A model to predict the probability of highway rail crossing accidents

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Abstract: In the current paper, a model to predict the probability of accidents, injuries, and fatalities resulting from collisions between trains and vehicles at highway rail crossings is presented. Logistic regression and two databases maintained by the US Federal Railroad Administration (FRA) are used to build the models. These models prove more than an order of magnitude more accurate than a previous model developed by the FRA, which is currently used to compute the cost effectiveness of crossing upgrades. A declining trend in the likelihood of an accident that cannot be explained by changes in crossings or highways over time is discovered. Possible causes of this trend and test one of these possibilities are discussed. The model is used to compute both the cost per life saved from upgrading each crossing without gates and the trend over time in the number of crossings that are cost effective to upgrade.

Keywords: railroad, crossing, accidents, injuries, fatalities, predictions, cost–benefit

1 INTRODUCTION

In the current paper, statistical models of accidents, injuries, and fatalities at highway railroad crossings that are less complicated and significantly more accurate than the current US Federal Railroad Administration's (FRA) model are presented. These models are then used to evaluate the current state of safety at 87 000 ungated public crossings in the USA and the economic efficiency of the use of safety funds to date in upgrading 15 000 crossings. The modelling approach developed is generally appropriate for statistically evaluating railroad crossings and easily transferable to other data sets such as those maintained in the EU.

From 1986 to 2001, approximately 9000 people were killed and 30 000 injured in collisions between motor vehicles and trains at US rail crossings. Approximately 23 per cent of fatalities occur at transit crossings, which are typically in heavily populated areas. Highway safety officials and the railroad industry have responded by closing crossings, upgrading warning devices, and sponsoring safety initiatives to warn drivers of the hazards of rail – highway intersections. These efforts appear to have been successful as the number of deaths and injuries from train – motor vehicle collisions has fallen by over 50 per cent and from trains colliding with pedestrians over 40 per cent from their high points in 1989 railroad employee fatalities show a similar trend to vehicle passengers. Deaths of railroad passengers are extremely uncommon in the USA – averaging six per year. Almost all of this improvement has occurred in the freight sector as transit rail crossing fatalities show no trend, at least over the last 10 years United States Bureau of Transportation Statistics, http://www.bts.gov/publications/national_transportation_statistics/excel/ table_02_33b.xls. In comparison, highway fatalities have fallen only 8 per cent over this same period, 25 per cent on a mileage-adjusted basis. Continued success depends ultimately on the ability of state highway departments to identify the most hazardous crossings for upgrade. Crossing upgrades compete with other highway safety projects and ranking of crossings for upgrade requires models to measure accident risk that are uniform across safety devices.

During the last three decades, the FRA has developed a series of models to predict the likelihood of accidents between trains and motor vehicles [**1**]. The models were developed primarily to assist government

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agencies in deciding which railroad–highway crossing are cost effective to upgrade and are fundamental to software that has been developed for the FRA to compare the costs and benefits of potential crossing upgrades [**2**]. The models are also useful to states within the USA in qualifying for federal funds from the Section 130 programme [**3**]. That programme requires that states rank crossings numerically according to the likelihood of an accident.

The most recent version of the FRAs model was completed in 1987 [**1**]. The model is based on (a) an inventory of crossing characteristics that has been maintained since 1976 and (b) data collected from accident reports that are submitted to the FRA. The model consists of several equations, which are combined to predict the frequency of accidents and two additional equations to predict the probabilities of a casualty or fatality when an accident occurs. The coefficients in the equations were estimated with non-linear least squares regression.

2 DATA

As the FRA has done in the past, two primary data sources are relied upon to build models to predict accident rates at railroad crossings. Both are maintained by FRAs Office of Safety Analysis and were downloaded from their website data were downloaded on 1/15/2003 from http://safetydata.fra.dot.gov/officeofsafety/. The models presented in this paper were estimated using data collected between 1991 and 2001. In addition, 5 years of previous accident history as an explanatory variable were tested.

The first source of data is accidents at highway–rail crossings, which must be reported to the FRA on Form 6180.57. This information is stored in the FRAs highway–rail grade crossing accident/incident data file. Fields of interest for modelling include the grade crossing identification number, type of motor vehicle involved, the dollar amount of damage to vehicles, and the number of people injured or killed. In the models, accidents that involved a pedestrian but no motor vehicles are excluded because it is likely that a different set of factors would predict these accidents and much of the data that might prove useful are not collected. Data are limited on damage to a train involved in a collision. The trend in damages and casualties from 1986 to 2001 resulting from these accidents is shown in Table 1. The number of people injured or killed fell during the 1990s.

The database of accident history was matched to the records in the second database, the highway–rail crossing inventory. Data for this source are collected by the FRA on Form 6180.71. Fields in this data set include information about tracks, train movements, warning devices, highway characteristics, and vehicle traffic.

In developing the models, private and pedestrian crossings and crossings that were not at grade (i.e. with overpasses or underpasses) are excluded. On the inventory form, only a small fraction of the fields are requested of private crossings, most of which have little vehicular traffic. The number of crossings meeting the criteria ranged from 154 075 in 2001 to 172 277 in 1991. Even though population, traffic, and the number of roads increased during the 1990s, the number of crossings fell because of closings for safety reasons

Table 1 Casualties and vehicle damage caused by accidents at railroad crossings

		Vehicle passengers		Railroad employees		Train passengers	
Year	Vehicle damage	Killed	Injured	Killed	Injured	Killed	Injured
1986	16 563 064	605	2244	2	92	0	63
1987	18 098 101	619	2263	2	117	0	4
1988	20 025 170	687	2379	0	149	0	19
1989	26 293 730	792	2546	4	203	0	80
1990	23 221 077	689	2192	5	165	0	11
1991	18 726 557	602	1895	1	141	0	22
1992	16 870 055	568	1709	2	145	0	82
1993	17 359 827	612	1634	2	138	0	44
1994	19 250 620	610	1734	1	123	0	84
1995	18 167 950	567	1710	2	122	0	30
1996	17 645 446	475	1476	1	80	0	24
1997	19 112 276	451	1360	0	49	0	4
1998	16 727 724	422	1161	2	65	0	3
1999	16 165 152	387	1208	2	137	11	43
2000	18 338 198	420	1099	3	91	0	10
2001	17 148 720	418	1035	1	92	0	20

Table 2 Means of crossing variables used in models

Field name	Description	Mean
DAYTHRU	# Through trains 6 a.m.–6 p.m.	5.14
DAYSWT	# Switch trains 6 a.m.–6 p.m.	1.26
NGHTTHRU	# Through trains 6 p.m.–6 a.m.	4.66
NGHTSWT	# Switch trains 6 p.m.–6 a.m.	0.52
MAXTTSPD	Max timetable speed	35.38
MINSPD	Minimum typical train speed	13.06
MAXSPD	Maximum typical train speed	33.80
MAINTRK	Through train tracks	1.00
OTHRTRK	Other train tracks	0.43
TRAFFIC	Vehicles/day	2100
TRAFICLN	Traffic lanes	2.01
PCTTRUCK	Trucks, % of traffic	0.09

For 130 305 public at grade crossings as of 31.12.01

Table 3 Frequency of warning devices

	WDCODE	Frequency	Per cent
1	No sign or signal	3206	2.5
2	Other signs	475	0.4
3	Stop signs	57 484	44.1
4	Crossbucks	9002	6.9
5	Non-train activated special protection	2137	1.6
6	Wigwags, bells, or highway traffic signals	1109	0.9
7	Flashing lights	22 737	17.4
8	Gates	34 129	26.2
	Not specified	26	0.0

and because line abandonment has reduced track mileage [**3**].

The numeric fields from the inventory database used are summarized in Table 2 for crossings that were in service at the end of 2001. In the model, crossings that had less than six or more than 100 000 vehicle crossings per day were eliminated. The types of warning devices found at these crossings are summarized in Table 3.* The stop sign is by far the most common device followed by gates and then flashing lights. Crossings that had either no sign or signal or an unspecified warning device were eliminated from the data set.

Table 4 shows the distribution of development surrounding crossings. Nearly 40 per cent of crossings are in rural areas surrounded by open space.

Table 5 shows that track runs down a street at about 6 per cent of crossings.

Table 6 shows the distribution of the angle between highways and tracks at crossings.

As an explanatory variable, the frequency of alcohol intoxication of drivers involved in fatal highway accidents was tested. The source of these data was the Fatality Analysis Reporting System maintained by the National Highway Traffic Safety Administration.† Data were tabulated by state and year, and for two blood alcohol concentrations (BACs), 0.08 and 0.16 per cent.

Table 4 Development in the vicinity of the crossing

DEVELTYP	Frequency	Per cent
Open space	50 945	39.1
Residential	30 352	23.3
Commercial	27 742	21.3
Industrial	19 487	15.0
Institutional	1776	1.4

Table 5 Track runs parallel to and within a street or highway

DOWNST	Frequency	Per cent
Yes	7317	5.6
No	122 954	100

Table 6 Smallest angle between the highway and the track

XANGLE	Frequency	Per cent
0°–29°	5178	4.0
30°–59°	20 737	15.9
60°–90°	104 389	80.1

3 METHODOLOGY

Two different approaches can be used to model accidents, injuries, and fatalities. First, the probability of an accident can be modelled, and then the probability that an accident could result in injuries or fatalities. The probability of a fatality, $P(f)$, would be computed as the probability of an accident $P(a)$ times $P(f|a)$, the conditional probability of a fatality given that an accident has occurred. Similarly, the probability of an injury would be computed as $P(i) = P(a)P(i|a)$. The FRA used this approach.

Another approach, the one adopted herein, is to model the probability of injuries and fatalities directly. The logit model (also called logistic regression) is used here to model the probabilities. The logit model is one of several commonly used equations to model probabilities, which must be between 0 and 1. The resulting probabilities easily convert to accidents per 1 000 000 crossings or to accidents per year. The logistic model takes the form

$$P = \frac{1}{(1 + e^{-Z})}$$

**We will refer to three generic crossing types which include gated (8), flashing lights (5, 6, or 7) and passive (1 through 4).*

† *http://www-fars.nhtsa.dot.gov/.*

where P is the probability of an accident, Z is the linear combination of explanatory variables $X_1, \ldots, X_n$, and regression coefficients $B_0, \ldots, B_n$

$$Z = B_0 + \sum_{i=1}^{n} B_i X_i$$

The observation unit in the regression is a single vehicle crossing. The dependent variable equals 1 for an unsuccessful crossing that results in an accident, injury, or fatality, and equals 0 for a successful crossing. The observations for unsuccessful crossings are constructed from the records in the accident file matched to the corresponding crossing characteristics extracted from the inventory file. The observations for the successful crossings are constructed from records in the inventory file along with a variable that represents the frequency of each observation. The frequency was computed as the average daily traffic times the number of days during which the record was valid. Each inventory record contains two fields that represent the beginning and ending date for the period the record was effective. For the observations representing unsuccessful crossings, the frequency variable equals either 1, the number of people injured or the number of fatalities depending on whether accidents, injuries, or fatalities are being modelled.

This approach was modified slightly to incorporate previous accident history as an explanatory variable. The inventory records were broken up by calendar year and the sum of accidents, injuries, and fatalities for the previous five calendar years was computed for each observation. However, we did not count any events that occurred prior to any previous crossing upgrade.

4 REGRESSION RESULTS

Coefficients for several sets of explanatory variables in models for accidents, injuries, and fatalities were estimated. These included versions with and without previous accident history. Versions in which one or more variables were not statistically significant at the 5 per cent level were rejected. Variables that were tested but not significant included the number of main tracks, the number of other tracks, whether the highway was paved, whether the crossing had signs providing advanced warning, the per cent of traffic consisting of school busses, the number of passenger trains, and the number of traffic lanes. It is interesting that, using a robust statistical procedure, many of the variables in the FRA model (e.g. number of tracks, highway paving) are found to be not statistically significant.

The coefficients for the final models are presented in Table 7. The variables that indicated the highest level of warning device employed at the crossing were highly significant. Each of these variables, WdCode2-WdCode7 equalled 1 if the device associated with that variable was the highest level of warning present at the crossing and equalled 0 if not. These variables, all with positive signs, measure the increased likelihood

Table 7 Statistics for logit model variables

		Coefficients			p-values		
Description	Variable	Accidents	Injuries	Fatalities	Accidents	Injuries	Fatalities
Intercept	Constant	−17.939	−20.483	−25.996	0.0000	0.0000	0.0000
Max typical train speed	MAXSPD	−0.024	−0.045	−0.087	0.0000	0.0000	0.0000
sqrt(maxSpd)	MAXSPD2	0.390	0.718	1.404	0.0000	0.0000	0.0000
sqrt(maxTTSpd)	MAXTTSP2	0.166	0.192	0.435	0.0000	0.0000	0.0000
# trains 6 a.m.–6 p.m.	DAYTHRU	0.003	0.008		0.0051	0.0001	
# trains 6 p.m.–6 a.m.	NGHTTHRU	0.037	0.030	0.040	0.0000	0.0000	0.0000
Switch trains/day	SWITCH	0.016	0.006		0.0000	0.0032	
% trucks	PCTTRUCK	−0.912	−1.006	−0.666	0.0000	0.0000	0.0020
Traffic/lanes	TRAFLANE	0.510	0.504	0.523	0.0000	0.0000	0.0000
sqrt(trafLane)	TRAFLAN2	−2.916	−2.819	−2.932	0.0000	0.0000	0.0000
Other signs	WDCODE2	0.970	1.552	1.311	0.0000	0.0000	0.0035
Stop signs	WDCODE3	1.231	1.681	1.714	0.0000	0.0000	0.0000
Crossbucks	WDCODE4	1.343	1.698	1.720	0.0000	0.0000	0.0000
Other activated protection	WDCODE5	0.501	0.693		0.0000	0.0000	
Wigwags, highway signals	WDCODE6	0.790	1.120	0.779	0.0000	0.0000	0.0003
Flashing lights	WDCODE7	0.795	1.162	1.093	0.0000	0.0000	0.0000
Angle 0°–29°	XANGLE1	−0.059	−0.231	−0.471	0.0304	0.0000	0.0000
Angle 30°–59°	XANGLE2	−0.157	−0.196		0.0000	0.0000	
Track down street	DNSTREET	−0.225	−0.242	−0.285	0.0000	0.0000	0.0055
Area residential	DEVLTYP2	−0.073	−0.119	−0.098	0.0000	0.0000	0.0148
Area commercial	DEVLTYP3		−0.102	−0.100		0.0000	0.0250
Area industrial	DEVLTYP4		−0.180	−0.293		0.0000	0.0000
Accident history, 5 years	ACCIDNT0	0.321	0.338	0.337	0.0000	0.0000	0.0000
Year-2001	Years	−0.048	−0.054	−0.056	0.0000	0.0000	0.0000
Obs, unweighted; R^2		1 862 612	1 837 353	1 830 136	0.066	0.075	0.103

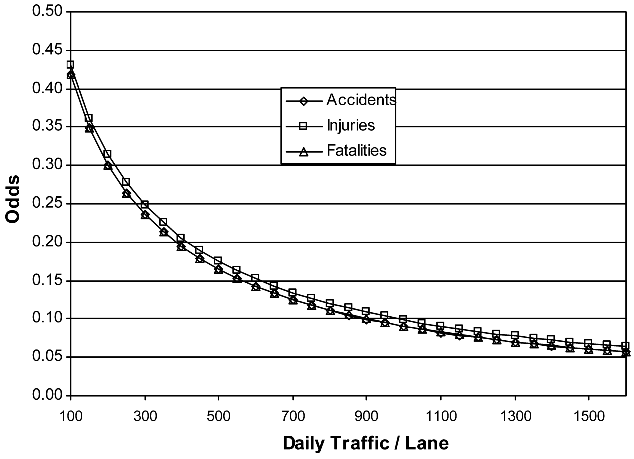

Fig. 1 Effect of traffic/lane on odds

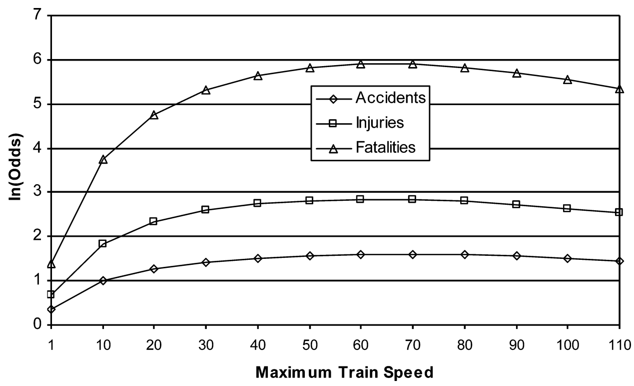

Fig. 2 Effect of train speed on log odds

of accidents relative to the reference case, gates (WdCode8). Note that the coefficients for crossbucks and stop signs are nearly equal.

The most significant variables were accident history and traffic congestion. The relative odds of an accident, injury, and fatality per vehicle crossing against the daily traffic per lane is plotted in Fig. 1. Note the sharp drop in the odds as traffic per lane increases. This result may initially seem counterintuitive. However, many accidents are caused by vehicles running through a crossing to beat a train, occasionally around gates that are deployed. Heavy traffic makes this more difficult, and in the presence of more witnesses, more socially unacceptable.

The number of through trains at night was very significant, but the number during the day was much less important. Several explanations for this result are (a) the number of trains at night and during the day is highly correlated, (b) visibility is reduced at night, and (c) at night, drivers are more likely to be fatigued or otherwise impaired.

The number of switch trains per day was very significant for accidents, less so for injuries, and even less so for fatalities. This is intuitive since their speed is much less than that for through trains and damage from a collision would therefore be less severe than for a through train.

The square root of the maximum speed allowed on a section of track, the maximum typical train speed and its square root were all highly significant. The log of the odds of an event against the maximum typical train speed is presented in Fig. 2. The log odds increases less rapidly as train speed increases. Increasing train speed has more effect on injuries than accidents and an even greater effect on fatalities, which is highly intuitive. The declining odds at very high speeds is likely because, in the USA, these levels of train speed are only allowed in very sparsely populated areas.

A particularly interesting result is that trucks are 60 per cent less likely to be involved in a crossing accident than a passenger automobile, all other things equal. Several factors explain this finding. First, in the USA, trucks and school buses are required to stop at a rail – highway intersection regardless of the state of the crossing device. Second, truckers are trained, professional and experienced drivers. Third, a trucker involved in an accident is likely to loose his job and/or commercial driver's license – a substantial economic penalty that reinforces safety. Finally, a truck driver is far less likely to be under the influence of drugs or alcohol or otherwise seriously impaired while operating a motor vehicle than an automobile driver.

A variable is included to capture any unexplained trend over time, which was computed as year-2001. This variable was highly significant in all three models with a negative coefficient, which implies the probability of an accident has decreased over time everything else being equal. One important trend over time has been to close and consolidate crossings, which would increase vehicle traffic through the remaining crossings. Upgrades to crossings would then be concentrated on a fewer number of crossings. However, these changes would be accounted for by the explanatory variables in the models. Other possible trends that would not be accounted for include greater penalties for driving while intoxicated, safer cars, increased use of seat belts, increased traffic enforcement at railroad crossings, and education programmes such as Operation LifeSaver.*

The effect of intoxication was tested by using the FAR data to compute the per cent of fatal traffic accidents in which a driver was found to have a BAC greater than 0.08 and 0.16 per cent. These percentages were computed by year and state and matched to the other data. Neither of these variables was significant in all three models, so drunk driving could

**Some safety innovations, such as antilock brakes, would reduce the likelihood of accidents. Other innovations, such as air bags, would reduce the likelihood of injuries and fatalities but not reduce the number of accidents.*

Table 8 Pseudo R^2

Model version	Accidents	Injuries	Fatalities
Accident history	0.066	0.075	0.103
No history	0.061	0.070	0.099
FRA	0.005	0.005	0.012

explain only a small portion of the decreasing trend in accidents. Data that would track activity in the educational programs or traffic enforcement over time are unavailable.

4.1 Goodness of fit statistics

The Pseudo R^2 statistics, which measure the goodness of fit of the models, are provided in Table 8. This statistic is computed as 1 minus the ratio of the log likelihood for the model divided by the log likelihood for a model estimated with only a constant term. It shows the percentage reduction of the likelihood function that is explained by the model. Table 8 compares the Pseudo R^2 for model versions estimated with and without using accident history as an explanatory variable and also for a version of the model that tests the prediction capability of the FRAs model, which is discussed in the next section. Note that accident history increases the accuracy of our model by only a modest amount. The comparison of predicted and actual number of accidents for the sample used to estimate this model is presented in Table 9. The bias in the model is almost zero.

4.2 Comparison of accuracy to previous models

As previously mentioned, the FRA model uses several equations to predict accident rates [**1**]. First, the number of accidents per year, a, is predicted for each crossing type (passive, warning lights, or gates) using non-linear regression on a set of crossing characteristics such as highway traffic volume, rail traffic volume, rail speed, number of tracks, and highway characteristics. The form of the so-called basic FRA formula is

$$a = \beta_0 \left(\frac{(ct+0.2)}{0.2}\right)^{\beta} 1 \left(\frac{(d+0.2)}{0.2}\right)^{\beta} 2\, e^{\beta} \times 3^{\mathrm{ms}}\, e^{\beta} 4^{\mathrm{mt}}\, e^{\beta} 5^{(\mathrm{hp}-1)}\, e^{\beta} 6^{(\mathrm{hl}-1)}$$

Table 9 Model calibration

	Accidents	Injuries	Fatalities
Actual	35 847	14 285	4235
Predicted	35 845	14 279	4234
Difference	2	6	1

where c is the number of highway vehicles per day, t the number of trains per day, d the number of through trains per day during daylight, ms the maximum timetable speed (mph), mt the number of main tracks, hp 1 if highway paved and 2 if not, and hl is the number of highway lanes.

The coefficients, $\beta_0, \ldots, \beta_6$, are estimated separately for each crossing type. The FRA uses a weighted average of the result from the basic formula and accident history to compute a final prediction for the number of accidents per year, A

$$A = \alpha \left(\left(\frac{T_0}{(T_0 + T)} \right) a + \left(\frac{T}{(T_0 + T)} \right) \frac{N}{T} \right)$$

where $T_0 = 1/(0.05 + a)$ and N is the number of accidents in T (usually 5) years.

α is a calibration coefficient that is estimated separately for each crossing type and updated every few years. The α coefficients usually decline over time since the accident rates are falling more rapidly than is predicted by the models, an effect similar to the time trend found in the logistic regression.

Approximately two thirds of public crossing have not had an accident in the last 5 years and 93 per cent have had two or less. Thus the weighted formula uses the outcomes of relatively rare events to predict the probabilities of these events in the future.

There are no published data comparing the predictions of the FRA model with subsequent accident experience. Such a study might justify the use of the model in practice in spite of its statistical weaknesses.

One method of evaluating the FRA model is to compare its accuracy to that of the logistic regression model. To do this, FRAs predictions from the basic formula are used as explanatory variables in the logit model. Statistical significance and goodness of fit of the resulting regressions are then compared to those from the models developed here. To perform this test, the prediction from the FRAs basic formula for accidents, a, are transformed by the logit, $L = (a/(1 - a))$. If the coefficient of this variable is 1 and all other coefficients are 0, the prediction from the logit model would be equal to a. Hence this is a test of that prediction in the context of the logit model framework. The time trend and accident history are included in this model. Also tested is the FRA model's predictions of casualties and fatalities by multiplying the conditional probabilities for each of these, as estimated by the second set of equations in the FRA framework, by the result from their basic formula. This product was also transformed with the logit.

A comparison of the goodness of fit statistics was shown in the previous section and the model coefficients are reported in Table 10. Although the coefficients for the FRA predictions are statistically significant, the signs are incorrect in the models for

Table 10 Logit model coefficients using the FRAs predictions

		Coefficients			p-values		
Description	Variable	Accidents	Injuries	Fatalities	Accidents	Injuries	Fatalities
Constant	Constant	−17.9158	−18.7692	−17.2596	0.0000	0.0000	0.0000
Accident history	ACCIDNT0	0.3227	0.2679	0.1480	0.0000	0.0000	0.0000
Year-2001	Years	−0.0513	−0.0616	−0.0631	0.0000	0.0000	0.0000
Logit, FRA model	FRA	−0.1717	−0.0745	0.5140	0.0000	0.0000	0.0000

Table 11 Reduction in probabilities resulting from crossing upgrades

			Spectrum		
From	To	FRA	Accidents	Injuries	Fatalities
Stop signs	Flashing lights	0.70	0.35	0.40	0.46
Crossbucks	Flashing lights	0.70	0.42	0.41	0.47
Stop signs	Gates	0.83	0.71	0.81	0.82
Crossbucks	Gates	0.83	0.74	0.82	0.82
Flashing lights	Gates	0.69	0.55	0.69	0.66

accidents and injuries. The FRA predictions from the basic formula, therefore, are not useful in this context.

4.3 Comparison of accident reduction rates

The FRA does not use its accident prediction formula to predict the number of lives that could be saved by crossing upgrades [**1**]. However, their model could be used for this purpose by computing the difference in accident rates predicted for a crossing before and after an upgrade. However, the FRA predictions are actually higher in some cases after an upgrade, for example upgrading from passive warning devices to flashing lights, which is counter intuitive.

Instead, the FRA uses a separate set of coefficients to predict the reduction in accidents. These coefficients vary somewhat by the number of trains per day and the number of tracks. The reductions implied by the logit model are compared in Table 11 to those of the FRA. The ratio of probabilities after and before the upgrade equals 1 minus the corresponding factor shown in the table. The reductions predicted by the logit model tend to be either close to or less than those from the FRA model.

5 USING THE RESULTS TO COMPUTE THE COST PER LIFE SAVED

The results of the FRA model are used to rank crossings for upgrade. The budgetary procedure is to begin upgrades with the most dangerous crossing and then proceed down the list until funds available for crossing safety are expired.* Even were the FRA model the appropriate statistical instrument, this procedure would not be efficient because it segregates crossings from other highway safety investments.

Money for upgrading crossings are generally a component of a larger state highway budget item earmarked for safety improvements. If the goal of the state safety programme is to minimize the number of lives lost in traffic accidents, all safety improvements should compete for the available pool of funds. To perform this calculation, one must have a uniform measure across all competing uses of funds. Probability of a train – vehicle collision is not such a measure.

One measure of cost effectiveness for safety devices is the cost per statistical life saved. This measure is widely accepted and used by governments and private firms and has a long history in the economic literature. The model is used to compute the expected annual number of lives that would be saved at each crossing were the warning devices upgraded. Expected lives saved are then divided by the annual life cycle cost of upgrading the warning devices, yielding the cost per statistical life saved.

The FRA has published purchase and annual maintenance costs for upgrading warning devices at crossings [**4**]. Using these estimates and the predictions from the models, the cost per life saved from upgrading the devices at each crossing in the sample is computed. A discount rate of 6.1 per cent and inflation rate of 2.2 per cent are assumed. In 2002, this results in annualized costs of $7378 to upgrade from passive devices to flashing lights and $10 382 to upgrade from flashing lights to gates.

The costs by type of upgrade, year, and cost range are summarized in Table 12. Three types of upgrades; passive to flashing lights, passive to gates and flashing lights to gates are considered. Cost categories are in increments of million dollars per life saved

**Crossings are also on occasion upgraded to accommodate expected changes in traffic and as the result of political*

Table 12 Number of crossings that are cost effective to upgrade

		Range of cost per life saved (million $)					
		<2	2–6	6–10	10–20	>20	
	Year	Number of crossings					Total
Passive to flashing	1991	9531	18 769	10 858	13 156	27 015	79 329
	1992	8705	17 832	10 536	13 043	27 665	77 781
	1993	7874	16 909	10 133	13 003	28 353	76 272
	1994	7021	16 063	9806	12 749	28 789	74 428
	1995	6413	15 182	9368	12 429	29 273	72 665
	1996	5703	14 154	9113	12 506	29 543	71 019
	1997	5278	13 262	9018	12 251	29 665	69 474
	1998	4683	12 526	8921	12 012	29 781	67 923
	1999	4331	11 451	8478	11 902	31 259	67 421
	2000	3976	10 740	8111	11 979	31 343	66 149
	2001	3633	9964	7650	11 528	31 285	64 060
Passive to gates	1991	5919	15 581	10 514	14 109	33 206	79 329
	1992	5379	14 658	10 118	13 992	33 634	77 781
	1993	4820	13 832	9571	14 003	34 046	76 272
	1994	4250	13 107	9112	13 546	34 413	74 428
	1995	3852	12 241	8785	13 019	34 768	72 665
	1996	3343	11 381	8461	12 707	35 127	71 019
	1997	3005	10 677	8104	12 490	35 198	69 474
	1998	2642	9973	7748	12 322	35 238	67 923
	1999	2377	9073	7132	11 994	36 845	67 421
	2000	2218	8395	6631	11 995	36 910	66 149
	2001	2009	7803	6130	11 382	36 736	64 060
Flashing to gates	1991	4329	7847	3848	3826	7858	27 708
	1992	3992	7566	3845	3910	8114	27 427
	1993	3678	7277	3757	4120	8274	27 106
	1994	3358	7061	3578	4304	8496	26 797
	1995	3084	6769	3490	4325	8691	26 359
	1996	2740	6508	3336	4298	9005	25 887
	1997	2507	6340	3301	4362	9275	25 785
	1998	2213	6162	3273	4370	9426	25 444
	1999	2144	5685	3185	4441	9780	25 235
	2000	1831	5279	3092	4416	9894	24 512
	2001	1698	4825	2890	4266	9517	23 196

up to $20 million. The number of crossings at which upgrades would cost less than $2 million per life saved is declining over time at a faster rate compared to crossings in the higher cost categories. This suggests that the more cost-effective crossings to upgrade were in fact more likely to be upgraded or closed as the hurdle rate for safety programs in the USA is typically $2 to 3 million per statistical life.

This level of cost per life saved is extremely high relative to other highway safety improvements. For example, according to cost and fatality reduction statistics developed by the State of North Carolina, for the same cost of saving a single life at a rail crossing, 150 lives could be saved by installing rumble strips, 23 saved by cable and Jersey barriers, and 21 saved by upgrading traffic signals.

The study is also, in a sense, incomplete because of data limitations. For example, many automobile–train collisions are blamed on vegetation or buildings restricting driver visibility at an intersection or engineer failure to provide a horn signal when approaching a crossing. These data are not included in our data sources. Accidents that appear to be suicides, an occurrence that US railroads claim are not uncommon, are also not explicitly noted.

Finally, more studies should be done and better statistics collected on behavioural aspects of collisions. Of the substantial reduction in accidents at crossings in the USA over the last decade, 93 per cent of the reduction is attributable to reductions at crossings that were and are not gated. In other words, the substantial expenditures made by railroads and state highway departments are responsible for only 7 per cent of the lives saved. A June 2004 The Department of Transportation, Office of the Inspector General study found 'Risky behavior or poor judgment accounted for ... 94 percent of public grade crossing accidents [between 1994 and 2003].' Clearly, the ability of mechanical devices to prevent accidents is limited and the rail safety community must better understand driver behaviour and how to modify it.

6 CONCLUSIONS

The models made available by the FRA are based on a weighted average of predictions from a 'basic formula' and the recent accident rate. The basic formula was tested and found to be a poor predictor of accident history with a Pseudo R^2 of 0.005 for accidents and injuries. The logit models yielded Pseudo R^2s that were more than ten times larger even when accident history was not used.

There is also a time trend in accident frequency that cannot be explained by either the FRA crossing data or data on alcohol use. If this finding is the result of greater public awareness of the dangers of train–motor vehicle accidents, an open research question, increased expenditures on public education would be prudent.

Finally, most of the crossings that are cost effective to upgrade based on the statistical value of a life saved have, in fact, been upgraded and that other safety improvements to highways are far more cost effective. This suggests that many of the crossings left to be upgraded are not cost-effective candidates and that highway safety funds might well be directed towards other programmes.

REFERENCES

1 **Farr, E. H.** Summary of the DOT rail–highway crossing resource allocation procedure-revisited. Report no. DOT/FRA/OS-87/05, Office of Safety, Federal Railroad Administration, June 1987.

2 Federal Railroad Administration, Office of Policy and Program Development. *GradeDec 2000 user manual*, version 2.0, November 2001.

3 General Accounting Office. Railroad safety, Status of efforts to improve railroad crossing safety, August 1995.

4 Federal Railroad Administration, Office of Policy and Program Development. *GradeDec 2000, Reference manual version 2.0*, January 2002.