Predicting Collision Risk between Trucks and Interstate Overpasses

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Abstract: A collision between a truck and an overpass bridge on an interstate highway is rare but can be catastrophic, especially if the bridge involved was designed and built in the early interstate highway era. Such collisions highlight the importance of developing a systematic and scientific method for evaluating at-risk bridges. The findings of this research offer a method for screening the safety risk of highway bridges and identifying bridges that require further review. A risk-based approach has been developed for this study from statistical models, probabilistic theories, and a comprehensive data set. Data include a five-year history of run-off-road (ROR) truck crashes, highway geometric characteristics, and traffic and weather information. The random coefficient Poisson model was used to model truck crashes so that data heterogeneity among highway segments could be captured. Monte Carlo simulation was employed to estimate the collision hazard envelope, given the uncertainties of truck size, encroachment, and vehicle orientation angle. Finally, collision risk was calculated for each bridge bent, and the maximum value was considered as the bridge collision risk. A risk analysis can effectively model rare events when there are uncertainties. Moreover, the bent-specific predictive method improves collision estimate accuracy because the impact is usually between the truck and the bridge bent. **DOI:** 10.1061/(ASCE)TE.1943-5436.0000848. *© 2016 American Society of Civil Engineers.*

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Introduction

The economic growth that North Dakota, South Dakota, and neighboring states have experienced in recent years is largely due to the rapid development of the energy industry, which includes oil, mining, and wind power sectors. This growth has led to an increase in freight activity on interstate highways in these states as more heavy vehicles pass through with equipment and goods to meet the needs of business and industry and supporting infrastructure. As truck traffic increases, crash risk also increases.

Among all truck-related crashes, collisions between trucks and interstate overpasses are of particular concern because the majority of overpass bridges on South Dakota interstates and other major highways were designed and constructed prior to the development of AASHTO collision load design requirements (AASHTO 2010). Thus, South Dakota highways were designed for low lateral-load demands that did not govern the design of columns. The confinement and shear reinforcement in columns was therefore kept to the minimum transverse steel requirements specified in the requirements of the time. In the case of a heavy-truck collision accident, columns that lack sufficient shear strength and ductility capacity because of inadequate transverse reinforcement are vulnerable to catastrophic failure and may lead to a bridge collapse.

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Between 2004 and 2008, there were a total of 860 single-truck run-off-road (ROR) crashes and 27 multivehicle ROR crashes involving trucks on Interstate Highways I-29 and I-90 in South Dakota. These collisions were caused by errant vehicles departing the roadway. Among these crashes, 36 were collisions between trucks and bridge guardrails.

The chances of a vehicle departing the roadway and colliding with a bridge located in its path can be very slim. A great deal of uncertainty exists surrounding factors that may impact this kind of situation, including drivers, weather, roadway and environmental conditions, and vehicle size and trajectory. In all aspects, an analytical method may not be able to competently model crash risk or the dimension of the hazardous object. However, a stochastic risk analysis can offer a more flexible method of associating uncertainties with probabilities for all possible values of the variables of interest. Compared with the deterministic approaches adopted in previous studies, the method of risk analysis developed in this study is expected to provide a more comprehensive assessment of the failure risk for a system consisting of drivers, vehicles, weather conditions, roadways, and bridges.

Literature Review

Risk analysis, the systematic use of available information to evaluate the likelihood of negative events and/or their potential consequences, helps uncover and identify possible undesirable external and internal conditions or situations. According to the National Cooperative Highway Research Program (NCHRP) Roadside Safety Analysis Program (RSAP) (Mak and Sicking 2003), roadside collision risk emerges from two primary sources: (1) a vehicle encroaching on the roadside and (2) the location and dimension of hazardous objects. By combining these two primary sources, collision risk can be calculated as the product of encroachment frequency and probability of an object on the encroachment trajectory. RSAP defines the hazard envelope as "along the travel way wherein an encroaching vehicle would impact the roadside feature under

consideration." Expressed in a formula, the hazard exposure to an erratic vehicle can be defined as a function of vehicle dimensions and orientation, vehicle encroachment angle, and hazard size and lateral offset. To assess the risk of a vehicle-bridge collision, each component of the crash risk should be carefully examined.

A roadside vehicle collision can be modeled either by an "accident-based" approach or by an "encroachment-based" approach (Miaou 1997). Compared with the encroachment-based approach, which depends on many restrictive and subjective assumptions, accident-based roadside collision models are more prevalent because they are crash data–driven (Qin et al. 2014). However, accident-based models may not be practical for crash types that seldom occur. A truck colliding with an overpass bridge is one such type. When a statistical model has relatively few observations, the properties of inference from maximum likelihood estimation do not hold, resulting in biased estimates or none at all.

Conventional accident-based roadside collision models such as Poisson and negative binomial (NB) models or their zero-inflated extensions assume fixed parameters, meaning that the effect of a risk factor is uniform across observations (Shankar et al. 1997). However, a risk factor may have a varying influence on a crash occurrence because of data heterogeneity; failure to account for the randomness associated with observations can be a critical limitation of fixed-parameter crash prediction models.

Studies have proven that allowing randomness in parameter estimation can effectively capture heterogeneity among roadway segments. Milton et al. (2008) were the first researchers to incorporate random parameters into a mixed logit model to study the relationship between injury severity, highway geometrics, traffic, and weather. Anastasopoulos and Mannering (2009) developed the random-parameter count model to define the relationship between crash frequencies, pavement conditions, roadway geometrics, and traffic characteristics. Their results show that the random-parameter NB model performs better than the traditional NB model. Crash count models with random coefficients have now become a viable approach to addressing the varying effect of crash risk factors. Venkataraman et al. (2013) developed 21 random-parameter count models based on different aggregations of crashes in order to find the effect of a particular variable on multiple outcome cases. Garnowski and Manner (2011) used the random-parameter NB model to explain the influence of several variables and their threshold effects on the number of crashes on highway connectors in Germany. Mitra and Washington (2012) compared two random-parameter count models with and without spatial variables to assess the influence of omitted spatial variables on intersection crash modeling. Ukkusuri et al. (2011) employed the random-parameter NB model to study the effects of sociodemographics and built-environment characteristics on pedestrian crash frequency in New York City. Recently Wu et al. (2013), using the random-parameter NB model, studied the safety impacts of warning signals

and speed control at high-speed signalized intersections. Venkataraman et al. (2011) reported that an underestimation of standard errors can easily occur with the use of a fixed-parameter NB model because it cannot incorporate time variations or segment-specific effects.

Similar to traditional approaches that rank sites for improvement by the expected number of crashes, the expected number of truck-bridge collisions is estimated in this study. Because of the rarity of truck-bridge collisions, a more common crash type, truck ROR, is used to ensure that sufficient data are available for effective model estimation. Hence, the concept of hazard envelope is brought in to account for the presence of bridges. The expected number of truck-bridge collisions is estimated to be the product of the number of expected truck ROR crashes per length unit and the bridge hazard envelope. Considering the uncertainty in parameter values in the modeling process, the random-parameter count model is applied to predict crash frequency and the Monte Carlo method is employed to estimate the possible size of a bridge hazard envelope given various bridge dimensions, vehicle sizes, vehicle orientation angles, and encroachment angles. Compared with the fixed-value method, the proposed probabilistic approach avoids restrictive assumptions, takes uncertainty in parameter values into consideration, and creates a full collision risk profile for each bridge to be evaluated.

Study Design

This study aims to develop a methodology for assessing the risk of collision between a truck and an interstate overpass bridge. The procedure is illustrated in Fig. 1. The study methodology comprises two major components, which are independent. The first component estimates the probability of truck ROR crashes $[P(N = n_i)]$ using random-parameter count models. Historical crash data, highway geometric data, weather data, and traffic information are collected to predict truck ROR crash frequency for each highway segment. The second component applies the stochastic approach to estimate the bridge-bent hazard envelope (HE). Because the probability of a truck departing the roadway is related only to segment-specific features and environmental factors such as weather and light, it is irrelevant to bridge size and location. The collision risk is specified in Eq. (1):

$$P(\text{collision risk}) = \frac{P(N = n_i)}{\text{segment length}} \times HE \qquad (1)$$

If the probability distribution of collision risk is not a closed form, Eq. (1) cannot be solved using an analytical method. Given this limitation, Monte Carlo simulation can be used to repeatedly generate random samples from this equation and therefore obtain the distribution of crash risk probability. Statistical analysis
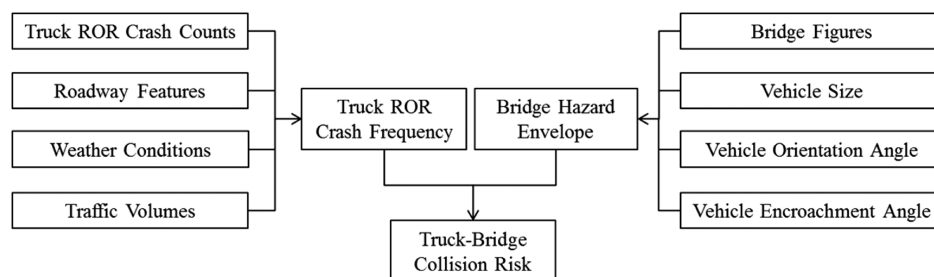

Fig. 1. Vehicle-bridge collision risk analysis flowchart

Table 1. Summary Statistics of Continuous Variables

Continuous variable	Description	Range	Mean	Standard deviation
Crash counts	5-year average of ROR crashes	[0,8]	0.704	1.096
Median shoulder width	Width of shoulder on the left to the direction [m (ft)]	[1.22 (4),3.05 (10)]	1.405 (4.607)	0.329 (1.081)
Right shoulder width	Width of shoulder on the right to the direction [m (ft)]	[1.22 (4),3.05 (10)]	2.929 (9.602)	0.243 (0.798)
Median width	Width of median grass or sod [m (ft)]	[4.88 (16),22.88 (75)]	8.025 (26.311)	2.825 (9.261)
Length	Length of segment [km (mi)]	[0.099 (0.062),60.973 (38.108)]	3.402 (2.126)	5.566 (3.479)
Truck ADT	Annual average daily truck traffic	[78,5603]	2,373.095	868.84
Horizontal curve	Degree of horizontal curve of segment	[0,36.9]	5.174	4.269
Vertical curve	K value of segment vertical curve	[0,110000]	1,722.111	7,631.683
Annual rainfall	5-year average [cm (in.)]	[44.60 (17.56),68.63 (27.02)]	59.56 (23.45)	6.35 (2.5)
Annual snowfall	5-year average [cm (in.)]	[74.47 (29.32),134.44 (52.93)]	98.22 (38.67)	8.51 (3.35)
Number of frost days	5-year average	[168,175]	171	1.15

can then be performed after the simulation model is run a certain number of times. A detailed simulation process is demonstrated later in the "Analysis and Discussion" sections.

Data Collection and Processing

The data in this study comprise five years (2004–2008) of truck ROR crash counts and weather, geometric, and traffic volume data from South Dakota's interstate system. According to police accident reports, a ROR crash is defined as a vehicle leaving the roadway and rolling over or hitting any roadside fixed object such as a bridge column, embankment, utility pole, tree, luminary, guardrail, or barrier. From 2004 to 2008, there were a total of 887 ROR crashes involving trucks on 2,147 km (1,342 mi) of I-29 and I-90.

Weather data include five years (2004–2008) of annual average rainfall, snowfall, and frost days (days on which the temperature was equal to or less than 32°F). These data are from 21 weather stations scattered along I-29 and I-90. The inverse distance weighting (IDW) method is used to interpolate the weather data into the corresponding highway segments. IDW is a deterministic spatial interpolation method that computes the value of unknown points as the weighted mean of known points. The equation is as follows:

$$z_j = \frac{\sum_{i=1}^{m} w_{ij} z_i}{\sum_{i=1}^{m} w_{ij}} \quad \text{and} \quad w_{ij} = \frac{1}{d_{ij}^k} \quad (2)$$

where d_{ij} = distance between point i and point j; w_{ij} = weight of the influence of point i on point j; and z_j, z_i = value of unknown point j and known point i.

The power parameter k was determined based on the minimum root-mean-square error (RMSE).

Data on geometric characteristics include roadway cross-sectional features, pavement types and rumble strips, and vertical

and horizontal alignment. Traffic data include annual average daily traffic (AADT) and truck AADT information. Tables 1 and 2 summarize the descriptive statistics for key variables used in the estimation of crash frequency.

Methodology

Crash Prediction Model

The dependent variable in the crash prediction model is the number of crashes, which is a non-negative integer. Probabilistic distributions for a discrete variable are usually considered in such count models. For several decades, the Poisson and NB models were the most extensively applied to describe the relationships between crash counts and various risk factors (Zegeer et al. 1988; Miaou 1997; Shankar et al. 1997; Anastasopoulos and Mannering 2009; Qin et al. 2014). Assuming that crash data have equal mean value and variance, the probability of y_i truck ROR crashes for a highway segment i can be estimated by a Poisson distribution, as shown in Eq. (3):

$$P(y_i) = \frac{\exp(-\lambda_i)(\lambda_i)^{y_i}}{y_i!} \quad (3)$$

where λ_i = Poisson mean, which can be canonically specified by a log-normal function in Eq. (4):

$$\lambda_i = \exp(\beta X_i) \quad (4)$$

where X_i = vector of geometric, weather, and traffic-related variables on segment I; and β = unknown coefficients for Xs.

When the equality of crash data mean and variance for a Poisson distribution is violated, a NB distribution is preferred by defining λ_i as

$$\lambda_i = \exp(\beta X_i + \varepsilon_i) \quad (5)$$

where $\exp(\varepsilon_i)$ = gamma-distributed error term with mean 1 and variance α.

The variance-mean function for the NB distribution becomes

$$\text{Var}(y_i) = E(y_i) + \alpha E(y_i)^2 \quad (6)$$

Thus, when α equals zero, the NB model collapses to a Poisson model. If the value of α is statistically different from zero, the NB model is more appropriate for estimating crash counts. Furthermore, if the issue of data heterogeneity exists among different highway segments, random-parameter models can be considered (Anastasopoulos and Mannering 2009; Ukkusuri et al. 2011; Venkataraman et al. 2013). In the random-parameter model, an individual parameter is specified as

Table 2. Summary Statistics of Categorical Variables

Categorical variable	Description	Category	Frequency	Percent
Number of lanes	Total number of lanes in segment	2	1,150	91.13
		3	100	7.92
		4	12	0.95
Lane width	Average width of each lane [m (ft)]	3.66 (12)	926	73.38
		3.96 (13)	336	26.62
Surface type	Pavement type of lanes	Asphalt	240	19.02
		Concrete	1,022	80.98
Shoulder type	Pavement type of shoulders	Asphalt	1,012	80.19
		Concrete	250	19.81
Rumble strips	Presence or absence	Exist	694	54.99
		None	568	45.01

$$\beta_i = \beta + \varphi_i \tag{7}$$

where β = average impact of a risk factor on crash frequency; and φ_i = randomly distributed term that represents the deviation of each individual site from the average impact.

According to the data, the random term can be assumed to follow a wide variety of distributions such as normal, lognormal, triangular, or logistic. Now the mean crash count for site i given the random term can be formulated as follows:

$$E(y_i)|\varphi_i = VMT_i^\alpha \times \exp(\beta_i X_i) \tag{8}$$

and the log-likelihood function of the random-parameter model can be specified as in Eq. (9):

$$LL = \sum_{i=1}^{n} \ln \int_{\varphi_i} g(\varphi_i) f(y_i|\varphi_i) d\varphi_i \tag{9}$$

The integration in Eq. (9) becomes computationally infeasible when there are two or more random parameters. A simulation-based approach using Halton draws can be used to solve this problem, as recommended by Anastasopoulos and Mannering (2009).

Bridge Hazard Envelope

The hazard envelope can be determined based on vehicle size, encroachment angle θ, and orientation angle φ. These parameters vary from case to case, and their distributions determine the range and mean of the hazard envelope. In RSAP (Mak and Sicking 2003), the hazard envelope is formulated as in Eq. (10):

$$HE = \left(\frac{1}{1,000}\right) \times \left[L_h + \left(\frac{W_e}{\sin \theta}\right) + W_h \cot \theta\right] \tag{10}$$

where HE = hazard envelope (km); L_h = length of hazard (m); W_e = effective width of vehicle (m) = $L_v \sin \varphi + W_v \cos \varphi$; L_v, W_v = length and width of vehicle (m); and W_h = width of hazard (m).

The placement of a bent determines its exposure to potential collisions. Fig. 2 shows a typical bridge layout with three bents and the bridge hazard envelope.

Simulation Method

The Monte Carlo method is a method of stochastic simulation. Based on statistical theories, it uses computer simulation to estimate the probability of a random variable. The procedure for drawing random seeds from a density function is known as random variable generation or Monte Carlo sampling. The generation of a sequence of draws is dependent on the distributional form and the approximation method.

In risk analysis, uncertain factors can be substituted by a range of values generated from different probabilities. A Monte Carlo simulation is repeated several times, each time using a different set of random values. After many iterations, the model outcome based on these factors can be constructed as a probability distribution. For example, the size of the hazard envelope is determined by vehicle encroachment angle, vehicle orientation angle, and vehicle dimensions. Each factor is intrinsically unknown, but the uncertainty can be described by a probability density function from reliable sources.

According to RSAP (Mak and Sicking 2003), when a vehicle speed reaches 103 km/h (70 mi/h), the extreme values and the most likely values of vehicle encroachment angle θ and vehicle orientation angle φ can be determined (Table 3). The project evaluation and review technique (PERT) distribution, which fits the minimum, most likely, and maximum values into a beta distribution, can be considered for the encroachment and orientation angles.
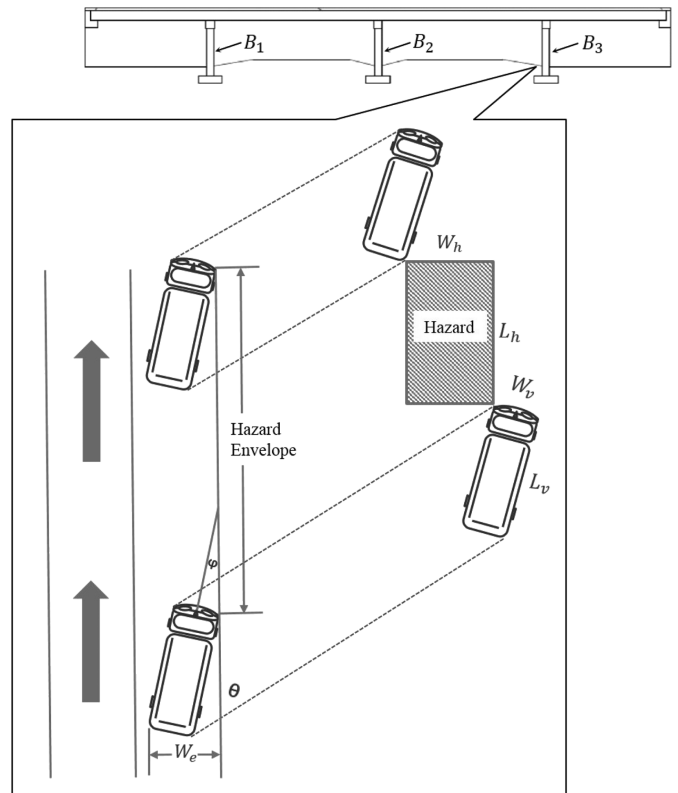

Fig. 2. Bridge hazard envelope

Table 3. Distribution of Vehicle Encroachment Angle and Orientation Angle (Degrees)

Variable	Minimum	Most likely	Maximum
Encroachment angle	2.5	10	32.5
Orientation angle	−180	0	180

The smooth curve of a beta distribution progressively places more emphasis on values around the most likely value than on values around the edges. According to the Federal Highway Administration (FHWA) vehicle classification, the most common trucks traveling on I-29 and I-90 range from Class 5 (2-axle, single unit) to Class 10 (tractor with single trailer). The widths of these trucks are about 2.6 m (8.5 ft), and the lengths range from 12.2 to 22.9 m (40 to 75 ft). Therefore, the probability distribution of the hazard envelope can be simulated based on the sample values of the vehicle encroachment and orientation angles, which are drawn from the PERT distribution. The size of the truck can be drawn from a uniform distribution.

Analysis and Discussion

Following the application of the aforementioned methodologies, truck ROR crash frequency is predicted using random-parameter models, and the crash density was calculated as expected crash frequency per kilometer. The collision risk for a bridge bent is obtained by multiplying truck ROR crash density by appropriate hazard envelope.

Truck ROR Crash Prediction Model

In this study, both the random-parameter Poisson and random-parameter NB distributions are considered. The results suggest that

Table 4. Random Parameter Poisson Estimation

Variable	Constant parameter		Random parameter				
	Coefficient	p value	Coefficient	p value	Standard deviation	p value	Positive%
Intercept	−3.1435	<0.0001	N/A	N/A	N/A	N/A	N/A
VMT	0.6643	<0.0001	N/A	N/A	N/A	N/A	N/A
Surface type (0 = asphalt; 1 = concrete)	—	—	0.3091	0.0027	0.0957	0.0087	99.94
Horizontal curve	—	—	0.0399	<0.0001	0.0422	<0.0001	84.13
Snowfall	—	—	0.0273	0.0053	0.0071	<0.0001	99.99

Note: N/A = results for random parameters are not applicable.

the dispersion parameter for the random-parameter NB model is not statistically significant. It is plausible that the random coefficients already explain a certain degree of randomness associated with crash occurrence (Garnowski and Manner 2011); therefore, the random-parameter Poisson model is chosen. After many experimental runs are performed, a normally distributed random-parameter model is determined to achieve the best performance. A parameter whose standard deviation is statistically different from zero is considered a random variable for the final model results; otherwise, it is considered fixed across observations. *LIMDEP* econometric software was used, and the coefficients are estimated based on 200 Halton draws. The output of the coefficient estimates is presented in Table 4.

The log-likelihood of the fixed-parameter model LL_f is −1,572.894, and the log-likelihood of the random-parameter model LL_r is −1,221.695. The chi-square test is used to compare the performance of the fixed-parameter and random-parameter models. The χ^2 value is 702.4 with 3 degrees of freedom and the resulting p value is close to 0, indicating 99.99% confidence that the random-parameter model is statistically superior to the fixed-parameter model.

The results show that the coefficient of truck vehicle miles traveled (VMT) is a fixed parameter, whereas surface type, degree of horizontal curve, and annual snowfall all have normally distributed random coefficients. The truck VMT is positively signed, which is consistent with the expectation that higher crash frequencies are associated with higher traffic exposures. The presence of a larger horizontal curve degree is found to increase truck ROR crashes because trucks are more likely to run off the road on sharp horizontal curves given their high center of gravity and off-tracking problems (Miaou 2001). It is not surprising that annual snowfall contributes to higher truck ROR crash frequency; however the snowfall effect differs across highway segments. The difference may be due to precipitation confounding other roadway factors such as pavement condition and visibility, which vary among segments. Most variables seem to behave rationally except for pavement type. The positive correlation of concrete surface with truck ROR crash frequency requires more investigation.

The effects of random coefficients on truck crashes vary from segment to segment and therefore present uncertainties for prediction. In Monte Carlo methods, the conditional distribution of each parameter is applied to estimate collision risk.
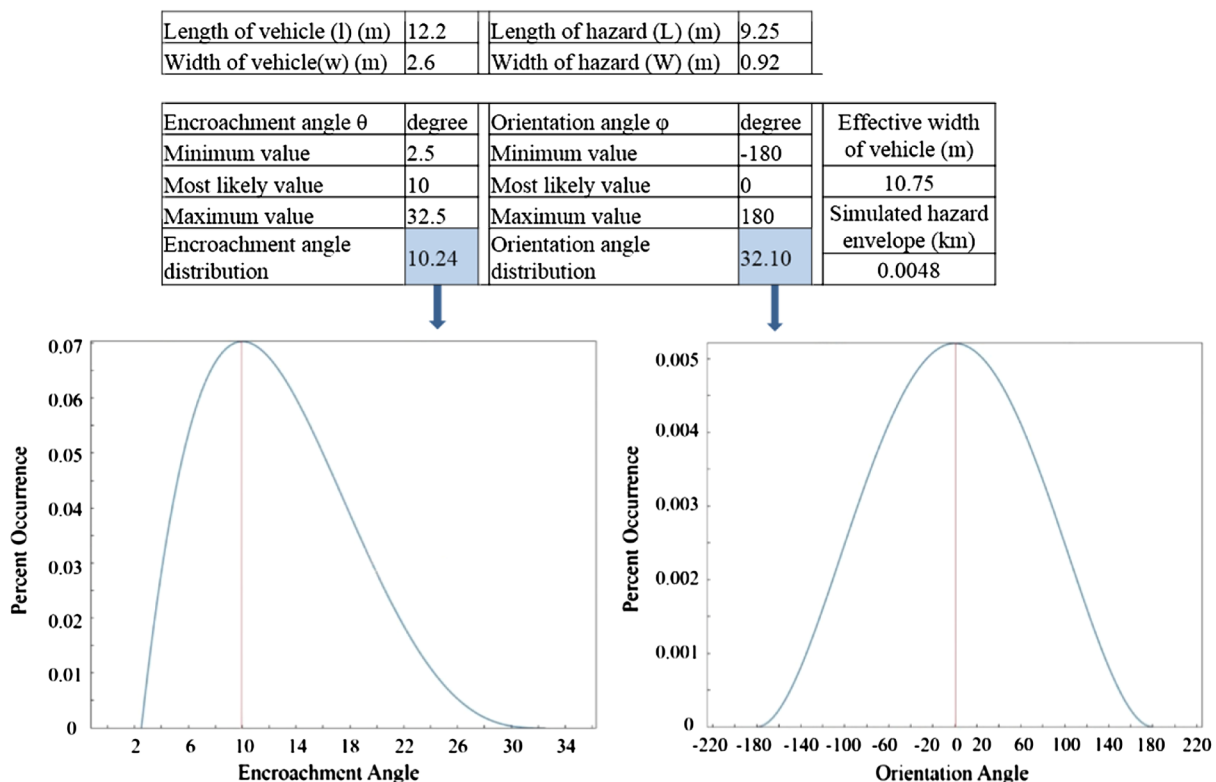
Length of vehicle (l) (m)	12.2	Length of hazard (L) (m)	9.25
Width of vehicle(w) (m)	2.6	Width of hazard (W) (m)	0.92

Encroachment angle θ	degree	Orientation angle φ	degree	Effective width of vehicle (m)
Minimum value	2.5	Minimum value	-180	
Most likely value	10	Most likely value	0	10.75
Maximum value	32.5	Maximum value	180	Simulated hazard envelope (km)
Encroachment angle distribution	10.24	Orientation angle distribution	32.10	0.0048

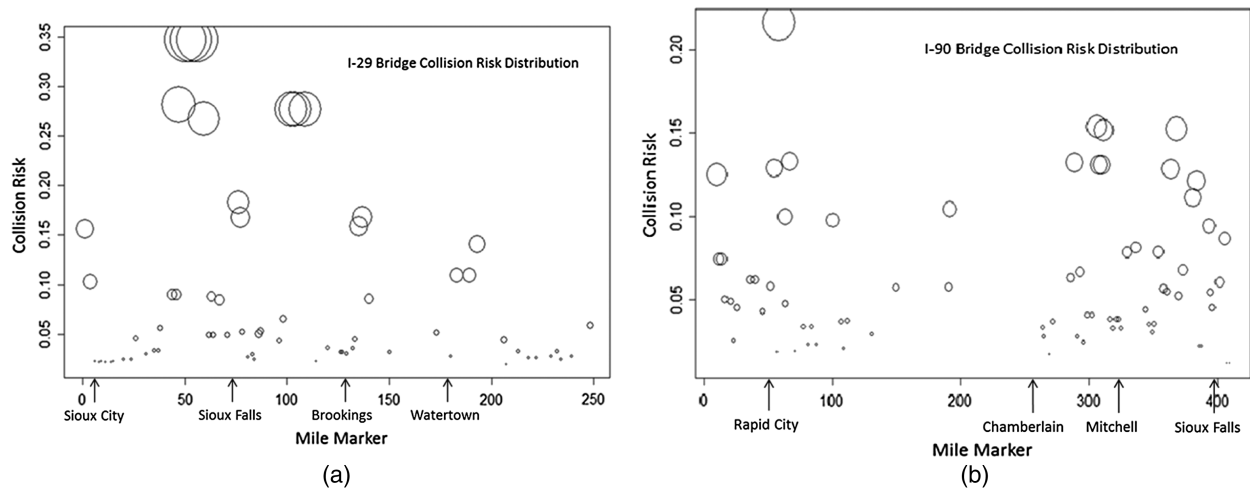**Fig. 3.** Hazard envelope estimation

Fig. 4. (a) Collision risk distribution of bridges on I-29; (b) collision risk distribution of bridges on I-90
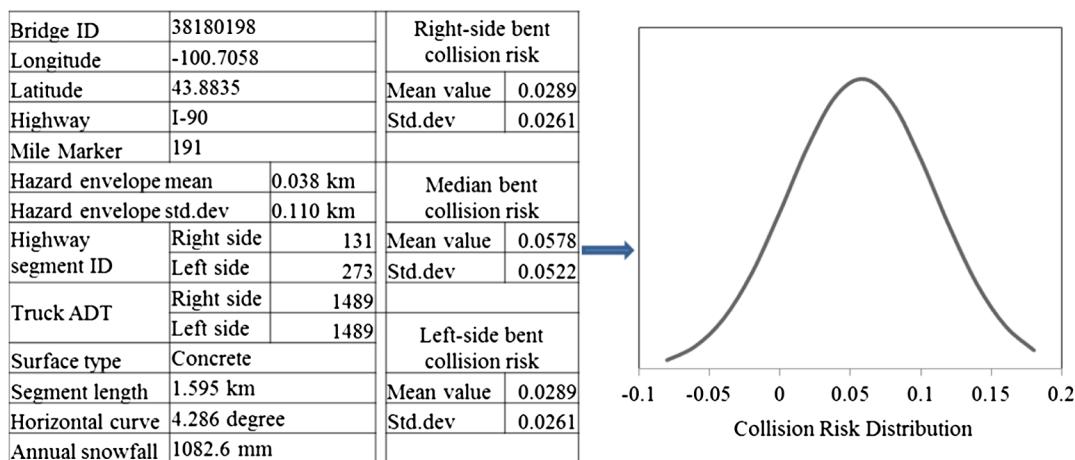

Fig. 5. Bridge collision risk profile

Monte Carlo Simulation Results

Monte Carlo simulation can be modeled in a structured manner using Microsoft Excel's Risk Solver add-in (Fig. 3). The possible outcomes of hazard envelope size are simulated by setting a 12.2–22.9 m (40–75 ft) range for truck length and using PERT distribution for vehicle encroachment and orientation angles.

Collision risk is simulated using a normal distribution for the hazard envelope and the random parameters. Both hazard envelope and collision risk are simulated 5,000 times. The collision risk for a bridge is calculated as the maximum value of all bridge bents. Figs. 4(a and b) show the risk for all overpass bridges on I-29 and I-90, respectively. The horizontal axis is the mile marker, and the vertical axis is the mean risk value; the radius is the standard deviation.

There are 68 overpass bridges on I-29 and 74 on I-90. The bubble plots indicate that most of them have very low collision risk. Higher collision risks are often accompanied by higher uncertainties. Most of the bridges with a high collision risk are located near urban areas such as Rapid City and Sioux Falls, largely because of high truck volume. In addition, the overpasses located in urban areas have large deck widths for more travel lanes to accommodate local traffic. The larger deck widths lead to more bridge hazard exposure. Moreover, the geometric data show that interstate

highways in urban areas have a high degrees of horizontal curve, largely due to land use constraints, which increase the risk of collision between trucks and overpasses. The correlation of bubble value (mean) with bubble size (standard deviation) is partially due to segment length. In the collision risk equation, crash count and hazard envelope are both random variables but segment length is a constant. Multiplication of a random variable by a constant increases not only the former's mean but also its standard deviation. A short segment results in a large mean and a large standard deviation, whereas a long segment decreases both the mean and standard deviation. Shorter segments are usually more common in urban than in rural areas because of the varying geometric and traffic characteristics.

The bridge risk profile is shown in Fig. 5, in which a detailed bridge inventory is provided. Collision risk is calculated for all bridge bents, among which the highest risk is considered the collision risk for the bridge.

Conclusions

Accelerated economic development has substantially increased freight activity on South Dakota highways. Much of this increased traffic is from heavy trucks, which escalate the probability of a

truck colliding with an overpass. In spite of extremely low odds, this type of collision can be catastrophic because many overpass bridges on South Dakota's interstate highways were designed and constructed prior to the development of collision load design requirements. A collision of this kind can cause partial or total collapse of a highway bridge, and can potentially lead to major road closures. If such an event were to take place, the social and economic impacts could be enormous, so it is crucial to identify vulnerable highway infrastructure and provide this information to the transportation agencies charged with preventing such accidents.

Because they may be affected by factors that are unknown or unobservable, crashes are random events. Such unobserved factors are the main contributors to data heterogeneity. To factor data heterogeneity into the crash risk analysis of this study, the random-parameter Poisson model is employed, the output of which reveals that high truck VMT, sharp horizontal curves, high annual snowfall, and a concrete pavement surface all increase truck ROR crash frequency. The effects change across different highway segments because of varying roadway conditions and other factors.

An overpass bridge may be hit by trucks of varying sizes and from different angles. These uncertainties lead to a range of outcomes for calculating the hazard envelope—that is, the physical exposure of a bridge to a collision. Therefore, Monte Carlo simulation is used to draw random samples from known distributions of truck size, orientation angle, and encroachment angle. The probability density function is calculated for the hazard envelope of each bridge bent. Coupled with unit crash counts, collision risk can be estimated for each bridge bent, and thereby the collision risk for a bridge can be determined by the maximum risk of all bridge bents. Compared with a deterministic, single-point estimate, this stochastic method provides a number of advantages including probabilistic results, accurate prediction, flexible modeling assumptions, and graphical presentation.

Acknowledgments

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