Prediction of Secondary Crash Frequency on Highway Networks

Afrid A. Sarker [a,c], Rajesh Paleti [b], Sabyasachee Mishra [a,c*], Mihalis M. Golias [a,c] , Philip B Freeze [d]

[a] Department of Civil Engineering, University of Memphis, 3815 Central Avenue, Memphis, TN 38152, United States
[b] Civil & Environmental Engineering, Old Dominion University, 135 Kaufman Hall, Norfolk, VA 23529, United States
[c] Intermodal Freight Transportation Institute, University of Memphis, Memphis, TN 38152, United States
[d] Tennessee Department of Transportation, Nashville, TN 37243, United States

ABSTRACT

Secondary crash (SC) occurrences are major contributors to traffic delay and reduced safety, particularly in urban areas. National, state, and local agencies are investing substantial amount of resources to identify and mitigate secondary crashes to reduce congestion, related fatalities, injuries, and property damages. Though a relatively small portion of all crashes are secondary, determining the primary contributing factors for their occurrence is crucial. The non-recurring nature of SCs makes it imperative to predict their occurrences for effective incident management. In this context, the objective of this study is to develop prediction models to better understand causal factors inducing SCs. Given the count nature of secondary crash frequency data, the authors used count modeling methods including the standard Poisson and Negative Binomial (NB) models and their generalized variants to analyze secondary crash occurrences. Specifically, Generalized Ordered Response Probit (GORP) framework that subsumes standard count models as special cases and provides additional flexibility thus improving predictive accuracy were used in this study. The models developed account for possible effects of geometric design features, traffic composition and exposure, land use and other segment related attributes on frequency of SCs on freeways. The models were estimated using data from Shelby County, TN and results show that annual average daily traffic (AADT), traffic composition, land use, number of lanes, right side shoulder width, posted speed limits and ramp indicator are among key variables that effect SC occurrences. Also, the elasticity effects of these different factors were also computed to quantify their magnitude of impact.

Keywords: secondary crash frequency, count models, prediction model, GORP, segment characteristics, freeways

[*] Corresponding author.: Tel.: +1 901 678 5043
E-mail addresses: aasarker@memphis.edu (A.A. Sarker), rpaleti@odu.edu (R. Paleti), smishra3@memphis.edu (S. Mishra), mgkolias@memphis.edu (M.M. Golias), Phillip.B.Freeze@tn.gov (P.B. Freeze)

1. Introduction

Urban areas are experiencing increasing traffic congestion and significant portion is non-recurring in nature. Secondary crashes (SCs) contribute up to 50% of nationwide urban congestion (Chimba et al., 2014; Kwon et al., 2006; Ozbay and Kachroo, 1999; Skabardonis et al., 1998). SCs are defined as crashes that occur in close proximity of the primary incident's location as a result of either queuing or driver distraction (Margiotta et al., 2012). Earlier studies suggest that up to 15% of reported crashes have occurred partly or entirely as the result of a primary crash (PC) (Raub, 1997). Though, SCs make up a relatively small portion of all the crashes, it is essential to identify the contributing factors and their characteristics. Reducing the occurrence of SCs is a major concern for traffic incident management (TIM) agencies, especially when dispatching rescue vehicles to manage incidents (Dunn and Latoski, 2003; Owens et al., 2010). Limiting the impact of nonrecurring events, such as SCs and disabled vehicles, through effective incident management is one of the objectives of emergency response professionals (Raub and Schofer, 1997) and "reduction of SCs" is considered as one of the performance measures. Understanding the characteristics of secondary crashes can help decision-makers to select better traffic operation practices and safety programs. If SCs can be predicted in real time, it would enable TIM agencies to contain the effects of the primary incident and disseminate the information to the users accordingly to prevent the occurrence of SCs. Such prediction models can be a first step towards alleviating SC effects on congestion, delay, fuel consumption and emissions.

Past researchers have developed econometric models to predict SC occurrence based on primary crash factors, crash severity, incident type, and driver characteristics (Karlaftis et al., 1999; Khattak et al., 2009, 2011, 2010; Zhang and Khattak, 2010). Several studies have focused on identifying contributing factors of SCs identifying peak hour during weekdays, clearance time, lane blockage duration, number of vehicles involved, vehicle type (car, tractor-trailer), and vehicle location as key factors associated with higher SC likelihood (Hirunyanitiwattana and Mattingly, 2006; Karlaftis et al., 1999). Alternatively, one could also model the total frequency of secondary crash occurrences as a function of roadway and traffic characteristics. Such a model would be useful tool to directly quantify the impact of different roadway improvements and policy interventions on "reduction of SCs". Given that segment and traffic characteristics play a crucial role in inducing SCs and they are also readily identifiable, they could be used as explanatory variables in SC frequency models enabling prediction of SC occurrences in real time. In this context, the primary objective of this paper is to develop a set of count data models to predict SC occurrences on freeways as a function of segment and traffic characteristics. This allows us to examine the characteristics of SCs on freeways and significance of their relation to geometric, land use and traffic characteristics. This paper aims to achieve the study objective by developing and comparing alternate count modeling methods for analyzing *SC frequency* on freeways using *only* segment and traffic characteristics that are readily available. The spatial unit of analysis considered in this study was a unit-mile long freeway segment. The study findings will help design effective incident management strategies and thus reduce the likelihood of SC occurrence.

The rest of the paper is organized as follows. The next section discusses best practices and published research on prediction of SC occurrences. The third section, presents the proposed methodology followed by a case study in the fourth section. The final section concludes the paper by summarizing findings.

2. Literature Review

In this section we present the relevant literature on different statistical models used in the past for analyzing SC occurrence along with their primary contributing factors. We also explore the application of count data models in prediction of crash frequency.

2.1. Statistical Models for SC Occurrence

Several past studies have focused on identifying contributing factors of SCs. One of the literature found that the peak hour during weekdays along with clearance time are associated with secondary incidents occurrence. A study by Karlaftis et al. developed a logit model to identify the relation between clearance time of primary incident and SC occurrence in which season, day of week, vehicle type (car, tractor-trailer) and vehicle location were found to be the most significant factors for higher secondary incident likelihood (Karlaftis et al., 1999). Zhan et al. developed a binary logit model to estimate the likelihood of SC occurrence. It was observed that longer the freeway lane blockage duration, higher the likelihood of SCs because of increased congestion and queue length (Zhan et al., 2009). The authors also concluded that SCs are more likely to occur during weekday morning, afternoon peaks and mid-day hours. Another past study found similar results concluding that incident type, lane blockage duration, number of lanes, time of day and number of vehicles involved are some of the key factors associated with SC occurrence (Zhan et al., 2008).

Khattak et al. developed several models for SC occurrence using logistic regression (Khattak et al., 2011). All the models were probit models with certain variations. Because of the presence of endogeneity, the authors used two stage least square (2SLS) method where SC occurrence is estimated using duration as the endogenous variable. The study also found that if the primary incident is a crash involving multiple vehicles and if it is occurring during peak hours on a roadway with high AADT, this primary incident is highly likely to induce a SC. In another study the authors focused primarily on the interdependence between SC occurrence and duration of primary incident and concluded that they are interdependent (Khattak et al., 2009). It suggested that secondary incidents are more likely to occur if the primary incident lasts long and simultaneously durations of primary incidents are expected to be longer if secondary incidents take place.

Yang et al. showed that more than half of SCs occurred from PC-induced queues lasting more than two hours, identifying associated congestion and longer clearance time as primary contributing factors (Yang et al., 2014). Results also revealed that the major contributing factor was "following too closely" along with improper lane change, distracted driving and unsafe speeds.

2.2. Application of Count Data Models in Predicting Crash Frequency

Crash frequency at any given location is a non-negative integer without any pre-specified upper bound. Such data is referred to as count data and parametric models such as the Poisson and Negative Binomial (NB) models were used for analyzing such data. These traditional count models have also been used for predicting SC frequency as a function of geometric and traffic characteristics of roadway segments (Khattak et al., 2011). However, these models have their own set of merits and limitations. For instance, the simple Poisson model is only suited for handling count data with the '*equi-dispersion*' property that implies that the mean and the variance are the same. To relax this restrictive assumption, researchers have used the Negative Binomial (NB) model that accounts for '*over-dispersion*' (variance > mean) that is often the case in crash frequency data. Another important characteristic of count data is over-representation of records with zero count outcome that is referred to as the '*excess zeroes'* problem. Researchers have used the hurdle and zero-inflated variants that assume that the data is generated from two different states – a zero state and normal count process state to account for the excess zeroes property (Lord et al., 2005).

Another aspect that is important to crash frequency analysis is *'unobserved heterogeneity'*. Crashes are rare and random events that depend on a wide array of factors including humans, vehicles, roadway, and weather conditions. It is very likely that the influence of different explanatory variables on crash frequency vary across crash locations and time periods due to the moderating influence of unobserved factors that are not controlled in the statistical model. Mannering *et al.* (2016) listed several standard explanatory variables used in safety research and the associated reasons for why there might be unobserved variation in the impact of these variables. Ignoring this unobserved heterogeneity and restricting the parameter effects to be the same across all locations can lead to biased estimates and thereby incorrect policy inferences. There are several methodological approaches available in the literature to address the unobserved heterogeneity problem. Mannering *et al.* (2016) provides an overview of these different approaches along with a detailed summary of their relative merits and limitations. A brief overview of these approaches is presented in this paper (Mannering et al., 2016). The most commonly used approach to address the unobserved heterogeneity problem is the random parameters count modeling approach. In this method, the parameters in the mean specification of standard count models are assumed to be realizations from multivariate random distributions (with normal being the most common distribution) and are integrated out during the evaluation of the log-likelihood function using simulation (Anastasopoulos and Mannering, 2009; Barua et al., 2016; Bullough et al., 2013; Venkataraman et al., 2011). While the random parameters approach is relatively straightforward and easier to estimate, other approaches may be better suited to uncover heterogeneity in certain cases. For instance, the latent class modeling approach is apt in cases where the parameters do not vary across all locations but instead there are clusters of locations with the same set of parameters (Buddhavarapu et al., 2016; Park and Lord, 2009; Peng and Lord, 2011; Zou et al., 2013). These latent class models may be estimated using the maximum likelihood or the expectation maximization methods. Also, the latent class approach is semi-parametric as it does not require making strict distributional assumptions regarding the parameters. However, it is difficult to estimate models with more than 3-4 latent classes and moreover the latent class approach assumes parameter homogeneity within each class. One way to relax the homogeneity assumption within each class is to assume parametric random heterogeneity within each class akin to the random parameter count models. Another class of models used in the literature are the Markov-switching models that can handle time-varying unobserved heterogeneity that arises due to variation in unobserved factors over time that is the most likely scenario in crash frequency models that analyze aggregate crash counts over an extended period of time (Malyshkina et al., 2009; Malyshkina and Mannering, 2010). Lastly, random parameters generalized ordered response models that subsume standard count models as special cases and are suited for accommodating correlations across multivariate counts, and temporal and spatial dependency are used in the literature (Bhat et al., 2014; Castro et al., 2012; Narayanamoorthy et al., 2013). More recently, standard count models were recast as generalized extreme value (GEV) models such as the multinomial logit model (Paleti, 2016). These GEV models may be extended to mixed logit class of models to account for unobserved heterogeneity. In this study, we adopted the random parameters generalized ordered response framework for analyzing secondary crash occurrences. Next, we briefly present the methodology used to identify SCs on freeways followed by the count modeling framework used in this study.

3. Methodology

In this section we first present the methodology used for identification of SCs using dynamic approach. Then the econometric framework behind the reformulation of count models as a special case of generalized ordered-response models is presented.

3.1. Identification of SCs using Dynamic Approach

The first step in identifying SCs is defining the spatiotemporal thresholds. Two types of thresholds have been prominent in the literature: static (predefined) and dynamic (varies based on primary incident characteristics and queuing of vehicles) (Chimba and Kutela 2014). In past literatures, the dynamic approach for SC identification used the influence area of the primary incident that depends on incident duration, crash severity, incident type, number of lanes blocked etc. (Khattak et al., 2011, 2010, Sun and Chilukuri, 2007, 2010; Zhang and Khattak, 2010). The dynamic approach used in this paper is queue length based which implements the shockwave principles. This method aims to better capture effects of traffic characteristics (e.g. flow, speed, and density), that change over time and space, and affect both queue formation from a PC occurrence. With a given state and lane specific traffic flow parameters, continuously monitored by sensors or other devices near the crash location (flow, density, speed, number of lanes, location of the crash on a specific lane etc.), it is possible to calculate queue lengths using shockwave theory (Lighthill and Whitham, 1955). In the following subsection, we present the dynamic approach to estimate the impact area of a PC created by a backward-forming shockwave and backward-recovery shockwave. Backward-forming shockwave leads to formation of queue due to PC. Once the PC is cleared, a backward-recovery shockwave is set in motion and eventually catches up with the backward-forming shockwave resulting in dissipation of the queue. A crash is identified as "secondary" if it occurred within the impact area of a PC.

The dynamic approach is only applied to freeways as arterials encounter different traffic flow dynamics compared to freeway because: (1) (un)signalized intersections causes discontinuity in traffic flow, and (2) turning movements dissipate the traffic flow from one roadway to another.

3.1.1. Directionality

Directionality refers to the direction of the PC as compared to the SC (i.e. same or opposite direction). Location refers to the upstream or downstream location of the SC with respect to the direction of flow and location of PC. For the static approach, five possible combinations of directionality and location were considered (shown in Fig. 1), capturing all possible types of SCs. These five cases are defined as follows:

- Case-1: Same Direction-Upstream: SC occurs in the upstream same direction of the PC,
- Case-2: Opposite Direction-Upstream: SC occurs in the upstream opposite direction of the PC,
- Case-3: Opposite Direction-Downstream: SC occurs in the downstream opposite direction of the PC,
- Case-4: (Combination of cases 1 and 2): SC occurs either in the downstream or upstream opposite direction of the PC,
- Case-5: Cases 1, 2, and 3 combined.

In this paper, the identified case-5 SCs are used when developing the crash prediction models to include both directionalities.

3.1.2. Estimation of shockwaves

A generalized density-flow curve is shown in Fig. 2(a) where $(k_{ini})_s$ and $(q_{ini})_s$ are the initial conditions of density and flow where the initial speed, $(u_{ini})_s$ is the slope of the curve. After the PC when one or more lanes are completely closed (often the case), that intermediate traffic state is represented by $(k_{int})_s$, $(u_{int})_s$ and $(q_{int})_s$ (until the clearance period). For freeways, lane specific traffic flow data are available which are used to capture the traffic flow conditions (flow, speed, density) before and after the crash. The methodology for dynamic approach makes sure that any flow/density state, represented by the parabola, can be used. Speed of backward-forming shockwave, is equal to:

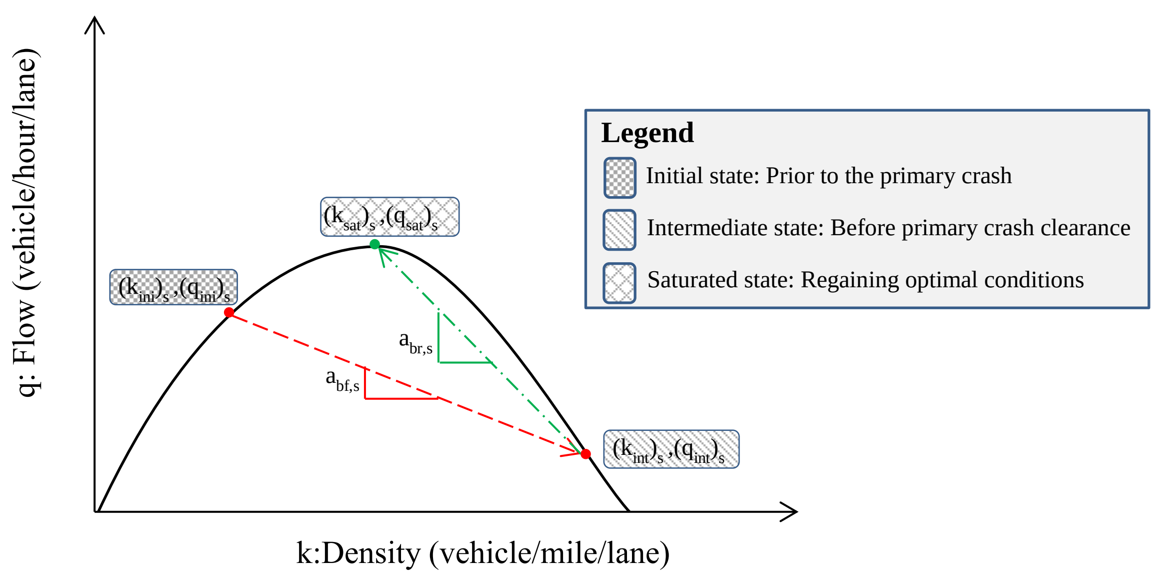
$$a_{bf,s} = \frac{(q_{ini})_s - (q_{int})_s}{(k_{ini})_s - (k_{int})_s}$$

After the PC is cleared, flow conditions will eventually reach saturated condition represented by $(q_{sat})_s$, $(u_{sat})_s$ and $(k_{sat})_s$. meaning a backward-recovery shockwave will set off with a speed of:

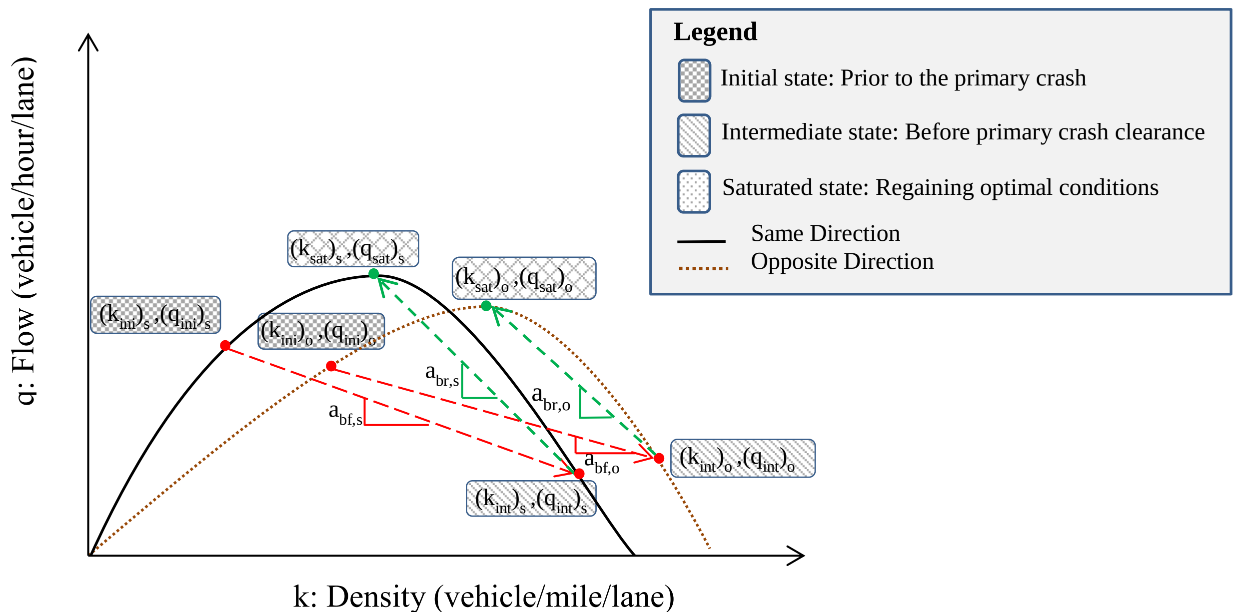
$$a_{br,s} = \frac{(q_{int})_s - (q_{sat})_s}{(k_{int})_s - (k_{sat})_s}$$

A similar approach can be adopted to analyze shockwaves in the opposite direction as shown in Fig. 2(b) which demonstrates traffic states for bi-directional traffic. HCM 2010 also refers to the rubbernecking factor that leads to the reduction of capacity in the opposite direction of the incident. The reduction in capacity ranges from 5% for a single-vehicle crash to 25% for a multivehicle crash. Using the reduction in capacity based on features of PC the flow conditions in the opposite direction to PC, represented by $(k_{int})_s$, $(u_{int})_s$ and $(q_{int})_s$ are calculated.

Fig. 1 Pictorial representation of directionality and locations of SCs.



(a) Determining shockwave speed in same direction using traffic flow characteristics.



(b) Determining shockwave speed in opposite direction using traffic flow characteristics.

Fig. 2. Shockwave speed for single and bi-directional traffic.

3.1.3. Impact Area Estimation

Determining the impact area of a PC requires the clearance time (T_c) and the time difference between occurrence of PC and the "potential" SC ($t = t_2 - t_1$). The impact area (d) is defined as:

$$a_{br,s} \times (t-T_c) \leq d \leq a_{bf,s} \times t, \text{ when } t > T_c$$

$$0 \leq d \leq a_{bf,s} \times t, \text{ when } t < T_c$$

In this paper, when estimating the impact area, clearance time used for the primary incident was obtained from the incident management database. Clearance time varies and depends on crash type and severity, number of vehicles involved, number of lanes, availability of shoulder area etc. Fig. 3 shows the impact area (shaded area between the backward-forming and backward-recovery shockwaves) which captures the portion of the queue, from the primary incident, which can induce a SC. Note that: a) the backward-recovery shockwave does not set off until the primary incident is cleared (i.e. size of the impact area depends on the PC clearance time) and, b) higher speed of backward-recovery shockwave results in faster queue dissipation.

Once the SCs are identified, they were attached to the freeway segments based on their location and directionality in ArcGIS environment. Since the objective of this paper is to predict SC frequency, during model development each link would be considered as an observation, its characteristics as explanatory variables and SC frequency in that link as response variable. Initially the segments in the network had varying length. In order to normalize the effect of segment length on SC frequency, we decided to create uniform segments with homogeneous characteristics meaning the segments begin and end when any of the characteristics change. A total of 570 freeway segments (both direction) were created ranging from 0.88 to 1.21 miles in length (with an average segment length of 1.068 miles). Once the database is prepared, next step is model development. In the following subsection, we present the methodology used in formulation of models.

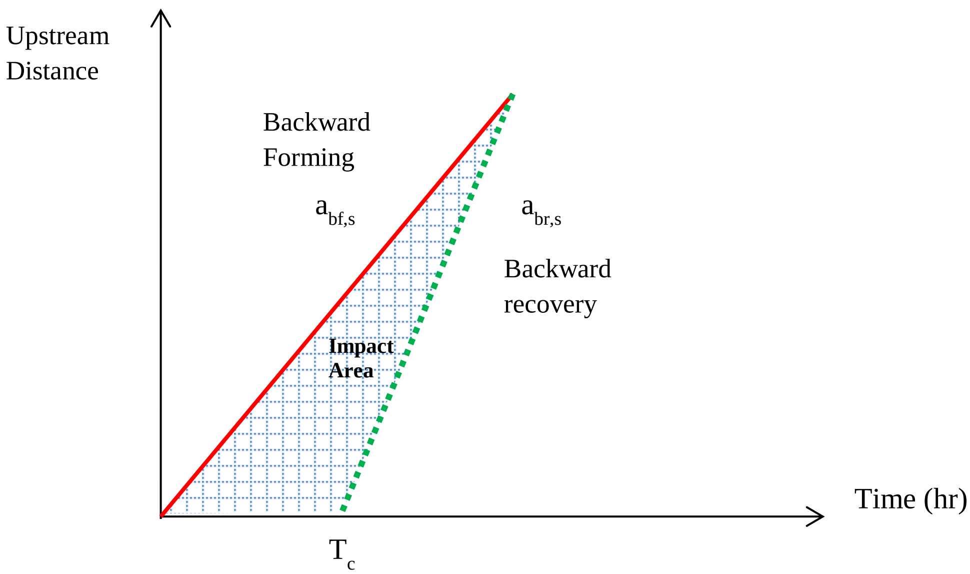


Fig. 3. Graphical representation of impact area.

3.2. Generalized Ordered Response Probit (GORP) Framework

Let *s* be the index for the roadway segment. In the GORP framework, a latent risk propensity y_s^* associated with segment *s* is mapped into observed count outcomes y_s by threshold parameters ψ_s^k where *k* is the index for all possible count outcomes. Assuming specific functional forms for these threshold parameters will result in the GORP framework replicating standard count models. The latent risk propensity y_s^* in the standard ordered response framework can be written as:

$$y_s^* = \boldsymbol{\gamma}'\boldsymbol{Z}_s + \varepsilon_s \qquad \text{Equation (1)}$$

Where $\boldsymbol{Z}_s$ is a vector of all exogenous variables and $\boldsymbol{\gamma}$ is the corresponding vector of coefficients; ε_s is the stochastic error term that represents all unobserved factors (not captured in the exogenous variables) that can impact y_s^* and is assumed to be an independent realization from a standard normal distribution, *i.e.*, $\varepsilon_s \sim N(0,1)$. In the GORP framework, the probability that the observed outcome is y_s is given by:

$$P(Y = y_s) = P\left(\psi_s^{y_s-1} < y_s^* < \psi_s^{y_s}\right) = P\left(\psi_s^{y_s-1} < \boldsymbol{\gamma}'\boldsymbol{Z}_s + \varepsilon < \psi_s^{y_s}\right) \qquad \text{Equation (1a)}$$

$$= P\left(\psi_s^{y_s-1} - \boldsymbol{\gamma}'\boldsymbol{Z}_s < \varepsilon < \psi_s^{y_s} - \boldsymbol{\gamma}'\boldsymbol{Z}_s\right)$$
$$= \Phi\left(\psi_s^{y_s-1} - \boldsymbol{\gamma}'\boldsymbol{Z}_s\right) - \Phi\left(\psi_s^{y_s} - \boldsymbol{\gamma}'\boldsymbol{Z}_s\right) \qquad \text{Equation (1b)}$$

Where $\Phi(.)$ is the cumulative distribution function of standard normal random variable

Standard count models including the Poisson and NB models can be obtained by imposing certain constraints on the GORP model, *i.e.*, the implied probability expressions for different count outcomes would be identical for the GORP and standard count models. To see this, consider the constraints and functional forms imposed on ψ_s^k parameters below:

3.2.1. Generalized Poisson Model

$$\psi_s^k = \Phi^{-1}\left(\sum_{p=0}^{k} \frac{e^{-\lambda_s} \times {\lambda_s}^p}{p!}\right) + \alpha_k \; \forall \, k \geq 0 \qquad \text{Equation (2)}$$

If (1) ψ_s^k is parameterized as shown in Equation (2), (2) all γ parameters in the propensity equation are equal to 0, and (3) all α_k parameters are equal to 0, then the GORP model collapses to the standard Poisson model.

3.2.2. Generalized Negative Binomial Model

$$\psi_s^k = \Phi^{-1}\left(\sum_{p=0}^{k}\left(\frac{r}{r+\lambda_s}\right)^r \times \frac{\Gamma(r+p)}{\Gamma(p+1)\Gamma(r)} \times \left(\frac{\lambda_s}{r+\lambda_s}\right)^p\right) + \alpha_k \ \forall \ k \geq 0 \qquad \text{Equation (3)}$$

If (1) ψ_s^k is parameterized as shown in Equation (3), (2) all γ parameters in the propensity equation are equal to 0, and (3) all α_k parameters are equal to 0, then the GORP model collapses to the standard NB model.

Although theoretically one could estimate one α_k parameter specific to each count outcome *k*, from a practical standpoint, α_k can be fixed as α_K where *K* is a pre-determined count outcome depending on the empirical context, *i.e.*, $\alpha_k = \alpha_K \ \forall \ k \geq K$. Also, the α_k parameters control for any additional probability mass that is not captured by the parameters in the λ_s and y_s^* specifications. So, the GORP versions of Poisson and NB models can easily handle over or under-representation of multiple count outcomes without necessitating a hurdle or inflated model set-up.

In the GORP versions of Poisson and NB models, the analyst must also estimate the γ parameters in propensity y_s^* and the α_k parameters in thresholds ψ_k in addition to the ψ_s^k parameters in $LOG(\lambda_s)$ specification and dispersion parameter *r* (in case of NB models).

3.2.3. Generalized Negative Binomial Model with Heterogeneous Dispersion

Standard negative binomial (NB) model assumes that the dispersion parameter is the same for all segments. However, this is a restrictive assumption because crashes along different groups of segments can have varying degrees of variance in crash occurrences. Recently, Barad *et al.* (2016) and Narayan *et al.* (2016) developed NB models with heterogeneous dispersion for modeling crash frequency. This model essentially parameterizes the over-dispersion parameter in the NB model component as follows: $r_s = e^{\delta' \boldsymbol{W}_s}$, where $\boldsymbol{W}_s$ is the vector of segment characteristics.

3.2.4. Generalized Negative Binomial Model with Heterogeneous Dispersion and Unobserved Heterogeneity

There may be several unobserved factors that influence secondary crash occurrences along a segment. These unobserved factors can moderate the influence of different exogenous variables considered in our study. As discussed earlier, this can lead to unobserved heterogeneity in the parameter estimates both in the expected mean λ_s specification as well as latent propensity. Ignoring the presence of this random heterogeneity can lead to biased parameter estimates. The fixed parameters GORP framework can be extended to capture unobserved heterogeneity by allowing random variation in the parameters in λ_s and y_s^* as follows:

$LOG(\lambda_s) = \boldsymbol{\beta}_s{}'\boldsymbol{X}_s$ where $\boldsymbol{X}_s$ is the vector of exogenous variables and $\boldsymbol{\beta}_s$ is the corresponding vector of coefficients for segment *s*. $\boldsymbol{\beta}_s$ is assumed to be a random realization from a multivariate normal distribution with mean $\boldsymbol{\beta}$ and variance $\boldsymbol{\Omega}$.

$y_s^* = \boldsymbol{\gamma}_s{}'\boldsymbol{Z}_s + \varepsilon_s$ where $\boldsymbol{X}_s$ is the vector of exogenous variables and $\boldsymbol{\gamma}_s$ is the corresponding vector of coefficients for segment *s*. $\boldsymbol{\gamma}_s$ is assumed to be a random realization from a multivariate normal distribution with mean $\boldsymbol{\gamma}$ and variance $\boldsymbol{\Sigma}$.

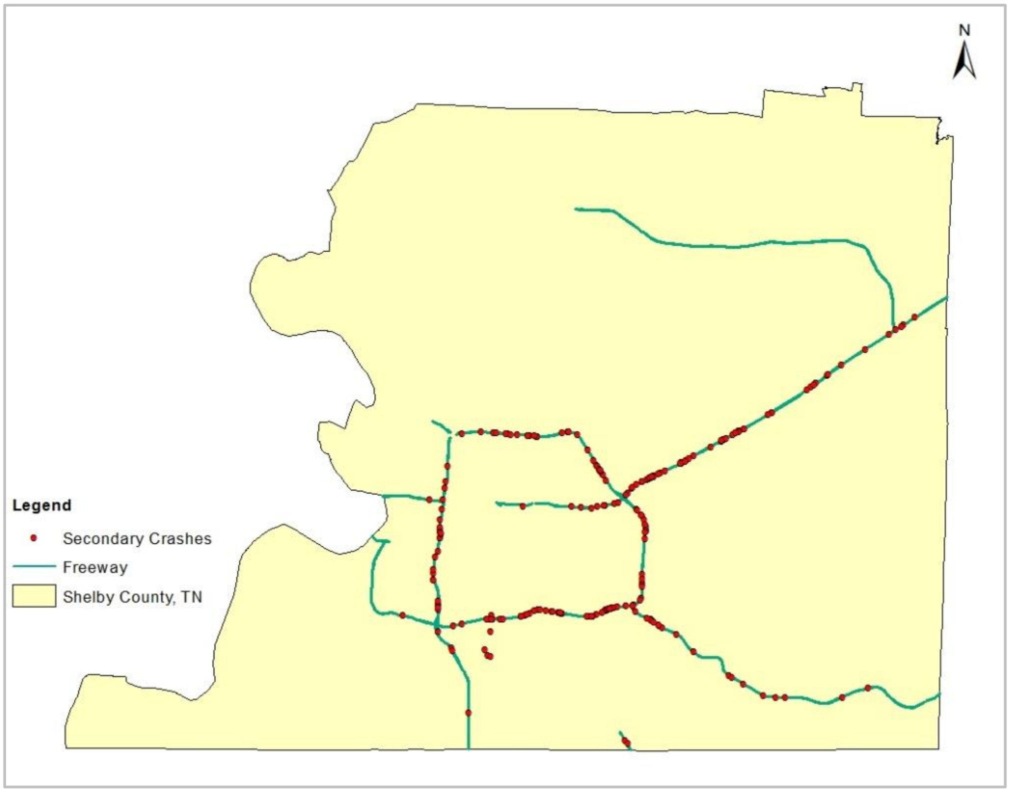
The analyst must also estimate the elements of the $\boldsymbol{\Omega}$ and $\boldsymbol{\Sigma}$ parameters in addition to the parameters in the fixed parameters GORP models. The resulting was estimated using the maximum simulated likelihood (MSL) inference approach using 200 Halton draws (Bhat, 2003, 2001).

4. Case Study

The transportation network of Shelby County, Tennessee (TN), in the United States (U.S.) is considered as the case study area to apply and evaluate the proposed model. Shelby County is the most populous county in the state of TN, home to one the largest freight intermodal hubs in the US, and the largest metropolitan planning organization in the tri-state encompassing portions of Tennessee, Arkansas and Mississippi, with a significant portion of inter-state traffic. The following describes the various data collected for the case study:

- Crash data: Three years (2010-2012) of crash data, from the Tennessee Roadway Information Management System (TRIMS); a total of 91,325 crashes. It also provides roadway and traffic characteristics.
- Freeway Traffic Data: Lane specific traffic data by minute (speed, flow, occupancy etc.) aggregated into 15 minute intervals.
- Incident Management data: Data on all reported incidents (e.g. time of crash occurrence, time taken for the rescue vehicle to reach incident location, clearance time, etc.) were available from the incident management system in TN.
- Roadway Network: A detailed transportation network of Shelby County containing 282 miles of freeways was available from TDOT.

In this paper, “incidents” and “crashes” are used interchangeably because for analysis purpose, only crashes are considered to be primary and secondary incidents. For identification of SCs, crash data collected from TRIMS are used along with freeway traffic data and incident management data. The segment characteristics, obtained from TRIMS, are used to examine the effects of geometric design features, traffic characteristics and other relevant attributes on the SC frequency. A total of 570 freeway segments (both direction) with an average segment length of 1.068 miles are analyzed in this research. These segments have homogenous characteristics because the segments begin and end when characteristics change. Using, these dataset, 114 SCs were identified for three years 2010-12. These SCs were then attached to the freeway segments based on their location and directionality as shown in Fig. 4. The frequency distribution of crashes is presented in Table 1 which shows the prevalence of segments not encountering any SCs (87.37%). This phenomenon is common particularly when modeling crash frequency as many locations will not encounter occurrence of any crashes. The proposed models in this paper allow presence of excess zeros in the count data and are able to successfully capture the crash causality (explained in the “Results” section).



a. GIS map showing the locations of Crashes.

b. Zoomed-in on a freeway segment showing SCs and some characteristics.

Fig. 4. Location of SC on Network.

TABLE 1

Frequency distribution of SCs

No. of Secondary Crashes	Count	(%)
0	498	87.37%
1	49	8.60%
2	9	1.58%
3	9	1.58%
4 or more	5	0.88%
Total	570	100.00%

Tables 2a and 2b present the sample characteristics of the 570 segments, including the: (a) posted speed limit (b) number of lanes in the segment (c) land use – whether that segment is in a urban or sub-urban area (d) median type - indicating segments with raised median barrier, (e) ramp indicator- indicating segments that contains at least one ramps, f) HOV indicator – specifying segments that contains high occupancy vehicle (HOV) lane, g) AADT and composition of traffic, and (h) Share of AM and PM peak hour traffic as percentage of daily traffic. Table 2a indicates that, for a majority of segments (about 54% of intersections), the posted speed limit is at most 55 mph. In terms of roadway characteristics, more than 44% of segments have three lanes, approximately 91% have raised median and about 41% contains ramps. Also, about 55% of the freeway is in the urban setting. It should be noted that none of the segments are in the rural setting.

TABLE 2a

Frequency distribution of Explanatory Variables (Categorical)

Explanatory Variable	(%)
Speed Limit	
Less than or equal to 55 mph	54.4%
Greater than 55 mph	45.6%
Number of Lanes	
2 Lanes	28.1%
3 Lanes	44.7%
4 Lanes	27.2%
Land Use	
Sub-Urban	44.9%
Urban	55.1%
Median Type	
Raised median	91.4%
No raised median	8.6%
Ramp	
Segment contains Ramp	40.6%
No ramp	59.4%
HOV Indicator	
Segment has HOV lane	22.5%
No HOV Lane	77.5%

TABLE 2b
Frequency distribution of Explanatory Variables (Continuous/Ordinal)

Variables	Min	Max	Mean	Std. Dev
Segment Length	0.882	1.214	1.068	0.070
Speed Limit	35.000	70.000	59.360	8.154
AADT	2645	86781	37640.678	18162.401
Truck traffic %	3.088	35.737	15.526	7.906
Single-unit truck %	2.958	8.097	5.504	0.827
Multi-unit truck %	1.042	30.216	10.021	7.618
Right Shoulder width	0.000	14.000	6.070	4.144
PM Peak share (% of AADT)	14.13	22.46	16.32	1.624
AM Peak share (% of AADT)	12.78	21.54	15.76	1.859

5. Results

The results section presents the statistically significant explanatory variables along with their estimated coefficients and t-statistics (in parenthesis) for each of the developed models as shown in Table 3. There are three components in the GORP framework: Expected Count, Propensity, and Dispersion. The expected count component enters the threshold specification of the GORP model and controls ‘‘instantaneous’’ translation of the SC ‘propensity’ to whether or not a SC will occur at any given time (that is, they determine the mapping of the latent propensity to the observed count outcome). Surprisingly, in spite of extensive testing, we did not find any evidence in support of significant unobserved heterogeneity either in the expected count or propensity components. Even attempts to estimate latent class or finite mixture negative binomial model with two latent classes did not yield results in support of parameter heterogeneity. However, it is important to note that these results are specific to the dataset used in this study and may not be extended to other studies. The log-likelihood ratio (LR) test statistic of comparison between the standard NB model (LL = -254.32) and the final GORP model (-251.27) was 6.10 that was greater than the critical chi-squared value of 5.99 corresponding to two degrees of freedom. This suggests the statistically superior data fit in the GORP model. For the sake of brevity, the results of only the final GORP model, *i.e.* the generalized negative binomial model with heterogeneous dispersion, are presented in this paper.

5.1. Model Estimation Results

5.1.1. Expected Count

Variables with significant effect on expected SC frequency include *AADT*, *type of median*, *right shoulder width, and speed limit*. As expected, higher exposure values were associated with higher SC occurrences. Roads with a raised median have more SCs than roads without a raised median. Along similar lines, roads with broad right shoulders (width>14 ft) have fewer SCs compared to roads with narrow right shoulders. This is because sufficient right shoulder allows the TIM agencies to manage the incident more effectively without compromising the capacity of the roadway significantly. Lastly, segments with higher posted speed limit (>55 mph) incur more SCs compared with lower speed limit roads. This is probably because road users have less time to react to the flow changes leading to higher likelihood of SC occurrence. These findings are similar to previous studies in the literature (Hirunyanitiwattana and Mattingly, 2006; Karlaftis et al., 1999).

5.1.2. Dispersion

The dispersion parameter was significant and improved the LL considerably (relative to the Poisson model) demonstrating over-dispersion in the SC frequency data. However, all roadway segments do not have the same dispersion or variance about the expected SC frequency. Specifically, roads in urban regions were found to have lower variation in SC crash frequency than roads in rural areas. Please note that the dispersion parameter r_s is inversely proportional to variance. So, a positive coefficient for a variable in $LOG(r_s)$ indicates lower variation and *vice-versa*. This result emphasizes the need for relaxing the homogeneous dispersion assumption of standard NB model while dealing with crash frequency data.

Table 3
Model Results

Variables	***Generalized NB Model with Heterogeneous Dispersion***
	Coefficient (t-stat)
Expected Count $LOG(\lambda_s)$	
Constant	-39.104 (-6.68)
LOG(AADT)	3.312 (6.18)
Presence of Raised Median	1.598 (3.87)
Right Shoulder Width <14 ft	1.477 (3.03)
Speed Limit > 55 mph	2.733 (5.63)
Dispersion $LOG(r_s)$	
Constant	-1.255 (-3.98)
Urban-Land Use	1.076 (1.69)
Propensity	
Two Lanes	0.432 (1.94)
Number of Observations	570
Number of Parameters Estimated	8
Log-composite likelihood at convergence	-251.27

5.1.3. Propensity

A positive coefficient indicates increased risk propensity and higher likelihood of translation into a SC. Each variable in the dataset was tested in both the expected count and propensity components. LL values was used to guide our decisions regarding the component where each variable belongs. Interestingly, we found that number of lanes provided better data fit in the propensity component than the expected count component. To be specific, roads with two lanes were found to have higher risk SC risk propensity and thus more SCs compared to roads with more than two lanes. As discussed in the methodology section, the GORP models also have additional $\boldsymbol{\alpha_k}$ parameters that account for residual probability masses associated with different count outcomes. However, none of these threshold parameters turned out to be significant in all the GORP models.

5.4. Elasticity Effects

In order to determine the magnitude of effects of the independent variables on SC frequency, it is necessary to compute their corresponding elasticity effects. Elasticity effect represents percentage change in the expected number of SCs due to a unit percentage change in an explanatory variable. Since standard elasticity calculations are not applicable to indicator variables, pseudo-elasticity is computed as average percentage change across all freeway segments in the expected number of SCs when the value of that particular variable changes from 0 to 1. From Table 4 it can be noticed that elasticity effects are consistent with the coefficient estimates. The results show that 10% increase in AADT is likely to increase the number of SC occurrences by 34.24%. Roads with a raised median have 267% more SCs compared to roads without a raised median. On average, roads with right shoulder width less than 14 ft have 257% more SC crashes than roads with higher shoulder width. Segments with speed limit greater than 55 mph, on average, incur

613.5% more SCs compared to segments with lower speed limits. Finally, two lane roads have 73% more SCs than roads with 3 or more lanes. Some of the elasticity numbers are large because the expected number of crashes in most of the segments is close to zero. The elasticity effect corresponding to urban land use is close to zero which is expected because this variable only enters the dispersion component but not the expected count component.

Table 4
Elasticity Effects

Variables	**Mean**
LOG(AADT)	34.242
Presence of Raised Median	266.967
Right Shoulder Width < 14 ft	257.605
Speed Limit > 55 mph	613.451
Urban Land Use	0.520
Two Lanes	73.082

5. Conclusion

Identifying the factors that lead to SCs is the first step towards preventing the occurrence of SCs. Past researchers have developed econometric models to predict the occurrence of SC using detailed variables describing the primary crash including crash severity, incident type, driver and vehicle characteristics, clearance time *etc.* While these disaggregate studies were useful in providing several useful insights into the occurrence of SCs, these are data-intensive models that are difficult to use in practice to quantify the impact of safety interventions on SCs. In this context, the objective of this paper is to develop SC frequency models that will enable us to predict the frequency of SC occurrences using segment and traffic characteristics. To this end, Generalized Ordered Response Probit (GORP) models that subsume standard count models as special cases were developed to analyze factors contributing to SC occurrences. This allows us to study the effect of geometric, land use and traffic characteristics of freeway segments on SC occurrences. The final model could successfully uncover as well as quantify (using elasticity effects) key relationships between segment and traffic characteristics and SC frequency.

References

Anastasopoulos, P.C., Mannering, F.L., 2009. A note on modeling vehicle accident frequencies with random-parameters count models. Accident Analysis & Prevention 41, 153–159. doi:10.1016/j.aap.2008.10.005

Barua, S., El-Basyouny, K., Islam, M.T., 2016. Multivariate random parameters collision count data models with spatial heterogeneity. Analytic Methods in Accident Research 9, 1–15. doi:10.1016/j.amar.2015.11.002

Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research Part B: Methodological 37, 837–855. doi:10.1016/S0191-2615(02)00090-5

Bhat, C.R., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. Transportation Research Part B: Methodological 35, 677–693. doi:10.1016/S0191-2615(00)00014-X

Bhat, C.R., Paleti, R., Singh, P., 2014. A Spatial Multivariate Count Model for Firm Location Decisions. Journal of Regional Science 54, 462–502. doi:10.1111/jors.12101

Buddhavarapu, P., Scott, J.G., Prozzi, J.A., 2016. Modeling unobserved heterogeneity using finite mixture random parameters for spatially correlated discrete count data. Transportation Research Part B: Methodological 91, 492–510. doi:10.1016/j.trb.2016.06.005

Bullough, J.D., Donnell, E.T., Rea, M.S., 2013. To illuminate or not to illuminate: Roadway lighting as it affects traffic safety at intersections. Accident Analysis & Prevention 53, 65–77. doi:10.1016/j.aap.2012.12.029

Castro, M., Paleti, R., Bhat, C.R., 2012. A latent variable representation of count data models to accommodate spatial and temporal dependence: Application to predicting crash frequency at intersections. Transportation Research Part B: Methodological 46, 253–272. doi:10.1016/j.trb.2011.09.007

Chimba, D., Kutela, B., Ogletree, G., Horne, F., Tugwell, M., 2014. Impact of Abandoned and Disabled Vehicles on Freeway Incident Duration. Journal of Transportation Engineering 140, 4013013. doi:10.1061/(ASCE)TE.1943-5436.0000635

Dunn, W.M., Latoski, S.P., 2003. Safe and quick clearance of traffic incidents. NCHRP Synthesis of Highway Practice.

Hirunyanitiwattana, W., Mattingly, S.P., 2006. Identifying Secondary Crash Characteristics for California Highway System. Presented at the Transportation Research Board 85th Annual Meeting.

Karlaftis, M.G., Latoski, S.P., Richards, N.J., Sinha, K.C., 1999. ITS impacts on safety and traffic management: an investigation of secondary crash causes. Journal of Intelligent Transportation Systems 5, 39–52.

Khattak, A., Wang, X., Zhang, H., 2009. Are incident durations and secondary incidents interdependent? Transportation Research Record: Journal of the Transportation Research Board 2099, 39–49.

Khattak, A.J., Wang, X., Zhang, H., 2010. Spatial Analysis and Modeling of Traffic Incidents for Proactive Incident Management and Strategic Planning. Transportation Research Record: Journal of the Transportation Research Board 2178, 128–137. doi:10.3141/2178-14

Khattak, A.J., Wang, X., Zhang, H., Cetin, M., 2011. Primary and Secondary Incident Management: Predicting Durations in Real Time (No. VCTIR 11-R11, Project No. 87648). Old Dominion University and Virginia Center for Transportation Innovation and Research.

Kwon, J., Mauch, M., Varaiya, P., 2006. Components of congestion: delay from incidents, special events, lane closures, weather, potential ramp metering gain, and excess demand. Transportation Research Record: Journal of the Transportation Research Board 1959, 84–91.

Lighthill, M.J., Whitham, G.B., 1955. On kinematic waves. II. A theory of traffic flow on long crowded roads. Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences 229, 317–345.

Lord, D., Washington, S.P., Ivan, J.N., 2005. Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory. Accident Analysis & Prevention 37, 35–46. doi:10.1016/j.aap.2004.02.004

Malyshkina, N.V., Mannering, F.L., 2010. Zero-state Markov switching count-data models: An empirical assessment. Accident Analysis & Prevention 42, 122–130. doi:10.1016/j.aap.2009.07.012

Malyshkina, N.V., Mannering, F.L., Tarko, A.P., 2009. Markov switching negative binomial models: An application to vehicle accident frequencies. Accident Analysis & Prevention 41, 217–226. doi:10.1016/j.aap.2008.11.001

Mannering, F.L., Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Analytic Methods in Accident Research 11, 1–16. doi:10.1016/j.amar.2016.04.001

Margiotta, R., Dowling, R., Paracha, J., 2012. Analysis, Modeling, and Simulation for Traffic Incident Management Applications (No. FHWA-HOP-12-045).

Narayanamoorthy, S., Paleti, R., Bhat, C.R., 2013. On accommodating spatial dependence in bicycle and pedestrian injury counts by severity level. Transportation Research Part B: Methodological 55, 245–264. doi:10.1016/j.trb.2013.07.004

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., Trego, T., 2010. Traffic incident management handbook.

Ozbay, K., Kachroo, P., 1999. Incident management in intelligent transportation systems.

Paleti, R., 2016. Generalized Extreme Value models for count data: Application to worker telecommuting frequency choices. Transportation Research Part B: Methodological 83, 104–120. doi:10.1016/j.trb.2015.11.008

Park, B.-J., Lord, D., 2009. Application of finite mixture models for vehicle crash data analysis. Accident Analysis & Prevention 41, 683–691. doi:10.1016/j.aap.2009.03.007

Peng, Y., Lord, D., 2011. Application of Latent Class Growth Model to Longitudinal Analysis of Traffic Crashes. Transportation Research Record: Journal of the Transportation Research Board 2236, 102–109. doi:10.3141/2236-12

Raub, R.A., 1997. Occurrence of secondary crashes on urban arterial roadways. Transportation Research Record: Journal of the Transportation Research Board 1581, 53–58.

Raub, R., Schofer, J., 1997. Managing Incidents on Urban Arterial Roadways. Transportation Research Record 1603, 12–19. doi:10.3141/1603-02

Skabardonis, A., Petty, K., Varaiya, P., Bertini, R., 1998. Evaluation of the freeway service patrol (FSP) in Los Angeles. California Partners for Advanced Transit and Highways (PATH).

Sun, C., Chilukuri, V., 2007. Secondary accident data fusion for assessing long-term performance of transportation systems. Midwest Trasportation Consortium, c/o Iowa State University.

Sun, C.C., Chilukuri, V., 2010. Dynamic incident progression curve for classifying secondary traffic crashes. Journal of Transportation Engineering 136, 1153–1158.

Venkataraman, N., Ulfarsson, G., Shankar, V., Oh, J., Park, M., 2011. Model of Relationship Between Interstate Crash Occurrence and Geometrics. Transportation Research Record: Journal of the Transportation Research Board 2236, 41–48. doi:10.3141/2236-05

Yang, H., Bartin, B., Ozbay, K., 2014. Mining the Characteristics of Secondary Crashes on Highways. Journal of Transportation Engineering 140, 4013024. doi:10.1061/(ASCE)TE.1943-5436.0000646

Zhan, C., Gan, A., Hadi, M., 2009. Identifying Secondary Crashes and Their Contributing Factors. Transportation Research Record: Journal of the Transportation Research Board 2102, 68–75. doi:10.3141/2102-09

Zhan, C., Shen, L., Hadi, M.A., Gan, A., 2008. Understanding the Characteristics of Secondary Crashes on Freeways. Presented at the Transportation Research Board 87th Annual Meeting.

Zhang, H., Khattak, A.J., 2010. Analysis of cascading incident event durations on urban freeways. Transportation Research Record: Journal of the Transportation Research Board 2178, 30–39.

Zou, Y., Zhang, Y., Lord, D., 2013. Application of finite mixture of negative binomial regression models with varying weight parameters for vehicle crash data analysis. Accident Analysis & Prevention 50, 1042–1051. doi:10.1016/j.aap.2012.08.004