Estimating the Crash Risk involving Heavy Vehicles and Bridge Piers

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Word Count: 4,064 + 3500 (11 tables + 3 figures) = 7,564 words

July 31, 2010

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ABSTRACT

In recent years, the United States has witnessed numerous crashes involving large truck-tractor-trailer collisions with bridge piers. Although not as frequent, bridge pier hit crashes have occasionally caused the spans of the bridge to collapse or become unusable. The objective of this study was to develop methodology for estimating the risk for crashes between heavy vehicles and bridge columns and abutments. To accomplish the study objective, crash data collected in the States of Texas and Minnesota were analyzed. Two types of analyses were conducted: 1. the crash risk estimated for a single bridge that crosses the highway, 2. crash risk estimated using negative binomial regression models as a function of truck exposure and covariates describing the physical characteristics of the road. Two examples are provided to describe the methodology. The study results show that lane width, shoulder width and bridge density were found to significantly influence the running-off-the-road and hit bridge pier crashes. The results also show that a bridge located on a horizontal curve is more likely to be hit by a heavy vehicle than if it is located on a tangent section.

INTRODUCTION

In recent years, the United States has witnessed numerous crashes involving large truck-tractor-trailer collisions with bridge piers. Although not as frequent, bridge pier hit crashes have occasionally caused the spans of the bridge to collapse or become unusable. When this happens, in addition to the likelihood for a heavy loss of human life, there are important costs associated to building a new bridge as well as the costs associated with cutting a vital link that is part of the transportation network a long time period. To address this potential problem, a pooled-fund study entitled "Guidelines for Designing Bridge Piers and Abutments for Vehicle Collisions" was initiated by the Federal Highway Administration. This multi-year study was managed by the Texas Department of Transportation (TxDOT) and was funded by 13 states. It covered many different topics, such as the actual design of the pier and crash data collision analysis. One of the tasks of this research project was to develop a risk analysis methodology for vehicle/bridge column and abutment collisions, which was analogous to AASHTO *LRFD* vessel impact requirements (*1*).

The objective of this paper is to present the methodology that was developed for estimating the risk of collision between a heavy vehicle and a bridge pier. The original study focused on the higher level highway network, such as principal arterials and collectors. Since probability for a bridge pier to fail is larger at higher speeds, under the condition that it is hit by a heavy vehicle, highways meeting the above criteria were selected. The analysis was carried out using data collected in the States of Texas and Minnesota. For this study, two types of analyses were conducted. For the first type, the crash risk is estimated for each bridge that crosses the highway individually. For the second type of analysis, negative binomial regression models were estimated to estimate crash risk as a function of truck flow or exposure and various covariates describing the physical characteristics of the road. The models could be used for transportation agencies who are interested in analyzing bridges located on segments or corridor rather than analyzing each bridge individually. The crash risk analysis and the models were estimated for undivided and divided highways separately.

This paper is divided into five sections. The first section describes the methodology used to estimate the crash risk for bridge pier hit crashes. The second section outlines the characteristics of the data. The third section describes the results of the crash risk analysis. The fourth section describes how the methodology developed in this work can be used to estimate the risk for a bridge pier to be hit by a heavy vehicle. Two examples are provided. The last section provides the summary and conclusions.

METHODOLOGY

This section describes about the probability analysis, regression analysis and the application of the empirical Bayes (EB) method used estimating crash risk.

Probability Analysis

This analysis was carried out for undivided and divided highways separately. It is important to point out that some important assumptions had to be made. For instance, the Truck Annual Average Daily Traffic (TAADT) values are estimates; the risk is the same for each truck; at least for a truck to run off ran-off-the-road; this is the exact approached used in the AASHTO *LRFD* vessel impact requirements (*1*). Furthermore, the probabilities do not account for the exposure associated with the number of bridge piers located on the sample network, which is incorporated in the second part of the methodology. The analysis only used information collected on truck crashes and traffic data.

The risk for a heavy vehicle to run-off-the-road can be estimated using the following equation:

$$P_{T\_ROR} = \frac{\text{the number of truck ROR crashes}}{\text{the number of opportunities (estimated from TAADT)}} \tag{1}$$

The number of opportunities is estimated using the summation of all TAADT on the network for the 4-year time period. The total number of opportunities is estimated as follows $4 \times \text{TAADT} \times 365$.

The risk for a heavy vehicle to hit a bridge pier is estimated using the probability that the heavy vehicle first had to ROR and then hit a bridge pier. This is defined as a conditional probability:

$$P_{HBP|T\_ROR} = \frac{\text{the number of trucks hitting a bridge pier}}{\text{the number of Truck ROR crashes}} \tag{2}$$

Now the risk for a truck traveling on the highway to hit a bridge pier on the sample network is given using the relationship:

$$P_{HBP} = P_{HBP|T\_ROR} \times P_{T\_ROR} \tag{3}$$

Regression Analysis

Several statistical models were developed for estimating the expected number of truck crashes running-off-the-road and hitting bridge piers. To increase the sample mean, the light trucks in Texas data were included during the model development but the intercept was later adjusted so that the regression models account for heavy trucks only. The probabilistic structure used for developing the models was the following: The number of crashes at the i-th segment, Y_i, when conditional on its mean μ_i, is assumed to be Poisson distributed and independent over all segments as (2):

$$Y_i \mid \mu_i \sim Po(\mu_i) \qquad \text{i = 1, 2, …, I} \tag{4}$$

The mean of the Poisson is structured as:

$$m_i = f(X;b)\exp(e_i) \tag{5}$$

Where,

$f(.)$ is a function of the covariates (*X*);

β is a vector of unknown coefficients; and,

e_i is a the model error independent of all the covariates.

It is usually assumed that exp(e_i) is independent and Gamma distributed with a mean equal to 1 and a variance $1/\phi$ for all i (with $\phi > 0$). With this characteristic, it can be shown that Y_i, conditional on $f(.)$ and ϕ, is distributed as a Negative Binomial (or Poisson-gamma) random variable with a mean $f(.)$ and a variance $f(.)(1+f(.)/\phi)$ respectively. The term ϕ is usually defined as the "inverse dispersion parameter" for the NB distribution.

Usually the dispersion parameter ($\alpha = 1/\phi$) or its inverse (ϕ) is assumed to be fixed, but recent research in highway safety has shown that the inverse dispersion parameter could potentially be dependent on the covariates (2-4). For simplifying the model development, the models were estimated using a fixed dispersion parameter.

An important characteristic associated with the development of statistical relationships is the choice of the functional form linking crashes to the covariates. For this work, two functional forms were used. The first one, defined as a general AADT model, only includes traffic flow as a covariate. This functional is the most popular among transportation safety analysts since they are easy to recalibrate and because flow is often the significant variable associated with crashes (*5*). The functional form is as follows and was only used for ROR crashes:

$$\mu_i = e^{\beta_0} L_i F_i^{\beta_1} \tag{6}$$

Where,

μ_i = the estimated number of crashes per year for site i;

F_i = vehicles per day (ADT) for segment i;

L_i = length of segment i in miles; and,

$\beta_0, \beta_i, \ldots, \beta_n$ = estimated coefficients.

The coefficients of the regression models were estimated using SAS (*6*). The GENMOD procedure in SAS estimates model coefficients using the maximum-likelihood method. Because of the low sample size issue, for some models, the dispersion parameter (or its inverse) was estimated using a weighted regression method (*7*). The residual deviance statistics were used to assess the goodness-of-fit of the regression models. Only variables that were statistically significant at the 5%-level were included in the models. The coefficients were also evaluated for consistency to ensure the sign of each coefficient reflected previously observed crash characteristics.

Empirical Bayes Method

The EB method can be used for refining the safety estimates (i.e., the long-term mean) of a given site. This method has now become the standard approach for conducting safety analyzes. The EB method takes into account crashes that ocurred at the given site and the safety performance of sites having similar characteristics (*8*). This method can be used for identifying hazardous istes (or sites with promise) (*9*-*10*), evaluating the safety effects of interventions, or assessing the potential safety benefits due to site improvements (*8*).

The EB estimate for site *i* over a period *t* can be estimated using the following equation (*8*):

$$\hat{\hat{\mu}}_i = (1-\omega_i)\, y_i + \omega_i \hat{\mu}_i \tag{7}$$

Where,

$\hat{\hat{\mu}}_i$ = EB estimate in crashes per year for given site *i*;

ω_i = weight factor for given site *i*;

y_i = observed number of crashes for given site *i*;

$\hat{\mu}_i$ = the estimated number of crashes by crash prediction models for given site *i* (usually estimated using a NB model).

The weight factor ω_i is given as follows:

$$\omega_i = 1/(1+\hat{\mu}_i/\phi) \tag{8}$$

Where,

ϕ = the inverse dispersion parameter for the given dataset [note: in the safety literature, analysts sometimes report the dispersion parameter $\alpha = 1/\phi$]. This value is given by SAS.

DATA CHARACTERISTICS

This section describes the characteristics of the Texas and Minnesota data used for the analysis. The highway segments were separated into two groups: divided and undivided highways. Divided highways include any segment that is separated by a grassy median (curbed and uncurbed) or a positive barrier where a bridge pier could be located (not verified by site visits). Also, to determine whether crash risk involving heavy vehicles differs between straight (tangent) and curved sections, separate analyzes were performed on both types of segments in Texas. It should be noted that the truck crashes in Texas also include pickup trucks, utility vehicles and small vans. Although, the crashes involving these vehicles were included in this section, they were eventually removed during the crash risk analysis.

Undivided Highways

Table 1 presents the summary statistics for variables related to undivided segments in Texas. 350 undivided segments were extracted from the data. Table 1 shows that truck percentages varied from 1.2% to 51.6%.

Table 1. Summary Statistics for Geometric and Operational Variables (Texas Data)

Variable	Min	Max	Average (Std Dev)	Sum
Segment Length (mile)	0.10	11.07	0.75 (1.10)	264.19
Lane Width (ft)	9	15	12.23 (1.05)	---
Number of Bridges	1	8	1.21 (0.61)	423
Bridges/Mile	0.09	19.87	3.91 (3.36)	---
Number of Curves	0	7	0.97(1.22)	339
Curves/Mile	0	19.61	2.07(3.00)	
Average Shoulder Width (ft)	0	17	5.81 (3.81)	---
AADT	128	51,250	7,380 (7,222)	---
Truck Percentages	1.2%	51.6%	16.13%	---
Truck AADT	12	5905	928 (790)	---

Table 2 summarizes the number of heavy vehicle crashes as a function of level of severity: (K) Fatal, Injury Type A (incapacitating), Injury Type B (non-incapacitating), Injury Type C (possible injury), PDO (Property Damage Only). The crash data cover a 4-year period (1998-2001). For the 4-year time period, very few crashes involved a heavy vehicle hitting a bridge pier were reported for undivided segments in Texas.

Table 2. Summary Statistics for Truck Crashes (Texas Data)

	ROR		Hit bridge pier	
Severity	**Number of crashes**	**Percentage**	**Number of crashes**	**Percentage**
Fatal (K)	20	3.1%	0	0.0%
Incapacitating injury (A)	67	10.5%	1	14.3%
Nonincapacitating injury (B)	140	21.9%	1	14.3%
Possible injury (C)	173	27.0%	3	42.9%
PDO (O)	240	37.5%	2	28.6%
Total	640	100.0%	7	100.0%

In Minnesota, there were very few truck run-off-the-road (1 fatal and 2 PDO) and hit bridge pier (2 PDO) crashes reported on undivided segments. Thus, the summary statistics for highway geometric and operational variables were not provided, and, as a result, regression models were not estimated.

Divided Segments

Table 3 tabulates the summary statistics for variables for divided highway segments in Texas and Minnesota. There were 2,486 divided segments used for this part of the analysis in Texas. The truck volume ranged from 168 to 25,086 vehicles per day per segment. Similarly, 552 divided segments were extracted from the Minnesota data. The heavy vehicle volume ranged from 200 to 10,480 vehicles per day per segment.

Table 3. Summary Statistics for Geometric and Operational Variables

Variable	Texas				Minnesota			
	Min	Max	Average (Std Dev)	Sum	Min	Max	Average (Std Dev)	Sum
Segment Length (mile)	0.10	13.43	1.15 (1.32)	2,862.92	0.002	14.098	1.006 (1.695)	555.319
Lane Width (ft)	8	15	12.01 (0.54)	---	11	15	12.23 (0.60)	---
Number of Bridges	1	32	2.25 (1.76)	5,599	1	9	1.59 (1.06)	879
Bridges/Mile	0.11	55.56	4.07 (4.37)	---	0.16	571.43	12.33 (40.91)	---
Number of Curves	0	17	1.11(1.38)	2,765	---	---	---	---
Curves/Mile	0	33.11	1.58 (2.55)	--	---	---	---	---
Average Outside Shoulder Width (ft)	0	24	9.54 (2.32)	---	---	---	---	---
Average Inside Shoulder Width (ft)	0	24	5.71 (3.31)	---	0	13	9.05 (2.42)	---
AADT	698	334,485	54,877 (54,298)	---	2900	2,02,000	59,882 (46,428)	---
Truck Percentages	1.6%	70.1%	19.08%	---				
Truck AADT	168	25,086	6,696 (4,657)	---	200	10,480	3,346 (2,110)	---

Table 4 summarizes the number of heavy vehicle crashes as a function of severity levels for divided segments in Texas and Minnesota. In Texas, around 9% of the truck hit bridge pier crashes ended into fatal crashes. However, only around 4% lead to a fatality in Minnesota.

Table 4. Summary Statistics for Truck Crashes

Severity	Texas				Minnesota			
	ROR		Hit bridge pier		ROR		Hit bridge pier	
	crashes	Percent	crashes	Percent	crashes	Percent	crashes	Percent
Fatal (K)	601	1.9%	14	8.8%	5	1.2%	1	3.6%
Incapacitating injury (A)	2239	6.9%	24	15.1%	5	1.2%	0	0%
Nonincapacitating injury (B)	6177	19.1%	39	24.5%	52	12.4%	3	10.7%
Possible injury (C)	10557	32.7%	50	31.4%	78	18.5%	1	3.6%
PDO (O)	12752	39.4%	32	20.1%	281	66.7%	23	82.1%
Total	32326	100.0%	159	100.0%	421	100.0%	28	100.0%

Distribution by Vehicle Body Style

Table 5 tabulates the distribution of truck run-off-the road and hit a bridge pier crashes by the heavy vehicle body style on undivided and divided roads in Texas.

Table 5. Distribution of ROR and Hit Bridge Bier crashes by Heavy Vehicle Body Style in Texas

Vehicle body style	Undivided roads		Divided Roads	
	Run-off-the-road crashes	Hit bridge pier crashes	Run-off-the-road crashes	Hit bridge pier crashes
Beverage	0	0	2	0
Bob-Tail (includes tractor without trailer)	4	0	196	1
Dump	16	0	347	1
Fire Truck	0	0	15	0
Flatbed, lowboy, platform, float, stake	19	0	601	1
Livestock (includes 2-story)	2	0	33	1
Garbage	3	0	48	0
Mixer (concrete)	3	0	54	0
Motor Home or Motor Camper	3	0	36	1
Panel/small van (Good Time, etc.)	56	1	4113	13
Pickup	336	3	14627	87
Pole (log)	1	0	13	0
Refrigerator	1	0	115	0
Utility vehicle	138	2	8193	29
Tank (oil, gas, chemicals, milk)	9	0	212	0
Travelall/Carryall	0	0	2	0
Van (large, furniture, etc.)	19	1	1965	17
Wrecker	1	0	72	0
P/U w/camper	0	0	4	0
Oilfield equipment (usually special design)	0	0	0	0
All Other styles not listed above	0	0	72	1
Unknown	29	0	1606	7
Total	**640**	**7**	**32326**	**159**

RESULTS

This section presents the results of probability and regression analysis conducted for the crash risk estimation.

Probability Analysis

Table 6 summarizes the risk analysis for all divided and undivided highways. This table shows that a bridge pier is more likely to be hit on an undivided facility than on a divided facility. Also, if a truck leaves the traveled way, it is more likely to hit a bridge pier on an undivided highway than on a divided highway. A heavy vehicle is more likely to run-off-the-road on an undivided highway than on a divided highway. The analysis for undivided segments in Minnesota may not be reliable because of very few sites.

Table 6. Crash Probability Analysis

	Texas		Minnesota	
Variables	**Undivided**	**Divided**	**Undivided**	**Divided**
Number of Sites	350	2486	54	552
Total Length (miles)	264.2	2862.9	26.8	555.3
ROR Crashes (4-year)	110	5393	3	421
Hit Bridge Pier Crashes (4-year)	1	30	2	28
Opportunities	$4.742*10^{8}$	$2.43*10^{10}$	$6.637*10^{7}$	$2.697*10^{9}$
P_{T_ROR}	$3.799*10^{-7}$	$2.986*10^{-7}$	$2.03*10^{-8}$	$3.29*10^{-7}$
$P_{HBP\|T\_ROR}$	0.0091	0.0056	0.67	0.067
P_{HBP}	$3.457*10^{-9}$	$1.672*10^{-9}$	$1.35*10^{-8}$	$2.19*10^{-8}$

Table 7 tabulates the risk analysis for straight sections and horizontal curves on divided and undivided highways in Texas. Due to the lack of information about horizontal curves, similar analysis could not be done in Minnesota. The risk analysis was adjusted to account for the differences in segment lengths; horizontal curves are usually always shorter than tangent sections. Since there were no reported hit bridge pier heavy vehicle crashes on undivided horizontal curves and tangent sections, the crash probability was not developed for those roads. The table 7 shows that a bridge pier is more likely to be hit on a horizontal curve than on a straight section. The tangent and curved sections on undivided roads have higher risk of running off the road than the tangent sections on divided roads but are safer than horizontal curves on divided sections. Also, if a truck leaves the traveled way, it is more likely to hit a bridge pier on a horizontal curve than on a straight section.

Table 7. Crash Probability Analysis on Tangent Sections and Horizontal Curves (Texas Data)

	Undivided		Divided	
Severity	**Tangents**	**Curves**	**Tangents**	**Curves**
Number of Sites	156	25	912	540
Total Length (miles)	64.2	6.9	707.8	161.4
ROR crashes (4yrs)	35	2	1422	541
Hit bridge pier crashes (4yrs)	0	0	5	3
Opportunities	$2.094*10^8$	$3.259*10^7$	$8.936*10^9$	$5.498*10^9$
P_{T_ROR}	$3.808*10^{-7}$	$3.462*10^{-7}$	$3.113*10^{-7}$	$3.970*10^{-7}$
$P_{HBP\|T\_ROR}$	--	--	0.0035	0.0055
P_{HBP}	--	--	$1.09*10^{-9}$	$2.18*10^{-9}$

The crash risk for a pier to be hit will be governed by the TAADT and is given as follows:

$$AF = TAADT \times P_{HBP} \times 365 \quad (9)$$

Where,

AF = Annual Frequency the bridge pier is hit;

P_{HBP} = the probability for a bridge pier to be hit by a heavy vehicle

Regression Analysis

Flow-only models (often referred to as general Annual Average Daily Truck Traffic or TAADT models) were initially developed. Although traffic-flow only models could suffer from omitted variables bias, they are still the most popular type of models developed and used by transportation safety analysts (5). They are often preferred over models that include several covariates because they can be easily re-calibrated when they are developed in one jurisdiction and applied to another (11). In fact, this type of model will be the kind of model used for estimating the safety performance of rural and urban highways as well as for intersections in the Highway Safety Manual (HSM) (12).

Table 8 summarizes the modeling results for the general TAADT models in Texas and Minnesota. Per unit of exposure, the Texas model estimate more ROR crashes than the Minnesota model on divided roads. Due to the lack of information about horizontal curves, models for straight and curves sections could not be developed separately with Minnesota data.

Table 8. General TAADT Regression Models for Run-off-the-Road Truck Crashes on all segments

Variables	Texas					Minnesota
	Undivided		Divided			Divided
	All Segments	Straight Sections	All Segments	Straight Sections	Horizontal Curves	All Segments
Constant (β_0)	-6.089 (0.576)	-6.354 (0.923)	-5.920 (0.231)	-4.676 (0.405)	-5.875 (0.597)	-9.184 (0.902)
Flow (β_1)	0.595 (0.085)	0.645 (0.136)	0.636 (0.027)	0.501 (0.047)	0.669 (0.069)	0.919 (0.111)
Inverse Dispersion Parameter (ϕ)	1.013 (0.169)	0.943 (0.271)	0.921 (0.028)	0.767 (0.039)	0.774 (0.055)	2.157 (0.639)
-2 Log-likelihood Deviance DOF	1090 347 348	405 140 154	17144 2860 2484	5806 1046 910	3054 607 538	1067 479 550

Figure 1 gives the relationship between ROR truck crashes and truck AADT on tangent sections and horizontal curves in Texas. The result shows that the curves experiences more crashes than tangent sections. However, the figure 1 shows that divided roads experience more crashes than undivided roads. This counter-intuitive result could be attributed to small sample size and low sample mean (for more details on this issue, the reader is referred to 7) and the omitted-variable bias for undivided roads.

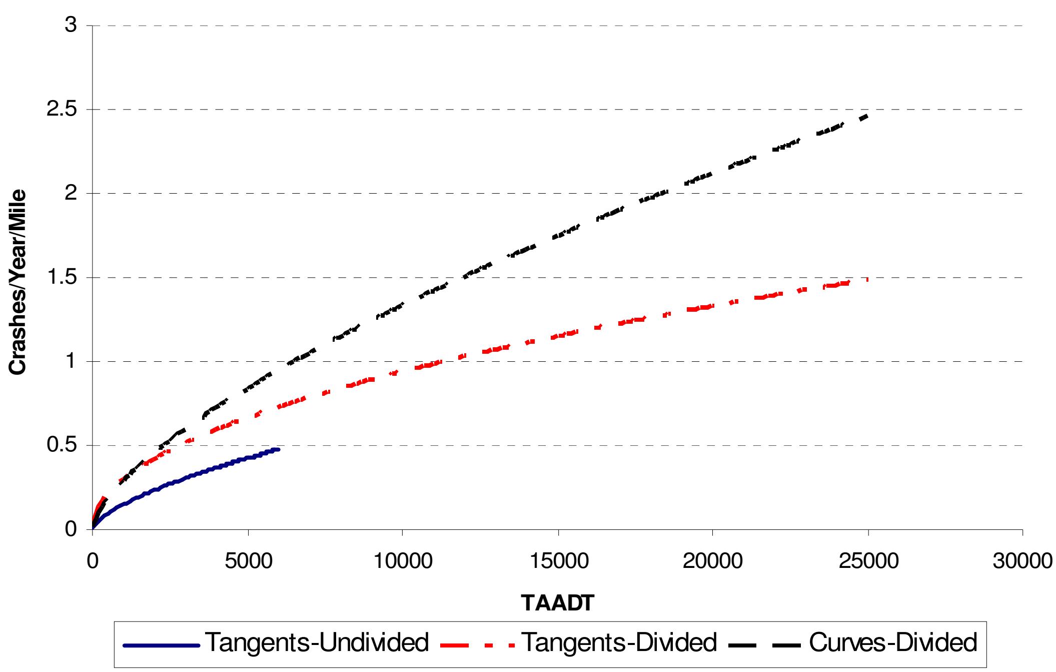

Figure 1. Relationship between Truck ROR Crashes and TAADT on Tangent Sections and Horizontal Curves (Texas Data).

The functional form in equation (10) models the covariates as a function of crash rate. Some researchers prefer this form to the one described above (*14*-*15*). The functional form is as follows:

$$\mu_i = \frac{L_i \times F_i \times 365}{1,000,000} e^{\beta_0} e^{(\sum_{j=1}^{n} \beta_j X_j)} \qquad (10)$$

Where,

μ_i = the estimated number of crashes per year for site i;

F_i = vehicles per day (ADT) for segment i;

L_i = length of segment i in miles;

x_i = a series of covariates; and,

$\beta_0, \beta_i, \ldots, \beta_n$ = estimated coefficients.

Table 9 summarizes the modeling results for the run-off-the-road crash models on tangent sections and horizontal curves in Texas. The ROR crash model for undivided horizontal curves and all hit bridge pier crash models could not be estimated due to the lack of data. The estimates for hit bridge pier crashes can be calculated indirectly by multiplying the ROR crash estimates with the probability calculated in table 7. As seen in table 9, with the increase in the degree of curvature, the number of ROR crashes increases.

Table 9. Crash Rate Regression Models for Run-off-the-Road Truck Crashes on Tangents and Horizontal Curves (Texas Data).

Variables	**Undivided**	**Divided**	
	Tangents	**Tangents**	**Curves**
Constant (β_0)	-0.627 (0.210)	-0.022 (0.203)	-0.045 (0.259)
Average Shoulder Width (β_1) (both sides)	-0.037 (0.031)	---	---
Average Right Shoulder Width (β_2)	---	-0.102 (0.021)	-0.089 (0.026)
Degree of Curvature (β_3)	---	---	0.057 (0.028)
Inverse Dispersion Parameter (ϕ)	0.902 (0.260)	0.714 (0.037)	0.772 (0.055)
-2 Log-likelihood Deviance DOF	410 142 154	5889 1072 910	3055 606 537

Figure 2 illustrates the relationship between ROR truck crashes and truck AADT with the change in degree of curvature for divided highways. As discussed above, with the increase in degree of curvature, the ROR crashes increase. The result is not surprising and has been documented elsewhere (*15*).

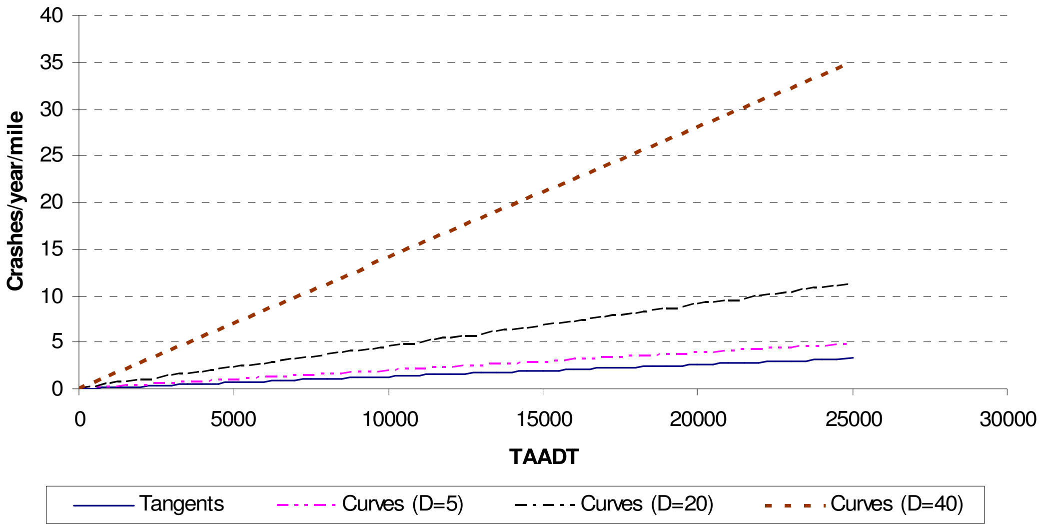

Figure 2. Relationship between ROR Crashes and TAADT with the Change in Degree of Curvature on Divided Segments (Texas Data).

Table 10 summarizes the modeling results for the run-off-the-road and hit bridge pier crash rate models on all divided and undivided road sections in Texas.

Table 10. Crash Rate Regression Models for Run-off-the-Road and Hit Bridge Pier Truck Crashes on All Road Sections (Texas Data).

Variables	**Undivided**		**Divided**	
	ROR Crashes	**Hit Bridge Pier**	**ROR Crashes**	**Hit Bridge Pier**
Constant (β_0)	0.038 (0.986)	-6.383 (0.601)	-0.638 (0.095)	-7.018 (0.113)
Average Lane Width (β_1)	-0.068 (0.079)	---	---	---
Average Shoulder Width (β_2) (both sides)	-0.031 (0.020)	---	---	---
Average Right Shoulder Width (β_3)	---	---	-0.061 (0.009)	---
Bridge Density (β_4)	---	0.210 (0.097)	---	0.098 (0.020)
Curve Density (β_5)	0.037 (0.029)	---	0.061 (0.010)	---
Inverse Dispersion Parameter (ϕ)	1.017 (0.175)	0.122 (0.154)	0.911 (0.028)	0.429 (0.147)
-2 Log-likelihood Deviance DOF	1106 363 346	61 30 348	17234 2926 2483	1138 643 2484

Figure 3 shows the relationship between truck hitting a bridge pier as a function of truck AADT for segments having 1 bridge per mile and 3 bridges per mile, respectively. As discussed above, bridge piers are more frequently hit on undivided highways.

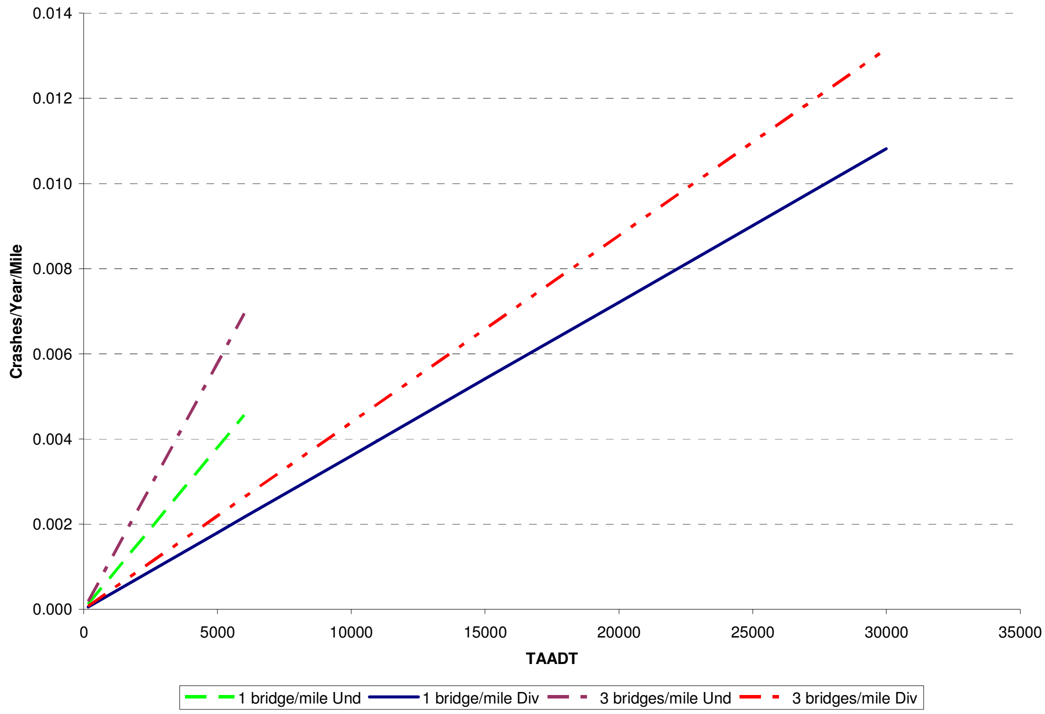

Figure 3. Relationship between Truck Hitting Bridge Pier Crashes and TAADT (Texas Data).

Table 11 summarizes the modeling results for the run-off-the-road and hit bridge pier crash models on all divided road sections in Minnesota. As opposed to the Texas model, the number of bridge piers per mile has a minimal effect on the total number of truck hitting bridge pier crashes. The functional form used here is as follows:

$$\mu_i = e^{\beta_0} L_i F_i^{\beta_1} e^{(\sum_{j=1}^{n} \beta_j X_j)} \tag{11}$$

Where,

μ_i = the estimated number of crashes per year for site i;

F_i = vehicles per day (ADT) for segment i;

L_i = length of segment i in miles;

X_j = a series of covariates; and,

$\beta_0, \beta_i, \ldots, \beta_n$ = estimated coefficients.

Table 11. Crash Regression Models for Run-off-the-Road and Hit Bridge Pier Truck Crashes on Divided Road Sections (Minnesota Data)

Variables	**ROR Crashes**	**Hit Bridge Pier**
Constant (β_0)	-8.414 (1.718)	-14.114 (3.294)
Flow (β_1)	0.943 (0.112)	1.209 (0.401)
Average Lane Width (β_2)	-0.02 (0.103)	---
Average Right Shoulder Width (β_3)	-0.076 (0.035)	---
Bridge Density (β_4)	---	0.011 (0.006)
Inverse Dispersion Parameter (ϕ)	2.187 (0.639)	0.248 (0.204)
-2 Log-likelihood Deviance DOF	1063 477 549	230 124 549

The models above could be used to estimate the crash risk when highway segments are analyszed.

APPLICATION OF METHODOLOGY

This section describes two example problems illustrating the application of analysis procedures. The first example covers the crash risk analysis when a new bridge is constructed on an existing freeway. The second example describes the comparison of the hit brige pier crash risk between two corridors.

Example 1: Crash Risk Estimate for an Individual Bridge

Due to an increased in residential activities located in a community located in the eastern part of Texas, an overpass is planned to be constructed on top of Interstate 10. At that location, the present truck average annual daily traffic (TAADT) is 10,000 vehicles/day. The highway segment has four lanes. The typical lane width is 12 ft and the right shoulder width is equal to 10 ft. Both traveled ways are separated by a 40-ft median.

Using the values found in Table 6, the probability for a truck to hit bridge pier (P_{HBP}) on a divided highway is estimated to be 1.672×10^{-9}. The annual frequency (AF) the bridge pier is hit can be calculated using Equation (9):

$$AF = TAADT \times P_{HBP} \times 365$$

$$AF = 10{,}000 \times 1.672 \times 10^{-9} \times 365 = 0.0061 \text{ crashes/year.}$$

This value means that a pier on this bridge may be hit about once every 164 years, if we assume that every factors, such as the number of lanes and vehicular traffic, remain constant.

Example 2: Crash Risk Estimate for Corridor Study

Due to a train derailment, a bridge spanning on top of that railway has been damaged. With temporary stabilization procedures, the bridge can still be used by passenger cars as well as light trucks until a new bridge is built. Due to current legal actions, the new bridge is not expected to be completed for another three years. During this time period, the state transportation agency will have to re-route heavy vehicles to another highway located within the vicinity of the damaged bridge. The alternative route is a four-lane undivided highway that is about 10 miles in length. The bridge density is 2 bridges per mile. One bridge pier has been hit over the last five years on this alternative route by a heavy truck. The alternative route's truck average annual daily traffic is 7,000 vehicles per day. By re-routing, the heavy vehicle's traffic on this route is increased to 12,000 vehicles per day. The agency would like to know what is the increased risk for bridge piers to be hit given the anticipated augmenttation in TAADT traffic over the next three years.This assessment will help the agency decide whether additional measures are needed to protect bridges along that route.

Step 1: Calculate the crash risk on the alternative route with existing traffic

Using equation (10), the expected hit bridge crashes is given as:

$$\mu_i = \frac{F_i \times L_i \times 365}{1,000,000} \beta_0 e^{\sum_{i=1}^{n} x_i \beta_i}$$

Here F_i is the TAADT which will be 7000 vehicles per day.

$$\hat{\mu} = \frac{7000 \times 10 \times 365}{1,000,000} e^{-6.383} \times e^{0.210*2} = 0.0661 \text{ crashes/year.}$$

Thus the predicted frequency of a heavy truck to hit a bridge pier is 0.0661 crashes/year. Over the last five years, the predicted crashes would be 0.0661*5= 0.331 crashes (for the 5-year period).

Step 2: Calculate the EB estimate with the existing traffic

Using equation (7), the EB estimate is given as:

$$\hat{\hat{\mu}}_{it} = (1-\omega_{it}) y_{it} + \omega_{it} \hat{\mu}_{it}$$

The weight factor ω_{it} in equation (8) is given as follows:

$$\omega_{it} = 1/(1+\hat{\mu}_{it}/\phi)$$
$$\omega_{it} = 1/(1+(0.331/0.122)) = 0.269$$

The EB estimate for hit bridge crashes over the last five years is:

$$\hat{\hat{\mu}}_{it} = (1 - 0.269) * 1 + 0.269 \times 0.567 = 0.884$$

Thus the EB estimate is 0.884/5= 0.177 crashes/year.

Step 3: Calculate the EB estimate on the alternative route with the new and existing traffic

Assuming that all the factors remains constant, the EB estimate for heavy truck hit bridge pier crashes in the next year is given as:

$$\hat{\hat{\mu}}_{it} = \frac{12000}{7000} \times 0.177 = 0.303 \text{ crashes/year.}$$

Thus, we can expect a hit bridge pier crash by heavy truck in the next three years on this route (0.909 crashes in the next three years).

SUMMARY AND CONCLUSIONS

The objective of this study was to describe the crash risk analysis for a heavy vehicle to run-off-the-road and hit bridge pier crash. To accomplish the study objective, crash data collected in Texas and Minnesota were used. The analysis was caried out in two parts.

The first part of analysis focused on the individual risk for a bridge pier to be hit by a truck. This part of the methodology is very similar to the risk analysis proposed AASHTO for bridge piers located on waterways. The crash probability analysis using the Texas data showed that the undivided segments have higher risk for a truck to run-off-the-road than for divided segments. Also, tangent sections experienced les truck ROR than horizontal curves for undivided highway segments. The second part of analysis focused on developing the regression models for heavy vehicle ROR crashes involving a bridge pier. Separate models were developed for undivided and divided roads, and as well for the straight sections and horizontal curves. Initially, models were developed with truck flow as the only variable. Subsequently, the models were developed with different variables that are known to influence the running-off-the road and hit bridge pier crashes. Lane width, shoulder width and bridge density were found to significant in these kinds of crashes in Texas and Minnesota. The Texas models also showed that curve density is also an important variable that influence running-off-the road and hit bridge pier crashes. In fact, a bridge located on a horizontal curve is more likely to be hit by a heavy vehicle than if it located on a tangent section.

The primary limitation of this study is not accounting for the influence of clearance distance between the bridge pier and traveled way on the hit bridge pier crashes. Although we attempted to gather the information about clearence distance, the state databases do not have any such information. Thus, it is recommended to conduct further analyses that would account for the distance between the traveled way and the location of the piers.

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