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Predicting Highway Crash Frequency: A Review of Statistical Regression Models

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Mitigating the losses of human lives owing to highway crashes needs better insights to the roadway locations as well as the performance of various safety measures. All these require the analysis of existing crash data for various roadway segments, both deemed "safe" and "unsafe" with different safety measures installed. Statistical models project the safety standards and their suitability into the future. Various tools and modeling techniques or regression models, primarily based on Poisson Regression, are employed to analyze crash data. This paper discusses some common methodological issues which are constraining the effectiveness of various existing models, then assesses the strengths and weaknesses of these models, followed by introducing more promising and advanced approaches that predict results with much more accuracy than the traditional statistical models.

Keywords: Highway Safety, Crash-frequency Modeling, Over and Under-dispersion

Field of Research: Civil Engineering (Transportation Engineering)

1. Introduction

Highway safety is a global concern owing to the vast amount of social and economic loss in terms of fatalities and property damages each year around the world. Therefore, gaining a better and comprehensive understanding of the factors that affect traffic safety is always emphasized in transportation engineering. Vehicle crash has been an area of research focus for many decades and public agencies have put great effort into preventive measures; however, the annual number of traffic accidents has not been significantly decreased yet. For instance, according to World Bank statistics, annual fatality rate from road accident is found 85.6 per 10,000 vehicles in Bangladesh. In global perspective, according to World Health Organization (2009) about 1.24 million people die every year in highway-related crashes and as many as 50 million more are injured costing over $500 billion in total and by 2030, highway-related crashes are projected to be the 5th leading cause of death in the world.

In order to improve traffic safety and provide directions for countermeasures aimed at reducing the number of crashes, numerous statistical models have been developed that identify factors contributing to crash frequency (the number of

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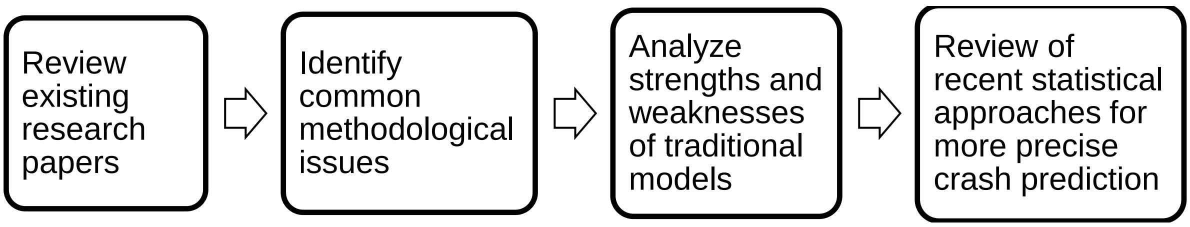
crashes occurring within a specific jurisdiction, on a roadway segment, or at an intersection over a specified period). A considerable number of studies have used various methodological approaches in modeling crash frequency. While the success of many of these efforts in reducing the likelihood of highway crashes and mitigating their impact cannot be denied, the toll that highway crashes continue to extract on humanity is clearly unacceptable.

Countless amounts of highway crash data are collected every year worldwide and the continual advancement in statistical methodologies has enabled researchers to extract more and more information from the enormous data sources. Although highway traffic safety has seen some improvements due to enhanced vehicle safety features and highway design in past decades, crash frequencies in many countries have not significantly decreased as expected. In this situation, it is very important to propose appropriate regression techniques in calibrating crash prediction model.

The paper has been organized in the following way: Section 1 deals with introduction focusing on the background of the study and justification behind adopting the approach. Section 2 presents the basic methodology applied to conduct this literature review. Section 3 deals with the review of existing literature: the subsections detail the methodological issues and analyze the advantages and disadvantages of existing crash frequency prediction models. A review of current advances in the prediction models is given in Section 4. Conclusion and directions for future research are provided in section 5.

2. Materials and Method

This study aims to provide a general overview and comparison of various statistical methods employed to analyze crash frequency. Gathering secondary data and information from various scientific papers on the regression models as well as published statistics on traffic crashes, this paper attempts to identify some common methodological issues which are constraining the effectiveness of the models. The strengths and weaknesses of various methodological approaches used to analyze crash frequency data have been probed, followed by several more radical and improved approaches that predict results with much more accuracy than the traditional statistical models. The approach employed in this study is outlined below:



3. Analyzing Highway Crash Data: A State-of-the-Art Review

If we take a look into the global statistics of road accidents, we can vividly see that the trend of road accidents over the past few decades is exponential in most of the developing countries where traffic is mostly composed of a wide category of vehicles. More than 1.2 million people die each year on the world's roads (WHO 2009) making road traffic injuries a leading cause of death globally. Although road traffic injuries have been a major cause of mortality for many years, most traffic crashes are both predictable and preventable with indigenous modeling of crash frequency data.

3.1 Trends in Highway Crashes: A Global Challenge

Ninety percent of road traffic deaths occur in low and middle-income countries, and while these countries also account for 82% of the world's population, they nevertheless bear a disproportionate number of deaths relative to their level of motorization, as they account for only 54% of the world's registered vehicles. Figure 1 and 2 show us the current scenario of death tolls by country income status and WHO region (Road traffic deaths per 100,000 population) [Source: Global Status Report on Road Safety by WHO 2015]

Figure 1: Road Traffic Deaths per 100,000 Populations, by Country Income Status

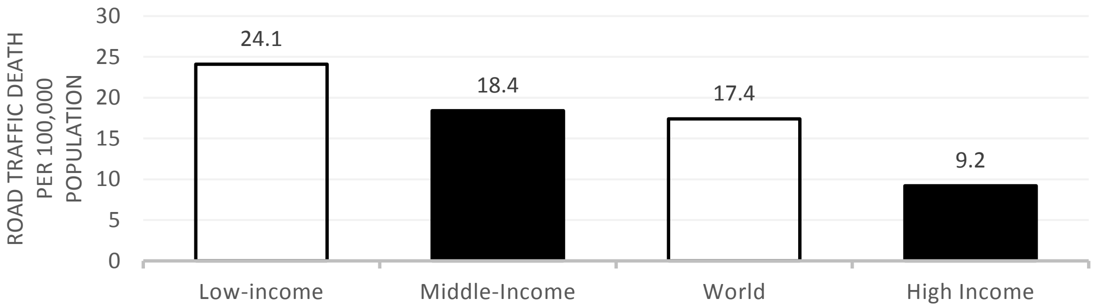
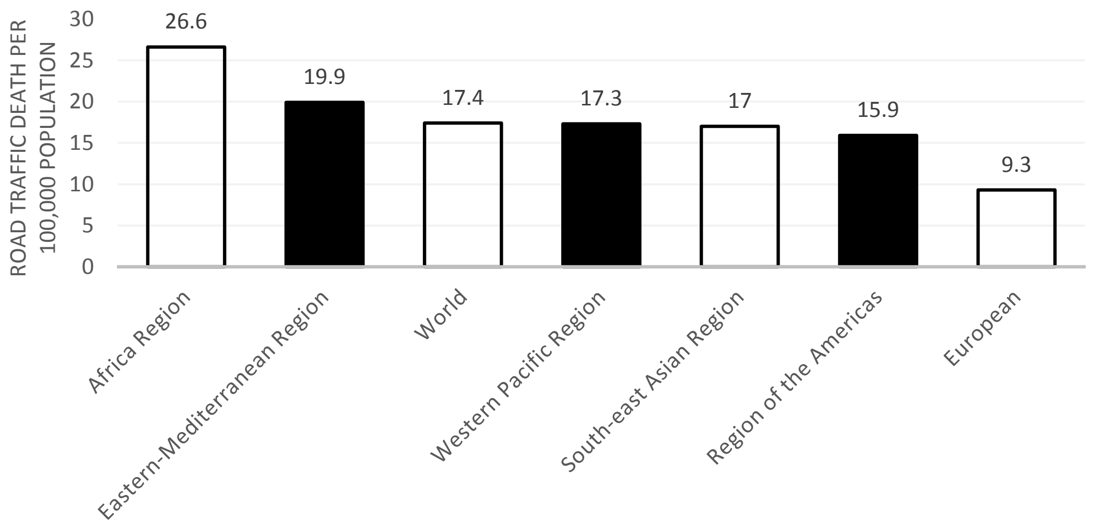


Figure 2: Road Traffic Deaths per 100,000 Populations, by WHO Region



The recent scenario is very alarming and it is deteriorating every year. This calls for a comprehensive analysis of highway crashes at the stage of planning and designing and developing more precise crash frequency models which would predict road crashes with reasonable amount of accuracy; in a way that safety is considered as one aspect of performance assessment of roads.

3.2 Methodological Issues

Crash frequency data are generally represented by discrete categories and beyond the discrete nature of these data, previous research has identified a number of data characteristics and methodological issues over the years that are critical in the development and application of an appropriate statistical model. Some of the most common methodological issues are: over-dispersion and under-dispersion in data, low sample mean and small sample size, injury severity and crash type correlation, under reporting, endogenous variables, time-varying explanatory variables etc. which may lead to erroneous crash frequency predictions and incorrect inferences relating to the factors that determine the frequency of crashes. The following section provides detailed insights on different statistical modeling approaches keeping in view the characteristics of crash data: over-dispersion, under-dispersion and low sample mean and small sample size.

3.2.1. Over-dispersion in Crash Data

One of the most common and fundamental method for crash data evaluation is Poisson Regression Model. When over-dispersed data are present, estimating a common Poisson model can result in biased and inconsistent parameter estimates which in turn could lead to erroneous inferences regarding the factors that determine crash frequencies (Lord and Mannering 2010). To overcome the problem of over-dispersion, Poisson Regression Model is extended to Negative Binomial or Poisson Gamma model in accident modeling (Lord et al. 2004). In count data, actual estimates of over-dispersion can be influenced by a variety of factors, such as the clustering of data, unaccounted temporal correlation, and model mis-specification (Madanat and Ibrahim 1995). Recently, some researchers have reported by improving the model specification, model estimated over-dispersion can be greatly minimized (Cameron and Trivedi 1998; Miaou and Song 2005). However, this model does have its limitations, particularly in its incapability to handle under-dispersed data and dispersion-parameter-estimation problems when the data are categorized by low sample mean values and small sample sizes (Conway and Maxwell 1962).

Poisson lognormal and Conway–Maxwell–Poisson (COM Poisson) distribution model, on the other hand, is more flexible than NBR and Poisson Gamma Model. The Poisson-lognormal model acts similar to the negative binomial model, however, the distributional assumption is gamma in case of later one (Miaou 1994). A few researchers have suggested the use of the Negative Multinomial Model as an alternative to the negative binomial model for modeling crash data (Miaou 2003). At times, Negative Binomial experiences correlation problem with observations, which could perhaps be alleviated by the Negative Multinomial approach (Shankar et al. 1998).

3.2.2. Under-dispersion in Crash Data

Although rare, crash data can sometimes be characterized by under-dispersion, where the mean of the crash counts on roadway entities is greater than the variance, especially when the sample mean value is very low. Previous work has shown that many traditional count-data models like Poisson Regression Model, Negative Binomial Model, Poisson Gamma Model, Poisson Lognormal Model, Negative

Multinomial Model etc. cannot handle under-dispersed data and produce incorrect parameter estimates in the presence of under-dispersed data (Oh et al. 2006; Lord et al. 2009). On the other hand, Conway-Maxwell-Poisson, Generalized Estimating Equation etc. are capable of handling under-dispersion in data set.

3.2.3. Low Sample Mean and Small Sample Size

Data collection is quite a costly process and so crash data is often characterized by a small number of observations. Additionally, some roadway entities may have few observed crashes which results in a preponderance of zeros. Data characterized by small sample size and low sample mean can cause estimation problems in traditional count-frequency models. Poisson Regression Model, Negative Binomial Model, Poisson Gamma Model, Poisson Lognormal Model, Negative Multinomial Model, Zero-inflated Poisson and Zero-inflated negative binomial, Poisson – Weibull etc. can adversely be influenced by low sample mean and small sample size. There are some parameter estimation techniques (for example, maximum likelihood estimation) which have large sample properties and with small sample sizes, those cannot be realized. Again, the distribution of crash counts will be skewed excessively toward zero with low sample means which can result in erroneous estimated parameters inferences (Lord and Mannering 2010).

3.3 Traditional Modeling Methods for Analyzing Crash Frequency Data

Modeling of crash count data is very important topic in highway safety analysis and it has been widely used as an indicator of the crash occurrence at highways or certain segments of the roads. In the past few decades, modelers have proposed a significant number of analysis tools for analyzing crash frequency data. In Table 1 some of these regression models are mentioned with their strengths and weaknesses.

Table 1: Strengths and Weaknesses of Traditional Regression Models used for Analyzing Highway Crash Data

Model Type	Strengths	Weaknesses
Poisson Regression Model (Caliendo, Guida and Parsi 2007; Lord and Mannering 2010)	Most basic and simple model; easy to estimate; Uses advanced modeling technique called the Generalized Linear Models (GLM)	Cannot handle over-dispersion and under-dispersion; Test statistics derived from the model will be incorrect for low sample mean; Can produce biased results in small samples
Negative Binomial Regression Model (Lord 2006)	An extension of Poisson Regression Model; Easy to estimate; Can handle over-dispersion in data set	Cannot handle under-dispersion; Low sample mean and small sample size can result in inadequate parameter estimates
Negative Multinomial Model (Lord and Mannering 2010)	Can handle over-dispersion in data set; Can work with the problem of correlation among observations	Cannot handle under-dispersion; Low sample mean and small sample size can result in inadequate parameter estimates
Poisson-lognormal Model (Miaou, Song and Mallick 2003)	An extension of Negative Binomial Model; Can handle both over-dispersion and under-dispersion	Model estimation is more complex; Adversely effected by low sample mean and small sample size; Cannot estimate a varying dispersion parameter
Zero-inflated Poisson and Zero-inflated Negative Binomial Models (Lord 2006; Lord, Washington and Ivan 2007; Lord and Mannering 2010)	Capable of handling the over-dispersion problems produced by excessive zeros in traffic data counts; Can model accident frequencies in both zero accident state and non-zero accident state	The long term mean equals to zero in the safe state and it can produce some biased estimates; This model cannot properly reflect the crash-data generating process; Adversely affected by low sample mean and small sample size

Model Type	Strengths	Weaknesses
Conway-Maxwell-Poisson Model (Kadane et al. 2006; Lord and Mannering 2010)	Can handle both over-dispersion and under-dispersion in data set; Forms an exponential family of distributions and has sufficient statistics of fixed dimension as the sample size varies	Negatively influenced by low sample mean and small-sample bias; There have not been any multivariate applications of the approach
Gamma Model (Oh, Washington and Nam 2006)	Can handle both over-dispersion and under-dispersion in data set; Reduces to the Poisson model when the variance is roughly equal to the mean	Dual-state model; Have a long term mean equal to zero
Generalized Estimating Equation Model (Lord and Persaud 2010; Liang and Zeger 1986; Oh, Washington and Nam 2006)	Can handle both over-dispersion and under-dispersion in data set; Analyzes to model crash data with repeated measurements; Estimate models with data characterized by serial correlation	Dual-state model; Have a long term mean equal to zero
Generalized Additive Model (Xie and Zhang 2008)	It uses smooth functions of each explanatory variable; Very flexible in modeling nonlinear relationships	Estimation process can become very difficult to be employed as they include more parameters than the traditional count models; Their applications to the crash frequency prediction are very limited
Hierarchical/Multilevel Model (Goldstein 1995; Kim et al. 2007)	Can handle levels of hierarchy in crash data	Their outputs are very difficult to be interpreted; Have not been popular in their applications
Bivariate/Multivariate Model (Bijleveld 2005; Song et al. 2006; Lord and Mannering 2010)	Analyzes more than one type of events simultaneously, since a number of different events may share the same set of risk factors; Considers the correlation among the severity levels	Complex to estimate since they require a formulation of a correlation matrix

4. Modeling Crash Data: Current Advances

The stream of methodological innovation has introduced some very exciting statistical approaches to work with crash frequency data in the past few years. Random Parameter Models, Artificial Neural Network Model, Finite Mixture Models, Markov Switching Models and others all hold great promise in improving our understanding of the factors that affect the frequency of crashes. Details of these modeling methods are described below.

4.1 Random Parameter Model

The use of a constant/fixed parameter can vary widely in actual observations and can lead to biased and inconsistent estimated coefficients, thus resulting in erroneous inferences. The shortcomings of the fixed parameter model that constrained the estimated parameters to be fixed across observations can be overcome by applying random parameters that can take into account unobserved heterogeneity from one roadway site to another (Park and Lee 2017).

Traditional crash-severity modeling uses detailed data gathered after a crash has occurred (number of vehicles involved, age of occupants, weather conditions at the time of the crash, types of vehicles involved, crash type, occupant restraint use, airbag deployment, etc.) to predict the level of occupant injury. However, for prediction purposes, the use of such detailed data makes assessing the impact of alternate safety countermeasures exceedingly difficult due to the large number of variables that need to be known. Random parameter statistical models use detailed crash-specific data and data that include the injury outcome of the crash. However, it does not incorporate detailed crash-specific data (only more general data are used such as roadway geometrics, pavement condition and general weather and traffic characteristics) (Anastasopoulos and Mannering 2011).

Poisson/negative binomial model assumes that parameters are fixed across observations and Greene (2007) developed a method to incorporate random parameters in count models. Parameters which allow for random parameters can be expressed as follows:

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

Where, φ_i is a randomly distributed term (for example a normally distributed term with mean zero and variance σ2). With this equation, the Poisson parameter becomes $\lambda_i|\varphi_i = e^{\beta X_i}$ in the Poisson model and $\lambda_i|\varphi_i = e^{\beta X_i + \varepsilon_i}$ in the negative binomial/Poisson gamma with the corresponding probabilities for Poisson or negative binomial now *P* $(\lambda_i|\varphi_i)$. Because each observation has its own parameters, the final model will often provide a statistical fit that is significantly better than a model with traditional fixed parameters (Lord and Mannering 2010).

4.2 Artificial Neural Network Model

Mathematically, Neural Network is a complex function, which is designed to learn from the collected data (Zeng et al. 2016). Artificial Neural Networks (ANNs) have many advantages over the classical statistical models. For instance, regression models need a pre-defined relationship or functional form between the dependent variable (crash frequency) and the independent explanatory variables that can be estimated by some statistical approaches, whereas the ANNs do not require the establishment of these functional forms and can be easily applied for the analysis. However, ANNs have the disadvantage of behaving as black-boxes and not providing interpretation for the parameter estimates related to the explanatory variables (Riviere 2006; Xie 2007; Lord 2010). Chang (2005) compared the use of Negative Binomial (NB) and Neural Network (NN) models for crash frequency analysis and found that the NN model has better predictive performance. Xie, Lord and Zhang (2007) developed a Bayesian Neural Network model for analyzing crash frequency and compared the Bayesian NN model (BNN), NB model, and NN model trained with a back-propagation (BP) algorithm (BPNN). The results showed that both BNN and BPNN had higher prediction accuracies than the NB mode.

While the Poisson regression models (both regular and negative-binomial) model can effectively explain the effects of the explanatory variables in crash frequency, the ANN model is more effective in assigning the level of significance these variables have. Abdulhafedh (2016) reported that the classification tool from the ANN model is very useful in determining the most influential explanatory variables that can contribute to the crash occurrence instead of using the coefficient estimates from the Poisson and NB models. This percentage importance is easier to be interpreted than the estimates and their signs in the other two regression models. Furthermore, the ANN does not require pre-defined relationships between the independent and the dependent variables and can be easily applied in the crash frequency analysis (Abdulhafedh 2016).

Zeng et al. (2016) developed a NN model and proposed a structured optimization algorithm to eliminate the possibility of over fitting and to deal with black-box characteristics. Compared with NB and NN models as employed in previous traffic safety studies, the improved NN techniques not only achieve better fits when modeling crash frequency, but also illustrate the effects of the risk factors. As NN is a universal approximator, these methods may also be useful in other aspects of highway safety analysis, such as jointly modeling crash frequency and injury severity, identifying sites with promise and evaluating countermeasure effectiveness.

4.3 Markov Switching Model

Another useful modeling tool for representing heterogeneous datasets is the Markov Switching Model. The key underlying principle of this type of model is that a number of underlying distributions generate the data and that individual observations can switch among these distributions over time (Lord 2010). Similar to traditional zero-inflated models, the Markov switching model attempts to statistically account for the preponderance of zeros (zero crashes occurring in a particular roadway segment) observed in accident count data (Malyshkina 2010). In addition to being a better statistical fit to crash frequencies, Markov switching models, which explicitly consider transitions between the zero-accident state and the normal-count state over time, permit a direct empirical estimation of what states roadway segments are in at different time periods. This estimation can help in a detailed study of individual roadway segments, which can lead to a better understanding of why some segments are considerably safer than others during certain period of time.

4.4 Random Effects Model

The NB model has demonstrated itself as a capable approach to deal with over-dispersed crashes, but it has limitations for managing temporal effects, such as the correlation of crashes occurring on the same segment with annual or seasonal changes. Consequently, the standard error of the regression coefficients might be underestimated. Shankar et al. (1998) developed a random effect negative binomial (RENB) model to deal with the temporal issues embedded in the crash data. It was found that the prediction accuracy was significantly improved. Chin and Quddus (2003) investigated the relationship between crash occurrence and potential factors of signalized intersections using an RENB model, which treated the data in a time-series cross-section panel. Hosseinpour et al. (2014) assessed the performance of seven models (Poisson, NB, RENB, hurdle Poisson, hurdle NB, zero-inflated Poisson, and zero-inflated negative binomial models) by predicting the frequency of head-on crashes on a federal road in Malaysia. It was found that the RENB model outperformed the other models subject to goodness-of-fit measures.

5. Conclusion

Although road traffic injuries have been a leading cause of mortality for many years, most traffic crashes are both predictable and preventable with indigenous modeling of crash frequency data. Of course, analysts are constantly seeking methods that offer greater consistency with the data generating mechanisms to provide better statistical fit and provide insight into data structure that was previously unavailable. While numerous research efforts have been conducted over the years to investigate and comprehend the factors influencing crash frequency on highway segments and intersections to provide effective countermeasures, much work still needed. Due to having some methodological issues, traditional models are incapable of predicting accidents and so minimizing the death tolls occurring every year. Recent crash frequency modeling methods like Random Parameter Model, Artificial Neural Network Model, Markov Switching, Random Effects Model etc. hold greater precision and better promises to improve the current scenario. This paper reviews the research efforts in these paradigms but does not hold any analytical component. Going forward, the methods suggested can be readily compared by applying on a fixed dataset. We hope that in future more research work will be done on these models for betterment and more precision to gain new insights of the factors that significantly influence crash frequency.

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