

A Disaggregate Model for Quantifying the Safety Effects of Winter Road Maintenance Activities at an Operational Level

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ABSTRACT

This research presents a disaggregated modeling approach for investigating the link between winter road collision occurrence, weather, road surface conditions, traffic exposure, temporal trends and site-specific effects. This approach is unique as it allows for quantification of the safety effects of different winter road maintenance activities at an operational level. Different collision frequency models are calibrated using hourly data collected from 31 different highway routes across Ontario, Canada. It is found that factors such as visibility, precipitation intensity, air temperature, wind speed, exposure, month of the winter season, and storm hour have statistically significant effects on winter road safety. Most importantly, road surface conditions are identified as one of the major contributing factors, representing the first contribution showing the empirical relationship between safety and road surface conditions at such a disaggregate level. The applicability of the modeling framework is demonstrated using several examples, such as quantification of the benefits of alternative maintenance operations and evaluation of the effects of different service standards using safety as a performance measure.

KEYWORDS: Winter road safety / Winter road maintenance / Disaggregate accident frequency models

1. INTRODUCTION

Winter snow storms have a significant impact on the safety and mobility of highway users. Highway collision rates often increase considerably during snow storms due to slippery road conditions and poor visibility (Andrey et al 2001; HASTE report 2002; Knapp et al 2000; Andrey and Knapper 2003; Eisenberg and Warner 2005; Velavan 2006; Qiu and Nixon 2008). Weather related collisions are costly to the society. Andrey et al. (2001) estimated that injury and property damage accidents occurring due to inclement weather cost around \$1 billion per year in Canada. Winter storms can cause substantial delay due to reduced traffic speeds and road capability as well as increased collisions.

To reduce the negative impacts of winter storms, transportation agencies spend significant resources every year to keep roads and highways clear of snow and ice for safe and efficient travel. Canadian road officials spend around \$1 billion each year on winter road maintenance and put around five million tons of salt on Canadian roads (Transport Association of Canada 2003). This amount excludes other related costs such as damage to the environment, road infrastructure, and vehicles due to salt use (Environment Canada 2002; Perchanok et al 1991). While important for maintaining road safety in Ontario, road salting has also raised significant concerns due to its potential damage to the environment, roadside infrastructure, and vehicles (Perchanok et al. 1991; Environment Canada 2002). A recent study by Environment Canada concluded that road salts at high concentrations pose a risk to plants, animals and aquatic systems (Transport Canada 2001).

While there is a consensus that winter road maintenance is beneficial to the nation's economy in general and to the safety and mobility of our highway system in particular, only a few efforts have been devoted to the problem of quantifying the safety and mobility benefits of winter road maintenance (Hanbali 1992; Norrman et al., 2000; Fu et al., 2006; Usman et al., 2010). Furthermore, most of the few existing studies have adopted highly aggregated approaches in terms of temporal and spatial levels (e.g., by month, season or year and over a city or region-wide). Usman et al. (2010) was among the first to develop collision models at a disaggregate level with the objective of

linking the number of collisions on highways over individual snow storms to the average road weather and surface characteristics and road characteristics. While this level of disaggregation is sufficient for evaluating the average effects of various storm-wise factors, including those of bare pavement policies and standards currently being used in practice, it is not applicable for quantifying the safety effects of specific maintenance treatments deployed over a given storm.

This paper describes a disaggregate modeling framework proposed for quantifying the impact of road surface conditions and weather factors on winter collision occurrence controlling for traffic exposure and site-specific characteristics. The significance of this effort is twofold. First, this work fills the knowledge gap on the quantitative understanding of how different road weather and surface conditions and traffic factors influence the road safety. Second, the disaggregate accident frequency model developed in this research is the first in the winter road safety literature, providing a foundation for allowing quantification of the safety effects of individual winter road maintenance operations. Given the limited resources available and the growing concern about negative environmental effects associated with some of the winter road maintenance practices such as salting, the ability to perform such detailed analyses is needed in order to develop outcome oriented performance measurement systems for evaluating winter road maintenance related policies and decisions. The paper illustrates the two potential applications of the developed models, namely, evaluation of the safety benefit of particular maintenance operations and maintenance standards. The developed models are expected to be used by local agencies for assessing different decisions related to winter road maintenance.

The paper is organized as follows. The next section provides a literature review of winter maintenance operations, weather and road safety. The proposed methodology, model structure and data, is explained in section three. Modeling results, their interpretation and application are given in section four. Section five highlights the main conclusions and outlines some directions for future research.

2. LITERATURE REVIEW

Limited efforts have been devoted to the problem of quantifying the safety benefits of winter road maintenance under various weather conditions. Most of the past research is directed towards establishment of a link between weather and safety (Knapp et al 2000; Andrey et al. 2001; Andrey and Knapper 2003; Eisenberg and Warner 2005; Hermans et al. 2006; Qin et al. 2006; Qin et al. 2007; and Qiu and Nixon 2008; Stern et al. 2011). Hanbali (1992) was among the first who studied effectiveness of winter road maintenance (salting) on safety. A before-after analysis was conducted on undivided and divided highways randomly selected in New York, Minnesota, and Wisconsin, U.S.A. Accidents rates were compared over varied number of hours before and after salting and it was found that for divided highways there was a significant difference in accident rate two hours before and after salting while for undivided highways the difference was significant over four hours. It was found that on average the accident rate was reduced by 87% and 78% for divided and undivided highways respectively. This study assumes that reductions in accident rates are only due to maintenance, ignoring the fact that other important factors such as storm characteristics and traffic volume could be different over the periods before and after salting.

Norrman et al. (2000), was among the first to attempt to quantify the relationship between road safety and road surface conditions. They classified road surface conditions into ten different types based on slipperiness, and then compared the crash rates associated with the different road surface

types. The accident risk for a specific road surface condition type was defined as the ratio of the accident rate under the specific road surface conditions to the expected number of accidents for each month. These rates were then compared with percent of time maintenance was done when an accident occurred under some specific road surface conditions. This comparison showed that the frequency of maintenance operations associated with high accident risks is low. From this they concluded that in general, increasing maintenance operation frequency could reduce the number of accidents. However, the approach taken in that study has several limitations. Firstly, it is an aggregate analysis, considering roads of all classes and locations together. This approach may mask some important factors that affect road safety. Secondly, the simple categorical method of determining crash rates may introduce significant biases if confounding factors exist, which is likely to be the case for a system as complex as highway traffic. Thirdly, the study uses the frequency of maintenance operations only, disregarding differences between various types of maintenance operations. The procedure cannot be used to compare the effect of different maintenance operations. Fu et al. (2006) investigated the relationship between road safety and various weather and maintenance factors, including air temperature, total precipitation, and type and amount of maintenance operations. They concluded that anti-icing, pre-wet salting with ploughing, and sanding have statistically significant effects on reducing the number of accidents. Both temperature and precipitation were found to have a significant effect on the number of crashes. Their study also presents several limitations. First, the data used was aggregated on a daily basis, assuming uniform road weather conditions over the entire day for each day of record. Second, their study did not account for some important factors due to data problems, such as traffic exposure and road surface conditions. One of the implications of these limitations is that their results are not directly applicable for quantifying the safety benefit of winter road maintenance of other highways or maintenance routes.

Usman et al (2010) attempted to establish a link between winter maintenance and winter road safety using data over three winter seasons from four maintenance routes in the province of Ontario, Canada. A generalized linear model was developed for collision frequency over individual snow storms and it was found that, in addition to some weather and traffic related factors, road surface conditions is a significant factor, suggesting that the model could potentially be applied for evaluating the effect of alternative maintenance standards.

Nordic countries have conducted extensive research on issues related to winter road safety and road maintenance. Wallman et al. (1997) provided a comprehensive review on this body of work. In terms of research methodology, most of these studies relied on simple comparative analyses instead of rigorous statistical modeling. Nevertheless, the findings were in general consistent, showing that winter weather increases the risk of accidents by virtue of poor road surface conditions and that maintenance lowers the crash risk by improving road surface conditions.

In terms of safety modelling methodology, the most commonly employed approach for modeling accident occurrence is the generalized linear mixed (Poisson) regression. In particular, the standard Negative Binomial (NB) model with fixed dispersion parameter and its extension, the generalized Negative Binomial (GNB) model, have been found to be suitable in many road safety studies (Hauer 2001; Shankar et al., 1995; Miaou and Lord 2003; Miranda-Moreno 2006; Sayed and El-Basyouny 2006). Both models help dealing with over-dispersion, a common issue in crash frequency data (Maher and Summersgill 1996; Miranda-Moreno, 2006, Lord and Mannering 2010). In several applications, the GNB model seems to perform better than the NB in terms of goodness-of-fit. Other model settings have been also used such as the Poisson Lognormal (PLN) and Zero-

inflated Negative Binomial (ZINB) models. The latter can deal with the over-dispersion problem due to excess of zero crash counts. However, ZINB has been criticised because of the assumption of a permanent safe state, which is against the logic of accident occurrence (Hauer 1999, Lord et al 2004, Lord et al 2007). The NB and PLN models have been also extended within a Bayesian framework, to deal with the spatial correlation among locations as well as the correlation among crash outcomes, e.g., correlation of accident frequency outcomes classified by injury severity types (Miranda-Moreno, 2006). Some recent empirical studies have applied other model settings, to deal with some particular issues such as presence of subgroups (clusters) and under-dispersion of the data (Geedipally et al. 2012). For a detailed literature review of the different models used in road safety, one can refer to Lord and Mannering (2010).

One of the main issues with most existing approaches to collision frequency analyses is that collision data are commonly aggregated at large spatial and/or temporal levels, which means that the resulting models cannot be applied for evaluating the safety effect of operational treatments such as winter road maintenance. While simpler in terms of modelling effort, such an aggregated approach could cause some serious problems, such as biased parameter estimates and reduced significance of some factors, due to loss of information (reduction in sample size) and averaging (Hutchings et al. 2003; Usman et al., 2011). On the other hand, collision data at a disaggregate level may be correlated, which could result in biased models if used directly in model calibration. This issue can be partially addressed by using a model structure that is capable of accounting for this correlation, such as multilevel models (Goldstein 1986; Goldstein and Rasbash 1996; Caldas and Bankston 1999; Ronald et al. 2000; Steenbergen and Jones 2002; Jones and Jørgensen 2003; Schreiber and Griffin 2004; Lenguerrand et al. 2006; and Gelman and Jennifer 2006). The degree of correlation among observations within the same group (i.e., storm event in this research) is measured using intra-class correlation coefficient (ICC), denoted by ρ (Newsom and Nishishiba 2002):

$$\rho = \frac{\sigma_{wg}^2}{\sigma_w^2 + \sigma_{wg}^2} \quad (1)$$

where σ_{wg}^2 is within group (storm) variance and σ_g^2 is between-group variance. Some studies (Goldstein, 1986; Usman et al. 2011) have shown that in the absence of strong correlation within the groups, single level models could adequately capture the effects of the major factors.

3. OVERVIEW OF MODEL STRUCTURE AND DATA SOURCES

3.1. Model Structure

Based on the literature review, two different model structures are examined for their suitability of modeling collision data at a disaggregate level. The first model structure considered in this research is a single level Generalized Negative Binomial (GNB) model which does not account for the within-storm correlation. Following the GNB model framework, let $Y_i \sim \text{Poisson}(\theta_i)$ with $\ln(\theta_i) = \ln(\mu_i) + \varepsilon_i$, where Y_i represents the number of accidents during event i ($i=1, \dots, n$), μ_i stands for the mean accident frequency at event i , and $\exp(\varepsilon_i) \sim \text{Gamma}(1/\alpha_i, 1/\alpha_i)$, where α_i is the over-dispersion parameter. The mean accident frequency (μ_i) is then assumed to be a function of a set of covariates through the log-link function commonly used in the road safety literature. In GNB, the dispersion parameter is assumed to be a function of a set of covariates instead of a constant as in NB models. It has been shown that using a varying dispersion parameter could improve model fit

(Hauer 2001; Miaou and Lord 2003; Miranda-Moreno et al. 2005; Sayed and El-Basyouny 2006; Miranda-Moreno and Fu 2006; Mitra and Washington 2007; Cafiso et al. 2010; Usman et al. 2010). Using an exponential link function we have:

$$\alpha_i = \exp(\gamma_0 + \gamma_1 z_{i1} + \dots + \gamma_k z_{ik}) \quad (2)$$

where (z_{i1}, \dots, z_{ik}) is a vector of factors that may be different from those explaining μ_i and $(\gamma_0, \gamma_1, \dots, \gamma_k)$ is a vector of parameters.

The second model structure considered in this research is the multilevel Poisson lognormal model (PLN) to account for the hierarchical nature of the data with two levels of nesting – snow storm events as the upper level and individual hours within each storm event as the lower level. PLN differs from NB model in the sense that a lognormal distributed error term, instead of gamma distributed error, is used to capture the unobserved heterogeneity. This model has the advantage that it can be extended to deal with multi-level datasets. Some statistical software packages such as STATA have built-in functions to calibrate the PLN in a multilevel framework. Again, the multilevel model structure is necessary because the dataset used in this research is longitudinal in nature with the hourly records grouped within individual storm event forming a set of repeated measures over time, making it different from a typical panel data. The potential within-storm correlation can be captured by a multilevel model (Miranda-Moreno, 2006). Moreover, the Lognormal tails are known to be asymptotically heavier than those of the Gamma distribution (Kim et al, 2002). This can be the case when working with datasets in the presence of outliers (Winkelmann, 2003).

In a multilevel setting, a PLN model for nested hourly observations at the event level can be represented as,

$$Y_{im} \sim \text{Poisson}(\theta_{im}), \text{ with } \ln(\theta_{im}) = \ln(\mu_{im}) + \gamma_m + \varepsilon_{im} \quad (3)$$

where, μ_{im} is defined as a function of observed factors in hour i over storm event m ; γ_m represents the event level random effect, assumed to follow a Normal distribution, i.e., $\gamma_m \sim N(0, \sigma_{wg})$; ε_{im} is the within-event model error, assumed to follow a Normal distribution, i.e., $\varepsilon_{im} \sim N(0, \sigma_g)$. Note that ε_{im} represents all the unobserved heterogeneities or random variations that are not captured by γ_m , where, γ_m represents event-level unobserved factors controlling for the potential within-event correlation. In this case, the equation for μ_{im} has the following functional form:

$$\mu_{im} = (\text{Exposure}_{im})^{\beta_1} \exp(\beta_0 + \beta_2 x_{i1m} + \dots + \beta_k x_{ik-1m}) \quad (4)$$

where m is an index indicating the event level and i the hour index. Moreover, (x_{i1}, \dots, x_{ik}) is a vector of factors (e.g., weather and road surface conditions), and $(\beta_0, \beta_1, \dots, \beta_k)$ is a vector of parameters to be calibrated. It should be noted that the random term in Equation 3 accounts only for the random effect on the intercept. A more complex extension would consider the random effects in the slopes, that is, the slopes could be assumed to vary by events. This variation is left for future investigation.

3.2. Study Sites and Data Sources

In order to calibrate the proposed models, we use a collision data set containing collision and other data from 31 highway routes located in the province of Ontario, Canada (Figure 1), over six winter

seasons (2000 – 2006). A detailed description on the sources of this data set is provided in the following section.



Figure 1: Study sites.

Traffic Collision Data

The Ontario Provincial Police (OPP) maintains a database of all of the collisions that have been reported on Ontario highways. A database including all of the collision records for the study routes was obtained from the Ministry of Transportation, Ontario (MTO). The database includes detailed information on each collision, including accident time, accident location, accident type, impact type, severity level, vehicle information, driver information, etc. Note that the data on the accident occurrence time and location are needed for data aggregation over space (e.g., highway maintenance route) and time (e.g., by hour). The data item related to road surface conditions in the accident data represents the conditions at the time and location associated with the observed collisions only. Therefore, they do not necessarily represent the condition of the whole maintenance route. As a result, we did not use this data field directly and instead used it to fill the missing road surface condition (RSC) data from road condition & weather information system data (RCWIS) and road & weather information system data (RWIS). For this analysis only number of accidents, the time (hour) they occurred and road surface condition data, when no information was available from RCWIS/RWIS data, are considered from this database. The data used for this research contains 13,775 collisions involving 39,564 people in 19,635 vehicles for the six winter seasons (2000 – 2006) on the selected routes.

Traffic Volume Data

Hourly traffic data was obtained from two sources: MTO COMPASS system and permanent data count stations (PDCS). Both COMPASS and PDCS use loop detectors for collecting traffic data such as volume, speed and density. The raw data from the sources was screened for any outliers

caused by detector malfunction and then merged into hourly traffic volume data. In cases where multiple readings are available for a segment (e.g. from both sources and/or multiple detectors), average values are used.

Road Condition Weather Information System (RCWIS) Data

This data contains information about road surface conditions, maintenance, precipitation type, accumulation, visibility and temperature. RCWIS data is collected by MTO maintenance personnel, who patrol the maintenance routes during storm events; 3 to 4 times on the average. Information from all patrol routes is conveyed to a central system six times a day. Instead of stations, this data is collected for road sections. Each observation contains information regarding the section of road to which it belongs. One of the most important pieces of information in this data source is the description of road surface condition, which is used in this study as a primary factor for accident modeling. A detailed description on this data field and its processing for the subsequent modeling analysis is given in later sections. This data is also used by MTO in their traveler's road information system; however, this is the first time that it has been utilized for such research.

Road Weather Information System (RWIS) Data

This data source contains information about temperature, precipitation type, visibility, wind speed, road surface conditions, etc., recorded by the RWIS stations near the selected maintenance routes. All data except precipitation was available on an hourly basis. Hourly precipitation from RWIS sensors was either not available or not reliable. As a result, this information is derived from the daily precipitation reported by Environment Canada (EC). Temperature and RSC data from RWIS were used to fill in the missing data from RCWIS. For visibility and wind speed, RWIS was used as the primary source. RWIS stations record data every 20 minutes. Data from 45 RWIS stations were used in this research. If more than one station exists for a given route, an average value was used.

Environment Canada (EC) data

Weather data from Environment Canada includes temperature, precipitation type and intensity, visibility and wind speed. With the exception of the precipitation intensity data, all other data is in hourly format. Most of the EC stations have missing data. For this reason EC data was obtained from 217 stations for the study routes. This data was processed in three steps: In step 1, a 60 Km arbitrary buffer zone was assumed around each route and all stations within this boundary were assigned to the particular route. In the next step using t-test, EC stations were identified, which on average are similar to EC stations near the routes. In the last step, data from different EC stations around a route were converted into a single dataset by taking their arithmetic mean. It was found that arithmetic means provide better results than weighted averages.

3.2.1 Representation of Road Surface Conditions (RSC)

MTO reports road surface conditions (RSC) using qualitative descriptions, i.e., a categorical measure (with 7 major categories and 486 subcategories). These categories have intrinsic ordering in terms of severity, which means that a more analytically useful measure would be an ordinal one. While binary variables could be used to code ordinal data, it would mean loss of information in the ordering. We therefore decided to use an interval variable to map the RSC categories and at the same time make sure that the new variable would have physical interpretations. Road surface condition index (RSI), a surrogate measure of the commonly used friction level, was therefore introduced to represent different RSC classes described in RCWIS. A friction surrogate is used since there have been a number of field studies available on the relationship between descriptive

road surface conditions and friction, which provides the basis to determine boundary friction values in each category. To map the categorical RSC into RSI, the following procedure was used:

1. The major classes of road surface conditions, defined in RCWIS, were first arranged according to their severity in an ascending order as follows:

Bare and Dry < Bare and Wet < Slushy < Partly snow covered < Snow Covered < Snow Packed < Icy

This order was also followed when sorting individual sub categories into major classes.

2. Road surface condition index (RSI) was defined for each major class of road surface state defined in the previous step as a range of values based on the literature in road surface condition discrimination using friction measurements (Wallman et al 1997; Wallman and Astrom 2001; NCHRP web document # 53, 2002; Transportation Association of Canada 2008; Feng et al 2010; Usman et al. 2010). For convenience of interpretation, RSI is assumed to be similar to road surface friction values and thus varies from 0.05 (poorest, e.g., ice covered) to 1.0 (best, e.g., bare and dry).
3. Each category in the major classes is assigned a specific RSI value. For this purpose, sub categories in each major category were sorted as per Step 1 above. Linear interpolation was used to assign RSI values to the sub categories.

The RSI values for major road surface classes are illustrated in Figure 2.

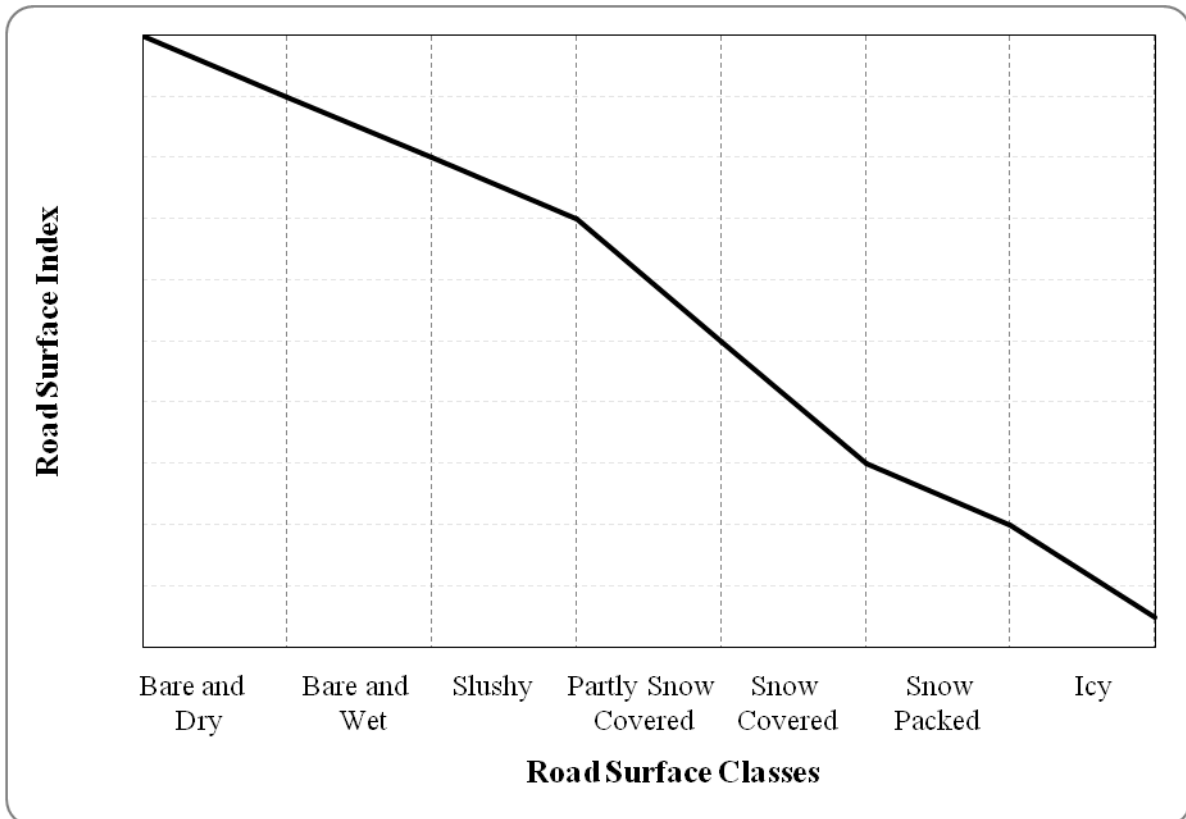


Figure 2: RSI for different road surface classes

The data obtained from all the data sources were subsequently processed, screened and combined to form an integrated data set for each site, treating location, date and time as the common basis for merging. In the next step data from all the sites were pooled into a single dataset with each site assigned a unique identifier (site specific variables) to retain its identity, which results in a complete data set of hourly observations for the six seasons and 31 sites. In the last step, hourly snow storm events were extracted from this data set as per the guideline set by Usman et al. (2010). The result was a data set including 122,058 hours of records nested within 10932 snow storm events. A total of 3035 collisions were recorded in this data set.

3.3. Model development

Once the dataset was created for the snow events for the six winter seasons, it was checked for any outliers using box plots of individual data fields in the database. The following variables were subsequently identified for consideration in model calibration:

- *Temporal trends:*
 Indicator for month (October – December as a dummy variable)
 Indicator for hour (after a storm starts)
- *Weather variables:*
 - Average air temperature (C°)
 - Average wind speed (km/hr)
 - Average visibility (km)
 - Hourly precipitation (cm)
 - Average RSI
 - Precipitation type (freezing rain/ snow = 1, Other = 0)
- *Winter maintenance treatments:* WRM (sanding = 1, salting = 2, sanding + salting = 3, ploughing = 4, ploughing + sanding = 5, ploughing + salting = 6, ploughing + sanding + salting = 7)
- *Traffic exposure measurement and site specific factors:*
 - Hourly traffic volume (vehicles/hr)
 - Exposure (product of segment length and hourly traffic, converted into Million vehicle kilometres or MVKm which represents the total vehicle kilometres covered during an hour of the event)
 - Site specific variable (site indicators were included in the analysis to capture the possible effect of other route specific factors, such as location, driver population, and road geometry, on road safety). Also, some geometric factors available in the data were tested.

The month and hour indicators were included to test the possible monthly trend over a season and hourly trend over a snow storm, respectively.

A number of two-way interactions were also considered for some of the variables such as visibility x precipitation type, visibility x precipitation intensity. Note that these interaction terms were identified on the basis of some possible physical interpretation; higher order interactions are not recommended in regression models due to difficulty in interpretation. A preliminary analysis indicated that the additional variation explained by the product terms was small; as a result, they were not included in the final model. Moreover, correlation analysis of the main effects revealed that precipitation type and maintenance operations were highly correlated with RSI across all datasets (with a correlation coefficient greater than 0.60) and were therefore removed from further analysis. Descriptive statistics are presented for variables found significant in Table 1.

For the data set used in our analysis, ρ was computed to be 6.05%, which represents a weak within-storm correlation and thus a single level model could be adequate without significant effect on the modelling results (Usman et al 2011).

Table 1: Descriptive Statistics (based on 122,058 hourly observations)

Variable	Min	Max	Mean	St.Dev
Accidents	0	7	0.020	0.180
Temperature (C°)	-33.55	28	-5.120	5.560
Wind Speed (Km/hr)	0	69	16.280	9.620
Visibility (Km)	0.07	40.2	11.160	7.910
Precipitation (cm)	0	13.8	0.240	0.370
RSI	0.05	1	0.7457	0.1978
Event Duration (hours)	2	47	19.44	11.64
Exposure (Total Vehicle Kilometres travelled)	43.3	1,545,981	57,025	80,841

4. MODEL CALIBRATION AND APPLICATION

Four different model structures were considered:

- PLN1: A model without any site effects
- PLN 2: A model with site effects
- GNB1: A model without any site effects
- GNB 2: A model with site effects

For models with site-specific effect, a dummy variable was included to capture the possible remaining effect of route specific attributes, such as location, driver population, and road geometry, on road safety. In addition, some route geometric factors were tested for their significance, instead of using site-specific fixed effects. Different trend components were considered to test the trend at different levels. For trend within events two models were considered - model with a dummy variable indicating whether or not the hour under consideration is the first hour of the storm (FH=1 for first hour, 0 otherwise), and model with a dummy variable indicating if the hour is the first or second hour of the storm (SH=1 for first two hours, 0 otherwise). Seasonal trend was tested using a month indicator.

All models were calibrated using Stata² (Version 11). A stepwise elimination process was followed to identify the significant factors. The best fit model was identified using the likelihood ratio test and Akaike Information Criterion (AIC) (Akaike 1974). The AIC statistic is defined as $-2LL+2p$, where LL is the log likelihood of a fitted model and p is the number of parameters, which is included to penalize models with higher number of parameters: a model with smaller AIC value represents a better overall fit.

Based on the AIC criterion, GNB and PLN models considering the site effects were found to have much better fit to the data than those without these effects. AIC for GNB2 (PLN2) model is 23,389 (23,520) which is less than the AIC value of 24,266 (24,099) for GNB1 (PLN1) model. For the sake of brevity only results from PLN2 (PLN hereafter) and GNB2 (GNB hereafter) are given in Table 2 along with their elasticities. Elasticity for a continuous variable is calculated as βX , where X is the mean value of the variable. This elasticity represents a change in the expected collision frequency that would result from a 1% change in the independent variable at its mean value. It should however be noted that selecting different values of X will result in different elasticities. For a categorical variable, elasticity is calculated as $[\exp(\beta) - 1]/\exp(\beta)$. This has further explained in section 5.1 through an example.

In addition to using AIC for identifying the best fit model, observed and estimated relative frequencies of collisions are compared (Maher and Summersgill 1996; Miranda-Moreno 2006, Usman et al. 2010) for both GNB and PLN (Table 3). The first column “Collisions” in Table 3 shows the total number of collisions observed over the 31 routes for the six winter seasons. The second column of Table 3 shows the observed frequency of the number of collisions in an hour whereas columns three and four document the estimated values from the models. For example, in the data set, there were 119,415 hours having no collisions whereas the GNB estimate is 119,434 hours and the PLN estimate 119,313 hours. Table 3 shows that GNB estimates are closer to the observed ones. Figure 3 shows the variation of site-specific factors, which represent the effects that were not captured by the model. These site-specific factors could be linked to site characteristics such as road geometry, which is part of our future research.

Figure 4 shows how the mean number of accidents is affected by some of the main factors, including those related to weather (precipitation, temperature, and wind speed), road surface conditions (RSI) and exposure. For each given factor, the expected collision frequency was obtained using the calibrated model while holding all other variables constant at their mean values. A detailed discussion on the effect of each factor is provided in the following section,

² <http://www.stata.com/>

Table 2: Summary Results of GNB and PLN Models

Category	Variable	GNB (Single Level)			PLN (Multilevel)		
		B	Sig	Elasticity	B	Sig	Elasticity
	Constant	-1.249	0.006		-2.082	< 0.001	
Temporal trends	October	0		0	0		0
	November	-1.029	< 0.001	-1.798	-1.023	< 0.001	-1.781
	December	-1.262	< 0.001	-2.531	-1.174	< 0.001	-2.235
	January	-1.308	< 0.001	-2.698	-1.238	< 0.001	-2.45
	February	-1.536	< 0.001	-3.648	-1.488	< 0.001	-3.43
	March	-1.278	< 0.001	-2.591	-1.229	< 0.001	-2.417
	April	-1.134	< 0.001	-2.108	-1.05	< 0.001	-1.858
	First hour (FH=1)	-0.302	0.001	-0.353	-0.271	0.001	-0.312
	Other Wise (FH=0)	0		0	0		0
Weather conditions	Temperature	-0.011	0.021	0.056	-0.013	0.014	0.065
	Wind Speed (Km/hr)	0.005	0.017	0.08	0.006	0.003	0.105
	visibility (km)	-0.039	< 0.001	-0.437	-0.038	< 0.001	-0.422
	Hourly Precipitation	0.097	0.079	0.023			
Surface conditions	RSI	-2.594	< 0.001	-1.934	-2.518	< 0.001	-1.878
Traffic exposure	Ln(Exposure)	0.235	< 0.001	1.888	0.276	< 0.001	2.215
Site Effects	Varies – See Figure 3						
	Overdispersion Model						
	Ln(Alpha)						
	Constant	2.711	0.012				
	RSI	1.347	< 0.001				
	Ln(Exposure)	-0.222	0.022				
	Observations	122058			122058		
	AIC	23388.91			23520.31		
	BIC	23854.38			23947.65		
	Number of level 1 units				122058		
	Number of level 2 units				10932		

Table 3: Observed vs. Estimated Accident Frequencies

Collisions/Hour	Observed from data	Estimated by GNB	Estimated by PLN
0	119415	119434	119313
1	2354	2299	2511
2	215	254	192
3	54	50	31
4	14	14	8
5	4	5	2
6	1	2	1
7	1	1	0
Sum	122058	122058	122058

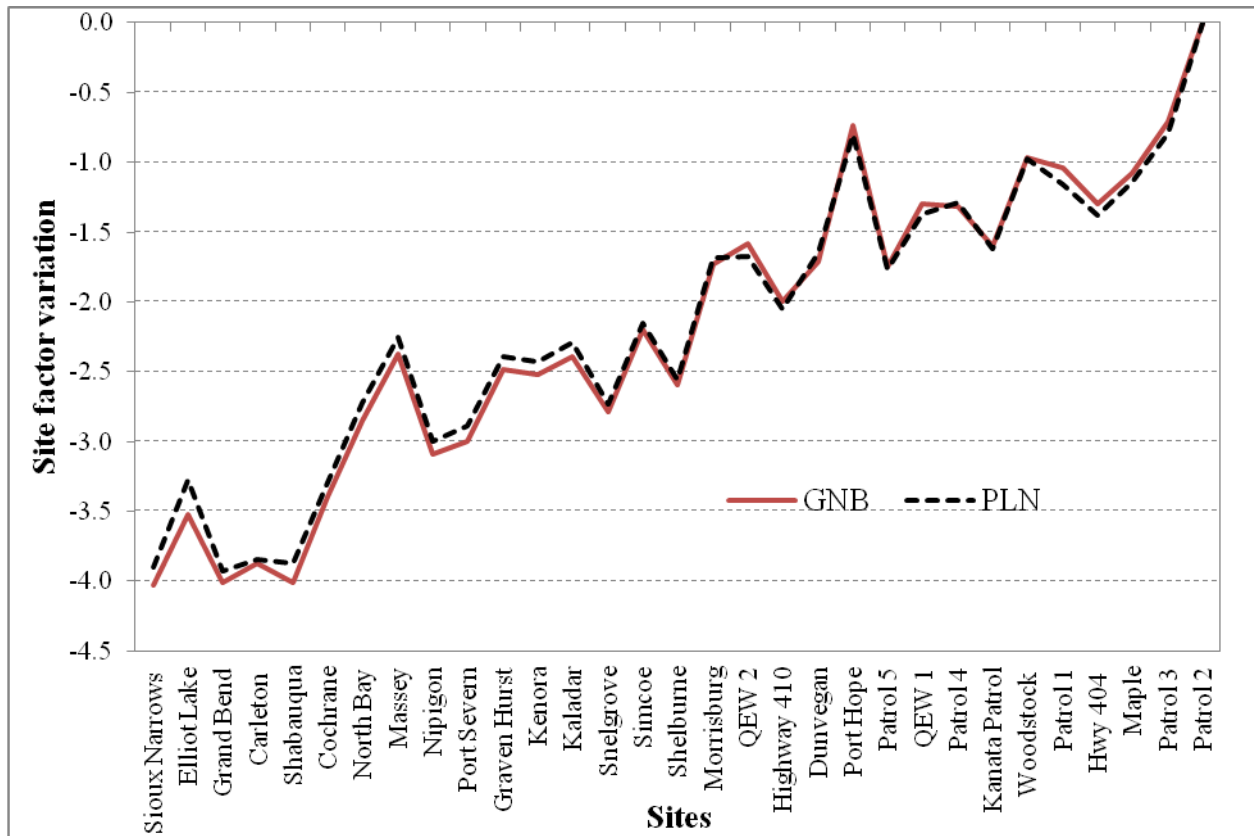


Figure 3: Variation of site specific factor

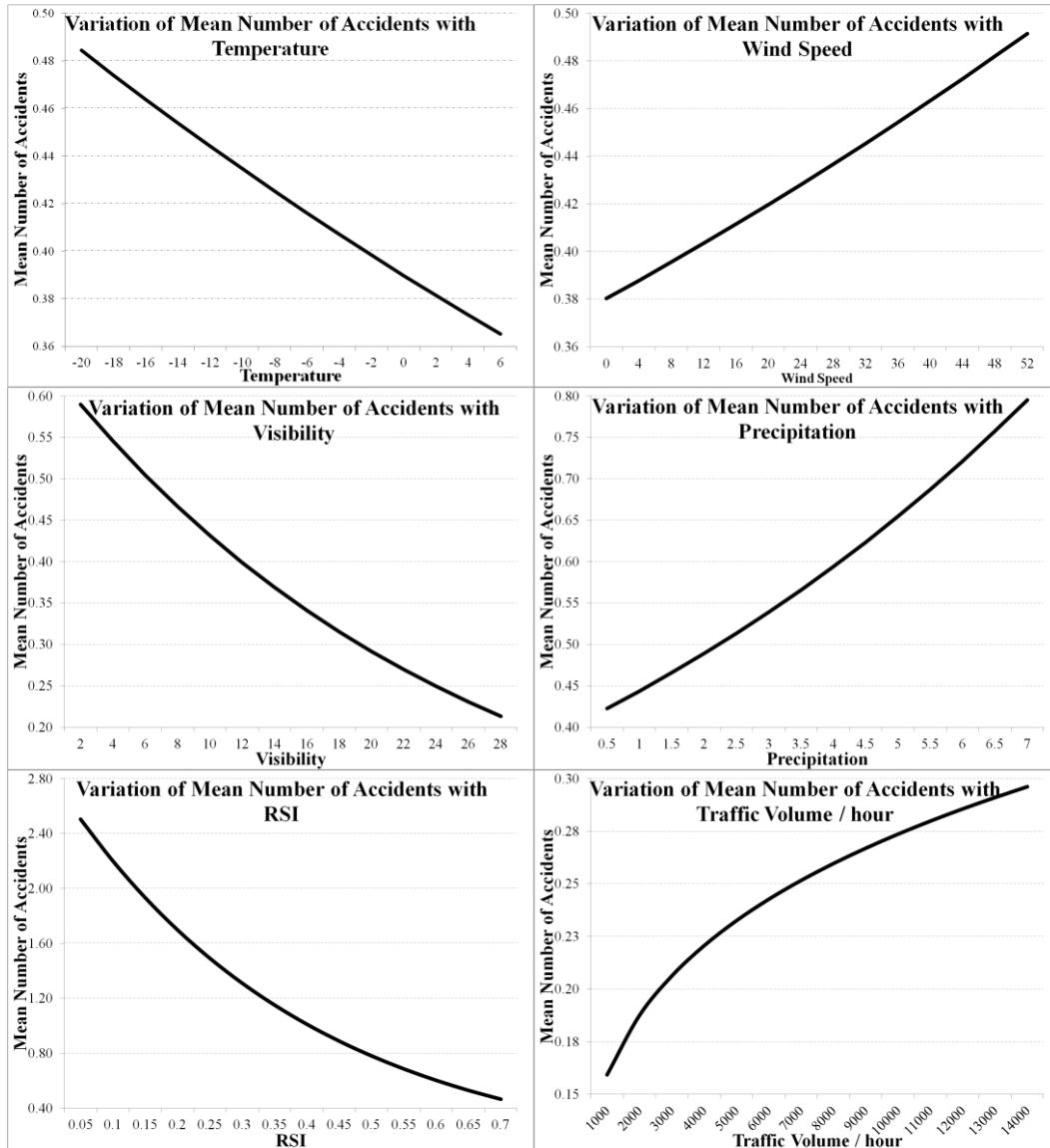


Figure 4: Collision frequency as a function of various influencing factors

4.1. Model Interpretation

As shown in Table 2, most results obtained in our research with respect to winter road safety and associated factors are consistent with those reported in the literature in terms of effect direction, with a few exceptions. For example, the signs of the coefficients associated with the factors representing storm severity, such as temperature, visibility, wind speed and precipitation, point to the expected relationship between the expected number of collisions and storm severity. Furthermore, because of the exponential functional form, the exponent in the model is a measure of sensitivity of crash frequency to the corresponding variable. For example, the coefficient associated with RSI in GNB model is -2.594, which suggests that a 1% improvement in RSI would lead to approximately a 2.59% reduction in the expected number of accidents. If the mean value of RSI (0.7457) is used, then a 1% increase in RSI will result in 1.93% (2.594×0.7457) reduction in mean number of crashes. The following section provides detailed interpretations of the expected effect of each factor on collision frequency based on the GNB model.

- **Road Surface Index (RSI)**

The most interesting result is perhaps that the road surface condition index (RSI) was found to be a statistically significant factor influencing road safety across all sites and models. This term could be considered as a measure to capture the effects of winter road maintenance operations. The negative sign associated to the factor suggests that higher collision frequencies are associated with poor road surface conditions. This result makes intuitive sense and has confirmed the findings of many past studies (Wallman et al 1997; Norrman et al 2000; Usman et al. 2010). However, this research is the first showing the empirical relationship between safety and road surface conditions at a disaggregate level – hour by hour within a snow storm, making it feasible to quantify the safety benefit of alternative maintenance goals and methods. Marginal effects for RSI show that it is the most influential factor affecting safety and a 1% improvement in road surface conditions from the mean value will cause approximately 2% reduction in mean number of accidents.

- **Visibility (km)**

Visibility is also found to have a statistically significant effect on accident frequency during a snow storm. The negative model coefficient also makes intuitive sense, as it suggests that reduced visibility was associated with increased number of accidents. Note that this result is different from those in a past study by Hermans et al. (2006), which found that visibility was significant only at two sites. Their study was, however, highly aggregated in both space (coastal areas vs. inter cities) and time (seasonal variation). Marginal effects for visibility show that, out of all the weather related factors, it is the most influential factor affecting winter road safety. An increase of 1% in visibility from the mean value will result in approximately 0.5% percent reduction in the mean number of accidents.

- **Exposure**

As expected, exposure, defined as million vehicle-kilometres traveled (product of the total traffic volume per hour and route length for disaggregate data), was found to be significant, suggesting that an increase in traffic volume in any hour within a snow storm or route length would lead to increase in the total number of collisions that would be expected to occur on the route in that hour in the snow event. Inclusion of this term ensures that traffic exposure is accounted for when estimating the safety benefits of some specific policy alternatives. The coefficient associated with the exposure term has a positive value with magnitude less than one, suggesting that the moderating effect of exposure is non-linear with a decreasing rate. This result is consistent with those from road safety literature (e.g. Andrew and Barred 1998, Lord and Persaud 2000; NCHRP 2001; Roozenburg and Turner 2005; Mustakim et al 2006, Sayed and El-Basyouny 2006; Sayed and Lovegrove 2007, Jonsson et al 2007 and Lord et al 2008 etc.). Exposure also has a great impact on safety and an increase in either length or traffic volume causing the exposure to increase by 1% from the mean value will cause the mean number of accidents to increase by 0.235%.

- **Precipitation Intensity (cm)**

Precipitation (GNB model) was also found significant with a positive sign suggesting that the mean number of collisions will increase with an increase in precipitation intensity. This finding also confirms previous studies e.g. Knapp et al (2000), Andrey et al (2001), Fu et al (2006) etc. Marginal effects for precipitation show that 1% increase in precipitation intensity from the mean value will cause the mean number of accidents to increase by 0.02%.

- **Air Temperature (°C)**

Air temperature was found significant with a negative sign suggesting that mean number of accidents will increase as temperature starts decreasing. Moreover temperature also accounts for extra variation that is not captured by RSI. For the same RSI, different temperatures will represent different levels of variation in road surface conditions which will increase with decrease in temperature. A low temperature will therefore also affect expected accident frequency by offering extra variation in the road surface conditions. This result confirms some of the previous findings e.g. Fu et al. (2006). Marginal effects for air temperature show that 1% increase in temperature from the mean value will cause the mean number of accidents to decrease by 0.06%.

- **Wind Speed (km/hr)**

Wind speed was found statistically significant and the positive sign indicates that higher wind speeds are associated with higher numbers of accidents. The results make sense intuitively as high wind speed could cause blowing snow effects or impair the visibility of drivers during snow storms. This is similar to the results from literature e.g. Knapp et al (2000). Marginal effects for wind speed show that 1% increase in wind speed from the mean value will cause the mean number of accidents to increase by 0.08%.

- **Monthly Trends**

Monthly trends were included both in categorical and continuous forms. Though both were significant, the categorical monthly factors make more sense than the continuous one as different months could have different effects. This also improved the model fit. Results from this analysis show that start of winter is more crash prone compared to other months. This could be due to an adaptation of drivers to driving in snow storm conditions with the passage of winter season. Similar results have been reported in literature, e.g., Eisenberg and Warner (2005) and Maze and Hans (2007).

- **Hourly Trends**

In addition to the monthly trends for seasonal variation, hourly trends (for capturing within storm trends) were included in the analysis to test the effects of hourly variation. It was found that the effect of first hour was found significant with a negative sign for the first hour. This means that first hour of the storm is safer than other hours.

- **Site Specific Variables**

Site specific variables -which were included in the analysis to capture the possible effect of other route specific factors (such as location, driver population, and road geometry, on road safety) - were also found significant. Models with site specific variables show better fit than models without any site specific variables. Figure 3 shows that different sites have different risk levels associated with them because of the difference in location, driver population, road geometry etc.

Alternatively, models were calibrated using road geometric features such number of lanes, speed limit, number of interchanges/intersections, number of bridges, percentage of fully and partially and gravel shoulders, etc. instead of fixed effects. It was found however that models with site-specific effects fit much better the data than models with geometric variables. Moreover, the impact of other variables (impact of weather and surface conditions)

on crash frequency was found to be consistent across models. For these reasons and due to unavailability of a large set of sites and geometric factors, site-specific models are reported and used in this analysis.

Site specific factors could also be modeled as a function of other variables related to site geometry (e.g. number of lanes, speed limit, number of curves, etc.), weather variables, and traffic volume. This approach could be used to generalize the frequency models developed to other road jurisdictions. This is, however, not tested here and is left for future investigation.

4.2. Model Application

The previous section has described a model that links road safety and RSI and other factors such as precipitation, visibility and air temperature. This section uses two case examples to illustrate how the selected model can be applied for assessing the safety benefits of alternative winter road maintenance Level of Service (LOS) goals for a specific maintenance route under a specific snow storm event. The first example shows the potential effect of a specific winter road maintenance operation on collision frequency while the second example shows the effect of a maintenance policy variable - bare pavement (BP) recovery time on safety. BP recovery time is defined as the time elapsed after the end of a snow storm until bare pavement is achieved through maintenance treatments.

4.2.1 Effect of Winter Road Maintenance Operation on Road Safety

In this example, the developed model is applied to assess the implications of some specific WRM operations, e.g., ploughing and salting, on safety. We consider a particular maintenance route that experiences a snow storm with the following characteristics:

- Precipitation intensity = 0.24 cm/hr
- Wind speed = 16.28 km/hr
- Air temperature = -5.12 C
- Visibility = 11.16 km
- Duration = 8 hrs
- Exposure = 8.03 MVKm

Furthermore, the road surface conditions of this route, as represented by RSI, are assumed to vary over the event as follows:

- At the start of the event, the road surface is bare and dry with a RSI of 1.0.
- At the end of the first hour, the road surface becomes “snow packed with icy” with an RSI value of 0.2.
- In the case that no maintenance operations are done, the road surface would remain in this condition (with RSI = 0.2) until the end of the event (i.e., 8 hours).
- For the case with maintenance operations, a combination of ploughing and salting operations are applied, which would improve the road surface condition to a mixed state of partially snow covered with an equivalent RSI of 0.8.

- It is assumed that the effect of salt would last for five hours. The RSI of the road surface conditions would decrease linearly from 0.8 to 0.2 (snow packed with icy) within the storm period.

The safety benefit of winter road maintenance is defined as the difference in the expected total number of collisions between the conditions of with and without winter road maintenance over the storm period. To show how this benefit is calculated, we consider the above storm with the maintenance operations (plowing and salting) completed at the start of the second hour. As shown in Figure 5, the shaded area represents the difference between doing nothing (no maintenance) and maintenance during hour 2 (salting & ploughing). Similarly, the safety benefit of other maintenance start/completion times can be calculated, as shown in Figure 6 (2nd, 4th and 6th hour).

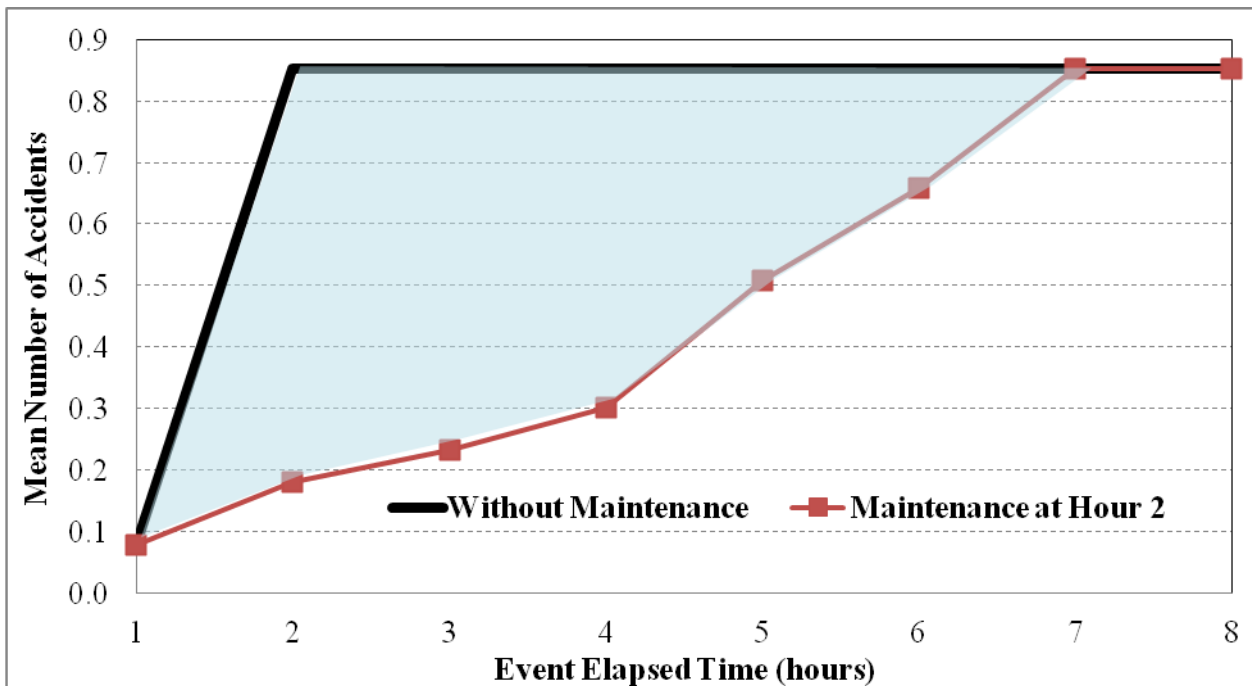


Figure 5: Calculation of safety benefit of maintenance operations

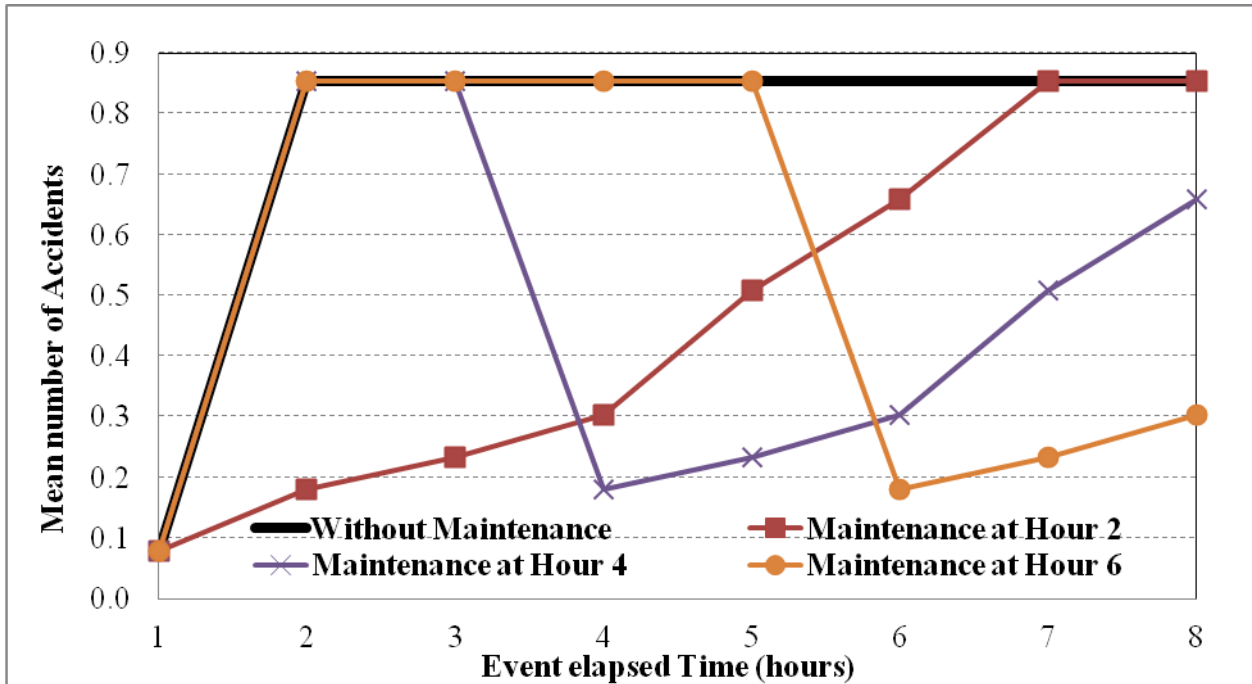


Figure 6: Safety benefit vs. maintenance timing

4.2.2 Effect of Bare Pavement Recovery Time on Safety

In the second example, the model is applied to assess the safety implications of bare pavement (BP) regain policy. Following the same example described previously, it is assumed that BP was recovered eight hours after the precipitation stopped.

Figure 7 shows the potential benefit of shortening the BP regain time, as represented by the relative decrease in the expected number of accidents. As shown in the figure, the relative benefit is proportional to the BP regain time. For example, the expected safety benefit of reducing BP regain time from eight hours to four hours would be a reduction of accidents of over 50% for this highway section over the eight hours. These values can be converted into monetary values by multiplying them by average accident cost.

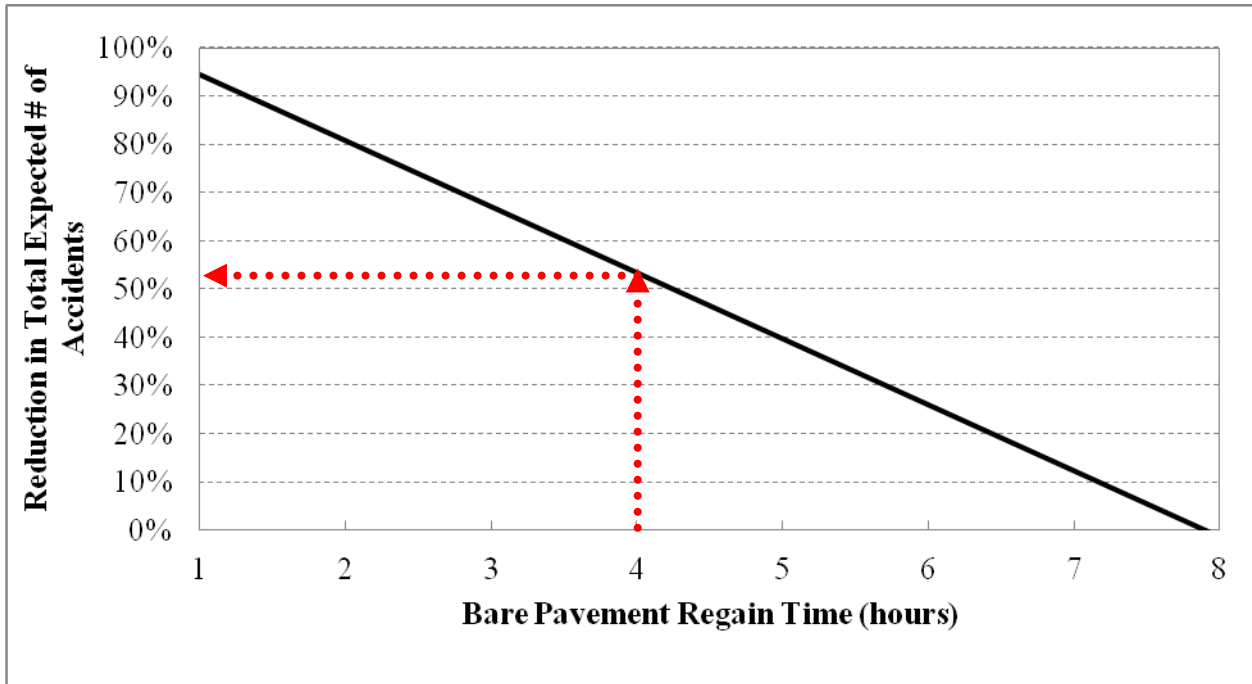


Figure 7: Effect of Bare Pavement Regain Time on Safety

5. CONCLUSIONS AND FUTURE WORK

This paper presents a disaggregate modeling approach aimed at identifying the factors affecting winter road safety and quantifying the effect of winter road maintenance on road collisions during snow storm events. Detailed hourly data on collision counts along with the corresponding road weather and surface conditions, and traffic on 31 patrol routes across Ontario, Canada, over six winter seasons (2000 - 2006) were obtained and used for model calibration. Two modelling structures were used - a multilevel Poisson lognormal model (PLN) accounting for within storm correlation and site-specific effects and a single level generalized negative binomial (GNB) model. Four different models were calibrated and it was found that the within storm correlation is relative weak and GNB has a better fit to the data by virtue of its ability to account for the heterogeneity in the data through varying dispersion parameter. Factors such as visibility, precipitation intensity, air temperature, wind speed, exposure, indicator for month, trend within storm, and site specific factors have statistically significant effects on winter road safety. Most importantly, road surface conditions as represented by a comprehensive measure called road surface index (RSI) were found to have a signification contribution to the variation of collisions within and between individual storms and maintenance routes. The practical significances of the developed models have been clearly illustrated in the two example case studies.

This research can be extended in several directions. First of all, the modeling approach should be applied to a larger number of study sites from different regions with winter weather of varying severity and duration. This extension is necessary to test the robustness and reliability of the proposed modeling methodology. Secondly, this research has primarily focused on the basic effect of the influencing factors; the potential non-linear effect of these variables as well as their interaction terms should also be investigated. Finally, detailed geometrical features of the highway

routes should be evaluated for their effects on collision frequency under adverse winter weather conditions. With this extension, the transferability of the models can be improved substantially.

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