Collision Prediction Models for Highway-Rail Grade Crossings in Canada

F.F. Saccomanno
Professor
Department of Civil Engineering
University of Waterloo
Waterloo, ON, Canada
Email: saccoman@uwaterloo.ca
Tel: (519)888-4567 ext 2631
Fax: (519)888-6197

Congming Ren
Research Assistant
Department of Civil Engineering
University of Waterloo
Waterloo, ON, Canada
Email: saccoman@uwaterloo.ca
Tel: (519)888-4567 ext 6596
Fax: (519)888-6197

Liping Fu
Assistant Professor
Department of Civil Engineering
University of Waterloo
Waterloo, ON, Canada
Email: saccoman@uwaterloo.ca
Tel: (519)888-4567 ext 3984
Fax: (519)888-6197

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ABSTRACT:

This paper presents a study of highway-rail grade crossing collisions based on data from all regions of Canada. A number of collision prediction models were calibrated and validated, including Poisson and Empirical Bayesian models. The Poisson models revealed a problem of under-dispersion caused by too many zero collision crossings. Notwithstanding the problems of under-dispersion in the data, the Poisson model yielded the best fit results and was used to investigate the sensitivity of collisions to different crossing attributes, including types of warning device, AADT, road speed, surface width and train speed, number of tracks and number of trains daily.

INTRODUCTION

Highway-rail grade crossing collisions are a source of concern to railway authorities and the public-at-large. Each year in Canada, about 50 people lose their lives as a direct result of grade-crossing collisions (Transport Canada, Railway Safety Facts, 1996). In response to safety concerns at grade crossings, Transport Canada established a permanent safety management program called “Direction 2006”. The goal of Direction 2006 is to reduce collisions in Canada by at least 50% by the year 2006. The question that needs to be addressed is how this goal can best be achieved.

It would be prohibitively expensive and impractical to improve safety at all grade crossings to a uniform standard. A recent report prepared by the Transport Research Laboratory (TRL) for the World Bank concluded that a reduction in grade crossing collisions is best achieved by directing appropriate countermeasures to Black Spot (BS) locations (http://www.worldbank.org/html/fpd/transport/). Blackspots refers to crossings with an unacceptably high collision risk. Since BS targets those crossings with unacceptable high risk, it makes the most effective use of safety budgets. The TRL report suggests that when we attempt to allocate funds to all problem areas, lack of funds and poor maintenance capability often results in the most dangerous problems being left untreated. Targeting Blackspots ensures that this issue is less likely to be a problem.

In this paper, we assert that Blackspots cannot be established solely with reference to the historical collision experience for a given period of time. Collisions are rare random events that vary significantly over time and space. We cannot assert that a given crossing is less safe simply because it experienced a large number of collisions last year. A longer term view of collision risk is needed to reflect potential risks involved over any period of time. Such estimates can only be obtained using accurate and reliable collision prediction models. The focus of this paper is to develop such a model for different types of crossings and warning devices.

This paper is organized into three main sections: 1) a review of the US-DOT collision prediction model and its application to Canadian crossing inventory and occurrence data. 2) development of a collision prediction model using the Canadian data, and 3) using the model to investigate the sensitivity of collisions to different crossing geometric and traffic characteristics.
A model was developed by the US Department of Transportation to predict collisions at highway-rail grade crossings (Farr, 1987). The US-DOT model predicts collisions for different types of crossings using three related components: a basic statistical model to obtain the expected number of collision per year, a quasi-Bayesian adjustment to incorporate historical collision observations at specific crossings, and an external adjustment to account for different types of warning device. The US DOT model consider three types of warning devices: signs only (Type S), signs + flashing lights (Type F), and signs + flashing lights + gates (Type G).

The expected number of collisions per year at crossing $j$ ($E(m_j)$) was obtained using the following expression:

$$E(m_j) = b_j \cdot \left[ \frac{T_{0j}}{(T_{0j} + T)} \cdot a_j + \frac{T}{(T_{0j} + T)} \cdot \frac{N}{T} \right]$$

(1)

Where:
- $T$ = number of years of collision history;
- $N$ = number of collisions recorded in $T$ years;

For different crossing types, adjustment factors for basic expected number of collisions were specified as follows:

$$b_j = \begin{cases} 
0.8644 & \text{for } j = S \text{ (Type S: Signs Only)} \\
0.8887 & \text{for } j = F \text{ (Type F: Signs + Flashing Lights)} \\
0.8131 & \text{for } j = G \text{ (Type G: Signs + Flashing Lights + Gates)}
\end{cases}$$

The term $a_j$ in Equation 1 was calibrated using a multiplication expression of the form:

$$a_j = K_j \cdot E_{ij} \cdot DT_j \cdot MS_j \cdot MT_j \cdot HP_j \cdot HL_j$$

(2)

The terms $K_j$, $E_{ij}$, $DT_j$, $MS_j$, $MT_j$, $HP_j$, $HL_j$ are crossing characteristics originally calibrated using non-linear multivariate regression applied to the RAIRS collision and inventory database for crossings in the US.

The term $T_{0j}$ was specified using the following expression:

$$T_{0j} = \frac{1}{0.05 + a_j}$$

(3)

Equations 2 for $a_j$ represents the basic statistical component of US DOT model. Table 1 provides the parameter estimates for this equation for three types of warning devices.
Table 1  Parameter Values in US DOT model for three types of Warning Devices

<table>
<thead>
<tr>
<th>Crossing Category</th>
<th>Crossing Characteristics Factors</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passive (Type S)</td>
<td>K = 0.000694, EI = ((c<em>t+0.2)/0.2)^(0.37), DT = ((d+0.2)/0.2)^(0.178), MS = e^(0.0077</em>ms), MT = 1.0, HP = e^(-0.5966*(hp-1)), HL = 1.0</td>
<td></td>
</tr>
<tr>
<td>Flashing Lights (Type F)</td>
<td>K = 0.000335, EI = ((c<em>t+0.2)/0.2)^(0.4106), DT = ((d+0.2)/0.2)^(0.1131), MS = e^(0.1917</em>mt), MT = 1.0, HP = e^(-0.1826*(hl-1))</td>
<td></td>
</tr>
<tr>
<td>Gates (Type G)</td>
<td>K = 0.000575, EI = ((c<em>t+0.2)/0.2)^(0.2942), DT = ((d+0.2)/0.2)^(0.1781), MS = e^(0.1512</em>mt), MT = 1.0, HP = e^(-0.1420*(hl-1))</td>
<td></td>
</tr>
</tbody>
</table>

Notation:
- c = number of highway vehicles per day
- t = number of trains per day
- mt = number of main tracks
- d = number of through trains per day during daylight
- hp = highway paved ? yes = 1.0 and no = 2.0
- ms = maximum timetable speed, mph
- hl = number of highway lanes

The US-DOT model was applied to Canadian crossing data, which were provided by Transport Canada and the Canadian Transportation Safety Board (TSB) for all regions of the country. This database is referred to as the RODS/TSB database and includes collision and inventory information for approximately 20,000 highway-rail grade crossings in Canada for the period of 1993 to 2001. During this period, a total of 2905 collisions were reported in this database.

A number of crossings in the RODS/TSB database were found to be poorly specified for the purpose of evaluating the US DOT model, and these were removed from the data used in the analysis. As a result, the database used in this analysis consists of a total of 10,381 crossings Canada-wide.

These crossings were aggregated into three types of warning device, three levels of train speed and two levels of traffic exposure. Differences between predicted and observed collisions were compared using the Chi-square goodness-of-fit test, with the results summarized in Table 2.
Table 2: Application of US-DOT model to Canadian data

<table>
<thead>
<tr>
<th>Train Speed</th>
<th>&lt; 30mph</th>
<th>30 - 50 mph</th>
<th>&gt; 50 mph</th>
</tr>
</thead>
<tbody>
<tr>
<td>Warning Type</td>
<td>Gates</td>
<td>Predicted Collisions</td>
<td>Observed Collisions</td>
</tr>
<tr>
<td>Exposure</td>
<td>Predicted Collisions</td>
<td>Observed Collisions</td>
<td>Predicted Collisions</td>
</tr>
<tr>
<td>&lt;1x10^4</td>
<td>8</td>
<td>6</td>
<td>76</td>
</tr>
<tr>
<td>&gt; 1x10^4</td>
<td>52</td>
<td>41</td>
<td>145</td>
</tr>
</tbody>
</table>

\[ \chi^2 = 138.67, \quad \chi^2_{0.05, 17} = 27.59 \]

From Table 2, the US-DOT model appears to be over-estimating the collisions for different crossing types. Overall, the model predicted 349 more collisions than were observed in the RODS/TSB database. The Chi-Sq is larger than critical value at the 5% level, suggesting a poor fit between observed and predicted collisions for different categories of crossings. The above results suggest the US DOT model does not adequately predict collisions for the Canadian data, and a separate collision prediction model needs to be developed.

**CANADIAN COLLISION PREDICTION MODELS**

A number of researchers have indicated that Poisson models are most applicable for predicting events that are discrete, non-negative and rare (Miao, 1993). In this research, we assume initially that collisions at grade crossings are Poisson distributed. In the Poisson model, the average number of collision occurrences is expressed as a function of selected independent variables (e.g. geometry, traffic, weather, etc.) that explain the variation in the number of collisions.
Maximum likelihood techniques were adopted to estimate Poisson model parameter values, using the software SAS (www.sas.com). In Poisson regression the expected number of collisions is set to equal to the variance, and the degree to which the variance differs to the mean is reflected in the Scaled Deviance measure. When the variance exceeds the mean, we assert that the data is over dispersed with respect to the Poisson distribution. The over-dispersion is reflected in a Scaled deviance greater than 1.0. In the similar fashion, when the variance is less than mean, the data is under-dispersed and the Scaled Deviance is less than 1.0. A good Poisson model yields scaled deviance close to 1.0. The literature suggests for data that is over or under-dispersed, other model types may be better able to predict collisions, such as Empirical Bayesian (EB) models used in conjunction with Poisson models (Persuad and Hauer, 1987).

Data Splitting

Before developing a new collision prediction model for Canadian crossings, we split the RODS/TSB data into two random samples, as illustrated in Figure 1. The first sample used to calibrate the new model consists of 5194 crossings, and the second sample used to validate the model consists of 5187 crossings.

![Data splitting diagram]

Figure 1: Data splitting for model calibration and validation

A total of 1805 collisions were reported in the usable RODS/TSB database for the period of 1993-2001 for all regions of Canada. The breakdown of crossings with observed collisions is summarized in Table 3. Over 86% of crossings did not experience
any collision over this 9-year period. Those crossings that reported collisions, experienced only one or two collisions in the 9-year period. This suggests the data is dominated by events with zero occurrence. This presents some unique problems in using Poisson models to predict collisions.

Table 3: No. of Crossings and Observed Collisions by Type of Warning Devices

<table>
<thead>
<tr>
<th>Warning Type</th>
<th>Total Data Set</th>
<th>Data used to Calibrating Model</th>
<th>Data used to Validating Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of Crossings</td>
<td>No. of Collisions</td>
<td>No. of Crossings</td>
</tr>
<tr>
<td>Type S</td>
<td>5196</td>
<td>2600</td>
<td>327</td>
</tr>
<tr>
<td>Type F</td>
<td>3723</td>
<td>1873</td>
<td>339</td>
</tr>
<tr>
<td>Type G</td>
<td>1462</td>
<td>721</td>
<td>258</td>
</tr>
<tr>
<td>Total</td>
<td>10381</td>
<td>5194</td>
<td>924</td>
</tr>
</tbody>
</table>

Statistical Description of Regression Data

Table 4 provides the summary of the statistics for the different variables used in the collision prediction models as reported in the RODS/TSB database. The traffic exposure in this paper is defined as the product of AADT and number of trains daily, and we note in Table 4 that there is a significant variation in exposure among various crossings in the database. The maximum number of collision observed at any specific crossing during the period of 1993 to 2001 is 7. A significant amount of variation was observed for the explanatory variables, such as train speed, road speed, number of track, etc.

A separate correlation analysis indicated that most of the variables, except road speed and road class, are uncorrelated. Hence, they can provide separate and unique explanatory inputs in collision prediction.
Table 4  Statistical Description of Regression Data

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Track_Angle</td>
<td>degree</td>
<td>70.259</td>
<td>75</td>
<td>367.398</td>
<td>90</td>
<td>5194</td>
</tr>
<tr>
<td>Track_NBR</td>
<td>No.</td>
<td>1.232</td>
<td>1</td>
<td>0.310</td>
<td>9</td>
<td>5194</td>
</tr>
<tr>
<td>Train_Speed</td>
<td>mile/hour</td>
<td>41.071</td>
<td>40</td>
<td>429.92</td>
<td>100</td>
<td>5194</td>
</tr>
<tr>
<td>Road_Speed</td>
<td>km/hour</td>
<td>59.393</td>
<td>50</td>
<td>446.66</td>
<td>110</td>
<td>5194</td>
</tr>
<tr>
<td>Surface_Width</td>
<td>m</td>
<td>10.607</td>
<td>9</td>
<td>28.740</td>
<td>99</td>
<td>5194</td>
</tr>
<tr>
<td>Exposure</td>
<td></td>
<td>21788.</td>
<td>1050</td>
<td>3.29E+10</td>
<td>8.23E+8</td>
<td>5194</td>
</tr>
<tr>
<td>Warning_Type</td>
<td></td>
<td>7.145</td>
<td>13</td>
<td>34.458</td>
<td>13</td>
<td>5194</td>
</tr>
<tr>
<td>Road_Class</td>
<td></td>
<td>5.196</td>
<td>5</td>
<td>6.939</td>
<td>11</td>
<td>5194</td>
</tr>
<tr>
<td>Highway_Paved</td>
<td></td>
<td>8.145</td>
<td>13</td>
<td>32.276</td>
<td>13</td>
<td>5194</td>
</tr>
<tr>
<td>No. Accident</td>
<td>No.</td>
<td>0.177</td>
<td>0</td>
<td>0.270</td>
<td>7</td>
<td>5194</td>
</tr>
</tbody>
</table>

Model Calibration and Validation

Two types of Poisson collision prediction models were developed, one type, which includes “Type of Warning Device” at each crossing as a separate explanatory variable in a single prediction expression (Model I). The other type of model treats the warning devices separately (Model II). Model II consists of three distinctive expressions for each type of warning device (signs, flashing lights and gates). Model II is similar to the approach adopted in the US-DOT model.

i. Model I

For Model I, the type of warning device was introduced as a dummy variable: 1 for crossings with signs and 0 for crossings with lights and/or gates. The “warning device” variable was found to be statistically significant at the 5% level of significance. A number of other variables were investigated including road class (arterial, or other road class), road pavement condition (paved or unpaved), track angle, number of tracks, train and road vehicle speed, road surface width and traffic exposure. Four of the eight factors were found to be statistically significant at the same level.

The expected number of collisions per year at each crossing (E(m)) is expressed as:

\[
E(m) = \exp(-11.9805 + 0.8383 \times \text{warning\_device} - 0.1310 \times \text{track\_no} + 0.005 \times \text{train\_speed} + 0.0116 \times \text{surface\_width} + 0.3814 \times \ln (\text{exposure}))
\]  

(4)

Where:

- \( \text{warning\_device} \) = type of device dummy variable (1 for signs, and 0 for flashing lights and/or gates)
- \( \text{track\_no} \) = number of railway tracks (both directions)
train speed = maximum train speed (mile/h)
surface_width = road surface width (m)
exposure = a product of AADT and number of trains daily

We note that the variables in equation 4 (bolded) were also included in the US-DOT model. Unlike the US-DOT model however, the above expression does not include variables representing “Number of Through Trains” or “Road Pavement Type”. “Number of lanes” in the US-DOT model has been replaced with “Road Surface Width” in our expression.

The above expression yielded a Scaled Deviance of 0.63, indicating some under-dispersion in the data, most likely due to the large number of zero-collision crossings. Despite statistically significant parameters, the above Poisson model does not appear to adequately reflect the observed collisions in Canadian data. At the aggregate level, Model I also yields poor Chi-square goodness-of-fit results. It was noted that traffic exposure related to three types of warning devices had different ranges. Crossings with gates had higher exposures than the other two types of crossings. The model would not yield accurate results for crossings with gates at lower level of exposure since there are fewer observations at this lower level of exposure for this type of warning device. Similarly, for crossings with signs we have fewer observations at higher levels of exposure. Model II can overcome this problem by separating the collision prediction for three types of warning devices. In Model II exposure is bounded in the range for which observations are available.

ii. Model II

For Model II, three separate regression expression were obtained for each of the three types of warning devices (Type S, F and G as defined above). The results are as follows.

Type S Crossings

The Poisson model for crossings with signs only is:

\[ E(m_S) = \text{Exp}(-11.6778 + 0.01 \times \text{train_speed} + 0.3973 \times \ln(\text{exposure})) \]  

In the above model, train speed and traffic exposure were found to be statistically significant. Despite these results, the model yielded a Scaled Deviation of 0.51 suggesting significant under-dispersion. The presence of Poisson under-dispersion is problematic, thus suggests a lower variation relative to the mean as predicted by the Poisson model. Again the problem appears to be caused by too many zero collisions in the data.

Next we used the above Poisson model to predict collisions at the crossings where these crossings were classified by train speed and traffic exposure. A Chi-square goodness-of-fit test was applied to the results. The calculated Chi-square (9.69) is less than critical value \( \chi^2_{0.05, 5} = 11.07 \) at the 5% level of significance. Notwithstanding the problem of under-dispersion in the data, the results are reasonable and statistically sound for crossings with signs.
Type F Crossings

The model for crossings with signs and flashing lights is of the form:

\[ E(m_F) = \exp(-14.9060 + 0.0091*\text{train\_speed} - 0.0077*\text{road\_speed} + 0.0312*\text{surface\_width} + 0.5161*\ln(\text{exposure})) \] (6)

where road speed = posted road speed (km/h)

This expression contains four statistically significant explanatory variables. Again the variables are consistent with the US DOT model for this type of warning device. A scaled deviance of 0.63 indicates under-dispersion in the data.

The Chi-square goodness-of-fit value (16.09) comparing observed and predicted collisions for different train speeds and traffic exposure is slightly higher than critical value \( \chi^2_{0.05, 5} = 11.07 \) at 5% level of significance.

Type G Crossings:

A third collision prediction expression was obtained for crossings with signs, flashing lights and gates. The expression is of the form:

\[ E(m_G) = \exp(-8.7407 - 0.1428*\text{track\_no} + 0.258*\ln(\text{exposure})) \] (7)

Only two explanatory variables were found to be statistically significant in this expression. These variables were also included in the original US-DOT model for this type of crossings. The additional variable that is included in the US-DOT model is the number of highway lanes. In our analysis, we found the number of highway lanes or surface width was not significant at the 5% level. We note that the data for gates is not Poisson over or under-dispersed (Scaled Deviance close to 1.0). For this type of warning device, the Poisson distribution provides a good prediction of collisions.

The Chi-square goodness-of-fit test also yielded good results, when crossings were classified by train speed and traffic exposure, ie. Chi-square value (2.822) less than the critical value at 5% level. This indicates a good match to the observed data.

Empirical Bayesian Model

A number of researchers have suggested that the Empirical Bayesian model provides a good solution for problems of data over-dispersion. It is not clear whether such model can also resolve problems of under-dispersion in grade crossing collision data. We have included the EB prediction model in this paper solely for the purposes of comparison.
As shown in Equation 8, the EB model provides an estimate of predicted collisions at individual crossings ($\varepsilon$) that includes both statistical (Poisson model) and historical inputs. The inclusion of historical input may be able to reflect the zero collision events in the observed data. As such, it is expected to give a better prediction than the Poisson model alone.

The expression is of the form:

$$\varepsilon = \alpha \times E(m) + (1 - \alpha) \times X$$

(8)

where: $E(m) = \text{Poisson predicted number of collisions from equation 5 \text{–} 7.}$

$X = \text{Observed number of collisions at a given crossing}$

This expression includes a factor ($\alpha$) that represents a weighted link between historically observed and Poisson predicted collisions at individual crossings. The expression for this factor is of the form:

$$\alpha = \frac{E(m)}{E(m) + K \times E(m)^2}$$

(9)

Since the EB method requires historical inputs, we split the RODS/TSB data set time-wise manner into two samples, as shown in Figure 1. The first sample includes collisions reported in the first four years (1993-96) and this sample was used to provide an estimate of $\varepsilon$ in the EB expression. The second sample (1997-2000) was used to validate the model.

In the EB approach, the degree to which the data is under or over-dispersed is expressed by the K-factor. This factor is estimated using iterative empirical methods in which we minimize the residual sum of squares (observed -- predicted) for all crossings in the calibration data set. The procedure is discussed at length by Hutchinson and Mayne (1977) and will not be discussed in this paper.

Three separate K-factors were estimated for each type of warning device, as follows:

<table>
<thead>
<tr>
<th>Type of Warning Device</th>
<th>K-Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type S</td>
<td>0.001</td>
</tr>
<tr>
<td>Type F</td>
<td>0.20</td>
</tr>
<tr>
<td>Type G</td>
<td>3.08</td>
</tr>
</tbody>
</table>

The EB model results were subsequently aggregated by warning device, train speed and traffic exposure and compared to observed collisions. From Figure 2, we note that the EB model does not yield much improvement over the previous Poisson model. The EB model estimates depend on historical observations. In our case, historical observations in the first four years were higher than in the latter four years. As such a
major requirement of the EB model is that we need to obtain sufficient years of observations to provide a realistic representation of historical collision risk at each crossing. Given the rare nature of crossing collisions, four years of observations may be insufficient. As a result, in this paper we have adopted the Poisson model to predict grade crossing collisions in Canada for the three types of warning devices.
Figure 2: Comparison of Poisson, EB and US DOT Model
SENSITIVITY ANALYSIS WITH THE MODELS

This section describes a sensitivity analysis to identify those risk factors that have a significant impact on collisions at grade crossings. This analysis can shed some light on possible cost-effective strategies for reducing collisions at these crossings.

Effects of Warning Device

Figure 3 (1) and Figure 3(2) show the ratios of expected collisions among the three types of warning devices as related to AADT and train speed. Three observations emerge from this analysis. Firstly, the ratios of predicted collisions for flashing lights (Type F) and gates (Type G) as compared to signs (Type S) are consistently lower than 1.0 for all levels of AADT and train speeds. This suggests that if crossings are upgraded from signs to flashing lights or gates, some reduction in the number of collisions would occur. A word of caution is advised here. The results could be affected by lack of crossings with flashing lights and gates in the lower ranges of exposure (AADT).

The second observation is that the expected benefit of upgrading from signs to flashing lights appears to be independent of train speed, but dependent on AADT. As expected, the higher the AADT, the higher the benefit obtained from the introduction of flashing lights.

Thirdly, the model suggests that while it is always beneficial to upgrade crossings from signs to flashing lights or gates, the effect of upgrading from flashing lights to gates is not always positive over all ranges of AADT. For example, it may be possible for AADT greater than 3500, but we are uncertain in the range of AADT less than 3500. Equations 5-7 suggests that the effect depend on the average daily traffic volume (AADT), train speed, road speed and surface width. In fact, under certain combinations of risk factors, such upgrades can have an adverse effect on collisions. For example, for a crossing with a train speed of 30 miles/h, road speed of 50 mile/h, 2 tracks, road surface width of 12 feet, 6 trains passing daily and an AADT of lower than 3500 vehicles/day, the number of predicted collisions is higher when the warning device is upgraded from flashing lights to gates. However, it should be noted that most crossings with gates have an AADT greater than 3500 vehicles/day. As a result, this relationship between warning device and collisions could be affected by an under representation of crossings with gates in the lower ranges of exposure. Similarly, for crossings with signs there is an under representation at the higher levels of exposure, and this could also affect the results.

At various train speeds, the collisions decrease significantly when the crossings are upgraded from signs to flashing lights or gates. However these benefits are not as obvious in the case of upgrading from flashing lights to gates.
Figure 3 (1): Relationship between collision ratios and AADT for three types of warning devices, (controlled by train speed = 30 mile/h, road speed = 50 km/h, no. of tracks = 2, surface width = 12 m, and no. of trains daily = 6)

Figure 3(2): Relationship between collision ratios and train speed for three types of warning devices (controlled by AADT = 8000veh./day, road speed = 50 km/h, no. of tracks = 2, surface width = 12 m, and no. of trains daily = 6)
Effects of Highway Characteristics

The key highway-related risk factors that explain collisions at grade crossings are highway traffic volume or AADT (included in the variable \textit{exposure}), Road Speed and Surface Width. \textbf{Figures 4 (1) and 4(2)} illustrate the relationship between expected collisions per year versus AADT and Road Speed for the three types of warning devices.

- As expected, traffic volume has a negative effect on the safety of grade crossings, regardless of type of warning device. The expected number of collisions at crossings increases as traffic volume increases. The rate of increase depends on the type of warning devices with the sign crossings having the highest rates of increase and the gate crossings having the lowest rate of increase. This means that traffic volume has a higher effect on collisions occurred at sign crossings than those at flashing light and gate crossings.

- Road speed has a negligible effect on the occurrence of collisions at sign and gate crossings, but a positive effect on crossings equipped with flashing lights. This is somewhat counter-intuitive, as it suggests that increased road speed leads to increased safety at crossings equipped with flashing lights. One possible explanation to this result is that higher road speeds usually correspond to better road design standards and increased safety, such as, longer sight lines, better alignment, width and safer environmental conditions.

- While other factors such as “width of road surface” were found to have a significant effect on collisions, their overall contribution was not as large as traffic exposure and road speed.

\textbf{Figure 4(1): Relationship between collisions and AADT for three types of warning devices} 
\begin{itemize}
  \item controlled by train speed =30 mile/h, road speed = 50 km/h,
  \item no. of tracks = 2, surface width = 12 m, and no. of train daily = 6)
\end{itemize}
Effects of Railway Characteristics

The railway-related characteristics that influence the expected number of collisions at crossings are “number of trains per day”, “train speed” and “number of tracks”. Figure 5(1), 5(2) and 5(3) illustrate the relationship between the predicted collisions and train speed, number of tracks and number of trains. Train speed has an adverse impact on collisions at sign crossings and flashing light crossings. With the increase of train speed, collisions at these two types of crossings increase. At crossings equipped with gates train speed has no effect on collisions. For the same train speed, sign crossings tend to experience more collisions than the other two types of crossings, and crossings with flashing lights tend to experience more collisions than crossings equipped with gates.

The number of tracks has no effect on collisions at crossings with signs and flashing lights, but has a positive effect on collisions for crossings with gates. The expected number of collisions tends to decline with more tracks. This implies that for a crossing with gates, increasing the clearance distance between the gates and the tracks could be an effective way to reduce the occurrence of collisions at the gate crossings.

More collisions are expected with increases in the number of trains daily. For the same number of trains daily, the sign crossings have the most collisions among the three types of crossings, followed by flashing light crossings. The crossings with gates experience fewer collisions than the other two types of crossings. It is obvious that equipping the crossings with flashing lights and gates has the expected effect of reducing the number of expected collisions.
Figure 5(1): Relationship between collisions and train speed for three types of warning devices (controlled by AADT = 8000 veh./day, road speed = 50 km/h, no. of tracks = 2, surface width = 12 m, and no. of train daily = 6)

Figure 5(2): Relationship between collisions and no. of tracks for three types of warning devices (controlled by AADT = 8000 veh./day, train speed = 30 mile/h, road speed = 50 km/h, surface width = 12 m, and no. of train daily = 6)
CONCLUSIONS

A systematic safety improvement program for highway-rail grade crossings relies on models and tools that can be used to identify Black Spot (BS) sites where the risk of collisions is unacceptably high and safety countermeasures are most warranted. This paper has presented a set of collision prediction models that were developed specifically for the Canadian occurrence and exposure data and environments. The US DOT model was evaluated and found not applicable to the Canadian data. Separate Poisson and Empirical Bayesian (EB) models were developed and evaluated for three different types of warning devices using crossing data for all regions of Canada. Chi-square goodness-of-fit tests indicated that the Poisson model was best able to fit the observed data when crossings were grouped according to warning device, road and train volume (traffic exposure) and train speed. A sensitivity analysis using the calibrated models has lead to the following findings:

1. For the same crossing conditions (AADT, train speed, road speed and number of tracks), crossings equipped with signs experience the highest collision rates among the three types of crossings. This would suggest that reduction in collisions should be expected if the warning devices at signed passive crossings are upgraded to active devices (flashing lights and/or gates).

2. While it is always beneficial to upgrade crossings from passive to active warning devices, the effect of upgrading from flashing lights to gates on expected number of collisions is not always positive, but depends on road traffic volume, road speed, train speed, number of tracks and surface width. Based on the Canadian model, under certain conditions and mix of mitigating factors, upgrades could have an adverse effect of actually increasing the expected number of collisions.

Figure 5(3): Relationship between collisions and no. of trains for three types of warning devices (controlled by AADT = 8000 veh./day, train speed = 30 mile/h, road speed = 50 km/h, no. of tracks = 2, and surface width = 12 m)
3. The expected number of collisions at crossings increases as traffic volume increases. Traffic volume has a higher effect on collisions occurred at sign crossings than those at flashing light and gate crossings.

4. Increased train speed has a significant adverse impact on collisions at crossings with signs only, a small effect on crossings with flashlights and no impact on crossings with gates.

Finally, we should note that Canada has reported noticeable reduction in collisions at grade crossings over the last 20 years. The above model indicates fewer collisions at crossings equipped with flashing lights and gates than at crossings with signs. This provides a possible explanation for the decreasing trend in collisions over time, that is, it could be due to an increased number of crossings being upgraded from passive to active warning devices. This assertion however needs to be investigated further, especially in the context of changing reporting thresholds.

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REFERENCES