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THE IMPACT OF PAVEMENT CONDITION ON ROAD SAFETY IN NEW BRUNSWICK

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Abstract: This study developed an understanding of the relationship between pavement condition and road safety on rural arterial and collector roads in the province of New Brunswick. The intent was to use this relationship for consideration as a decision-making criterion in asset management programs. Two crash prediction models were developed for single-vehicle and multiple-vehicle collisions using a negative binomial regression that relates pavement condition indicators to accident frequency. International Roughness Index was found to be significant in both models which indicate that IRI is a contributing factor to single-vehicle and multiple-vehicle accident involvements. It is noteworthy that the model coefficient for IRI was determined to be negative in both models which reflects that a higher number of collisions is expected to occur on road sections with smoother pavement surfaces. Crash modification functions were developed for both single-vehicle and multiple-vehicle collisions. The results indicate that a unit of increase in IRI in m/km is expected to decrease single and multiple-vehicle accidents by 7.7% and 14.8%, respectively. It was also found that the percentage of change in multiple-vehicle collisions due to pavement roughness changes, while all other variables in the models remain constant, is approximately two times greater than the percentage of change in single-vehicle accidents. According to the crash modification functions (CMF) associated with pavement age, the results indicated that collector roads are slightly more impacted by pavement roughness than arterial roads.

1 INTRODUCTION

There were 1,669 fatal and 116,735 injury motor vehicle accidents in Canada in 2015 where more than 1,800 lives were lost and nearly 162,000 people were injured (Transport Canada 2015). Statistics Canada (2018) information shows accidents were the fourth or fifth leading cause of deaths in Canada from 2009 to 2014. These results indicate that, despite many recent studies undertaken with the goal of reducing collisions, safety remains a significant issue necessitating further investigations to identify more efficient approaches to reduce accidents.

Most of the studies on traffic safety have evaluated the impact of human factors, road geometrics, roadway environmental factors, and vehicle attributes on collisions. Few studies have investigated the impact of pavement condition on road safety due to a lack of a quantitative pavement data collection technology before the 1990s (Chan *et al*. 2009).

Pavement condition is assessed using pavement condition indicators which are used to translate agency objectives into specific, quantifiable measures required for pavement management (TAC 2013). Exploring the relationship between pavement condition indicators and collision experience can help transportation agencies to quantitatively evaluate their pavement condition in terms of safety to provide baseline data for asset management systems.

2 IMPACT OF PAVEMENT CONDITION ON COLLISION OCCURRENCE, TYPE, AND SEVERITY

Several studies have quantitatively evaluated the impact of pavement condition on accidents using various pavement condition indicators including the impact on accident occurrence, collisions types, and accident severity. It is noted that only international roughness index (IRI) and rut depth (RD) were used in this study. Pavement roughness is defined as the deviation of a surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads and drainage, for example, longitudinal profile, transverse profile, and cross slope. International roughness index is used to quantify pavement roughness. The profile of the road is measured by road profilers which produce a series of offsets related to the "true profile" of the road allowing IRI to be calculated in m/km or in/mi.

Start *et al*. (2007) quantified the impact of rutting on collision rates on rural undivided highways where he found that rut depth levels greater than 7.6 mm significantly affect road safety. Anastasopoulos and Mannering (2009) found that international roughness index (IRI) is an excellent binary variable significantly influencing collision occurrences on low volume rural interstate highways. They also indicated that a unit increase in the maximum IRI (1 in/mi = 0.016 m/km), results in an average of 0.8 percent increase in the number of annual collisions.

Chan *et al*. (2009) revealed that IRI is a significant variable to predict collision frequency on urban interstate highways with moderate to high traffic volumes, while RD is not a contributing factor. According to their analysis, a 100 in/mi increase in IRI would increase collision frequency by 1.6 times. Li and Huang (2014) found that impact of poor pavement condition on accidents is more significant on urban collectors, and high-speed roads (speed limits of greater than 104.6 km/hr).

Al-Masaeid (1997) found that the increase in the IRI level would reduce the single-vehicle accident rate while increasing the multiple-vehicle accident rate on two-lane undivided roads in Jordan. He also indicated that IRI has no statistical effect on the total accident rate. He suggested that it would be beneficial from a safety perspective to keep the IRI below 5 m/km on rural two-lane roads.

Li *et al*. (2013) quantified the impact of pavement condition on crash severity and found the severity is more significant on multi-lane, non-freeway arterials with relatively high-speed limits, dry pavement surface, and daylight conditions. They determined that fatal or incapacitating crash severity level is more impacted by IRI than other crash severity levels. Zeng *et al*. (2014) conducted a before-after study to quantitatively evaluate the safety effectiveness of good pavement conditions versus deficient pavement conditions. They found that good pavement condition can reduce fatal and injury crashes by 25% on rural two-lane undivided primary highway segments with a traffic volume of from 76 to 29,142 vehicles per day. Lee *et al*. (2015) investigated the impact of poor pavement condition on crash severity levels for low (≤56.3 km/hr), medium (64.4 km/hr -72.4 km/hr), and high (≥80.5 km/hr) speed roads. They indicated that pavement condition increases the severity of multiple-vehicle crashes on all three speed-level roads.

3 RESEARCH GOAL AND OBJECTIVES

The overall goal of this study was to develop a better understanding of the relationship between pavement condition and safety in the province of New Brunswick for consideration as a decision-making criterion in the New Brunswick Department of Transportation and Infrastructure's (NBDTI) asset management system.

The specific objectives set out to meet the study goal were to:

1. Develop crash prediction models for single-vehicle and multiple-vehicle accidents to relate collision frequency to the pavement condition indicators.

2. Develop crash modification factors (CMF) for single-vehicle and multiple-vehicle accidents to estimate the effectiveness of pavement condition improvements on collisions.

4 METHODOLOGY

The targeted facility types were segments (control sections) of rural two-lane, two-way, undivided collector and arterial roads throughout the province of New Brunswick. For these facility types, nearly 3,100 kilometres of roads in the province were found to be appropriate for this study which included about 950 kilometres of arterial roads and over 2,100 kilometres of collector roads.

The following variables were gleaned from the selected control sections and included for analysis:

1. HORIZONTAL CURVATURE (>4 degrees): including the number of sharp horizontal curves per kilometre (NSHCPK) and weighted average degree of sharp horizontal curves (ADHC)

2. GRADIENT (>5%): including number of sharp grades per kilometre (NSGPK), and weighted average of sharp grades (AVSG)

3. INTERSECTION DENSITY: number of intersections per kilometre (IPK)

4. POSTED SPEED LIMIT (km/hr): weighted average posted speed (APSL)

5. TRAFFIC VOLUME: average annual daily traffic (AADT) of the selected control sections were obtained for use as potential predictors in the crash prediction models

6. PAVEMENT CONDITION INDICATORS: data were used to calculate the average IRI and RD on the control sections available on arterial roads

7. ACCIDENT FREQUENCY: To reduce the number of control sections with zero accident frequency and consequently improve the accuracy of the models, three-year total accident frequencies (single and multiple) from NBDTI datasets were used in this study.

5 STATISTICAL ANALYSIS

Since collision frequencies are count data which refer to observations that have only non-negative integer values ranging from zero to some greater undetermined values such as accident frequency, Poisson and Negative Binomial (NB) distributions can be used for developing the crash prediction models (Abdel-Aty and Radwan 2000). If collision data are equi-dispersed then Poisson regression is an appropriate approach. Given that the variance of the collision frequencies for the control sections were found to exceed the means, the Negative Binomial (NB) regression was a more appropriate modelling approach to employ for this study.

The NB model is a two-parameter model-with mean (μ) and dispersion parameter (α). The traditional parameterization of the negative binomial is known as the NB2 negative binomial model which was used in this study. Different methods have been proposed for estimating the coefficients of the NB models with the method of maximum likelihood estimation (MLE) being the most widely used. With respect to the dispersion parameter of the NB model, the traditional negative binomial model (TNB) which assumes that the dispersion parameter of the negative binomial distribution is fixed for all locations was selected for use in this study.

The minimum sample size requirements recommended by Lord (2006) as a function of the sample mean values were used in this study resulting in minimum required sample size for single-vehicle and multiple-vehicle collision models estimated to be 84 and 218, respectively which were satisfied given the number of available control sections (243).

5.1 Model Specification

The mathematical form of the crash prediction models should meet the following two criteria: it must yield logical results, meaning that it should not lead to the prediction of a negative number of accidents and it should ensure a prediction of zero accident frequency for zero values of the exposure and length variables.

There must exist a known link function that can linearize this form for the purpose of coefficient estimation (Sawalha and Sayed 2001). The following model used in this study satisfies these criteria.

[1] $AF = a_0 * L^{a_1} * AADT^{a_2} * \exp\left(\sum_{j=1}^{m} b_j * x_j\right)$

where, AF: Predicted accident frequency

L: Segment length (km)

AADT: Average annual daily traffic

x_j: Any of m variables additional to length and AADT

a_0, a_1, a_2 and b_j: Model parameters to be estimated

Explanatory variables for the final models were selected in a stepped approach beginning with AADT and length. Correlation and multicollinearity among variables were tested to ensure independence. Outlier data were identified with a procedure known as Cooks distance (Cook 1977, SAS/STAT 2015).

5.2 Assessment of Fit

While there are several measures that can be used for estimating how well a model fits the base data, in this study two approaches were used. The Scaled Deviance and Pearson χ^2 are asymptotically χ^2-distributed with n-p degree of freedom where n is the number of observations used in the model and p is the number model parameters including intercept and predictors included in the model. A model is valid if its scaled deviance and Pearson χ^2 are less than ${\chi^2}_{0.05,n-p}$ where ${\chi^2}_{0.05,n-p}$ is critical χ^2 value at the 95% confidence level which can be obtained from the chi-square distribution table.

The second criterion used in this study to assess goodness-of-fit of crash prediction models was the plot of the observed crash frequency versus predicted crash frequency. For a perfect model, the linear trendline fitted to the data, should have the equation y=x, while R^2 is equal to 1 or close to 1. In this study, regression analysis was performed to evaluate the intercept and slope of the linear trendline fitted to the data.

5.3 Pavement Deterioration Equations

Transportation agencies use pavement deterioration curves to predict how pavement condition will change over time in their road network. NBDTI uses different pavement deterioration curves in terms of IRI for the road classification types in New Brunswick. In order to simplify the application of these pavement deterioration curves, pavement deterioration equations were obtained through fitting the best trend line (highest R^2) to the data that the curves were based on using Microsoft Excel. Therefore, the following local pavement deterioration models were obtained for arterial and collector roads separately:

Arterial Roads:

[2] $IRI\_i = 0.8803*Exp(0.0442*i)$

Collector Roads:

[3] $IRI\_i = 1.18*Exp(0.0395*i)$

where:

IRI_i: IRI in the i^{th} year

i: Pavement age.

5.4 Crash Modification Factors (CMF)

According to FHWA (2010), A CMF is simply defined as a multiplicative factor used to reflect the expected change in safety performance associated with the corresponding change in highway design and/or the traffic control feature. CMF for a countermeasure i ($\mathrm{CMF_i}$) is calculated as follows:

$$[4]\ \mathrm{CMF_i} = \frac{\text{Expected number of crashes if change I is made}}{\text{Expected number of crashes if change I is not made}}$$

There are several methods for developing CMFs including before-after with a comparison group, full Bayes, cross sectional, case control, etc. (FHWA, 2010). Since the method used in this study was a cross-sectional approach, crash modification functions (CMFunctions) associated with IRI for single-vehicle accidents and multiple-vehicle accidents were developed assuming that only IRI changes, while all other predictors in the models remain constant. For practical purposes, pavement deterioration equations were used to translate CMFunctions to pavement age.

6 ANALYSIS AND RESULTS

6.1 Single-Vehicle Collision Model

For the single-vehicle accident model, average annual daily traffic (AADT), length (L), number of intersections per kilometre (IPK), average vertical grades (AVG), and international roughness index (IRI) were identified to be significant. The highest value in the correlation matrix was determined to be -0.51 (between AADT and IRI) which shows that there is no major correlation between the pairs of variables included in the model. All the VIFs were calculated to be below two which is an indication that, there is no significant multicollinearity among the variables. Indeed, five observations were detected as outliers and removed from the model. As a result, the final model was developed using 238 observations (243 total -5 outliers). The result of the maximum likelihood parameter estimation analysis is presented in Table 1. The mathematical form of the single-vehicle accident model can be written as follows:

$$[5]\ \mathrm{SAF} = 0.0085 * \mathrm{AADT}^{0.59} * \mathrm{L}^{1.04} * \mathrm{Exp}(0.2 * \mathrm{IPK} + 0.03 * \mathrm{AVG} - 0.08 * \mathrm{IRI})$$

where: SAF: Single-vehicle accident frequency (accidents/3 years)

AADT: Average annual daily traffic (vehicles/day)

L: Length (km)

IPK: Intersection density per kilometre

AVG: Weighted average gradient (%)

IRI: International roughness index (m/km)

Table 1: Analysis of maximum likelihood parameter estimates (single-vehicle collision model)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	p-value
Intercept	1	-4.77	0.51	-5.76	-3.77	88.18	<.0001
AADT	1	0.59	0.05	0.5	0.69	147.62	<.0001
Length	1	1.04	0.11	0.83	1.24	96.74	<.0001
IPK	1	0.2	0.07	0.07	0.33	9.43	0.0021

IRI	1	-0.08	0.04	-0.15	-0.01	4.89	0.027
AVG	1	0.03	0.01	0.01	0.06	8.36	0.0038
Dispersion Parameter	1	0.1017	0.02	0.07	0.14	31.92	<.0001

The degrees of freedom of the single-vehicle accident model were determined to be 232; therefore the critical chi-squared value for this model at the 95% confidence level was estimated to be 268.53. The Scaled deviance (SD) and Pearson Chi-squared (Pearson χ^2) of this model were obtained to be 251.06 and 235.64 respectively which are both below $\chi^2_{0.05,232}$ (268.54). This is an indication that according to the first criteria, the single-vehicle accident model is valid. The plot of the actual accident frequency versus predicted accident frequency can be found in Figure 1.

Performing regression analysis, the intercept of the linear trendline fitted to the data was estimated to be 0.8 which was found not to be significantly different than 0. The slope was estimated to be 0.93 which is close to 1 and was identified to be significant at the 95% confidence level as its p-value is below 0.05. Finally, the R-squared was determined to be 0.58 which means that the model explains about 60% of the variability of response data.

These results indicate that the model is valid as the equation of the trend line is not significantly different from the ideal equation (y=x), although there is an indication of missing some important variables for predicting single-vehicle accident occurrence such as variables related to roadside condition.

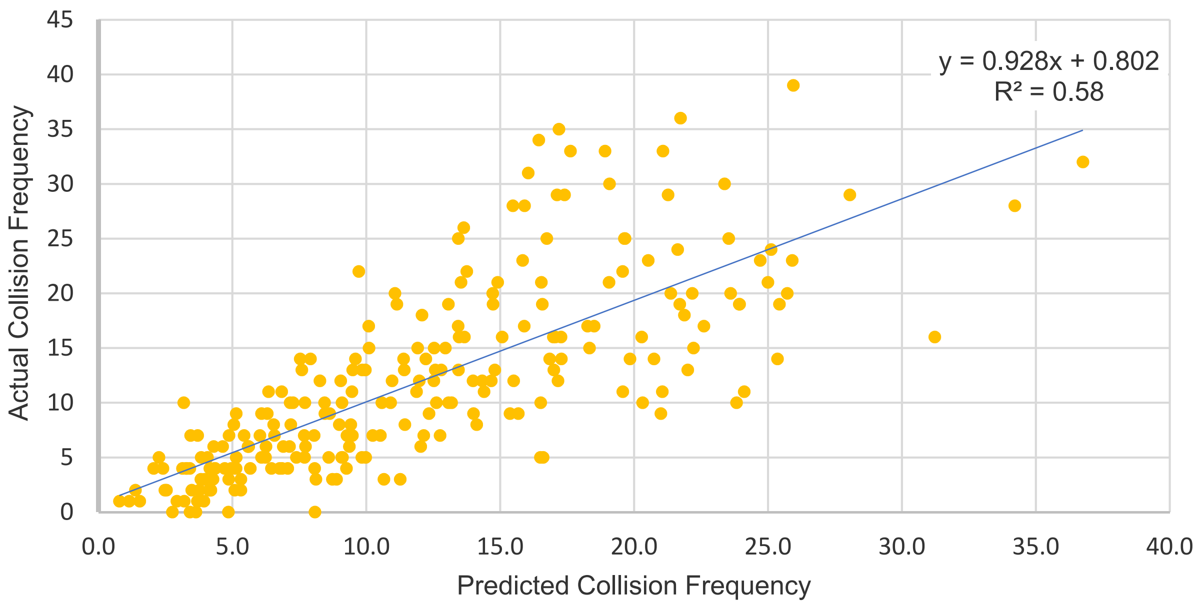

Figure 1: Actual collision frequency versus predicted frequency (single-vehicle)

6.2 Multiple-Vehicle Collision Model

For the multiple-vehicle collision model, average annual daily traffic (AADT), length (L), number of intersections per kilometre (IPK), average posted speed limit (APSL), and international roughness index (IRI) were identified to be significant. The highest value in the correlation matrix was determined to be -0.51 (between AADT and IRI) which shows that there is no strong correlation between the pairs of variables included in the model. All the VIFs were calculated to be below two which is an indication that, there is no significant multicollinearity among the variables. Indeed, only one observation was detected as an outlier and removed from the model. As a result, the final model was developed using 242 observations

(243 total -1 outlier). The result of the maximum likelihood parameter estimation analysis is presented in Table 2.

Table 2: Analysis of maximum likelihood parameter estimates (multiple-vehicle collision model)

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	P-value
Intercept	1	-4.43	0.92	-6.23	-2.63	23.26	<.0001
LOGA	1	1.01	0.08	0.86	1.16	170.53	<.0001
LOGL	1	0.89	0.15	0.58	1.19	32.97	<.0001
IPK	1	0.49	0.1	0.3	0.68	25.16	<.0001
APSL	1	-0.05	0.01	-0.06	-0.04	67.77	<.0001
IRI	1	-0.16	0.06	-0.27	-0.04	6.91	0.0086
Dispersion Parameter	1	0.14	0.04	0.09	0.23	16.83	<.0001

The mathematical form of the multiple-vehicle accident model can be written as follows:

[6] $\mathrm{MAF} = 0.0119 * \mathrm{AADT}^{1.01} * \mathrm{L}^{0.89} * \mathrm{Exp}(0.49 * \mathrm{IPK} - 0.05 * \mathrm{APSL} - 0.16 * \mathrm{IRI})$

where: MAF: Multiple-vehicle accident frequency (accident/3 years)

AADT: Average annual daily traffic (vehicles/day)

L: Length (km)

IPK: Intersection density per kilometre

APSL: Average posted speed limit (km/h)

IRI: International roughness index (m/km)

The degrees of freedom of the multiple-vehicle accident model was determined to be 236, therefore the critical chi-squared value for this model at the 95% confidence level was estimated to be 272.84 ($\chi^2_{0.05,236}$). The Scaled deviance (SD) and Pearson Chi-squared (Pearson χ^2) of this model were obtained to be 262.76 and 254 respectively which are both below $\chi^2_{0.05,236}$ (272.84). This is an indication that according to the first criteria, the multiple-vehicle accident model is valid.

The plot of the actual accident frequency versus predicted accident frequency is very similar to that shown in Figure 1. Performing regression analysis, the intercept was estimated to be 0.16 which is statistically no different than 0. The slope was estimated to be 0.96 which is statistically no different than 1. These results indicate that the equation obtained from the plot is very close to the y=x line which is the ideal relationship. Finally, the R-squared was determined to be 0.67 which means that the model explains about 70% of the variability of the response data. In summary, the model is valid and fits the data better than the single-vehicle accident model.

Rut depth (RD) was not found to be significant in both models which is an indication that rut depth is not a contributing factor in accident occurrence on rural two-lane undivided arterial and collector roads. One of the reasons might be the range of RD used in this study which was between 0.07mm and 12.7mm, while according to TxDOT, RD values below 12.7 mm are classified in “no rutting” category.

The coefficient of IRI was estimated to be negative in both models, which means that as pavement deteriorates, while all other significant variables in the models remain constant, single-vehicle accidents and multiple-vehicle accidents are predicted to be decreased. One of the main reasons might be that people are more cautious on rougher roads and tend to slow down on poor pavements.

6.3 Crash Modification Functions

Crash modification functions (CMFunctions) were developed for single-vehicle and multiple-vehicle accidents using equation 4 as follows:

$$[7]\ \mathrm{CMF_s} = \mathrm{Exp}\big(-0.08(\mathrm{IRI_2} - \mathrm{IRI_1})\big)$$

$$[8]\ \mathrm{CMF_M} = \mathrm{Exp}\big(-0.16(\mathrm{IRI_2} - \mathrm{IRI_1})\big)$$

where: $\mathrm{CMF_s}$: CMFunction for the single-vehicle accidents

$\mathrm{CMF_M}$: CMFunction for the multi-vehicle accidents

$\mathrm{IRI_1}$: The initial IRI (m/km)

$\mathrm{IRI_2}$: The IRI value at the time of safety evaluation (m/km)

CMFunctions indicate that one-unit increase in IRI in m/km, while all other variables in the models remains constant, is predicted to reduce single-vehicle and multiple-vehicle accident frequencies by 7.7% and 14.8%, respectively.

In order to make the CMFunctions more practical, CMFunctions associated with pavement age were developed using available pavement deterioration equations. Since deterioration rates on arterial and collector roads are different, four CMFunctions were obtained which can be found in Table 3.

In order to compare the safety performance of new pavements with deteriorated pavements, CMFs associated with $\mathrm{PA_1}$ of 0 and $\mathrm{PA_2}$ of from 0 to 15, were calculated and are depicted in Figures 2 and 3. These figures indicate that, as pavement deteriorates, single-vehicle and multiple-vehicle accident frequencies are expected to decrease gradually on both road classifications types. The percentage reduction in multiple-vehicle accident frequency is approximately two times higher than single-vehicle accident frequency. Collector roads are slightly more impacted by road roughness than arterial roads.

Table 3: CMFunctions Associated with Pavement Age

Road Classification	Single-Vehicle Accidents	Multiple-Vehicle Accidents
Arterial Roads	$\mathrm{Exp}(-0.0704(1.0452^{\mathrm{PA_2}} - 1.0452^{\mathrm{PA_1}}))$	$\mathrm{Exp}(-0.1408(1.0452^{\mathrm{PA_2}} - 1.0452^{\mathrm{PA_1}}))$
Collector Roads	$\mathrm{Exp}(-0.0944(1.0403^{\mathrm{PA_2}} - 1.0403^{\mathrm{PA_1}}))$	$\mathrm{Exp}(-0.1888(1.0403^{\mathrm{PA_2}} - 1.0403^{\mathrm{PA_1}}))$

where: $\mathrm{PA_1}$: Initial age of the pavement section.

$\mathrm{PA_2}$: Pavement age in which safety evaluation is performed.

With respect to pavement treatment, the results indicate that applying pavement treatments is predicted to (counter-intuitively) increase accidents. The main reason may be that drivers tend to increase their speed on pavements with excellent condition which can result in higher collision experience. For example, if it is assumed that pavements are reconstructed after 15 years, single-vehicle and multiple-vehicle accidents are predicted to increase by 7% and 14% respectively, on collector roads.

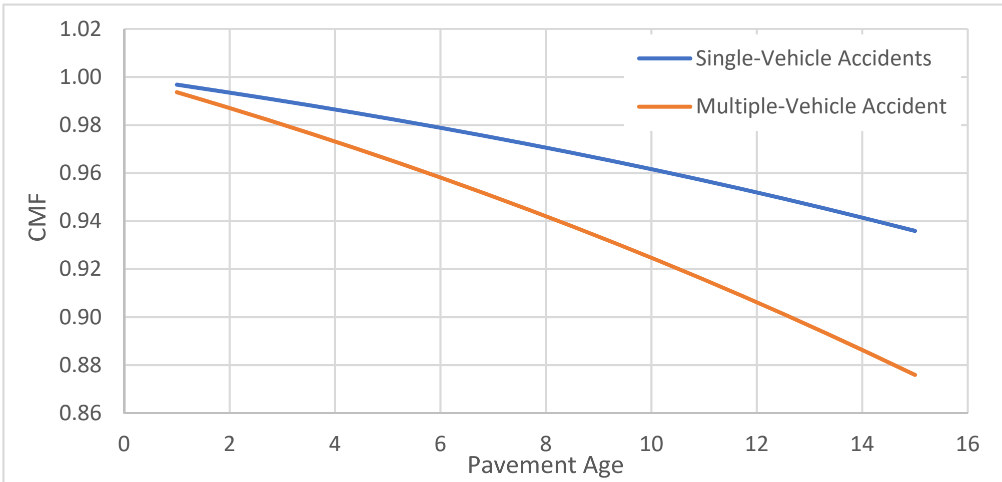

Figure 2: CMF Associated with Pavement Deterioration on Arterial Roads

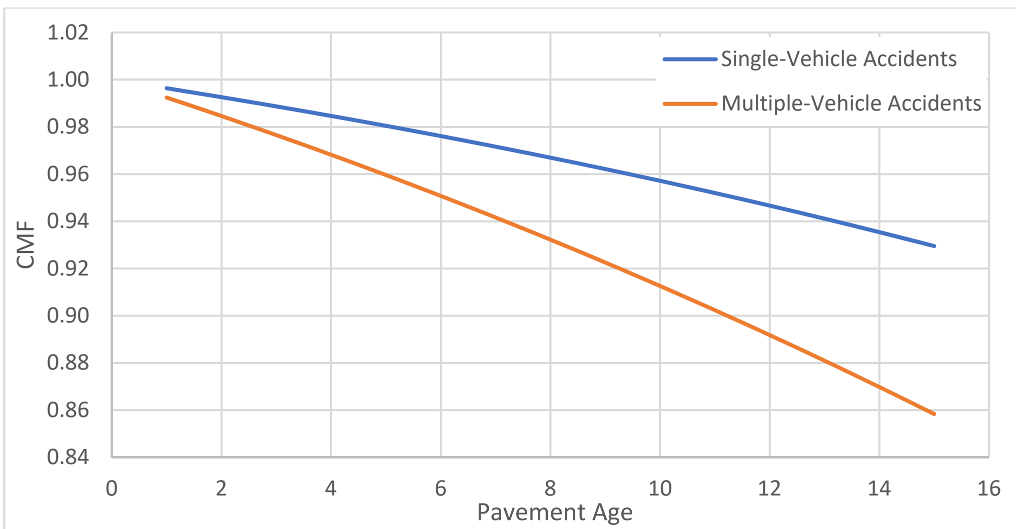

Figure 3: CMF Associated with Pavement Deterioration on Collector Roads

7 CONCLUSIONS

Two crash prediction models were developed separately for single and multiple-vehicle collisions. International roughness index (IRI) was found to be significant in both models which indicates that road roughness contributes to collision experience on rural two-lane undivided arterial and collector roads. An inverse relationship was found between IRI and collision experience (collisions tend to decrease with rougher roads). Rut depth (RD) was not found to be significant in both models which is an indication that rut depth is not a statistically significant explanatory variable for collision occurrence on rural roads.

Crash modification functions were developed for single-vehicle and multiple-vehicle collisions using a cross-sectional approach recommended by FHWA (2010). The results indicate that the impact of road roughness on multiple-vehicle accidents is twice the impact of road roughness on single-vehicle accidents (a unit of increase in IRI in m/km is expected to decrease multiple and single-vehicle accidents by 14.8% and 7.7%, respectively). Developing crash modification functions associated with pavement age, it was found that pavement deterioration decreases accidents gradually.The results also indicate that the impact of pavement roughness is slightly more significant on collector roads than on arterial roads.

8 RECOMMENDATIONS

The crash prediction models and crash modification functions developed in this study are applicable only for rural-two-lane undivided arterial and collector roads and are calibrated for the province of New Brunswick. Transferability of these models to other jurisdictions may require reformulation/calibration.

AADTs on the roads used in this study are between 60 and 8,000 vehicles/day. It is highly recommended that new models be developed for application to roads with AADTs outside of this volume range.

It is recommended that higher values of rut depth (RD) (0.07mm to 12.7mm used in this study) be investigated to identify if greater values have a predictive impact on collision occurrence.

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