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Investigating the relationship between run-off-the-road crash frequency and traffic flow through different functional forms

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ABSTRACT

Crash prediction models play a major role in highway safety analysis. These models can be used for various purposes, such as predicting the number of road crashes or establishing relationships between these crashes and different covariates. However, the appropriate choice for the functional form of these models is generally not discussed in research literature on road safety. In case of run-off-the-road crashes, empirical evidence and logical considerations lead to conclusion that the relationship between expected frequency and traffic flow is not monotonously increasing.

1. Introduction

Crash prediction models play a major role in highway safety analysis. These models can be used for various purposes, such as predicting the number of road crashes or establishing relationships between these crashes and different covariates. However, the appropriate choice for the functional form of these models, relating crash frequency and traffic flow, is generally not present from research literature on road safety.

As suggested by Lord et al. (2005a), it may be preferable to begin to develop models that consider the fundamental crash process rather than making efforts for the most-fitted model.

In case of run-off-the-road (ROR) crashes, empirical evidence and logical considerations lead to conclusion that the relationship between expected frequency and traffic flow is not a linear one. For low traffic flows one may expect the number of ROR crashes per unit of time to be proportional to traffic flow. But, as traffic flows increase it becomes more and more difficult not to hit another car. Hence, for ROR crashes, proportionality cannot be expected to hold at high flows. In traffic congestion, ROR crashes are, in fact, impossible, except for very low skid resistance conditions, such as ice and snow covered pavements. This is a reflex of the fact that drivers behave differently in sparse, heavy or congested traffic and that ROR crash frequency depends on the actual state of the system (flow, speed and density) in time and space (Hauer, 1997).

Two main approaches have been followed to model the relationship between roadway and roadside characteristics and ROR crash risk (Pardillo-Mayora et al., 2010).

One method, usually referred to as encroachment-based, uses a set of conditional probabilities of the sequence of events that lead to a ROR crash following the encroachment of an errant vehicle on the roadside (Mak, 1995; Mak et al., 1998; Ray et al., 2012). The main obstacle in the development of this type of models is the shortage of encroachment data. Data collected in the 1960s and 70s in North America (Hutchinson and Kennedy, 1966; Cooper, 1980) are still the main source of information on these manoeuvres (Pardillo-Mayora et al., 2010). In the development of the recently updated version of the Roadside Safety Analysis Programme (RSAP) – a computer programme for performing cost benefit analyses on roadside design developed under NCHRP Project 22–27 – the Cooper data was re-analyzed to attempt to resolve some of its longstanding problems (Ray et al., 2012).

A second approach is the development of generalized linear regression models fitted to cross-sectional data, to estimate ROR crash frequencies using exposure and relevant highway and roadside variables as covariates. The frequency of crashes in a given highway segment is treated as a random variable which takes discrete integer non-negative values distributed following a Poisson distribution. A generalization of the Poisson form that allows the variance of the model to be over-dispersed results in the Negative Binomial (NB) model. Lee and Mannering (2002) and Geedipally

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and Lord (2010) used Poisson and NB regression models to develop ROR crash prediction models. In both cases, crash prediction models use the following functional form:

$$\lambda_i = \beta_0 Q_i^{\beta_1} e^{\sum_i \gamma_i x_i} \quad (1)$$

The mean number of the crashes per unit of time for segment i (λ_i) is a function of traffic flow, Q_i, and a set of risk factors, x_i. In Eq. (1) the effect of traffic flow on crashes is modelled in terms of an elasticity, which is a power, β_1, to which traffic volume is raised. The effects of various risk factors that influence the probability of crashes, given exposure, is generally modelled as an exponential function, that is as e (the base of natural logarithms) raised to a sum of the product of coefficients, γ_i, and values of the variables, x_i, denoting risk factors. In its most basic form, traffic flow is the sole explanatory variable in crash prediction models. For road segments, several crash prediction models also include segment length as covariate which in some cases is assumed as an offset, with $\gamma_i = 1$. Depending on the road network characteristics, there are cases in which this simplification is not appropriate, both from the operational and purely statistical points of view (Mountain et al., 1996). According to Reurings et al. (2005), the segment length, the access density, the carriageway width and the shoulder width are a desirable minimum list of risk factors for road segments.

Eq. (1) is the conventional functional form of crash prediction models (Reurings et al., 2005). However, as noted by Hauer (2004), the crash phenomenon does not necessarily have to follow a simple monotonous, mathematical function. If the model functional form is not appropriate, the regression coefficients obtained are inaccurate, and in several cases the estimated values are ambiguous. One way to mitigate this problem is to set the traffic flow interval (lower and upper bounds) for which the modelled equations are valid; an alternative way is to fit equations with a different functional form, with overall shapes that are in better agreement with road operation characteristics. However, *ADT* is the average of the annual distribution of traffic volumes on selected road segments. Therefore, it is just a moment statistic of a highly non-uniform distribution, where seasonal, monthly, daily, hourly periodic trends may be detected. From traffic census, it is known that the ratios between daylight and nighttimes traffic or between winter and summertime traffic are not the same for all segments on a road network. For that reason, it is still open to debate whether *ADT* is an appropriate macroscopic variable to solely represent exposure and the underlying crash mechanisms directly related to traffic volume, given the increasing availability of automatically collected data that may be used to calculate complimentary traffic distribution statistics. Nevertheless, one must acknowledge that the mentioned traffic time trends show, at least partially, a scale factor depending on the *ADT* value.

Following a comprehensive and systematic bibliographic search, few studies addressing the issue of crash prediction model functional form selection were identified. So far, little interest has been dedicated to study alternative functional forms to express the relationship between specific crash types and traffic flow. Reurings and Janssen (2007) compared models using the functional form expressed in Eq. (1) with models where Annual Average Daily Traffic (AADT) could be considered as a property of the carriageway under consideration and hence as a sort of continuous dummy-variable. They concluded that not only these last models did not have the desired structure but also that adding the variable AADT/1000 was indeed an improvement of the models for urban carriageways. Kononov et al. (2011) related traffic flow parameters, such as speed and density, to the choice of the functional form of crash prediction models. It compared models for urban freeways developed with sigmoid and exponential functional forms. Neural networks (NN) were used to explore the underlying relationship between accidents and other variables for urban freeway segments. The results were then compared with models calibrated by using these same data with generalized linear modelling and an NB error structure. The functional form generated through the training of NNs suggests that a sigmoid may be a reasonable approximation of the operational characteristics of crash occurrence on urban freeways.

The objective of this paper is to document the application of NB generalized linear models with different functional forms in the analysis of ROR crash data, exploring the underlying relationships between ROR crashes and traffic flow for interurban road segments.

The study objective was accomplished using observed and simulated datasets. The models were applied to single and dual carriageway road datasets. Subsequently, the models were applied to simulated datasets to show their general performance (Geedipally et al., 2012).

2. Methodology

This section describes the probabilistic structure of the negative binomial models, the functional form used for linking ROR crashes to covariates, the procedure employed for estimating the confidence intervals, and characteristics of the Monte Carlo simulation study.

2.1. Negative binomial models

In applying Poisson regression to crash frequency analysis, let y_{ij} be the number of ROR crashes on highway element i during period j. The Poisson model is (Washington et al., 2011):

$$p(y_{ij}) = \frac{\exp(-\lambda_{ij})\lambda_{ij}^{y_{ij}}}{y_{ij}!}, \quad (2)$$

where $P(y_{ij})$ is the probability of y crashes occurring on highway element i during time period j and λ_{ij} is the expected value of y_{ij}:

$$E(y_{ij}) = \lambda_{ij} = \exp(\beta X_{ij}), \quad (3)$$

for a roadway section i in time period j, β is the vector of parameters to be estimated and X_{ij} is a vector of explanatory variables describing roadway section geometric and environmental characteristics, as well as other relevant features such as traffic, that may affect crash frequency.

A feature of the Poisson distribution refers to the equality between the counts expected value and its variance. However, it is not always possible to assume that λ_{ij} is constant. On the one hand, the decreasing trend in time of accident risk, as observed in many countries, weakens the validity of the hypothesis of constancy in time of probability of occurrence. On the other hand, there are unknown factors that may contribute to crash occurrence as well as factors which, although known, are quantified with measurement errors, in both cases justifying that the individual risks on each entity in a homogeneous group of entities are not identical. Thus, the ratio of the variance to the expected value differs from one, i.e., overdispersion or subdispersion are observed (Roque and Cardoso, 2013).

The negative binomial model is an extension of the Poisson regression model that accommodates data overdispersion. The negative binomial model is derived by rewriting Poisson parameter for each observation i at a given time interval j as (Washington et al., 2011):

$$\lambda_{ij} = \exp(\beta X_{ij} + \varepsilon_{ij}) \quad (4)$$