Risk-Based Model for Identifying Highway–Rail Grade Crossing Blackspots

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A risk-based model is presented for identifying highway–rail grade crossing blackspots. This model consists of two prediction components: collision frequency and collision consequence. A graphic approach is adopted to identify crossings with unacceptable risks (high expected frequencies or consequences or both). These crossings are referred to as blackspots. The model was applied to Canadian inventory and collision occurrence data for the period 1997–2001. Poisson and negative binomial (NB) frequency prediction expressions were developed for crossings with three types of warning devices (signs, flashing lights, and gates). The NB model was found to provide a better fit to the collision frequency data. A weighted consequence score was introduced to represent combined collision severity. The weights used in this combined consequence score were obtained from insurance claims. An NB expression was developed for the collision consequence model. The spatial distribution of blackspots is discussed with respect to the type of warning device, upgrades in warning device, geographic location, and historical collision occurrence. A geographic information system platform was developed for the Ontario region and used to illustrate the spatial pattern of expected and historical collision frequency and associated blackspots.

Highway–rail grade crossing collisions are a source of concern to railway authorities and the public at large. The Canadian Transportation Safety Board (TSB) reported that, between 1993 and 1999, an average of 45 fatalities and 60 injuries per year took place in Canada as a result of grade-crossing collisions (*1*). In response to safety concerns at grade crossings, Transport Canada established a safety management program called Direction 2006. The goal of Direction 2006 is to reduce collisions nationwide by at least 50% by the year 2006. The question that needs to be addressed is how this goal can best be achieved (*2*).

It would be prohibitively expensive and impractical to improve safety at all grade crossings to a uniform standard, and a reduction in collisions is best achieved by directing appropriate countermeasures to blackspot locations. Blackspots are crossings with unacceptably high collision risk. It has been suggested that when one attempts to allocate funds to all problem areas, lack of funds and poor maintenance capability often result in the highest risk crossings being left unattended (*3*). Targeting blackspots, on the other hand, ensures that scarce funds target those crossings where safety improvements are most needed.

In this paper, it is asserted that blackspots cannot be established solely on the basis of historical collision experience. Collisions are rare random events that vary significantly over time and space. High risk one year on a given crossing does not necessarily mean high risk the next year. A longer term view of collision risk is needed to reflect the expected risks over a given period of time. Such estimates can be obtained only with accurate and reliable collision frequency and consequence prediction models.

Blackspot identification based solely on the expected number of collisions does not provide a complete view of the risk involved at each crossing. Collision risk consists of two components: frequency and consequence (severity). Ignoring consequences could lead to a lack of intervention at crossings with high collision severity, and a risk-based model is needed to identify blackspots.

This paper has three specific objectives:

- Review existing risk methodologies for predicting collision risk at highway–rail grade crossings for different control factors and conditions,
- Present a risk-based model for identifying blackspots based on expected collision frequency and consequence, and
- Demonstrate the model by applying it to grade crossings in Canada on a regional and national basis and obtain a prioritized list of blackspots for safety intervention.

LITERATURE REVIEW

Over the past several decades, a number of collision frequency models have been developed. These models generally adopt one of two basic perspectives: absolute or relative collision risk. Absolute models yield the "expected number of collisions" at a given crossing for a given period of time, while relative models yield a "hazard index," which represents the relative risk (frequency and/or consequence) of one crossing compared with another.

Typical absolute collision prediction models were developed by Coleman and Stewart (*4*) and the U.S. Department of Transportation (USDOT) (*5*). The USDOT model is generally recognized as being the industry standard for collision risk prediction at highway–rail grade crossings.

In the USDOT model, the expected numbers of fatalities and casualties are expressed as a function of different track and road geometric characteristics, traffic controls, and train and road volumes. Fatal collisions are defined as collisions that result in at least one fatality, while casualty collisions are defined as collisions that result in either at least one fatality or at least one injury. Both types of collisions are reported in the Federal Railroad Administration (FRA) occurrence databases (*5*).

The USDOT model was developed by fitting a nonlinear multivariate expression to historical FRA collision occurrence and Association of American Railroads inventory data for individual crossings

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in the United States. The USDOT model consists of three analytical components: basic statistical model, quasi-Bayesian adjustment for historical observations, and subjective external adjustment for the type of warning device. Three types of warning devices were considered: Type S (signs or crossbucks), Type F (signs with flashing lights), and Type G (signs plus flashing lights plus gates). The expected number of collisions per year per crossing was found to be a function of variables such as number of years of collision history, number of collisions recorded in determined years, and crossing characteristics (type of warning device, number of highway vehicles per day, number of trains per day, number of main tracks, number of through trains per day during daylight, etc.).

Many relative hazard index models were developed in the United States between 1950 and 1970, including the Mississippi Formula, the New Hampshire Formula, the Ohio Method, the Wisconsin Method, the Contra Costa County Method, the Oregon Method, the North Dakota Rating System, the Idaho Formula, the Utah Formula, and the City of Detroit Formula (*5*). Two representative relative risk models are the Ohio and City of Detroit models. In the Ohio model the hazard index is a function of factors such as collision probability, train speed, approach gradient, angle of crossing, number of tracks, and sight distance rating. The City of Detroit model includes factors such as average 24-h train volume; number of passenger, switch, and freight trains in 24 h; sight distance rating; and number of tracks.

The USDOT collision consequence model for highway–rail grade crossings considers two levels of severity: fatalities and casualties. In this model, the probability of a fatal collision given the prior occurrence of a collision is expressed as a function of variables such as maximum train speed, trains per day, switch trains per day, and location area of the crossing (urban or rural crossing). The probability of a casualty collision is related to maximum train speed, regional affiliation, and number of tracks.

It should be noted that the USDOT model treats all fatal collisions in a similar fashion regardless of the number of fatalities experienced. The focus of this consequence model is on the likelihood of a fatal and/or casualty collision and not on the numbers of fatalities or casualties associated with each collision. This limits its use in distinguishing differences in severity among different collisions as experienced at a given crossing.

DATA SOURCES

This analysis makes use of the combined RODS/IRIS inventory and occurrence database provided by Transport Canada and TSB. The IRIS database contains an inventory of about 29,500 grade crossings for all regions in Canada and includes information on highway and railway geometric characteristics, traffic volumes, and selected train operating features. The RODS database includes information on collision occurrence at these crossings for the period 1993–2001. This database is administered by TSB. The inventory and occurrence data share a common reference number that permits linkage between collision occurrence and crossing inventory characteristics for public and private crossings by municipality and province (*2*).

A number of grade crossings have been upgraded from signs to flashing lights and/or gates. Information provided by Transport Canada was used to match the inventory and occurrence attributes for each year to the applicable warning device for the year being considered (in the occurrence data).

Inventory Data Set (IRIS)

This data set provides information on the geometric characteristics, traffic control, and volume for each grade crossing. Five attributes are included in the inventory data: location data, type of warning device, highway geometric data, railway geometric data, and traffic volume data.

Five types of grade crossings were reported: public automated, public passive, private, farm, and grade separation. For this study, only public grade crossings (automated and passive) were considered, which account for about 75% of crossings nationwide.

Risk factors refer to crossing attributes that explain variation in the expected number of collisions and consequences. In this analysis, the following four types of risk factors were considered: type of warning device, highway geometry, railway geometry, and traffic volume.

Collision Occurrence Data (RODS)

The collision occurrence data collected by TSB include detailed information on each collision for the 29,500 crossings for the period 1993–2001. The collision occurrence database is organized into four types of information:

- Basic collision data: including the collision reference number, the date and time of collision, location, weather condition, road condition (wet or dry), road and rail geometry, traffic volume, trains daily, and so forth;
- Involved driver and vehicle data: including information on driver action, visibility, gender and age, and so forth;
- Involved person data: data providing information on the number of vehicles involved in the collisions and average occupancy of each vehicle; and
- Severity consequence data: data including information on the number of fatalities, serious injuries, and property damage level for each collision.

A number of crossings were found to be poorly specified for the purposes of this study (i.e., they did not include information on variables needed in the models). These crossings were removed from the database. Fortunately, most of the removed crossings were private, farm, and pedestrian and bike path crossings. As a result, the data set used in this study includes collision history and inventory information for 10,381 usable crossings in Canada for the period 1993–2001. The crossings for which the warning devices were changed over this period were considered twice in the database (before and after warning device change) with appropriate adjustments for exposure.

The collision occurrence data and grade-crossing inventory were specified in two separate data tables, which were linked by using a common crossing reference number. The combined inventory and occurrence database was subsequently used to calibrate and validate the collision frequency and consequence prediction models. Table 1 presents a brief statistical description of the variables used in this work. Exposure is defined as the product of the average annual daily traffic (AADT) and the number of trains traversing each crossing per day.

TABLE 1 Variables and Statistics of Data Used in Collision Frequency and Consequence

Data	Variables	Description	Mean	Standard Deviation
Collision Frequency	Track Angle	Degrees	70.26	19.17
	No. Tracks	Number	1.23	0.58
	Train Speed	km/h	65.97	33.34
	Road Speed	km/h	59.39	21.16
	Surface Width	Meters	10.62	5.42
	Road Class	1, arterial; 0, others		
	Highway Paved	1, paved; 0, unpaved		
	Warning Type	Signs: 5184 (50 %), Flashing lights: 3695 (36 %), Gates: 1502 (14 %)		
	AADT	Vehicles/day	1602.32	4054.34
	No. Trains Daily	Trains/day	9.5	13.06
	No. Collisions	Over 9-year period	0.18	0.52
Collision Consequence	Track Angle	Degrees	71.64	18.18
	No. Tracks	Number	1.36	0.72
	Train Speed	km/h	71.46	35.08
	Road Speed	km/h	57.8	19.63
	Surface Width	Meters	12.58	5.95
	Road Class	1, arterial; 0, others		
	Highway Paved	1, paved; 0, unpaved		
	AADT	Vehicles/day	3689.03	6287.01
	No. Trains Daily	Trains/day	13.46	13.04
	No. Fatalities	Over 5-year period	0.13	0.36
	No. Serious Injuries	Over 5-year period	0.2	0.48

PREDICTING COLLISION FREQUENCY AND CONSEQUENCE

Before frequency model calibration, the RODS/IRIS database was split into two random samples, one consisting of 8,098 crossings for calibration and the other consisting of 2,679 crossings for validation (75%/25% split). The data set used for the calibrated consequence model contains 826 collisions on 720 crossings Canada-wide for the period 1997–2001. The data were split randomly into two samples of 413 collisions for calibration and 413 collisions for validation. This section provides the calibration and validation results of frequency and consequence models for evaluating risk at grade crossings in Canada.

Collision Frequency Models

In the past, safety researchers have commonly adopted generalized linear models to model count data such as accident frequency. Two of the most common types of generalized linear model distributions are Poisson and negative binomial (NB) (*6*).

A Poisson model was developed for predicting collision frequency (y_i). This model implies that the conditional mean of collision frequency (μ_i) is equal to the variance. A log-link function is commonly assumed for the mean, $\mu_i = e^{\mathbf{x}_i\boldsymbol{\beta}}$, where $\boldsymbol{x_i}$ is the vector of explanatory variables and $\boldsymbol{\beta}$ is the vector of parameters. This function has the advantage that the predicted number of collisions is nonnegative. Parameters in the Poisson model were obtained by using maximum likelihood in the SAS computer program (*7*).

Table 2 presents the calibration results for the Poisson collision frequency model for three types of warning device (signs, S; flashing lights and signs, F; and gates, flashing lights, and signs, G). The following should be noted:

- Based on the χ^2 statistic, which tests the hypothesis of the parameter being equal to 0, the significant parameters in each model were selected at a 5% level of significance. Factors that were found not to be significant were excluded from the final Poisson expressions. In

TABLE 2 Poisson Regression Models: Estimated Parameters and Associated Statistics

	Warning Device S				Warning Device F				Warning Device G			
Variable	Estimate	Std Error	ChiSq	Pr>ChiSq	Estimate	Std Error	ChiSq	Pr>ChiSq	Estimate	Std Error	ChiSq	Pr>ChiSq
Intercept	-5.662	0.2348	581.73	<.0001	-9.1651	0.3783	587.01	<.0001	-7.2324	0.6868	110.9	<.0001
Road Speed	-	-	-	-	-	-	-	-	0.0118	0.0048	5.96	0.0147
Surface Width	-	-	-	-	0.0151	0.0063	5.83	0.0158	-	-	-	-
No. of Tracks	-	-	-	-	-	-	-	-	0.1912	0.061	9.84	0.0017
Train Speed	0.012	0.002	40.64	<.0001	0.0112	0.002	31.97	<.0001	-	-	-	-
Exposure	0.379	0.023	262.81	<.0001	0.6103	0.0311	386.18	<.0001	0.3526	0.0423	69.5	<.0001
Criterion	**DF**	**Value**	**Value/DF**		**DF**	**Value**	**Value/DF**		**DF**	**Value**	**Value/DF**	
G^2	3980	1982.273	0.498		2978	1758.419	0.591		1129	757.643	0.671	
X^2	3980	4121.524	1.036		2978	3455.403	1.160		1129	1286.053	1.139	
L(β)		-1379.956				-1241.934				-522.093		

crossings with signs (S), train speed and exposure proved to be significant in explaining expected collision frequency. For crossings with flashing lights (F), the three significant factors are surface width, train speed, and exposure. For crossings with gates (G), the three significant explanatory variables are number of tracks, road speed, and exposure. The signs of the explanatory variables are all intuitively acceptable.

- The standard goodness-of-fit measures for Poisson regression models are the Pearson (X^2) and scaled deviance (G^2). The closer the X^2 (or G^2) value is to 1.0, the better the assumed model. An X^2 (or G^2) value greater than 1.0 suggests that the collision frequency is more dispersed than that associated with the Poisson model. This is evidence of overdispersion in the data (*8*).
- There are circumstances in which these statistics are not applicable for evaluating the fitness of a model. For example, Wood (*9*) and Maher and Summersgill (*10*) show that, when the mean was low (<0.5), the G^2 statistic failed to provide a good measure of the goodness-of-fit of a model. They argued that the X^2 statistic should be used to evaluate the model adequacy in these circumstances. In this study, note that the scaled deviance (G^2) is considerably less than 1.0 for all three collision frequency prediction models as the mean observed number of collisions per crossing in the data was found to be low (0.177 collision per crossing over 9 years). Based on the Pearson (X^2) values, it can be concluded that the data are overdispersed and the Poisson distribution should not be used for predicting collision frequency at grade crossings. In this case, X^2 values of 1.036 for signs (S), 1.16 for flashing lights (F), and 1.139 for gates (G) were obtained.

The problem of overdispersion is commonly addressed by considering an NB expression in lieu of the Poisson expression. In the NB expression, the variance is assumed to be as a quadratic function of the mean, such that $\mathrm{Var}[y_i \,|\mathbf{x}_i] = \mu_i + \alpha\mu_i^2$, where α is the dispersion parameter to be estimated.

The overdispersion problem can be identified by first estimating both Poisson and NB models and then testing the null hypothesis H_0: $\alpha = 0$. For this purpose, two classical statistics can be used: the likelihood ratio (T_{LR}) and the Wald (T_W) statistics. T_{LR} is equal to −2 times the difference in the fitted log-likelihood of the two models and T_W is equal to the estimate of α divided by its standard error (*11*).

Table 3 presents the calibration results for the NB collision frequency model. The values of the parameters in this model were found to be very similar to the Poisson values. From Tables 2 and 3, the T_{LR} test statistic for crossings with signs (S) is $-2[-1379.96 - (-1370.19)] = 18.34$, which exceeds the 1% critical value of $\chi^2_{.98}(1) = 5.41$. The Wald test statistic is $T_W = 0.738/0.216 = 3.417$, which exceeds the 1% critical value of $z_{.99} = 2.33$. The two tests suggest a rejection of the null hypothesis that $\alpha = 0$ and indicate the presence of Poisson overdispersion. Similar test statistics for Poisson against NB for crossings with flashing lights (F) are $T_{LR} = 25.82$ and $T_W = 3.86$. For crossings with gates, there are $T_{LR} = 22.08$ and $T_W = 3.24$, rejecting also the assumption of equidispersion. From Table 3, it can be observed that the X^2 values for the NB models are closer to 1.0 than those for the Poisson models, suggesting that they fit the historical data better.

The goodness of fits of the Poisson and NB models were also evaluated by comparing the observed versus estimated relative frequencies of the collisions at grade crossings. The observed frequency (O_y) is the percentage of crossings with $y = 0, 1, 2, \ldots,$ collisions during the period of time considered. The estimated relative frequency (E_y) is obtained as $E_y = \Sigma_i\, p(y_i = y)$, $p(y_i = y)$ being the estimated probability of having y collisions, given the estimated parameters.

Table 4 presents the observed and estimated collision frequencies and their differences, for both Poisson and NB models. In most of the categories, the NB performs better than the Poisson model. Nevertheless, for the expected number of collisions equal to 3 and 4, the Poisson model performs quite well for crossings with signs. The same situation was observed for $y = 3$ for crossings with flashing lights and for $y \geq 4$ for crossings with gates. Therefore, it is concluded that the NB models perform better than the Poisson models, especially when estimating the probabilities of having 0, 1, and 2 collisions. In 89% of crossings with signs and in 85% of crossings with flashing lights and gates, zero collisions were reported. Crossings with signs and multiple collisions (more than one) represent 1.6% of the total. Crossings with flashing lights and gates represent 3.1%.

Collision Consequence Models

Fatalities and personal injuries were observed to be a very small subset of total crossing collisions in the Canadian data. Instead of developing separate models for each type of casualty as in the USDOT approach, a combined model was adopted that reflects the total consequence of a given collision. The total consequences of a collision are expressed in terms of a collision severity score, defined as the

TABLE 3 NB Regression Models: Estimated Parameters and Associated Statistics

	Warning Device S				Warning Device F				Warning Device G			
Variable	**Estimate**	**Std Error**	**ChiSq**	**Pr>ChiSq**	**Estimate**	**Std Error**	**ChiSq**	**Pr>ChiSq**	**Estimate**	**Std Error**	**ChiSq**	**Pr>ChiSq**
Intercept	-5.7521	0.2581	496.56	<.0001	-9.2894	0.4207	487.54	<.0001	-7.5503	0.8099	86.92	<.0001
Road Speed	-	-	-	-	-	-	-	-	0.0122	0.0054	5.06	0.0245
Surface Width	-	-	-	-	0.0171	0.0077	5.01	0.0252	-	-	-	-
No. of Tracks	-	-	-	-	-	-	-	-	0.2029	0.0747	7.38	0.0066
Train Speed	0.0131	0.0022	35.55	<.0001	0.0115	0.0022	26.59	<.0001	-	-	-	-
Exposure	0.3883	0.0262	219.60	<.0001	0.6176	0.0350	311.35	<.0001	0.3737	0.0509	53.96	<.0001
α	*0.7375*	*0.2158*	-	-	*0.5790*	*0.1497*	-	-	*1.0625*	*0.3282*	-	-
Criterion	**DF**	**Value**	**Value/DF**		**DF**	**Value**	**Value/DF**		**DF**	**Value**	**Value/DF**	
G^2	3980	1681.433	0.423		2978	1481.306	0.497		1129	580.674	0.514	
X^2	3980	3777.039	0.949		2978	3162.330	1.062		1129	1078.592	0.955	
L(β)		-1370.187				-1229.019				-511.053		

TABLE 4 Observed Versus Estimated Frequencies of Collisions at 8,098 Rail–Road Crossings

Type of Warning Device	Number of Collisions (y_i)	Observeved Frequency of Crossings with y_i	Estimated Relative Frequency of Crossings with y_i Collisions (f_y in percent)			
			Poisson		NB	
Signs (S)	$y = 0$	89.380	88.770	-(0.610)	89.419	(0.039)
	$y = 1$	9.013	10.130	(1.117)	9.054	(0.041)
	$y = 2$	1.456	0.983	-(0.473)	1.234	-(0.222)
	$y = 3$	0.100	0.102	(0.002)	0.221	(0.121)
	$y = 4$	0.025	0.013	-(0.012)	0.050	(0.025)
	$y \geq 5$	0.025	0.002	-(0.023)	0.021	-(0.005)
	$y \geq 0$	100	100	(0.0)	100	(0.0)
Flashing Lights (F)	$y = 0$	85.480	84.434	(1.045)	85.25	(0.232)
	$y = 1$	11.402	12.965	-(1.563)	11.38	(0.020)
	$y = 2$	2.247	2.114	(0.133)	2.53	-(0.285)
	$y = 3$	0.671	0.390	(0.281)	0.57	(0.105)
	$y = 4$	0.168	0.077	(0.090)	0.18	-(0.008)
	$y \geq 5$	0.034	0.020	(0.014)	0.10	-(0.063)
	$y \geq 0$	100	100	(0.0)	100	(0.0)
Gates (G)	$y = 0$	85.172	83.565	(1.607)	84.078	(1.094)
	$y = 1$	11.650	14.316	-(2.666)	12.379	-(0.729)
	$y = 2$	2.560	1.833	(0.726)	2.519	(0.040)
	$y = 3$	0.530	0.242	(0.288)	0.665	-(0.135)
	$y = 4$	0.088	0.044	(0.044)	0.218	-(0.130)
	$y \geq 0$	100	100	(0.0)	100	(0.0)

weighted sum of different types of consequence. This approach has several advantages: it considers both fatalities and injuries in a single expression, rendering the approach easier to use in blackspots identification; it makes better use of crossing data, with all crossings with collisions considered and not just those with casualties or fatalities; and, most importantly, it accounts for colinearity between fatalities and personal injuries, so that nesting of the models is not required as in the USDOT expressions.

Because fatalities, injuries, and property damage contribute disproportionately to collision severity, each of these consequences was first weighted according to the reported costs. These costs form a uniform value or "yardstick" by which different collision consequences can be compared, such as severity of fatalities, personal injuries, and vehicle and property damages. The weighted sum of collision consequences yields a "consequence score." This score can be related statistically to a number of crossing characteristics, control factors, and measures of exposure to yield an estimate of expected consequences (or severity) at each crossing.

The weights assigned to fatality and person injuries were based on 1995 United States National Safety Council cost estimates. For property damages, weights were obtained from estimates provided by FRA with a willingness-to-pay approach (*12*).

The average costs of different collision consequences were reported as follows:

Fatality:	\$2,710,000/fatality
Injuries:	\$65,590/injury
Average property damage:	\$61,950/train collision

The weight for property damages was set equal to 1.0 and scaled accordingly for other consequences to yield a crossing collision consequence score (CS_i) of the following form:

$$CS_i = 44.0 \times (NF_i) + 1.0 \times (NI_i) + 1.0 \times (PD_i) \quad (1)$$

where

NF_i = number of fatalities,
NI_i = number of injuries, and
PD_i = property damage.

This score reflects the severity of collisions at grade crossings based on the number of fatalities and injuries and property damage (in 1995 U.S. dollars).

In RODS, property damage was reported in terms of 12 types of property (including vehicle type) and 4 categories of damage. The value equivalence was assigned based on average values of each type of property from published values. The 4 categories of damage in the RODS database include totally destroyed, major damage (80% destroyed), minor damage (30% destroyed), and no damage. The percentage values were assigned in this study by using best judgment. The consequence score was summed over all collisions reported at each crossing for the period 1997–2001 and divided by the number of collisions reported during this period. This yielded a consequence score per collision, which served as the dependent variable in the consequence prediction model.

The modeling process was repeated for the consequence prediction model. As before, a Poisson model was first attempted and was found to be very overdispersed. For consequence prediction, a more flexible NB expression of the following form was adopted:

$$E(\text{consequence}/\text{collision}) = e^{0.3426 \times PI_i \; 0.2262 \times TN_i + 0.0069 \times TA_i + 0.0250 \times TSPD_i} \quad (2)$$

where

PI_i = number of persons involved,
TN_i = number of railway tracks (both directions),
TA_i = track angle, and
$TSPD_i$ = maximum train speed (mph) at crossing *i*.

The $G^2 = 1.079$ and $X^2 = 2.83$ values for this NB consequence model are closer to 1.0 and are much better than the Poisson consequence model values, which are $G^2 = 17.7$ and $X^2 = 38.3$. The use of the consequence score resulted in mean values greater than 1, suggesting that the G^2 statistic could be used to measure overdispersion. For the preceding consequence model, the NB model provided a good representation of the data.

BLACKSPOT ANALYSIS

Based on a pre-set frequency and consequence threshold of 0.10%, a list of 22 blackspots was obtained for Canada-wide data—11 blackspots based on expected frequency and 11 blackspots based on expected consequence. These were compared with the 0.10% list of blackspots based on historical observations for frequency and consequence. The 0.10% threshold reflects frequency and consequence scores that are exceeded 0.1% of the time in the reported data. In the absence of a more objective definition of thresholds, these values are high enough to be considered unacceptable. Crossings that exceed these thresholds are candidates for countermeasures.

Table 5 indicates the locations of crossings identified as blackspots based on the Poisson and NB frequency models. The same crossings were assigned to the blackspots list for the two types of prediction models, but their rankings in the list differ. None of these crossings was included in the Transport Canada list of upgraded crossings for the period of analysis. These blackspots were then compared with the top 11 crossings based on historical collision frequency as reported in the 1997–2001 RODS/IRIS database. The results are presented in Table 6. Only one crossing was common to both the predicted and the historical blackspots list.

Eleven blackspot crossings were obtained from the collision consequence NB model, and these are presented in Table 7 with their warning device, location, and last registered upgrade. Three cross-

TABLE 5 Blackspots List Based on Predicted Frequency per Year

Crossing No.	Warning Device	Street or Road	Municipality	Province	Poisson Frequency/Year	Poisson Rank	NB Frequency/Year	NB Rank
30438	F	22nd St	Saskatoon	SK	0.219	1	0.242	1
12651	F	Albert St (Hwy 6)	Regina	SK	0.213	2	0.224	2
12833	F	Pasqua St	Regina	SK	0.197	3	0.200	3
16972	S	21-22-36-6	Corman Park No. 344	SK	0.184	4	0.195	4
28813	F	3rd Avenue North	Saskatoon	SK	0.163	8	0.174	5
24833	G	Heritage Dr	Calgary	AB	0.153	11	0.173	6
30951	F	Essex Road 22	Tilbury East	ON	0.169	5	0.171	7
12640	F	Ring Road	Regina	SK	0.165	6	0.168	8
8281	F	Adelaide St	Oshawa	ON	0.163	7	0.167	9
30240	F	Main St	Saint John	NB	0.157	9	0.167	10
20573	F	Cartier Hy	Onaping Falls	ON	0.156	10	0.164	11

NOTE: SK = Saskatchewan; AB = Alberta; ON = Ontario; NB = New Brunswick.

TABLE 6 Blackspots List Based on Collision Frequency History (1997–2001)

Crossing No.	Warning Device	Street or Road	Municipality	Province	Upgraded (type of work)	Installed	No. of Collisions	Rank
32379	F	Reg Rd #102-Clifton	Niagara Falls	ON	-	-	6	1
28813	F	3rd Avenue North	Saskatoon	SK	Preemption	18/06/2000	5	2
18061	F	Grand Bernier Road	Saint-Jean-S-Richelieu	QC	-	-	4	3
23696	F	Kimberly Avenue	Winnipeg	MB	-	-	4	4
24123	G	Ross Avenue	Regina	SK	Add gates, CWD & lights	29/11/2001	3	5
17073	S	Grid Road 675	Senlac No. 411	SK	-	-	3	6
7044	G	Torbram Road	Brampton	ON	-	-	3	7
13174	G	Third St	Portage La Prairie	MB	-	-	3	8
23164	G	Municipal Road	Sherwood No. 159	SK	FLBG, CWD & sensors	09/11/1999	3	9
21521	G	Marion St	Winnipeg	MB	Add gates	06/11/2001	3	10
10492	G	Rue De Courcelles	Montreal	QC	-	-	3	11

NOTE: QC = Quebec; MB = Manitoba; CWD = constant warning device; FLBG = flashing light signals and bells with gates.

TABLE 7 Blackspots List Based on Predicted Consequence/Collision

Crossing No.	Warning Device	Street or Road	Municipality	Province	Upgraded (type of work)	Installed	Conseq. Collision/Yr.
4843	G	Chemin du 3e Rang	Saint-Cyrille-de-W	QC	Add gates & CWD	13/03/2000	4.93
4863	G	Rang St-Georges	Saint-Simon	QC	Add light units	22/08/1994	4.93
4860	F	Chemin 2e Rang	Sainte-Helene-de-B	QC	-	-	4.93
36581	G	County Road 16	Wolford	ON	-	-	4.93
3261	G	Rourte Line	Maidstone	ON	-	-	4.93
4788	S	Route du 3e	Val-Alain	QC	-	-	4.93
4852	F	Chemin du 8e Rang	Saint-Germain-de-G	QC	-	-	4.93
4858	F	Rang St-Augustin	Sainte-Helene-de-B	QC	-	-	4.93
3258	G	Ducharme Road	Belle River	ON	-	-	4.93
19647	F	Kilmarnock Road	Wolford	ON	-	-	4.93
300759	G	Couture Road	Tilbury North	ON	FLBG & CWD	24/11/1998	4.93

ings on this list were included in the Transport Canada upgraded crossing file for 1997–2001.

The top 11 blackspot crossings from the consequence models were then compared with historical consequences based on personal injury severity reported for the period 1997–2001. These data are presented in Table 8.

The top 22 crossings based on both historical frequency and consequences were found to be more spatially dispersed among regions in Canada. The model designated blackspots were more confined to a few regions of the country.

The top 11 blackspots based on historical collisions differ from the top 11 blackspots based on predicted frequency. The predicted frequency list includes mostly crossings with flashing lights (F), while the historical frequency list includes a mix of crossings with signs (S), flashing lights (F), and gates (G). Many crossings in the historical list were upgrading from signs and flashing lights to gates. It should be noted that many of the predicted frequency blackspots were not upgraded during the analysis period, suggesting that possible high-risk crossings as predicted by the model were not considered for safety intervention.

The list of blackspots in Table 5 indicates that the top 11 high-frequency crossings are located in urban areas, especially in Saskatchewan. The top 11 high-consequence crossings in Table 7 are mostly located in rural areas, especially in Ontario. One possible explanation for this result is that crossings located in urban areas are usually associated with higher traffic volumes than those in rural areas, thus leading to an increased expected number of collisions. Because in rural areas there is less traffic volume, both trains and road vehicles traverse each crossing at higher speeds, and, given a collision, the consequences can be more severe than in urban areas. Figure 1 provides a geographic information system representation of blackspots in Ontario at the municipal level for predicted collision frequency and consequence.

The top 11 crossings with the highest consequence per collision reflect crossings with higher train speeds than the top 11 frequency crossings. The mean value of train speed for the top 11 consequence crossings is 114 km/h (71 mph), significantly higher than the average value of 42 km/h (26 mph) for the top high-frequency crossings. This confirms that train speed has a more pronounced effect on collision severity than frequency.

TABLE 8 Blackspots List Based on Collision Consequence History (1997–2001)

Crossing No.	Warning Device	Street or Road	Municipality	Province	Upgraded (type of work)	Installed	Fatalities	Serious Injuries	Rank
6398	G	4th Line Road	Halton Hills	ON	-	-	4	1	1
5019	S	Mckeand Ave	Ingersoll	ON	-	-	3	0	2
7091	G	Derry Road R 25	Halton Hills	ON	-	-	2	0	3
32033	F	Dolph St	Cambridge	ON	FLB & Cant	08/06/2000	2	0	4
19657	G	County #28	Elizabethtown	ON	Gates	02/10/2000	2	0	5
27477	S	Ns W15-33-1-5	Mountain View C 17	AB	-	-	2	0	6
35559	F	Yellowhead Hwy 16	Arlington No 79	SK	AAWS	07/06/1996	2	1	7
36755	S	Rge Rd 245	Leduc County No. 25	AB	-	-	2	0	8
713	F	Slater Road	Whitchurch-Stouffville	ON	-	-	2	1	9
21282	F	9th Ave	Crowsnest Pass	AB	-	-	2	2	10
18061	F	Grand Bernier Road	Saint-Jean-S-Richelieu	QC	-	-	1	1	11

NOTE: FLB = flashing light signals and bells; AAWS = active advance warning signals; Cant = cantilever.

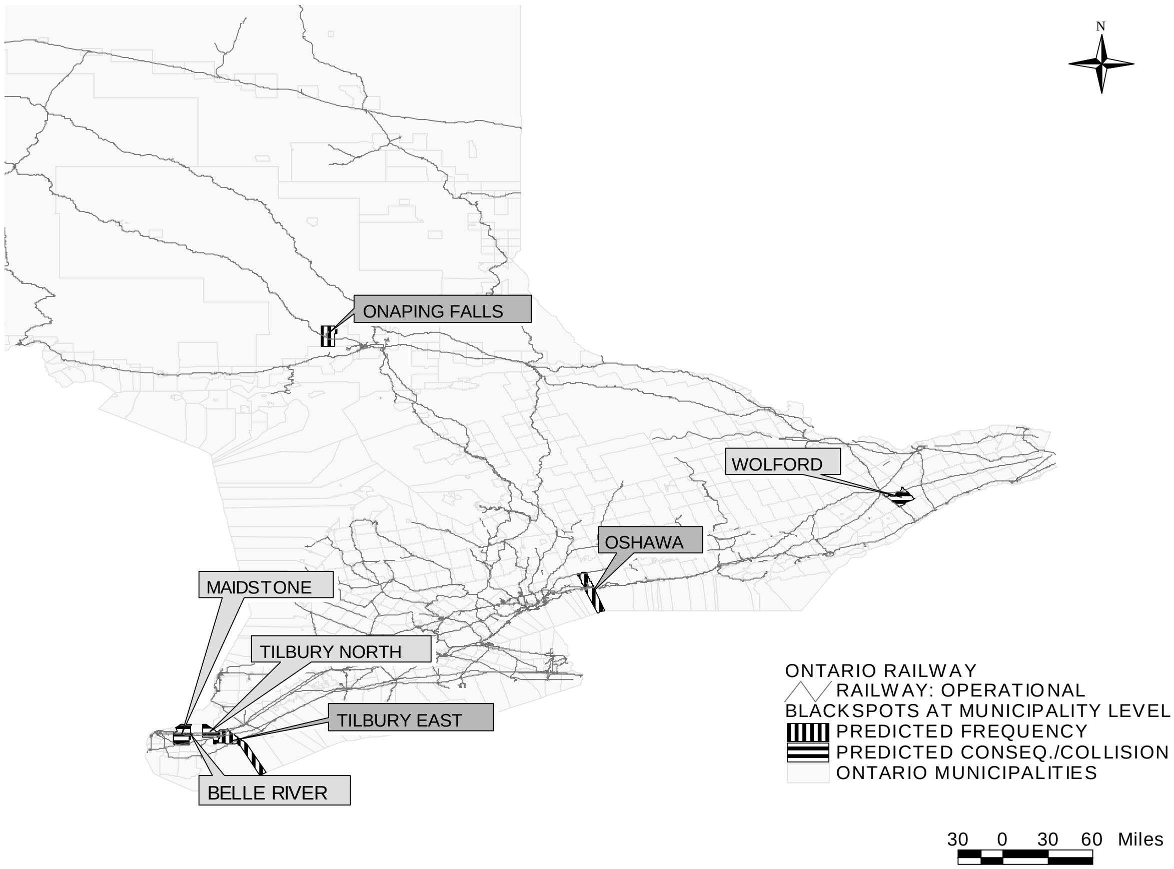

FIGURE 1 Blackspots in Ontario at municipality level based on predicted frequency per year (Onaping Falls, Oshawa, and Tilbury East) and consequence per collision (Belle River, Maidstone, Tilbury North, and Wolford).

CONCLUSIONS

This paper presents a risk-based methodology for identifying highway–rail grade crossing blackspots in Canada. The main conclusions obtained from the research are summarized as follows:

- NB collision frequency and consequence models produced better results than Poisson models, although for the frequency prediction the differences are not as pronounced as for the consequence prediction model. Separate collision prediction models for each type of warning device were found to yield better results than were obtained for a single prediction expression with warning device included as an independent variable.
- Traffic exposure (log of cross product of AADT and number of trains daily) was found to be the most important factor explaining the expected frequency of collisions for all types of highway–rail grade crossings. The nature of this relationship was found to be nonlinear and dependent on the type of warning device. For passive crossings (e.g., signs only), the factors train speed and exposure were found to provide the highest explanation for the expected frequency of collisions per year. For active crossings with flashing lights, the significant input factors were train speed, road surface width, and exposure. For crossings with gates, the input factors for predicting collision frequency were road speed, number of tracks, and exposure. Because road speed in this expression is the posted speed, it reflects possible geometric factors affecting collisions at grade crossings, such as number of lanes, sight distances, vertical and horizontal alignments, and so forth.
- A consequence score was developed based on average costs associated with different levels of collision severity, including fatality, serious injury, and property damage. By using a single consequence score, the full spectrum of damages resulting for each collision could be obtained and incorporated into the blackspots identification. In a similar fashion, different prediction models were investigated for collision consequences, and the NB was found to provide the best results.
- Unlike collision frequency, warning device was not found to yield a statistically significant explanation for collision consequences. It was found that train speed, number of tracks, track angle, number of vehicles, and involved persons had a significant effect on expected collision consequence at crossings.
- A list of blackspots was identified on the basis of both predicted frequency and consequence for an assumed threshold of 0.1% exceeding. It was found that the identified blackspots clustered in Saskatchewan (due to high traffic frequency) and in Ontario and Quebec (due to high consequence). Most blackspots based on collision frequency were found to cluster in urban areas with high AADT. Blackspots based on collision consequence, on the other hand, were situated in rural areas with high train speeds but not necessarily high AADT volumes.

Canada has reported noticeable reductions in collisions at grade crossings over the last 20 years. The risk models developed in this research indicate fewer collisions at crossings equipped with flashing lights and gates than at crossings with signs. This finding provides one possible explanation for the decreasing trend in collisions (i.e., the IRIS database has indicated an increased number of crossings that were upgraded in the last few years from passive to active warning devices—in particular, gates).

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