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Influence of Road Geometry and Traffic Characteristics on Highway Crash Frequencies Under Heterogenous Traffic Conditions

Rezwana Kabir[1], Moazzem Hossain[2,*]

Abstract

This study aims to model the influence of highway geometric and traffic characteristics on road crash frequency under heterogenous traffic conditions using the Negative Binomial regression technique. Over a span of three years, data from 618 road accidents on the Dhaka–Aricha highway (N5) in Bangladesh were analyzed to develop the model. The model variables include Annual Average Daily Traffic (AADT), % of heavy vehicle and non-motorized vehicles (NMV), pavement carriageway width (m), shoulder width (m) and presence of median. The model outcome showed that heavy traffic volume, NMV, reduced pavement carriageway, narrow shoulder width and absence of median increase the likelihood for overall crash involvement. But for pedestrian crash analysis increased traffic volume, % of heavy vehicle, narrow pavement, narrow shoulder width and absence of median increase the likelihood; and % of NMV was not found to be significant in this case. Again, in case of NMT crashes, more crashes resulted in higher percentage of heavy vehicles and reduced shoulders and narrow pavement width having no median. The developed model was further analyzed using an elastic approach to determine the key factors influencing accident occurrence and to assess their relative importance. The research results may provide significant guidance to highway improvement and related investment policy in developing countries conditions like Bangladesh.

Keywords: Negative binomial, accident frequency, elasticity, developing countries and Bangladesh

INTRODUCTION

In Bangladesh safety situation is rapidly deteriorating as road accidents and injuries and deaths have been increasing at an alarming rate on highways with heterogenous traffic conditions. Nearly 4500 accidents were reported by the police in Bangladesh each year among them around 40 percent accidents take place on national highways [1]. Various factors contributing to road crashes have been identified, including pavement conditions, geometric design, traffic patterns, driver behavior, vehicle features, driver characteristics, and environmental conditions. This study specifically focuses on how roadway geometry and traffic-related factors impact the frequency of crashes on highway segments. To guide the research, a review of existing studies on crash occurrences in relation to geometric design and traffic conditions was carried out, which informed the selection of a suitable modeling approach for this study [2]. Finally, findings of the modelling exercise and their implications to real world situation and some concluding remarks are provided.

***Author for Correspondence**
Moazzem Hossain
E-mail: moazzem@ce.buet.ac.bd

Professor, Department of Civil Engineering, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh

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LITERATURE REVIEW

The empirical relationships between traffic accidents and highway geometric design/traffic related variables have been investigated through statistical models in numerous studies [3–13]. However, most of these models were developed using the conventional linear regression and have been reported to have several unsatisfactory statistical properties in describing vehicle accident events on the road [14–17].

Miaou and Lum [18] stated that the conventional linear regression modeling technique cannot properly represent the distributional features of road crash events describing adequately the randomness, and discrete, non-negative, and typically sporadic nature. Although the Poisson regression model can accommodate the distributional features of road crashes it is someway constrained with the fact that the mean and variance of the crash data need to be equal. The negative binomial regression model can overcome this constraint to be relaxed and as such widely used to model road crash phenomenon [19–24]. Additionally, zero-inflated Poisson and zero-inflated negative binomial models have also been used to model crash frequencies to deal with the overdispersion problem potentially caused by the excessive zeroes in traffic accident data population [25–27].

The negative binomial regression model has been widely employed in numerous studies to investigate the crash frequencies on different parts of rural highways, arterial roadways, urban motorways, rural motorways, two-lane or multilane roadways and intersections [7, 12, 20, 22, 28–33]. Applied Negative Binomial models to estimate accident frequencies by considering various roadway design and traffic-related factors on a major arterial in Central Florida. They observed that accident frequency data tend to be over-dispersed, highlighting the limitations of the Poisson model and the suitability of the Negative Binomial approach for more accurate estimation [4]. Their analysis identified AADT (Annual Average Daily Traffic) per lane as a key predictor of accidents. They also found that factors, such as narrow shoulder width, sharp horizontal curves, reduced lane width, a higher number of lanes, narrower medians, and increased traffic volume, are all likely to contribute to higher accident rates. Chang [28] investigated the frequency of freeway accidents with a comparison between NB regression and artificial neural network models using variables, such as ADT per lane, the percentage of trucks in the traffic flow, and concluded that increased exposure to potential risks of accidents correlated with an increasing number of vehicles and trucks. Ayati & Abbasi [30] applied both Poisson and negative binomial (NB) regression models to model the accidents including the independent variables, such as passenger cars, heavy vehicles, and light non-passenger car vehicles, concluding that the negative binomial regression model is a valid and efficient model for modeling and predicting the accidents on urban highways.

RESEARCH OBJECTIVE

The main aim of this study was to create a model that explains how road crash frequency is influenced by highway geometric and traffic characteristics using the Negative Binomial regression method. Additionally, an elasticity analysis was conducted on the developed models to identify the most significant factors contributing to accident occurrences and their relative impacts.

DATA COLLECTION

To establish a mathematical relationship between accident frequency and highway geometry and traffic features, it was necessary to select a highway section that exhibited diverse geometric and traffic conditions. The purpose of this data collection effort was to divide the roadway into segments with similar characteristics for analysis. After reviewing several highways across Bangladesh, the Dhaka–Aricha Highway (N5) was chosen as the most suitable candidate for this modeling approach.

This highway serves as a critical link for inter-district and interregional transportation, connecting the northwestern and northern regions of Bangladesh with Dhaka, the capital city. Due to its heterogeneous traffic patterns, it also forms part of the Asian Highway Route AH1. The highway extends from Mirpur Bridge to Banglabandha, covering approximately 526.59 km in length, with around 509 km being a single carriageway and 18 km comprising dual carriageways. This length provided enough segments to conduct a robust modeling exercise. The number of lanes along the highway varies between 2, 4, and 6 lanes. High accident rates along this route have been attributed to complex road geometry and challenging traffic conditions. The road also experienced minimal changes during the three-year study period from 2007 to 2009, ensuring consistency in the analysis. For modeling, the same road segments in different sample periods were treated as separate data points [34–37].

Traffic and roadway data were sourced from the Roads and Highways Department (RHD) database. Geometric features, such as pavement width and shoulder dimensions (in meters), as well as traffic-related factors including volume and vehicle composition, were collected. The N5 highway was divided into 249 segments based on any changes in geometry or traffic characteristics. This approach ensured that each segment was uniquely defined by one or more variables recorded by the RHD.

The dataset included variables such as AADT (Annual Average Daily Traffic), the percentage of heavy vehicles, the percentage of non-motorized vehicles (NMV), presence or absence of a median, pavement width, and shoulder widths. Binary (dummy) variables, coded as 0 or 1, were used to indicate the presence or absence of specific conditions. For example, the impact of medians on accidents was evaluated by assigning a value of 0 if the median was absent and 1 if present.

Accident data was collected from the Accident Research Institute (ARI) of BUET, Bangladesh, covering the years 2007 to 2009. These records were compiled from Highway Thana Police reports, which are submitted using an Accident Reporting Form (ARF). The data was processed and analyzed using the MAAP software (Micro-computer Accident Analysis Package), developed by the Transport Research Laboratory (TRL) in the U.K. This database, widely known as the MAAP dataset, forms the basis for current road safety analyses in Bangladesh.

In total, information on 618 accidents was available for the N5 highway during the study period. The final dataset provided comprehensive details about accidents for each segment along with corresponding geometric and traffic-related variables.

METHODOLOGY

To derive the negative binomial model, we first start with the Poisson model. For the Poisson model, the probability of having a specified number of accidents (n_i) on highway segment is:

$$P(n_i) = \frac{\exp(-\lambda_i)\lambda_i^{n_i}}{n_i!} \quad (1)$$

where $P(n_i)$ = probability of an accident occurring on highway segment i, n_i is the number of accidents on highway section i over a time period t and λ_i = Poisson parameter for highway segment i, which is equal to expected mean number of accidents on highway section i.

Including the error term in Poisson parameters and the explanatory variables relation, the form of resulting negative binomial probability distribution is obtained, which is a conditional probability, and is given as:

$$P\,(n_i|\varepsilon) = \frac{\exp[-\lambda_i \exp(\varepsilon)]\lambda_i^{n_i}}{n_i!} \quad (2)$$

where, n_i is the number of accidents on highway section i over a time t.

Integrating ε out of this produces unconditional distribution of n_i. The formulation of this distribution, which is used in maximum likelihood estimation, is:

$$P(n_i) = \frac{\Gamma(\theta+n_i)}{(\Gamma(\theta)n_i!)} u_i^{\theta}(1-u_i)^{n_i} \quad (3)$$

where $u_i = \frac{\theta}{(\theta+\lambda_i)}$ and $\theta = \frac{1}{\alpha}$ and $\Gamma(.)$ is a value of the gamma function.

The Negative Binomial model can be estimated by standard maximum likelihood methods. The corresponding likelihood function is:

$$L(\lambda_i) = \prod_{i=1}^{N} \frac{\Gamma(\theta+n_i)}{\Gamma(\theta)n_i!} u_i^{\theta}(1-u_i)^{n_i} \quad (4)$$

Given, N is the total number of highway sections under study. Unlike the Poisson model, this has an additional parameter α (the variance of the gamma-distributed error term) = a measure of dispersion and is estimable by standard maximum likelihood techniques, such that:

$$\mathrm{var}[n_i] = E[n_i]\{1 + \alpha E[n_i]\} \quad (5)$$

It is noted that if α is significantly different from zero, the data can be considered as over-dispersed or under dispersed and the Negative Binomial is a suitable modeling approach.

For the current non-linear model (e.g., negative binomial regression), a pseudo-R^2 statistic is used as a test for goodness of fit. Various forms of pseudo-R^2 have been proposed, but the most widely used is calculated using the following formula, commonly referred to as the log-likelihood ratio:

$$\rho^2 = 1 - LL(\beta)/LL(0) \quad (6)$$

where $LL(\beta)$ represents the log-likelihood at convergence with the estimated coefficient vector β, and $LL(0)$ represents the initial log-likelihood with all coefficients set to zero. The value of ρ^2 reflects how much additional variance in crash frequency is explained by the model compared to a model containing only the intercept term. The value of ρ^2 ranges between 0 and 1, with higher values indicating a better model fit. To assess the overall goodness of fit, the deviance, defined as,

$2(LL(\beta) - LL(0))$, is used and follows a chi-square distribution. According to Agresti, if the deviance is large enough such that the p-value is less than 0.05, the null hypothesis is rejected, indicating that the full model provides a good fit to the data. In this study, models with higher log-likelihood values are preferred.

To understand how independent variables influence crash frequency, elasticities were calculated. Elasticity measures the percentage change in the average crash frequency (λ) resulting from a one-percent change in an independent variable. Shankar et al. proposed this method as a means of quantifying the relative importance of each variable in the model and its true impact on crash occurrences. In general, elasticity is computed as:

$$E(y) = \frac{\partial\lambda}{\partial x}\frac{x}{\lambda} \quad (7)$$

where λ is the mean number of accidents, x is the value of the explanatory variables.

Differentiating (3) and applying (9) gives,

$$E(y) = \beta x \quad (8)$$

where β = coefficient estimate of explanatory variable.

Average elasticities (averaged over all highway section) for all continuous explanatory variables are presented here. Elasticities for indicator variables (i.e., those variables that take values of zero or one) are not computed because their elasticity has no meaningful interpretation so only the elasticities of continuous variables are calculated here.

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ANALYSIS OF RESULTS

Modeling for All Crash Types

Negative binomial estimation modeling results of crash frequency utilizing all types of crash data are presented in Table 1. The results presented are the estimated coefficients, associated t-statistics, and log-likelihood for the model. It was observed that all variables had expected signs – positive signs indicating an increase in crash frequency and negative signs indicating a decrease – along with statistically significant results. To assess the model's goodness of fitness, the deviance value.

$2(LL(\beta) - LL(0))$, was found to follow a chi-square distribution with a value of 310 and 6 degrees of freedom. At a 95% confidence level, the critical chi-square value for 6 degrees of freedom is 12.6, which is much lower than the observed deviance, leading to the rejection of the null hypothesis that the model with only a constant term explains the data equally well. This confirms that the full model provides a strong statistical fit.

Additionally, the pseudo-R^2 value of 0.25 suggests a reasonable level of explanatory power. The dispersion parameter, α was found to be significantly different from zero (t=4.78), indicating overdispersion in the data and supporting the use of the Negative Binomial model over the Poisson approach.

The analysis identified six key variables that significantly influence crash frequency. Based on the t-statistics and coefficient estimates, factors, such as the logarithm of AADT per lane, the percentage of heavy vehicles, and the percentage of non-motorized vehicles, were shown to have a positive relationship with crash frequency, meaning that higher values of these variables are associated with an increased likelihood of accidents. Among the predictors, pavement carriageway width, the logarithm of AADT per lane, median presence, and the percentage of non-motorized vehicles were statistically significant at a p-value less than 0.05.

Table 1. Negative binomial model of accident frequency (all types).

Independent Variable	Co-Efficient	t-Statistics	p-Value
Constant	–1.818	–1. 13	0.266
Pvt. Carriageway width, m	–0.181	–6.03	0.000
Shoulder width, m	–0.913	–1.01	0.353
Log of AADT per lane	1.301	4.34	0.000
% of heavy vehicle	0.009	1.13	0.276
% of NMV	0.019	2.37	0.030
Median presence (dummy variable) (1 if presence, 0 if absent)	–1.311	–4.37	0.000
Over dispersion parameter(α)	0.335	4.78	-
Summary statistics			
Number of sections	-	249	-
Log-likelihood at zero	-	–622.565	-
Log-likelihood at convergence	-	–467.961	-
$\rho^2 = 1 - LL(\beta)/LL(0)$	-	0.25	-
$2(LL(\beta) - LL(0))$	-	310	-

AADT (Average Annual Daily Traffic) appears to have a strong positive effect on accident frequency, indicating the traffic conditions. This result can be attributed to conflicts between vehicles in congested traffic flow conditions on highway sections with increasing number of vehicles and trucks. Frequent traffic accidents also correlate with higher percentage of heavy vehicles, attributed to the fact that trucks & buses unduly occupy faster lanes with frequent lane changing and thus increasing number of collisions. The model's finding that highway segments with a higher proportion of non-motorized vehicles (NMV) are associated with increased accident frequency can be attributed to greater congestion and significant differences in speed between NMVs and motorized vehicles.

Based on information from the Roads and Highways Department (RHD), the highway has sections with 2, 4, or 6 lanes. However, in practice, most segments lack clearly marked lanes, making it difficult for this study to analyze the impact of lane count on accident frequencies. No effect of vertical and horizontal alignment has been estimated from the model because the selected highway sites having almost flat topography (i.e., little variation in slopes).

Pavement carriageway and shoulder width (m) both have negative effects on crash frequency. As for shoulders, the negative sign in the model explains that wider shoulder reduces accident number and wider pavement is also found to have beneficial effects on the safety of highway sections by reducing conflict among traffic and extra space helping to ward off any potential collision conflict. Accident frequency is negatively associated with median presence in the highway segments. If median is present, then accident number on the highway is significantly reduced whereas no median presence is found to have predominant effect on increasing number of accidents. So, presence of median is found especially significant in the model. This is since presence of median can help avoiding the head on collision between opposing traffic stream on the highway and pedestrians can take refuse on the median in the process of completing their road crossing maneuver.

Elasticity analysis estimates for the selected influencing variables are presented in Table 2. The results show that AADT per lane has the greatest relative effect on the accident frequency among all the independent variables. Regarding AADT, an elasticity of 4.55 is found which means that a 1% increase in AADT per lane will result in a 4.55% increase in total accidents. This is considered elastic (an absolute value greater than one) and emphasis the importance of AADT in total accident frequency. Pavement carriageway and shoulder width have negative elastic effects on accident frequencies. Table 2 also provides more explanation about inelastic (elasticity less than unity) variables.

Table 2. Accident frequency elasticity estimates.

Variable	Elasticity
Pvt. Carriageway width, m	–1.53
Shoulder width, m	–1.35
Log of AADT per lane	4.55
% of heavy vehicle	0.48
% of NMV	0.56

Modeling for Pedestrian Accident

Pedestrian Accident Model

A Negative Binomial model was estimated to explain pedestrian accident involvement, as shown in Table 3. The variables used in this model are largely the same as those applied in the general accident frequency model presented earlier in Table 1, except for the percentage of non-motorized vehicles (% NMV), which was excluded due to its lack of statistical significance in this case.

The deviance value for the pedestrian accident model, calculated as:

$$2(LL(\beta) - LL(0)) = 1922(LL(\beta) – LL(0)) = 1922(LL(\beta) - LL(0)) = 192$$

with 5 degrees of freedom, follows a chi-square distribution and is significant at the 95% confidence level (with a critical value of 11 for df = 5). This suggests that the model has a moderate fit. Additionally, the likelihood ratio index (ρ^2) for the pedestrian accident model was found to be 0.25, matching the value obtained for the general accident frequency model. This indicates that the model's predictive ability remains consistent when applied specifically to pedestrian accident involvement.

The overdispersion parameter, α, was estimated to be significantly different from zero (t = 3.68), confirming that the Negative Binomial model is more appropriate than the Poisson formulation for this dataset, as it accounts for variability beyond the mean.

Key predictors, such as pavement carriageway width, log of AADT per lane, percentage of heavy vehicles, and median presence, were found to be statistically significant ($p < 0.05$). The results show that higher traffic volume and a greater percentage of heavy vehicles are associated with increased pedestrian accident involvement. Furthermore, pedestrian accident frequencies are more likely to rise during periods of heavy traffic. The absence of a median also contributes to higher accident involvement, possibly due to increased pedestrian road crossings. A negative relationship between pavement width and pedestrian accidents was identified, suggesting that wider carriageways are linked to fewer incidents. Similarly, narrower shoulder widths were found to significantly increase pedestrian accident involvement (Tables 3 and 4).

Table 3. Variables coefficient t-static p-value.

Independent Variable	Coefficient	t-Statistic	p-Value
Constant	–4.587	–1.99	0.050
Pavement carriageway width (m)	–0.207	–2.96	0.006
Shoulder width (m)	–3.000	–1.61	0.108
Log of AADT per lane	2.818	5.62	0.000
% of heavy vehicles	0.012	2.40	0.042
Median presence (1=yes, 0=no)	–1.170	–2.93	0.005
Overdispersion parameter (α)	0.368	3.68	—

Summary Statistics

- *Number of sections:* 249.
- *Log-likelihood at zero:* –387.027.
- *Log-likelihood at convergence:* –290.913.
- $\rho^2 = 1 - LL(\beta)/LL(0)$: 0.25.

Deviance
$2(LL(\beta) - LL(0))$: *192*

Table 4. Pedestrian accident frequency elasticity estimates.

Variable	Elasticity
Pavement carriageway width (m)	–1.76
Shoulder width (m)	–4.53
Log of AADT per lane	9.86
% of heavy vehicles	0.58

The elasticity estimates show that increases in AADT and heavy vehicle percentage significantly raise pedestrian accident involvement. These factors have a stronger relative impact on pedestrian accidents compared to general accident occurrences. Wider shoulders and carriageways, on the other hand, are associated with fewer pedestrian accidents, though these effects are more pronounced for pedestrian incidents.

Modeling for Non-Motorized Vehicle (NMV) Accidents

A separate Negative Binomial model was developed to examine accident frequency involving non-motorized vehicles, as detailed in Table 5. The variables included in this model are like those in the general accident frequency model from Table 1.

The deviance for this model was:

$$2(LL(\beta) - LL(0)) = 1332(LL(\beta) - LL(0)) = 1332(LL(\beta) - LL(0)) = 133$$

with 6 degrees of freedom, which is significant at the 95% confidence level (critical χ^2 value of 12.6 for df = 6). This confirms that the model provides a moderate statistical fit.

However, the likelihood ratio index for the NMV model ($\rho^2 = 0.22$) is lower than that for the general accident frequency model ($\rho^2 = 0.25$), indicating a slight decline in predictability when focusing on non-motorized traffic accidents. This may be due to behavioral factors affecting non-motorized traffic that are not fully captured by the model.

The overdispersion parameter, α, was significant (t = 2.48), reinforcing the appropriateness of the Negative Binomial approach over the Poisson model for this type of accident prediction.

This model shows that an increase in AADT, higher percentage of heavy vehicles and NMV has significant positive effect on non-motorized traffic accident involvement. This shows that NMT tends to face more accidents when highway segments are occupied with heavy volume of non-motorized and motorized traffic. This result can be attributed to higher level of congestion and associated high speed variance between NMT and motorized vehicles. Presence of median and pavement carriageway width affect negatively the frequency of accident involvement in a significant way. Shoulder width also affects negatively the accident involvement frequency.

Table 5. Negative binomial model of NMT accident frequency.

Independent Variable	Co-efficient	t-Statistics	p-Value
Constant	–6.989	–2.25	0.025
Pvt. Carriageway	–0.190	–2.38	0.029
Shoulder width	–2.557	–1.28	0.203
Log of AADT per lane	2.426	3.47	0.001
% of heavy vehicle	0.036	3.60	0.029
% of NMV	0 .050	5.00	0.004
Median presence dummy variable (1 if presence, 0 if absent)	–1.502	–2.50	0.028
Over dispersion parameter(**α**)	0.743	2.48	
Summary statistics			
Number of sections	-	249	-
Log-likelihood at zero	-	–297.602	-
Log-likelihood at convergence	-	–230.840	-
$\rho^2 = 1 - LL(\beta)/LL(0)$	-	0.22	-
$2(LL(\beta) - LL(0))$	-	133.5	-

Table 6. NMT accident frequency elasticity estimates.

Variable	Elasticity
Pvt. Carriageway width, m	–1.62
Shoulder width, m	–3.85
Log of AADT per lane	8.49
% of heavy vehicle	1.74
% of NMV	1.40

The elasticity result depicted in Table 6 shows that the relative effect of % of heavy vehicle and NMV as well as AADT on accident involvement is higher for NMV accidents than general accident frequencies. Therefore, NMV accidents tend to occur more with higher level of traffic flow.

CONCLUSIONS

The understanding of the influence of roadway geometry and traffic characteristics is vital for highway planners and policy makers alike for reducing the road crash related losses, especially, in heterogenous traffic conditions, like Bangladesh, with relatively higher crash frequencies. Current research results showed that several roadway geometry and traffic factors affect the safety condition of highways. Among those, AADT was identified as the most critical factor in the model denoting significantly increase in crash frequency with increase in AADT. Narrow pavement and shoulder width (m) are also potential geometric features resulting in increases in crash occurrences. Highway segments with higher percentage of heavy vehicles and NMV are more likely to have higher crashes than other segments. Presence of median has a negative effect on accidents and thus it could improve highway safety. The results also showed that increased traffic volume and % of heavy vehicles, narrow pavement, narrow shoulder width and absence of median increase the likelihood for pedestrian accident involvement. The model also indicated that NMV experience more accidents with higher % of heavy vehicle and NMV, and with reduced shoulder and narrow pavement having no median. The methodology used in this paper can be employed for prediction of road crash frequency for given profile of a roadway to assess the safety performance and road improvement investment options; and identify hazardous locations for important highway corridors in Bangladesh and other developing countries.

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