Development of a Simplified Approach for Assessing the Level of Safety of a Highway Network Associated with Pavement Friction

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ABSTRACT

One of the most important indicators of level of service for a highway network is safety. Each year, thousands of motorists across North America are involved in motor vehicle collisions, which result in property damage, congestion, delays, injuries and fatalities. In Ontario, the Ministry of Transportation (MTO) is responsible for the maintenance and construction of approximately 39,000 lane-kilometres of highway. In 2004, the province estimated the value of the total highway system at $39 billion dollars. The MTO estimated that in 2002, vehicle collisions in Ontario cost the province nearly $11 billion. It also estimated that for every dollar spent on traffic management, 10 times that amount could be saved on collision-related expenditures, including health care and insurance claims.

The safety of highway networks are usually assessed using various levels of service indicators such as ride quality (IRI), surface friction (SN), or number of collisions. This paper presents a simplified framework for assessing the level of safety of a highway network in terms of the risk of collision based on pavement surface friction. The developed safety framework can be used by transportation agencies (federal, state, provincial, municipal, etc.) or the private sector (consultants, contractors, concessionaires, etc.) to evaluate the safety of their highway networks and to determine the risk or probability of a collision occurring given the level of friction along the pavement section of interest.
INTRODUCTION

Civil infrastructure is a vital component of our society’s health, safety, and economy. Each year, billions of taxpayer’s dollars are invested in constructing, maintaining, and rehabilitating all forms of civil infrastructure. In Canada, civil infrastructure represents a $1.6 trillion dollar asset [1]. Despite the significant investment in civil infrastructure, a $60 billion dollar backlog in municipal infrastructure exists, and 79% of the infrastructure has reached the end of their service life. In the United States, this problem is even more profound. According to the American Society of Civil Engineers (ASCE), a total investment needs budget of $1.6 trillion dollars is required over the next 5 years. Furthermore, deteriorated roads cost U.S. motorists $54 billion dollars in repair and operating costs each year [2].

Pavements are an integral component of civil infrastructure and our nation’s highway system. Everyday, billions of dollars in goods and services are transported along our highway networks. The Canadian transportation network is comprised of 1,042,300 kilometres of roadway, of which 415,600 km are paved (including 17,000 km of interstate) and 626,700 km of unpaved roadway [3]. Canada ranks next to the United States in per capita use of motor transport, with one passenger car for every two persons. In 2000, motor vehicles in use totalled 18,449,900, including 14,147,300 passenger cars and 4,302,600 trucks, buses, and taxis [4]. In Ontario, the Ministry of Transportation (MTO) is responsible for the maintenance and construction of approximately 39,000 lane-kilometres of highway. In 2004, the province estimated the value of the total highway system at $39 billion dollars [5]. Due to the size and significance of this considerable infrastructure asset, cost-effective maintenance and management practices are essential.

Highway Safety

One of the most important indicators of level of service for a highway network is safety. Each year, thousands of motorists across North America are involved in motor vehicle collisions, which result in property damage, congestion, delays, injuries and fatalities. The Ontario Ministry of Transportation estimated that in 2002, vehicle collisions in Ontario cost the province nearly $11 billion. It also estimated that for every dollar spent on traffic management, 10 times that amount could be saved on collision-related expenditures, including health care and insurance claims [6]. In 2000, all the provinces and territories in Canada endorsed Road Safety Vision 2010. The aim of this nation-wide initiative is to make Canadian roads among the safest in the world and to reduce the average number of fatalities and serious injuries resulting from motor vehicle collisions by 30% for the years 2008 to 2010 [6].

A strong relationship exists between safety, highway design and pavement performance. Outdated and poor geometric design practices along with deteriorated pavement conditions influence the safety of highway alignments. In the United States, over 43,000 fatalities occur on the nation’s roadways and 30% of all fatal highway collisions can be attributed to these factors [2]. As a result of this complex relationship, an effective framework and methodology is required to evaluate, analyze, research and manage our highway networks. The fundamental objective of this is to provide the public with the safest and most cost effective, transportation system within all known constraints.

Surface Friction

Surface friction between the tire of the vehicle and the pavement surface has a profound affect on highway safety. A driver must be able to adapt their behaviour to changing friction conditions in order to maintain an acceptable level of safety [7]. When road surfaces are dry, the friction generated between the tires and pavement is generally sufficiently high to provide adequate levels of safety. During wet or winter weather conditions, water can create a critical situation by increasing the potential for hydroplaning or skidding, especially when skid resistance of a pavement is low [8]. When skid resistance is low, the driver may not be able to stop the vehicle or retain stability on wet pavement. Skid resistance is defined as the force that resists the sliding of tires on a pavement when the tires are prevented from rotating.

The impact of surface friction on highway safety is a very complex problem. It consists of a relationship that involves the driver and vehicle, environmental conditions, and the pavement surface. The ability of a driver to accurately assess or estimate the friction conditions is poor [7]. This perspective is supported by several research studies such as speed measurements during different roadway conditions, driver interviews during slippery conditions, and vehicle simulator experiments. The main premise for these studies is that if the stopping distance for dry pavement conditions is considered an indicator of safe speed, then a reduction in speed as a result of poor surface friction (wet or icy conditions) should result in an equivalent stopping distance [3]. A study was carried out...
where vehicle speeds were recorded under different road conditions. For the studied highway (7-m wide, posted speed of 90 km/h), the average speeds were found to be 85 km/h to 95 km/h for dry pavement conditions. During winter conditions, a 6 to 10 km/h decrease in the posted speed limit was recorded despite icy and snow packed pavement conditions. To maintain equivalent “dry” pavement surface stopping distances, the speed of the vehicle should have been reduced to 56 km/h [7].

Several other studies have shown similar findings. A number of research studies examining collision data and surface friction in European countries such as the Netherlands, Germany, and France have shown that the number of collisions and the relative proportion of collisions at skid-prone sites increase sharply when the friction coefficient decreases. For example, when the level of friction is 0.35 to 0.44, the collision rate is 0.20 (personal injuries/million veh-km). When the level of friction is less than <0.15, the collision rate increases by 300%. Recent research has shown the benefits of mix design and hot mix asphalt technologies on the surface friction of newly constructed pavements [9]. A review of the literature reveals that there are no specific guidelines when it comes to acceptable levels of surface friction. However, pavements with a skid number (SN) below 35 could potentially be problematic from a safety standpoint [10]. The Transportation Association of Canada (TAC) recommends that a pavement section with a skid number below 32 is a potential risk and preventative maintenance should be considered [11].

ANALYSIS METHODOLOGY

The purpose of this study is to develop an approach for assessing the level of safety of a highway network using network level friction and collision data. No previous studies of this kind have been performed in the Province of Ontario at the network level. As a part of this research study, a significant data collection program consisting of network level friction data, traffic data, collision data, and highway attribute data was undertaken. The development of any models or statistical analysis requires both high quality data and a structured database. To assess the safety and risk of collision on the highway network, a multi-step procedure was developed (Figure 1). This section provides an outline of the various data elements, provides an overview of the data integration and linkage, and presents the results of the statistical analysis and model development.

DATA ATTRIBUTES

All data for this study was obtained from the Ontario Ministry of Transportation (MTO). Each data element was checked for completeness; QA/QC’d, and formatted prior to analysis. The next sections provide an overview of the various data elements of this study.

Surface Friction

In preparation for a considered Long Term Area Maintenance Contract, a project was initiated by the Ontario Ministry of Transportation (MTO) to collect network level friction data across three regions in the Province of Ontario. In 2006, approximately 1,800 km of the MTO highway network was surveyed a part of this study. Due to the sensitivity of the data and the potential risk to the agency, the regions will be referenced within as Regions A, B, and C. Friction data was collected to determine a baseline of the current network friction levels in terms of a skid number. In addition to friction data, traffic and collision data were also obtained from the Traffic department within MTO. A trailer mounted locked-wheel skid tester was used to collect the friction data.

A 1.0 km sampling interval was selected as a reasonable measuring interval to perform the skid testing. At each test point, the skid number (SN), average test vehicle speed, and kilometre post were recorded. The average network level skid number for the three regions is 37.5. The average skid number for Regions A, B, and C are 36.27, 37.68, and 51.76 respectively.

Traffic Data

A critical component of any pavement or safety related study is traffic data. Factors such as the annual average daily traffic (AADT), annual average daily truck traffic (AADTT), and % commercial truck traffic all influence pavement performance and the level of safety of a highway alignment. Traffic data was obtained from the MTO between the years 2003 and 2005. This data was collected from various fixed traffic data collection sensors (WIM and weigh scales) located across the three regions.
FIGURE 1 Analysis Framework

Data Collection MTO

Traffic  Collision  Friction  Highway Attribute

Data Manipulation & Integration

Development of Database

Data Completeness Checks - QA/QC

Data Aggregation  Factorial Design

Statistical Analysis & Modeling

TRB 2009 Annual Meeting CD-ROM Paper revised from original submittal.
Collision Data

The Traffic Department at the MTO is responsible for collecting and maintaining a comprehensive vehicle collision database. When a collision occurs on a highway segment, provincial police officers produce a detailed record of the collision including such factors as collision type, weather conditions, surface conditions, location, object of impact, etc. This data is then entered into a Traffic Management System that can be queried to extract data and key fields of interest. Due to the sensitivity and confidentiality of the collision data, only information related to the driver’s age, gender and mental condition is provided. No personal information such as name or address is available to the public or researchers. Presented in Figure 2 are distributions of collision data by Region, Season, Severity Type, and Surface Conditions for all highways within the three Regions.

Highway Attribute Data

The MTO uses the Linear Highway Referencing System (LHRS) to section their highway segments into manageable pavement sections. Each highway segment is referenced with a unique highway identification number. As an example, a highway might have a length of 100 km and have 12 unique individual LHRS sections each of varying length. Each unique LHRS section “resets” the linear offset distance at the start of each new section. All collision data and locations are referenced to the LHRS and the correct linear offset.

The Highway Network

The highway network in question is comprised of approximately 1,800 km of highway located across three regions in Southern Ontario. This data was collected across 33 individual highway segments consisting of an assortment of functional classes (2 lane undivided, 4 lane divided, interstate, etc.).

FIGURE 2 Distribution of Collision Data by Region, Season, Severity Type, and Surface Condition
DATA INTEGRATION

An important component of any statistical analysis is a structured and complete data set. This section outlines the linkage and aggregation of the various data sets and attributes.

Data Linkage

Friction data in terms of a skid number (SN) was collected along a single direction of each highway segment in the network. The data was collected continuously with increasing chainage (kilometres) for the positive directions (north and east) and decreasing chainage for the negative directions (south and west). It is important to note that the referencing is different than the LHRS and collision locations, by referencing cross roads, bridges, and jurisdictional boundaries.

The collision data is referenced by the kilometre-post at the location of the collision and is referenced to the LHRS and correct offset. Each highway section is segmented into manageable LHRS sections that “reset” the linear offset distance along the length of each new section (LHRS).

As previously mentioned, skid data was collected at an interval of 1.0 km along the length of each highway section (and LHRS) and a collision record can occur anywhere along the length of each LHRS. To correctly assign a friction value to a collision location, the nearest friction value (SN) was assigned to the corresponding collision location. Since the skid data and collision data are referenced using different linear offsets, a considerable effort was undertaken to link or integrate the two independent datasets. Unfortunately, due to the inconsistency in the file formats of the collected skid data, a computer program or macro could not be written to carry out this task. As a result, the data integration was done “manually” and took considerable time and efforts. This was a critical step for any model development and statistical analysis and stresses the importance of an integrated test-setup, protocols, and procedures when performing any data collection activities.

Data Aggregation

The vehicle collision database is a comprehensive data set with several fields related to various attributes and characteristics of the collision. Each data field is typically a categorical or descriptive variable. Since many of the categorical variables are similar in nature, they were “grouped” or aggregated into similar variable classes. This reduces the complexity and size of the dataset and redundancy within the variable classes.

As an example, for the data field “visibility”, the following variables are attributed to visibility: clear, sunny, snowy, windy, raining, foggy, etc. The visibility field was reduced from 8 descriptive variables into 4 as a result of the aggregation.

RESULTS AND ANALYSIS

The following sections discuss the various statistical analyses and model development components of this study. A multi-step approach was used to develop the safety framework to assess the level of risk or probability of collision occurrence as a function of the friction level along a pavement section or highway network.

Categorization of Data and Descriptive Statistics

As a first step, the friction and collision data was examined on a point-by-point basis. At this level, a relationship between the collision rate (or number of collisions) and the level of friction (skid number) were developed. As can be seen in Figure 3, there is no significant trend or strong correlation in the data ($R^2 =0.0024$). In addition, when the friction levels were examined in detail within each region, the pavements in Region C showed significantly higher friction levels compared to the other two regions.
Figure 3: Relationship Between Friction and Collision Rate on a Point-by-Point Basis

The minimum, maximum, and average skid number values in Region C are 35.1, 68.6 and 51.8 respectively. Since Region C is located within the Canadian Shield, which is well known for its very hard rock formations, the aggregate sources in this region have excellent skid resistance properties. As a result, other factors such as geometric design and site distance have a more profound affect on highway safety within this region. Due to this fact, Region C was removed from the analysis since it did not represent typical friction levels in Southern Ontario, where the greatest part of the province’s highway network is located.

Since the first method did not provide meaningful relationships or strong correlations, the friction and collision data were examined in grouped ranges or bins. At this level, a relationship between the total number of collisions within a given friction level were examined at the network level (with Region C now removed from the study).

The friction data was categorized or grouped into the following bins:

- **Bin 1**: SN <=32
- **Bin 2**: 32 <= SN < 34
- **Bin 3**: 34 <= SN < 36
- **Bin 4**: 36 <= SN < 38
- **Bin 5**: 38 <= SN < 40
- **Bin 6**: 40 <= SN < 42
- **Bin 7**: 42 <= SN < 44
- **Bin 8**: 44 <= SN < 46
- **Bin 9**: 46 <= SN < 48
- **Bin 10**: 48 <= SN < 50
- **Bin 11**: 50 <= SN < 52
- **Bin 12**: SN >= 52

The bin ranges were established by examining the distribution of the skid number within each region (Region A and B), a review of the literature [TAC] & [VTRI], and engineering judgement. Descriptive statistics summarizing the average, minimum, maximum, range and standard deviation for Regions A and Region B are presented below in Table 1.
TABLE 1 Descriptive Statistics for Regions A and B

| MTO Region | Bin No. | Bin Range | Total Number of Collisions | SN<sub>avg</sub> | SN<sub>min</sub> | SN<sub>max</sub> | SN<sub>range</sub> | SN<sub>stdev</sub> |
|------------|--------|-----------|----------------------------|------------------|----------------__|----------------|----------------|----------------|
| Region A   | 1      | 1 <=32    | 241                        | 29.04            | 10.30          | 31.90          | 21.60          | 2.61           |
|            | 2      | 32 to 34  | 77                         | 33.01            | 32.10          | 34.00          | 1.90           | 0.62           |
|            | 3      | 34 to 36  | 70                         | 35.08            | 34.10          | 35.80          | 1.70           | 0.52           |
|            | 4      | 36 to 38  | 91                         | 37.24            | 36.10          | 38.00          | 1.90           | 0.46           |
|            | 5      | 38 to 40  | 63                         | 39.12            | 38.10          | 40.00          | 1.90           | 0.68           |
|            | 6      | 40 to 42  | 50                         | 40.72            | 40.10          | 41.70          | 1.60           | 0.49           |
|            | 7      | 42 to 44  | 24                         | 43.06            | 42.20          | 44.00          | 1.80           | 0.53           |
|            | 8      | 44 to 46  | 38                         | 44.91            | 44.20          | 45.80          | 1.60           | 0.42           |
|            | 9      | 46 to 48  | 41                         | 47.11            | 46.30          | 47.90          | 1.60           | 0.49           |
|            | 10     | 48 to 50  | 9                          | 48.84            | 48.20          | 49.80          | 1.60           | 0.72           |
|            | 11     | 50 to 52  | 4                          | 51.05            | 50.40          | 51.50          | 1.10           | 0.54           |
|            | 12     | >=52      | 5                          | 55.36            | 52.50          | 57.70          | 5.20           | 2.65           |
| Region B   | 1      | 1 <=32    | 107                        | 30.20            | 25.00          | 31.90          | 6.90           | 1.48           |
|            | 2      | 32 to 34  | 63                         | 33.08            | 32.20          | 34.00          | 1.80           | 0.56           |
|            | 3      | 34 to 36  | 86                         | 35.14            | 34.20          | 36.00          | 1.80           | 0.53           |
|            | 4      | 36 to 38  | 61                         | 37.21            | 36.10          | 37.90          | 1.80           | 0.53           |
|            | 5      | 38 to 40  | 61                         | 38.93            | 38.10          | 40.00          | 1.90           | 0.55           |
|            | 6      | 40 to 42  | 44                         | 40.84            | 40.20          | 42.00          | 1.80           | 0.53           |
|            | 7      | 42 to 44  | 37                         | 43.09            | 42.10          | 44.00          | 1.90           | 0.68           |
|            | 8      | 44 to 46  | 28                         | 45.05            | 44.10          | 45.90          | 1.80           | 0.55           |
|            | 9      | 46 to 48  | 20                         | 46.90            | 46.10          | 48.00          | 1.90           | 0.49           |
|            | 10     | 48 to 50  | 8                          | 48.74            | 48.10          | 49.30          | 1.20           | 0.47           |
|            | 11     | 50 to 52  | 11                         | 50.45            | 50.10          | 50.90          | 0.80           | 0.36           |
|            | 12     | >=52      | 3                          | 61.63            | 55.10          | 64.90          | 9.80           | 5.66           |

Model Development

As previously mentioned, the friction and collision data were examined in grouped ranges or bins. At this level, the number of collisions within a given friction level were analyzed at the network level. A non-parametric linear regression was performed to develop a number of Model Classes with the number of collisions as the dependent variable and the level of friction (SN) as the independent variable. Linear, logarithmic, power and exponential based models were all used to obtain a best fit of the data. In total, 7 Model Classes were developed and a summary of the developed models for each class is presented in Table 2. The shaded boxes represent the “best fit” model. It is important to note that the R<sup>2</sup> value represent the best fit model through the binned averages. In addition, statistical testing was performed on the seven Model Classes using an Analysis of Variance (ANOVA) or a Student’s T-Test to determine if the various groups within the model class are significantly different at the 95% confidence interval.

Region

Three regions were examined as a part of this study; Regions A, B and C. As previously mentioned, Region C was removed from the analysis. In total, 3 models were developed within the Region Model Class. A model was developed for each region as well as a combined model representing both regions. Region A had 719 collisions, while Region B had 529 collisions for a total of 1,242 collisions. An exponential model was used to best fit the data with R<sup>2</sup> values ranging from 0.852 to 0.934. A summary of the Region Model Classes is presented in Table 2. The results of the ANOVA indicate that the region Model Classes are significantly different at the 95% confidence interval as presented in Table 3.
Collision Severity

The vehicle collision database identified three collision severity types; fatal, personal injury, and property damage. In total, 3 models were developed within the Collision Severity Model Class. A model was developed representing each collision severity type. Within the two regions, there were 12 fatal collisions, 253 personal injury collisions, and 977 collisions involving property damage. For the personal injury and property damage collision severity types, an exponential based model was used to best fit the data with $R^2$ values of 0.768 and 0.917 respectively. For the fatal collisions, a power based model was used to best fit the data with an $R^2$ value of 0.332. A summary of the Collision Severity Model Classes is presented in Table 2. The results of the ANOVA indicate that the collision severity type Model Classes are significantly different at the 95% confidence interval as presented in Table 3.

Environmental Condition

Seven environmental condition classes were examined as a part of this study; clear, drifting snow, fog, freezing rain, rain, snow, and wind. For the environmental condition classes, clear had the highest number of collisions with 800, followed by snow with 271, rain with 69, drifting snow with 45, fog with 20, freezing rain with 18, and wind with 18.

The higher number of collision for the clear conditions could be attributed to human factors. When environmental conditions are clear, drivers tend to exceed the posted speed limit and the 85th percentile operating speed. For clear, drifting snow, fog, and snow conditions, an exponential based model was used to best fit the data with $R^2$ values of 0.875, 0.914, 0.038, and 0.883 respectively. For freezing rain, rain, and wind conditions, power based models were used to best fit the data with $R^2$ values of 0.6872, 0.801 and 0.183 respectively.

The low correlations for the fog and wind conditions could be attributed to the fact that friction was probably not a significant factor since visibility (fog) and vehicle dynamics/driver error (wind) were the probable cause of those collisions. A summary of the Environmental Condition Model Classes is presented in Table 2. The results of the ANOVA indicate that the environmental condition Model Classes are not significantly different at the 95% confidence interval as presented in Table 3.

Season

Four models were developed to represent each season of the year – winter, spring, summer and fall. The winter had the highest number of collisions with 581, followed by the summer with 329, the spring with 173, and the fall with 159. For the winter, summer and fall seasons, an exponential based model was used to best fit the data with $R^2$ values ranging from 0.73 to 0.938. For the spring season, a power based model was used to best fit the data with an $R^2$ value of 0.929. A summary of the Season Model Classes is presented in Table 2. The results of the ANOVA indicate that the season Model Classes are not significantly different at the 95% confidence interval as presented in Table 3.

Road Surface Condition

Four models were developed within the Road Surface Condition Model Class. A model was developed for dry, ice, snow and wet pavement surfaces. For road surface condition, dry surface condition had the highest number of collisions with 676, followed by snow surface condition with 308, wet surface condition with 164, and ice surface condition with 90. The higher number of collision for the dry surface could be attributed to human factors. When road surfaces are covered in snow or ice, drivers tend to reduce their speeds and drive with more caution. When pavement surfaces are dry, drivers tend to exceed the posted speed limit and 85th percentile operating speed. In addition, there could have been more “dry surface” days over the year compared to the snow or ice covered surfaces due to winter maintenance activities. For the dry and snow covered surfaces, an exponential based model was used to best fit the data with $R^2$ values of 0.855 and 0.900 respectively. For ice and wet surfaces, a power based model and logarithmic based model were used to best fit the data with $R^2$ values of 0.915 and 0.822 respectively. A summary of the Road Surface Condition Model Classes is presented in Table 2. The results of the ANOVA indicate that the surface type Model Class is not significantly different at the 95% confidence interval. As a result, the data was re-grouped into dry and wet collisions and a student’s t-test was performed which showed that there was a significant difference between the two surface conditions as presented in Table 3.
Visibility

Visibility is directly related to weather and climatic conditions. In total, 4 models were developed within the Visibility Model Class. A model was developed to represent the following visibility conditions – clear, fog, rain and snow. Clear visibility had the highest number of collisions with 811, followed by the snow with 323, rain with 87, and fog with 20. For clear and snow visibility conditions, an exponential based model was used to best fit the data with $R^2$ values of 0.873 and 0.939 respectively. For the fog visibility conditions, a linear based model was used to best fit the data with an $R^2$ value of 0.042. For the rain visibility condition, a power based model was used to fit the data with an $R^2$ value of 0.862. A summary of the Visibility Model Classes is presented in Table 2. The results of the ANOVA indicate that the visibility Model Classes are not significantly different at the 95% confidence interval as presented in Table 3.

Roadway Location

Four models were developed within the Roadway Location Model Class. A model was developed to represent the following conditions – intersection, mainline, off-road and shoulder. The mainline location had the highest number of collisions with 719, followed by the off-road location with 260, intersection with 132, and shoulder with 109. For the winter, summer and fall, an exponential based model was used to best fit the data with $R^2$ values ranging from 0.753 to 0.914. A summary of the Roadway Location Model Classes is presented in Table 2. The results of the ANOVA indicate that the roadway location Model Classes are significantly different at the 95% confidence interval as presented in Table 3.

### TABLE 2 Summary of Model Classes and Best Fit Curve

<table>
<thead>
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<th>MODEL CLASS</th>
<th>CLASS ID</th>
<th>MODEL</th>
<th>LINEAR</th>
<th>LOGARITHMIC</th>
<th>POWER</th>
<th>EXPONENTIAL</th>
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<td></td>
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<td>$b$</td>
<td>$R^2$</td>
<td>$m$</td>
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TABLE 3 Results of ANOVA and Student’s T-Test

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ESTIMATING LEVEL OF RISK

To estimate the level of risk, or probability of a collision occurring given a known level of friction along a pavement section, the normal distribution of the skid number (SN) for Regions A and B were examined. With the normal distribution known, the risk of a collision occurring given a known level of friction can be estimated by calculating the area under the normal curve.

A random variable $X$ whose distribution has the shape of a normal curve is called a normal random variable. The random variable for this case is the skid number, or level of friction. This random variable $X$ is said to be normally distributed with mean $\mu$ and standard deviation $\sigma$ if its probability distribution given by:

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$  \[1\]

The standard normal distribution is a special case of the normal distribution. It is the distribution that occurs when a normal random variable has a mean of zero and a standard deviation of one. The normal random variable of a standard normal distribution is called a standard score or a z-score. Every normal random variable $X$ can be transformed into a z-score via the following equation:

$$Z = \frac{X - \mu}{\sigma}$$  \[2\]

For this study, each normal random variable (or skid number) was transformed into its corresponding z-score using the above equation. The standard normal probability distribution function of the skid numbers (SN) for Regions A and B was then generated using the calculated z-scores and the probability distribution function. The standard normal probability distribution function for Regions A and B is presented below in Figure 4.

Area Under the Curve

The probability of a continuous normal variable $X$ found in a particular interval $[a, b]$ is the area under the curve bounded by $x = a$ and $x = b$ and is given by:

$$P(a < X < b) = \int_{a}^{b} f(x)dx$$  \[3\]

This area is dependent upon the values of $\mu$ and $\sigma$. The areas under the curve bounded by the ordinates $z = 0$ and any positive value of $z$ are found in a $z$-Table. From this table the area under the standard normal curve between any two ordinates can be found by using the symmetry of the curve about $z = 0$. The level of risk or probability of collision occurrence was determined for various levels of friction. A model was then generated to represent the risk of collision as a function of the level of friction as presented below in Figure 5. This model can be used to estimate the risk of collision for a given pavement section when the Skid Number is known. It can also be used as a tool to estimate the benefits in terms of “a reduction in risk” as a result of increasing the level of friction on a pavement section due to a maintenance, rehabilitation, or reconstruction (M, R, and R) activity such as an asphalt overlay, slurry seal, or chip seal.
SUMMARY

Several advanced methods such as Bayesian Statistical Techniques, Cluster Analysis, and Artificial Neural Networks are used by transportation and safety experts to assess the level of safety of a highway network. Some disadvantages to those analysis techniques are they are very complex and require someone with an advanced statistical background/education. Many agencies do not have the resources or in-house expertise to carry out such types of analyses. This research study presents a simplified framework that a transportation agency, contractor, or
consultant can use to assess the level of safety of a highway network. As a part of this framework, data collection requirements, data integration and linkage methods, statistical analysis and estimating the probability of collision based on the level of friction were presented and outlined.

CONCLUSIONS AND RECOMMENDATIONS

Based on this research study, the authors present the following conclusions and recommendations.

- Pavement surface friction has an affect on highway safety and on the probability of collision occurrence.
- A pro-active approach is required to deal with the friction-collision problem. Network level friction testing should be carried out on an annual or bi-annual basis to screen the network and identify potential collision prone locations.
- Other factors such as highway geometrics (curve radius, tangent length, superelevation, sight distance, etc.) have an affect on the driver, vehicle and highway safety. Unfortunately, at the time of this research study, no comprehensive geometric data set was available from MTO. It is recommended that once this data is available, it should be closely examined to identify any relationships and correlations.
- One of the most difficult components of this study was the integration and linkage of the data sets. A major reason for this issue is a problem many DOTs currently face - each data attribute was obtained from different departments within the agency (i.e., Pavement and Materials, Transportation and Safety, etc.). This demonstrates the benefits of integrating management systems such as a Traffic Safety Management System and a Pavement Management System.

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REFERENCES
