-Weibull model case is more realistic compared to the made-up transition matrix, it only models the transition probability when no maintenance activities are employed. The simplification of the transition matrix after maintenance activities leads to some unrealistic results. Further research and data collection to model the transition matrix after maintenance activities are needed in the future.

Sensitivity to the average annual truck traffic

Crash frequency is tightly correlated to the traffic volume. Therefore, the impact of safety cost on MR&R planning varies under different traffic loads. The average annual daily traffic (AADT) used for the experiment in Section 4.1 is the average AADT of all pavements in the dataset, which is 3,196 vehicles/day. In this section, two comparative case studies with low AADT levels (e.g., 1,100 vehicles/day) and high AADT levels (e.g., 11,000 vehicles/day) are analyzed to explore the impact of traffic load.
For different AADT levels, the associated user cost, e.g., fuel consumption in this study, safety cost, e.g., predicted crash frequency for each unit length of a segment are different, and the transition matrix varies as well. The user cost and safety cost for different AADT levels are shown in Figure 3.6.

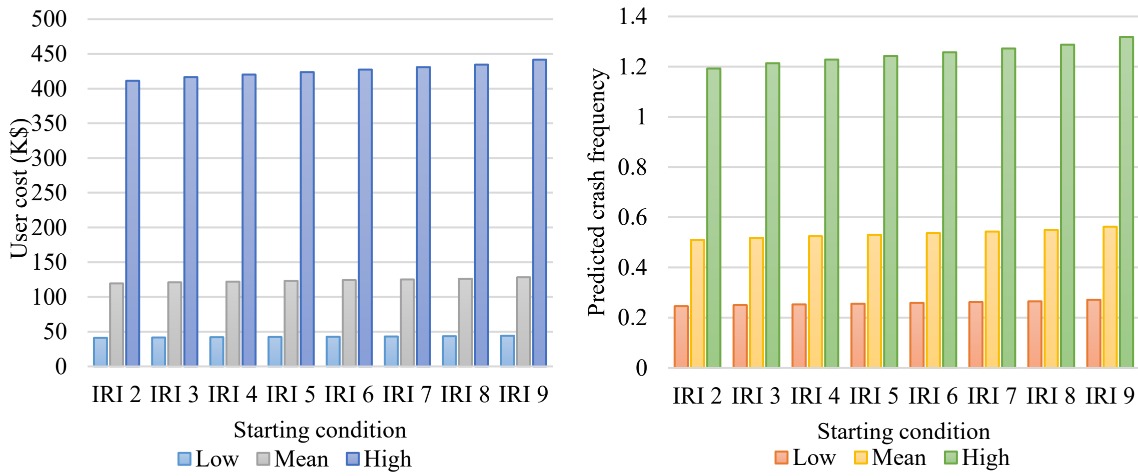


Figure 3.6. User cost and predicted crash frequency for different AADT levels.

A pavement starting from IRI 2 is selected to test the influence of traffic load. The two comparison cases have the same parameters except for the AADT level. Figure 3.7 shows that agency cost changes as the safety cost increases.

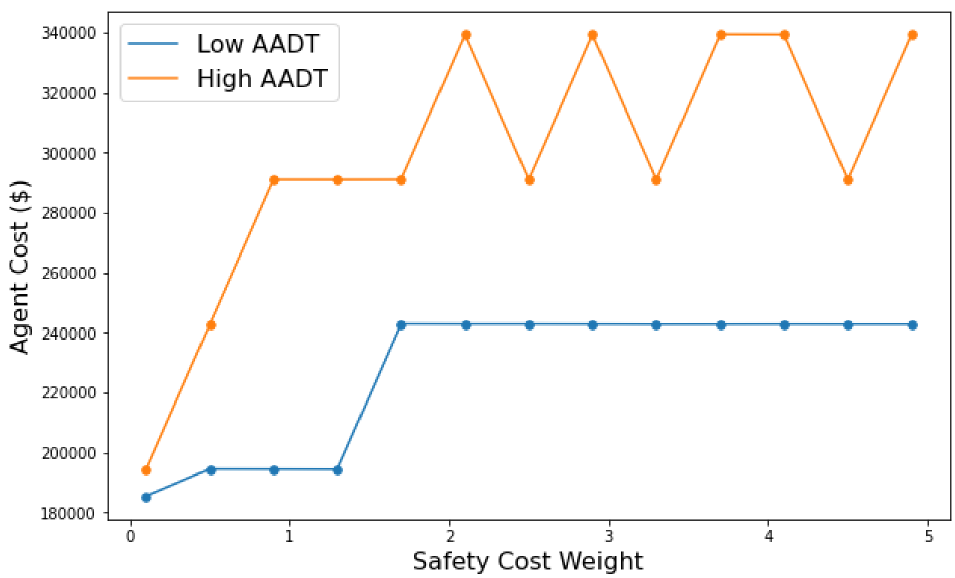


Figure 3.7. Agency costs change as safety weight varies for different AADT levels.

From Figure 3.8, it can be found that the safety cost has a higher impact on the MR&R planning when the AADT is high. The agency cost increases more in the high AADT situation when taking safety costs into consideration. In fact, when the safety cost weight increased to 7 E_S, the necessary number of actions increased from 4 to 9 in the high AADT situation, while it only increased to 6 in the low AADT condition. This is understandable, since as the traffic load increases, the predicted crash frequency increases as well. This will push the agent to conduct more maintenance activities to improve the pavement condition, thereby reducing the safety cost.

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CHAPTER 4

Conclusions

This study first developed a safety prediction model that considers IRI, and then explored the impacts of safety on MR&R planning.

The results of the safety prediction model that considers IRI suggest that if traffic is low (e.g., low AADT), the errors associated with not considering IRI in crash prediction are small (e.g., between 1% and -4 % for low and high truck percentages, respectively). However, for roadways with large AADT, not considering IRI can lead to larger errors in crash prediction (e.g., between -5% and -21% for low and high truck percentages, respectively). Further, the results also show that maintenance activities that reduce IRI can significantly reduce crash outcomes.

The results of incorporating safety into MR&R activities show that as more weight is put on the safety cost, the required maintenance activities increase so that the pavement can maintain a good condition. Specifically, when adding the safety cost into the objective function with a weight of E_S, the predicted crash frequency decreased by 0.0088 fatal or injury crashes, which led to the agency cost increasing to $241,825 for pavement deteriorated from IRI 2. In other words, when the safety cost is considered in the MR&R planning with an economic cost suggested by *Pennsylvania Crash Facts & Statistics*, the agency cost increased 32% for the pavement starting from IRI 2. The optimal MR&R plans suggested that one extra maintenance activity is needed in 50 years of MR&R planning when considering the cost of crashes in an economic manner for pavements starting from IRI 2. This indicates that traffic safety has a higher impact on worse condition pavement MR&R planning compared to that of pavement in good condition. The results also show that the impact of safety on MR&R planning is highly sensitive to the transition matrixes. A slight variation of transition probability could lead to different preferences for maintenance activities. Therefore, a well-performed deterioration model is critical in MR&R planning. Finally, this study examined the impact of safety costs on MR&R planning for segments with different traffic loads. More additional maintenance activities are needed for segments with higher traffic load compared to segments with low AADT.