A Risk Analysis of Collisions 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 it 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 comprehensive datasets. Data include a five-year history of run-off-road (ROR) truck crashes, highway geometric characteristics, traffic information, and weather data. The random coefficient Poisson model was used to model truck crashes so that the data heterogeneities among highway segments could be captured. The 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 the accuracy of the collision estimate, as the impact is usually between the truck and the bridge bent.
INTRODUCTION

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

Amongst all truck-related crashes, collisions between trucks and interstate overpasses is of particular concern as the majority of overpass bridges on South Dakota interstates and other major highways were designed and constructed prior to the development of the collision load design requirements (1). Thus, South Dakota highways were designed for low lateral load demands that did not govern the design of the columns. Therefore, the confinement and shear reinforcement in such columns was kept to the minimum transverse steel requirements specified in the codes. In the case of a heavy truck collision accident, columns which lack sufficient shear strength and ductility capacity due to inadequate transverse reinforcement would be vulnerable to catastrophic failure and may lead to a bridge collapse.

Between 2004 and 2008, there were a total of 860 single-truck ROR crashes and 27 multi-vehicle 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 chance of a vehicle departing the roadway and colliding with a bridge that is located right on its path can be very slim. A great deal of uncertainties exist surrounding factors that may impact this kind of situation, including the drivers, the weather, roadway and environmental conditions, the size and trajectory of vehicle. 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 every possible value of the variables of interest. Compared to the deterministic approaches adopted in previous studies, the method of risk analysis developed in this study is anticipated to provide a more comprehensive view of assessing the risk of failure for a system consisting of drivers, vehicles, weather conditions, roadways and bridges.

LITERATURE REVIEW

Risk analysis is the systematic use of available information to evaluate the likelihood for negative events to occur, as well as their potential consequences. Risk analysis helps to uncover and identify possible undesirable external and internal conditions or situations. According to the National Cooperative Highway Research Program (NCHRP) report 492 - Roadside Safety Analysis Program (RSAP) (2), roadside collision risk emerges from two primary sources: the risk for a vehicle to encroach the roadside, and the location and dimension of the hazardous object(s). By combining these two primary sources, collision risk can be calculated as the product of the encroachment frequency and the probability of having an object on its trajectory. The risk of vehicle ROR can be a collective effect of roadway features, weather and environmental conditions, as well as driver characteristics (3-6). The hazard exposure to an
erratic vehicle can be defined as a function of the dimension and orientation of the vehicle, the vehicle encroachment angle, and the size and lateral offset of the hazard. In order to assess the risk of a vehicle-bridge collision, each component within the crash risk should be carefully examined.

The roadside vehicle collision can be modeled by either an “accident-based” approach or an “encroachment-based” approach (3). Accident-based roadside collision models are more prevalent because they include readily available crash data (6). Conventional accident-based roadside collision models assume fixed parameters, meaning the effect of a risk factor is uniform across observations. However, a risk factor may have varying influence on a crash occurrence due to data heterogeneity, and failure to account for the randomness associated with observations can be a critical limitation of fixed-parameter crash prediction models.

Previous studies have proven that allowing randomness into parameter estimation can effectively capture the heterogeneities among roadway segments. Milton, Shankar and Mannering 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 (7). Anastasopoulos and Mannering (8) developed the random parameter count model to define the relationship between crash frequencies, pavement condition, roadway geometrics, and traffic characteristics. Results showed that the random parameter negative binomial (NB) model performs better than the traditional negative binomial model. Crash count models with random coefficients have now become a viable approach to addressing the varying effect of crash risk factors. Venkataraman (9) developed 21 random parameter count models based on the different aggregations of crashes in order to find the effect of a particular variable on multiple outcome cases. Garnowski (10) utilized the random parameter negative binomial model to explain the influence of several variables and their threshold effects on the number of crashes happening on highway connectors in Germany. Mitra and Washington (11) compared two random parameter count models with and without spatial variables to assess the influence of omitted spatial variables on the intersection crash modeling. Ukkusuri et al. (12) employed the random parameter negative binomial model to study the effects of socio-demographics and built-environment characteristics on the pedestrian crash frequency in New York City. Recently, Wu et al. (13) studied the safety impacts of warning signals and speed control at high-speed signalized intersections by using the random parameter negative binomial model. Venkataraman (14) stated that an underestimation of standard errors can easily occur by using a fixed parameter NB model because it cannot incorporate time variation or segment-specific effects.

In addition to using random parameter count models to estimate crash frequency, researchers also used random parameter models to evaluate the crash severity. Anastasopoulos and Mannering (15) proved the statistical superiority of the random parameter logit model, also known as mixed logit (MXL) model, compared to the fixed-parameter logit model in terms of crash severity evaluation. Islam and Hernandez (16) utilized the MXL model to analyze the injury severity caused by large-truck crashes that happened on interstate highways in Texas. Malyskina and Mannering (17) applied the random parameter multinomial logit model and the random parameter NB model to assess the effect of design exceptions on the severity and frequency of accidents. Romo et al. (18) employed the MXL model to estimate the probability of three crash types (rear-end, angle, and sideswipe) between trucks and cars on interstate highways.
based on the roles and precrash actions of the cars and trucks. Another noticeable study conducted by Chen et al. (19) applied the MXL model to study the injury severity of truck drivers on rural highways. They treated single-vehicle accidents and multi-vehicle accidents involving trucks separately to identify various risk factors that affect crash injury severity.

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 Figure 1.

\[
P(Collision \ Risk) = \frac{P(N=n_i)}{segment \ length} \times P(HE)
\]

If the probability distribution of collision risk is not a closed form, the equation cannot be solved by using an analytical method. Given this limitation, the Monte Carlo simulation can be utilized to repeatedly generate random samples from Equation 1 and therefore obtain the distribution of the probability for crash risk. Statistical analysis 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 is comprised of five years (2004 to 2008) of truck ROR crash counts, as well as weather, geometric, and traffic volume data from South Dakota’s interstate system. According to the police accident reports, a ROR crash is defined in this report as a vehicle that

FIGURE 1 Vehicle-bridge collision risk analysis flow chart.
leaves the roadway and rolls over or hits any roadside fixed objects 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 1,342 miles of I-29 and I-90. The weather data includes five years (2004-2008) of annual average rainfall, snowfall and frost days (days in which the temperature was equal to or less than 32 degrees Fahrenheit). The weather data was collected from 21 weather stations scattered along I-29 and I-90. The inverse distance weighting (IDW) method was used to interpolate the weather data into the corresponding highway segments. IDW is a deterministic spatial interpolation method that computes the value for unknown points as the weighted mean of known points. The equation is as follows:

\[
    z_j = \frac{\sum_{i=1}^{m} w_{ij} z_i}{\sum_{i=1}^{m} w_{ij}} \quad \text{and} \quad w_{ij} = \frac{1}{d_{ij}^k}
\]

Where: \( z_j \), \( z_i \) = the value for unknown point \( j \) and known point \( i \); \( w_{ij} \) = the weight for the influence of point \( i \) on point \( j \); \( d_{ij} \) = distance between point \( i \) and point \( j \). The power parameter \( k \) was determined based on the minimum root mean square error (RMSE). Data on geometric characteristics included roadway cross-sectional features, pavement types and rumble strips, as well as vertical and horizontal alignment. Traffic data included annual average daily traffic (AADT) as well as truck AADT information. Table 1 shows the descriptive statistics for key variables used in the estimation of crash frequency.
TABLE 1 Summary Statistics of Explanatory Variables

<table>
<thead>
<tr>
<th>Continuous Variable</th>
<th>Description</th>
<th>Range</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash counts</td>
<td>5-year average of ROR crashes</td>
<td>[0, 8]</td>
<td>0.704</td>
<td>1.096</td>
</tr>
<tr>
<td>Median shoulder width</td>
<td>Width of shoulder on the left to the direction (in feet)</td>
<td>[4, 10]</td>
<td>4.607</td>
<td>1.081</td>
</tr>
<tr>
<td>Right shoulder width</td>
<td>Width of shoulder on the right to the direction (in feet)</td>
<td>[4, 10]</td>
<td>9.602</td>
<td>0.798</td>
</tr>
<tr>
<td>Median width</td>
<td>Width of median grass or sod (in feet)</td>
<td>[16, 75]</td>
<td>26.311</td>
<td>9.261</td>
</tr>
<tr>
<td>Length</td>
<td>Length of segment (in miles)</td>
<td>[0.062, 38.108]</td>
<td>2.126</td>
<td>3.479</td>
</tr>
<tr>
<td>Truck ADT</td>
<td>Annual average daily truck traffic</td>
<td>[78, 5603]</td>
<td>2373.095</td>
<td>868.84</td>
</tr>
<tr>
<td>Horizontal curve</td>
<td>Degree of horizontal curve of segment</td>
<td>[0, 36.9]</td>
<td>5.174</td>
<td>4.269</td>
</tr>
<tr>
<td>Vertical curve</td>
<td>K value of vertical curve of segment</td>
<td>[0, 110000]</td>
<td>1722.111</td>
<td>7631.683</td>
</tr>
<tr>
<td>Annual rainfall</td>
<td>5-year average (in inches)</td>
<td>[17.56, 27.02]</td>
<td>23.45</td>
<td>2.5</td>
</tr>
<tr>
<td>Annual snowfall</td>
<td>5-year average (in inches)</td>
<td>[29.32, 52.93]</td>
<td>38.67</td>
<td>3.35</td>
</tr>
<tr>
<td>Number of frost days</td>
<td>5-year average number of annual frost days</td>
<td>[168, 175]</td>
<td>171</td>
<td>1.15</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Categorical Variable</th>
<th>Description</th>
<th>Category</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of lanes</td>
<td>Total number of lanes in segment</td>
<td>2</td>
<td>1150</td>
<td>91.13%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>100</td>
<td>7.92%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>12</td>
<td>0.95%</td>
</tr>
<tr>
<td>Lane width</td>
<td>Average width of each lane (in feet)</td>
<td>12</td>
<td>926</td>
<td>73.38%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>13</td>
<td>336</td>
<td>26.62%</td>
</tr>
<tr>
<td>Surface type</td>
<td>Pavement type of lanes</td>
<td>Asphalt</td>
<td>240</td>
<td>19.02%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Concrete</td>
<td>1022</td>
<td>80.98%</td>
</tr>
<tr>
<td>Shoulder type</td>
<td>Pavement type of shoulders</td>
<td>Asphalt</td>
<td>1012</td>
<td>80.19%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Concrete</td>
<td>250</td>
<td>19.81%</td>
</tr>
<tr>
<td>Rumble strips</td>
<td>The presence of rumble strips</td>
<td>Exist</td>
<td>694</td>
<td>54.99%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>None</td>
<td>568</td>
<td>45.01%</td>
</tr>
</tbody>
</table>

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. When assuming crash data have equal mean value and variance, the probability of having $y_i$ truck ROR crashes for a highway segment $i$ can be estimated by a Poisson distribution shown in Equation 3:

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

(3)

Where $\lambda_i$ is the Poisson mean that can be canonically specified by a log-normal function in Equation 4.

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

(4)
Where $X_i$ denotes a vector of geometric, weather and traffic-related variables on segment $i$ and $\beta$ is the unknown coefficients for $X$s.

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

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

(5)

Where $\exp(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance $\alpha$. The variance-mean function for the NB distribution becomes:

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

(6)

Thus, when $\alpha$ equals zero, the NB model collapses to a Poisson model. If the value of $\alpha$ 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. In the random parameter model, an individual parameter is specified as:

$$\beta_i = \beta + \varphi_i$$

(7)

where $\beta$ represents the average impact on crash frequency that a risk factor inflicts and $\varphi_i$ is a 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 the normal, log-normal, triangular, or logistic. Now, the mean crash count for site $i$ given the random term can be formulated as follows:

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

(8)

and the log-likelihood function of the random parameter model is specified in Equation 9.

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

(9)

The integration in Equation 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 (8).

**Bridge Hazard Envelope**

The hazard envelope can be determined based on vehicle size, encroachment angle $\theta$, and orientation angle $\varphi$. These parameters vary from case to case and their distributions will determine the range and the mean of the hazard envelope. In RSAP (2), the hazard envelope is formulated as follows in Equation 10;

$$HE = \left(\frac{1}{5280}\right) \times \left[L_h + \left(\frac{w_t}{\sin \theta}\right) + W_h \cot \theta\right]$$

(10)
where: $HE =$ hazard envelope ;
$L_h =$ length of hazard(ft.);
$W_e =$ effective width of vehicle(ft.) $= L_v \sin \varphi + W_v \cos \varphi$;
$L_v, W_v$: length and width of vehicle(ft.); and
$W_h =$ width of hazard(ft.).

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

![FIGURE 2 Bridge hazard envelope (2).](image)

**Simulation Method**

The Monte Carlo method is a method of stochastic simulation. Based on statistical theories, it utilizes 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 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 dimension.
Each factor is intrinsically unknown, but the uncertainty can be described by a probability
density function from reliable sources.

According to RSAP (2), when a vehicle speed reaches 70 mph, the extreme values and the most
likely values of vehicle encroachment angle \( \theta \) and vehicle orientation angle \( \phi \) can be determined
(see Table 2). The Project Evaluation and Review Techniques (PERT) distribution which fits the
minimum value, the most likely value, and the maximum value into a beta distribution can be
considered for the encroachment and orientation angles. The smooth curve of a beta distribution
places progressively more emphasis on values around the most likely value favoring values
around the edges. According to the Federal Highway Administration (FHWA) Vehicle
Classification (20), 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 8.5
feet, and the lengths range from 40 to 75 feet. Therefore, the probability distribution of the
hazard envelope can be simulated based on the sample values of vehicle encroachment angle and
vehicle orientation angle, which are drawn from the PERT distribution. The size of the truck can
be drawn from a uniform distribution.

<table>
<thead>
<tr>
<th>TABLE 2 Distribution of Vehicle Encroachment Angle and Orientation Angle (Degrees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>min value</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>vehicle encroachment angle</td>
</tr>
<tr>
<td>vehicle orientation angle</td>
</tr>
</tbody>
</table>

ANALYSIS AND DISCUSSION

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

Truck ROR Crash Prediction Model

In this study, both the random parameter Poisson and random parameter NB distributions have
been considered. The results suggest that the dispersion parameter for the random parameter NB
model was not statistically significant. It is plausible that the random coefficients have already
explained a certain degree of randomness associated with crash occurrence (10); therefore, the
random parameter Poisson model was chosen. A normally distributed random parameter
achieved the best model performance after many experimental runs were performed. A
parameter whose standard deviation is statistically different from zero was considered as a
random variable for the final model results; otherwise, it is considered fixed across observations.
LIMDEP econometric software was used, and the coefficients were estimated based on 200
Halton draws. The output of the coefficient estimates is presented in Table 3.
TABLE 3 Random Parameter Poisson Estimation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Constant Parameter</th>
<th>Random Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>P-value</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.1435</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>VMT</td>
<td>0.6643</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Surface Type (0 if asphalt, 1 concrete)</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>Horizontal Curve</td>
<td>N.A.</td>
<td>NA</td>
</tr>
<tr>
<td>Snowfall</td>
<td>N.A.</td>
<td>NA</td>
</tr>
</tbody>
</table>

The log-likelihood of the fixed-parameter model $LL_f$ is -1572.894, and the log-likelihood of the random parameter model $LL_r$ is -1221.695. The Chi-square test is used to compare the fixed-parameter and random parameter model performance. The $\chi^2$ value is 702.4 with three degrees of freedom and the resulting p-value is close to 0, indicating a 99.99 percent confidence that the random parameters 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 the surface type, the degree of horizontal curve, and the 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. 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 due to their high center of gravity and off-tracking problems (21). It is not a surprise to find that annual snowfall contributes to a higher truck ROR crash frequency, but it is worth mentioning that the snowfall effect differs across highway segments. The difference may be due to precipitation confounding with other roadway factors such as pavement condition and visibility, which vary among roadway segments. Most variables seem to behave rationally except for the pavement type. The positive correlation between concrete surface and 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 the Monte Carlo methods, the conditional distribution of each parameter was applied in order to estimate the collision risk.

Monte Carlo Simulation Results

The Monte Carlo simulation process can be modelled in a structured manner by using the Excel add-in application “Risk Solver” (see Figure 3). The possible outcomes of hazard envelope size were simulated by setting a range (40 to 75 ft.) to the length of the truck and the PERT distribution to vehicle encroachment and vehicle orientation angles.
The collision risk was simulated by setting a normal distribution to the hazard envelope and the random parameters. Both hazard envelope and collision risk were simulated 5000 times. The collision risk for a bridge was calculated as the maximum value of all bridge bents. Figures 4a and 4b illustrate the collision risk for all overpass bridges on I-29 and I-90, respectively. The horizontal axle is the mile marker and the vertical axle is the mean value of collision risk, with the radius being the standard deviation.
There are 68 overpass bridges on I-29, and 74 on I-90. The bubble plots indicate that most bridges have very low collision risk, and higher collision risks are often accompanied by higher risk.
uncertainties. Most of the bridges with a high collision risk are located near urban areas such as Rapid City and Sioux Falls, which is largely due to the high truck volume. In addition to high truck volume passing through the overpasses, the overpasses located in urban areas have a large deck width for more travel lanes to accommodate local traffic. The larger deck width leads to a larger bridge hazard envelope. Moreover, the geometric data show that the Interstate highways in urban areas have a high degree of horizontal curve, which is largely due to the constraint of land use. The high degree of horizontal curve increases the collision risk between trucks and overpasses, and increases the standard deviation of the collision risk because of the random coefficient.

The bridge risk profile is illustrated in Figure 5 in which detailed bridge inventory is provided. Collision risk was calculated for all bridge bents among which the highest risk is considered as the collision risk for the bridge.

<table>
<thead>
<tr>
<th>Bridge ID</th>
<th>38180198</th>
</tr>
</thead>
<tbody>
<tr>
<td>Longitude</td>
<td>-100.7058</td>
</tr>
<tr>
<td>Latitude</td>
<td>43.8835</td>
</tr>
<tr>
<td>Highway</td>
<td>I-90</td>
</tr>
<tr>
<td>Mile Marker</td>
<td>191</td>
</tr>
<tr>
<td>Hazard envelope mean</td>
<td>0.024 mile</td>
</tr>
<tr>
<td>Hazard envelope std.dev</td>
<td>0.069 mile</td>
</tr>
<tr>
<td>Highway segment ID</td>
<td>Right side</td>
</tr>
<tr>
<td>Truck ADT</td>
<td>1489</td>
</tr>
<tr>
<td>Truck ADT</td>
<td>Right side</td>
</tr>
<tr>
<td>Surface type</td>
<td>Concrete</td>
</tr>
<tr>
<td>Segment length</td>
<td>0.997 mile</td>
</tr>
<tr>
<td>Horizontal curve</td>
<td>4.286 degree</td>
</tr>
<tr>
<td>Annual snowfall</td>
<td>42.622 inches</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

The accelerated economic development has substantially increased freight activities on the South Dakota highway system. A large amount of increased traffic is from heavy trucks, which escalates 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. Therefore, it is crucial to identify vulnerable highway infrastructure and provide valuable information to the transportation agencies that are charged with preventing these accidents.

Crashes are random events, as they may be affected by several factors that are unknown or unobservable. The unobserved elements are the main contributors to data heterogeneity. In order to factor the data heterogeneities into the crash risk analysis of this study, the random parameter
Poisson model was employed. The model output reveals that high truck VMT, sharp horizontal curves, high annual snowfall precipitation, and a concrete pavement surface all increase the truck ROR crash frequency. The effects change across different highway segments, due to varying roadway conditions and other factors.

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

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