Modeling of Incident Type and Incident Duration Using Data from Multiple Years

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6th June 2020

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ABSTRACT
The paper presents a model system that recognizes the distinct traffic incident duration profiles based on incident types. Specifically, a copula-based joint framework has been estimated with a scaled multinomial logit model system for incident type and a grouped generalized ordered logit model system for incident duration to accommodate for the impact of observed and unobserved effects on incident type and incident duration. The model system is estimated using traffic incident data from 2012 through 2017 for the Greater Orlando region, employing a comprehensive set of exogenous variables, including incident characteristics, roadway characteristics, traffic condition, weather condition, built environment and socio-demographic characteristics. In the presence of multiple years of data, the copula-based methodology is also customized to accommodate for observed and unobserved temporal effects (including heteroscedasticity) on incident duration. Based on a rigorous comparison across different copula models, parameterized Frank-Clayton-Frank specification is found to offer the best data fit for crash, debris, and other types of incident. The value of the proposed model system is illustrated by comparing predictive performance of the proposed model relative to the traditional single duration model on a holdout sample.

Keywords: *Incident type; Incident duration; Scaled multi-nominal logit; Grouped generalized ordered logit; Joint framework*

1 INTRODUCTION

1.1 Background

The prevalence of sub-urban life in North American cities in the latter half of the 20th century and early 21st century has resulted in an over-reliance on the private vehicle mode. The high private vehicle dependency burdens existing roadway infrastructure resulting in high congestion levels in metropolitan areas. Specifically, the economic costs of traffic congestion – direct costs (time and fuel wastage) and indirect costs (increase in transportation costs) – amount to nearly 305 billion dollars in 2017 (INRIX, 2018). The annual economic costs add up to nearly $3000 per resident in large urban regions such as Los Angeles and New York City. Traffic congestion can generally be attributed to either recurring or non-recurring events. Congestion arising from recurring events is generally a result of mismatched transportation demand and supply (or capacity). Non-recurring congestion, on the other hand, is a result of unexpected (or irregular) events such as abandoned vehicles, adverse weather, spilled loads, highway debris, and traffic crashes. It is estimated that delays arising from non-recurring congestion contribute between 40 to 60% of total congestion delays on the US highways (Tavassoli Hojati *et al.*, 2013). Among non-recurring events, the US Department of Transportation (DOT) reports that traffic incidents alone contribute to 25% of the total delays leading to an annual loss of about 2.8 billion gallons of gasoline (FHWA EDC, 2012). The proposed research contributes to reducing traffic congestion on roadways by understanding the factors influencing incident duration and providing remedial solutions to improve clearance times.

The overall incident duration, as identified by the Highway Capacity Manual (*HCM 2010*), is composed of the following four phases: Notification time, Response time, Clearance time and Traffic recovery time. The first three phases are directly affected by the traffic incident and the incident management response infrastructure in the urban region. On the other hand, the traffic recovery time (fourth phase) is a function of total duration of the first three phases and the traffic demand on the facility. Any improvements in reducing the duration of the first three phases of the incident will contribute to lower traffic recovery time. The objective of the proposed research effort is to study the factors influencing incident duration (estimated as the sum of the first three phases) with a goal of understanding what factors influence incident duration and providing recommendations for improved traffic incident management plans. Specifically, accurate estimation of incident duration can allow traffic operations staff to tailor their diversion messages at the occurrence of an incident.

1.2 Existing Literature

Given the significant influence of traffic incidents on roadways, several research efforts have examined the factors influencing incident duration focusing either on total duration or the individual components of duration (see Laman *et al.*, 2018 for a detailed review). The most commonly employed outcome variable includes total incident duration and duration of individual incident components (such as notification, response and clearance time).

The methodologies can be broadly classified into two groups: parametric methods and non-parametric methods. Among parametric methods, the commonly used methodologies include (a) Linear regression analysis (Garib *et al.*, 2002), (b) Truncated regression based time sequential method (Khattak *et al.*, 2007), (c) Parametric hazard-based model (Chung, 2010; Junhua *et al.*, 2013; Tavassoli Hojati *et al.*, 2013, 2014; Ghosh *et al.*, 2014; Chung *et al.*, 2015; Li *et al.*, 2015) (d) Copula based grouped ordered response model (Laman *et al.*, 2018), (e) Binary probit and regression model based joint framework (Ding *et al.*, 2015). In terms of non-parametric methods, approaches employed include (a) Tree based model (Valenti *et al.*, 2010; Zhan *et al.*, 2011), (b) Bayesian networks (Ozbay and Noyan, 2006), (c) Support vector machine (Valenti *et al.*, 2010; Wu *et al.*, 2011), (d) Artificial neural network (Lee and Wei, 2010), (e) Partial least square regression (Wang *et al.*, 2013). Based on these models developed, the most important independent variables identified in literature include: incident characteristics (such as incident type, number of responders involved, first responder), roadway characteristics (such as functional classification, geometric characteristics, Average Annual Daily Traffic (AADT), Truck AADT), traffic conditions (such as time of the day, weekday/weekend), and weather conditions (such as season, rain, temperature).

1.3 Critique of Earlier Work and Current Study

In earlier studies, while the importance of incident type has been highlighted, it is mostly considered as an independent variable. The consideration potentially imposes several major restrictions on the analysis approaches. ***First***, the analysis approaches restrict the influence of independent variables to be the same across all incident types *i.e.* the incident duration profile is restricted to be the same across all incident types. The only variation across incident types is estimated through the incident type indicator variables. However, it is possible that the impact of various independent variables is moderated by the incident type indicator. For example, consider the difference between two incidents: a traffic crash and an abandoned vehicle on roadway. In the traffic crash event, given the potential possibility of injury (or even fatality), the resource deployment urgency might be significantly different relative to the abandoned vehicle incident. This is an example of the same infrastructure availability acting at a different pace based on incident type. It is plausible to consider that several other independent variable effects are also affected by incident type.

Second, factors that have led to a particular incident might also affect the incident duration. For instance, the absence of a shoulder on a roadway facility reduces room for error and might lead to traffic crashes. The same factor by not allowing adequate room for traffic incident management vehicles might result in longer incident clearance times. This is an example of an observed factor (absence of a shoulder) influencing incident type and incident duration. Such factors can be easily considered in the incident duration model. However, it is also possible that various unobserved factors that affect incident type might also influence incident duration. Consider a roadway facility that has a high share of tourist drivers that are unfamiliar with the roadway. In the presence of tourist drivers, the probability of a traffic crash might be higher. In this scenario, traffic incident management vehicles might also take longer to arrive at the scene as the tourist drivers are not aware of the appropriate maneuvers to allow these vehicles. While it is possible to ascertain locations with higher presence of tourist drivers, it is close to impossible to determine the exact share of these drivers on roadways. Thus, we have an unobserved factor (share of tourist drivers) on roadway facility that may affect incident type and incident duration. Accommodating for the influence of unobserved factors warrants the development of a model system that examines incident type and incident duration as a joint distribution. *Finally*, earlier research typically employed one cross-sectional sample of data for incident duration analysis. However, with availability of data for several years from various transportation agencies, it is important to develop model structures that incorporate for the influence of temporal factors (observed and unobserved) in modeling incident duration.

Toward addressing the aforementioned issues, the current study develops a joint model system with a scaled multinomial logit model (SMNL) system for incident type and a grouped generalized ordered logit (GGOL) model system for incident duration. The scaled model accommodates for common unobserved heterogeneity by allowing the variance of the unobserved component to vary by time period (see Mannering, 2018 for discussion on temporal instability)[1]. The grouped generalized ordered system (employed in Laman *et al.*, 2018) offers a flexible non-linear formulation for modeling duration variables. The approach retains a parametric form similar to traditional hazard duration models while also allowing for alternative specific effects. The two model components are stitched together as a joint distribution using the flexible copula-based approach. In the presence of multiple years of data, the copula-based methodology was also customized to accommodate for observed and unobserved temporal effects (including heteroscedasticity) on incident duration. In our analysis, we employ six different copula structures - the Gaussian copula, the Farlie-Gumbel-Morgenstern (FGM) copula, and set of Archimedean copulas including Frank, Clayton, Joe and Gumbel copulas (a detailed discussion of these copulas is available in Bhat and Eluru, 2009). The model system is estimated using traffic incident data from 2012 through 2017 for the Greater Orlando region. The incident data is augmented with a host of independent variables including traffic characteristics, roadway characteristics, incident characteristics, weather conditions, built environment and socio-demographic characteristics. Further, the value of the proposed model system is illustrated by comparing predictive performance of the proposed model relative to a single incident duration model (ignoring incident type profile) on a holdout sample (not used in estimation). The reader would note that such joint model systems have been employed in travel behavior and transportation safety literature. However, to the best of the authors' knowledge, it is the first application in the incident duration modeling area.

2. ECONOMETRIC METHODOLOGY

The main focus of this paper is to jointly model incident type and incident duration using a copula-based scaled multinomial logit-group ordered logit model (SMNL-GGOL). In this section, econometric formulation of the joint model is presented.

2.1 Incident Type Component

Let q $(q = 1, 2, \dots, Q)$, and k $(k = 1, 2, \dots, K; K = 3)$ be the indices to represent incident and the corresponding incident type, respectively. In the joint framework, the modeling of incident type follows a SMNL model structure. Following the random utility theory, the propensity of an incident q being incident type k takes the following form:

$$\mu_{qk}^{*} = \beta_k x_{qk} + \xi_{qk} \tag{1}$$

Where, x_{qk} is a vector of independent variables and β_k is a vector of unknown parameters specific to incident type k. ξ_{qk} is an idiosyncratic error term (assumed to be standard type-I extreme value distributed) capturing the effect of unobserved factors on the propensity associated with incident type k. An incident q is identified as incident type k if and only if the following condition holds:

[1] In transportation research domain, most recently, several studies have addressed parameter stability over time (see Behnood and Mannering (2015), Marcoux et al. (2018), Anowar et al. (2016), Dabbour (2017)). A detailed review of these articles is beyond of scope of current study. Mannering (2018) presented a detailed discussion on temporal instability.

$$\mu_{qk}^{*} > \max_{l=1,2,....,K,\ l\neq K} \mu_{ql}^{*} \tag{2}$$

The functional form presented in Equation (2) can also be represented as binary outcome models for each incident type k. For example, let η_{qk} be a dichotomous variable with binary outcome $\eta_{qk} = 1$ if an incident be incident type k and $\eta_{qk} = 0$ if otherwise. Let us define ν_{qk} as follows:

$$\nu_{qk} = \xi_{qk} - \left\{\max_{l=1,2,....,K,\ l\neq K} \mu_{ql}^{*}\right\} \tag{3}$$

Now, using equation (1), we can rewrite equation (3) as:

$$\nu_{qk} = \mu_{qk}^{*} - \beta_k x_{qk} - \left\{\max_{l=1,2,....,K,\ l\neq K} \mu_{ql}^{*}\right\} \tag{4}$$

We can update equation (4) as follows

$$\nu_{qk} + \beta_k x_{qk} = \mu_{qk}^{*} - \left\{\max_{l=1,2,....,K,\ l\neq K} \mu_{ql}^{*}\right\} \tag{5}$$

Now, using Equation (2) we can conclude that the RHS of Equation (5) can be modified as >0, thus providing the following expression

$$\eta_{qk} = 1 \ if\ \nu_{qk} + \beta_k x_{qk} > 0 \tag{6}$$

In Equation (6), probability distribution of incident type outcome depends on distributional assumption of ν_{qk}, which in turn, depends on distribution of ξ_{qk}. Thus, an assumption of independent and identical Type I Gumbel distribution[2] for ξ_{qk} provides a logistic distribution of ν_{qk}. In the presence of multiple years of data, one can also estimate the variance of the error term with an appropriate base year. To accommodate for this, a scale parameter (φ) can be introduced to form a SMNL model and the probability expression takes the following form:

$$Pr(\nu_{qk} < \upsilon) = \frac{exp\left(\frac{-\upsilon}{\varphi}\right)}{exp\left(\frac{-\upsilon}{\varphi}\right) + \sum_{l\neq k} exp\left(\frac{\beta_k x_{ql}}{\varphi}\right)} \tag{7}$$

Where, φ is the scale parameter of interest and is parameterized as $\exp(\varrho\tau)$ and τ is a set of year specific factors such as time elapsed variable (computed as the time difference between the

[2] The reader would note that under different Generalized Extreme Value distributional assumptions for ξ_{qk} (as opposed to independent and identical Type I Gumbel distribution) would result in more complex probability structures for the incident type component with and without closed form expressions.

analysis year (2012-2017) from the base year (2012) considered), thus takes the values of 0, 1, 2,3,4 and 5 with 2012 as the base case.

2.2 Incident Duration Component

Let j_k be the index for the discrete outcome that corresponds to incident duration category for incident type k. In joint model framework, incident duration is modelled using a GGOL specification. In group ordered response model, the discrete incident duration levels (y_{qk}) are assumed to be associated with an underlying continuous latent variable (y_{qk}^*). This latent variable is typically specified as the following linear equation:

$$y_{qk}^* = \alpha_k z_{qk} + \sigma_{j_k} + \varepsilon_{qk}, y_{qk} = j_k \text{ if } \psi_{j_k} < y_{qk}^* < \psi_{j_k+1} \tag{8}$$

Where, z_{qk} is a vector of exogenous variables for incident type k in incident q, α_k is row of unknown parameters, ψ_{j_k} is the observed lower bound threshold for time interval level j_k for incident type k. ε_{qk} captures the idiosyncratic effect of all omitted variables for incident type k. Further, σ_{j_k} is vector of time interval category specific coefficient for time interval alternative j_k for incident type k. The ε_{qk} terms are assumed identical across incident types. The error terms are assumed to be independently logistic distributed with variance λ_{qk}^2. The variance vector is parameterized as follows:

$$\lambda_{qk} = exp\left(\delta + \rho g_{qk}\right) \tag{9}$$

Where, δ is a constant, g_{qk} is a set of exogenous variables associated with incident type k for an incident q and ρ is the corresponding parameters to be estimated. To be sure, g_{qk} also include the time elapsed variable, thus accommodate the effect of heteroscedasticity within the grouped ordered framework. The parameterization allows for variance to be different across incidents and also across time points accommodating heteroscedasticity. The probability for incident type k for time interval in category j_k is given by:

$$Pr(y_{qk} = j_k) = \Lambda\left(\frac{\psi_{j_k+1} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right) - \Lambda\left(\frac{\psi_{j_k} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right) \tag{10}$$

Where, $\Lambda(.)$ is the cumulative standard logistic distribution.

2.3 The Joint Model: A Copula Based Approach

The incident type and incident duration components discussed in previous two subsections can be brought together in the following equation system:

$$\begin{aligned} &\eta_{qk} = 1 \text{ if } \beta_k x_{qk} > -\nu_{qk} \\ &y_{qk}^* = \alpha_k z_{qk} + \sigma_{j_k} + \varepsilon_{qk} \text{ if } y_{qk} = 1[\eta_{qk} = 1]\, y_{qk}^* \end{aligned} \tag{11}$$

However, the level of dependency between incident type and duration category of an incident depends on the type and extent of dependency between the stochastic terms ν_{qk} and ε_{qk}. These dependencies (or correlations) are explored in the current study by using a copula-based approach.

In constructing the copula dependency, the random variables (ν_{qk} and ε_{qk}) are transformed into uniform distributions by using their inverse cumulative distribution functions, which are then coupled or linked as a multivariate joint distribution function by applying the copula structure. Let us assume that $\Lambda_{\nu k}(.)$ and $\Lambda_{\varepsilon k}(.)$ are the marginal distribution of ν_{qk} and ε_{qk}, respectively. Moreover, $\Lambda_{\nu k,\varepsilon k}(.)$ is the joint distribution of ν_{qk} and ε_{qk}. Subsequently, a bivariate distribution can be generated as a joint cumulative probability distribution of uniform [0, 1] marginal variables U_1 and U_2 as below:

$$\begin{aligned} &\Lambda_{\nu k,\varepsilon k}(\nu,\varepsilon) = Pr(\nu_k < \nu, \varepsilon_k < \varepsilon) \\ &= Pr(\Lambda_{\nu k}^{-1}(U_1) < \nu, \Lambda_{\varepsilon k}^{-1}(U_2) < \varepsilon) \\ &= Pr(U_1 < \Lambda_{\nu k}(\nu), U_2 < \Lambda_{\varepsilon k}(\varepsilon)) \end{aligned} \tag{12}$$

The joint distribution (of uniform marginal variable) in Equation (12) can be generated by a function $C_{\theta q}(.,.)$ (Sklar, 1973), such that:

$$\Lambda_{\nu k,\varepsilon k}(\nu,\delta_2) = C_{\theta q}(U_1 = \Lambda_{\nu k}(\nu), U_2 = \Lambda_{\varepsilon k}(\varepsilon)) \tag{13}$$

Where, $C_{\theta q}(.,.)$ is a copula function and θ_q the dependence parameter defining the link between v_{qk} and ε_{qk}. It is important to note here that, the level of dependence between incident type and incident duration level can vary across incidents. Therefore, in the current study, the dependence parameter θ_q is parameterized as a function of observed incident attributes as follows:

$$\theta_q = fn(\gamma_k s_{qk}) \tag{14}$$

Where, s_{qk} is a vector of exogenous variable, γ_k is a vector of unknown parameters (including a constant) specific to incident type k and fn represents the functional form of parameterization. In our analysis, six different copulas structure – Gaussian, FGM, Frank, Clayton, Joe and Gumbel copulas are employed. Based on the dependency parameter permissible ranges, alternate parameterization forms for the six copulas are considered in our analysis. For Normal, FGM and Frank Copulas, we use $\theta_q = \gamma_k s_{qk}$, for the Clayton copula we employ $\theta_q = \exp(\gamma_k s_{qk})$, and for Joe and Gumbel copulas we employ $\theta_q = 1 + \exp(\gamma_k s_{qk})$.

2.3.1 Estimation Procedure

The joint probability that the incident q is identified to be incident type k and the resulting incident duration level j_k, from equation (7) and (10), can be written as:

$$\begin{aligned} &Pr(\eta_{qk} = 1, y_{qk} = j_k) \\ &= Pr\left\{(\beta_k x_{qk} > -v_{qk}), \left(\left(\frac{\psi_{j_k-1} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right) < \varepsilon_{qk} < \left(\frac{\psi_{j_k} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right)\right)\right\} \\ &= Pr\left\{(v_{qk} > -\beta_k x_{qk}), \left(\left(\frac{\psi_{j_k-1} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right) < \varepsilon_{qk} < \left(\frac{\psi_{j_k} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right)\right)\right\} \end{aligned} \tag{15}$$

$$= Pr\left(\left(v_{qk} > -\beta_k x_{qk}\right), \left(\varepsilon_{qk} < \left(\frac{\psi_{j_k} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right)\right)\right)$$
$$- \; Pr\left(\left(v_{qk} > -\beta_k x_{qk}\right), \left(\varepsilon_{qk} < \left(\frac{\psi_{j_k-1} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right)\right)\right)$$

$$= \Lambda_{\varepsilon k}\left(\left(\frac{\psi_{j_k}-(\alpha_k z_{qk}+\sigma_{j_k})}{\lambda_{qk}}\right)\right) - \; \Lambda_{\varepsilon k}\left(\left(\frac{\psi_{j_k-1}-(\alpha_k z_{qk}+\sigma_{j_k})}{\lambda_{qk}}\right)\right) - \left(Pr\left[v_{qk} < -\beta_k x_{qk}, \varepsilon_{qk} < \left(\frac{\psi_{j_k}-(\alpha_k z_{qk}+\sigma_{j_k})}{\lambda_{qk}}\right)\right] - Pr\left[v_{qk} < -\beta_k x_{qk}, \varepsilon_{qk} < \left(\frac{\psi_{j_k-1}-(\alpha_k z_{qk}+\sigma_{j_k})}{\lambda_{qk}}\right)\right]\right)$$

The joint probability of Equation (15) can be expressed by using the copula function in equation (13) as:

$$Pr(\eta_{qk} = 1, y_{qk} = j_k)$$
$$= \Lambda_{\varepsilon k}\left(\frac{\psi_{j_k} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right) - \; \Lambda_{\varepsilon k}\left(\left(\frac{\psi_{j_k-1} - (\alpha_k z_{qk} + \sigma_{j_k})}{\lambda_{qk}}\right)\right)$$
$$- \; \left[C_{\theta q}\left(U_{q,j}^k, U_q^k\right) - C_{\theta q}\left(U_{q,j-1}^k, U_q^k\right)\right] \tag{16}$$

Thus, the likelihood function with the joint probability expression in equation (16) for incident type and duration level outcomes can be expressed as:

$$L = \prod_{q=1}^{Q}\left[\prod_{k=1}^{K}\prod_{j=1}^{J}\left\{Pr(\eta_{qk} = 1, y_{qk} = j_k)\right\}^{\omega_{qjk}}\right] \tag{17}$$

where, ω_{qjk} is dummy with $\omega_{qjk} = 1$ if the incident q sustains incident type k and an incident duration level of j and 0 otherwise. All the parameters in the model are then consistently estimated by maximizing the logarithmic function of L. The parameters to be estimated in the model are: β_k and ϱ in the SMNL model component, α_k and ψ_{j_k} in GGOL model component, and finally γ_k in the dependency component.

3 DATA DESCRIPTION

The main data source for the current study is the incident management dataset compiled by the Florida Department of Transportation (FDOT). Event management data collected over six years from 2012 to 2017 for Greater Orlando region was processed to prepare the final dataset. The study region consists of a number of major highways of the Greater Orlando Region including Interstate - 4 (I-4), East-West expressway (toll road 408), Beachline expressway (toll road 528), Central Florida Greenway (toll road 417), Daniel Webster Western Beltway (toll road 429) and other arterials, collectors and local roads.

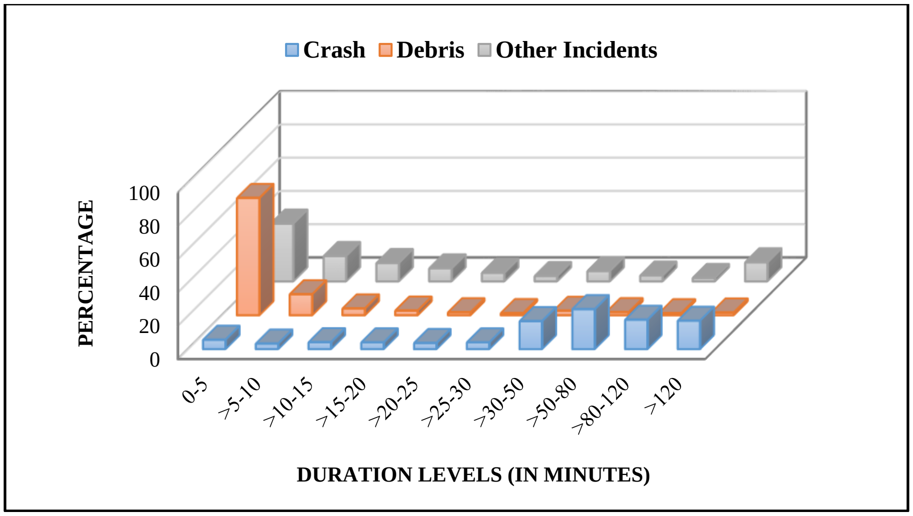


FIGURE 1 Distribution of Incident Duration for Different Incident Types

The study is confined to the incidents with an official reported response compiled by FDOT. The final dataset, after removing events without any response, consists of 326,348 incident records. In preparation of estimation sample, 2000 incidents were randomly sampled for each year (2012 to 2017), to create an overall estimation sample of 12,000 records. For validation test, on the other hand, 2500 records from each year were sampled randomly from the unused data resulting in a validation dataset of 15,000 records. Three incident types indicating crash, debris and other incidents were considered. Other incidents include disabled vehicles, abandoned vehicle, and tire blown. Initial model estimation efforts considered "other category" as separate categories. However, the model estimation results indicated the absence of substantial differences between disabled, abandoned and tire blown categories. Hence, these alternatives were merged in the other category. For incident duration, we have considered 10 categories (>0-5, >5-10, >10-15, >15-20, >20-25, >25-30, >30-50, >50-80, >80-120 and >120minute). Distribution of incident duration categories for each incident type is presented in Figure 1. From Figure 1, we can observe that incident duration profile varies substantially across different incident type categories. Crash events has a left skewed duration distribution while the other two incident types have a right skewed distribution. Given these clear differences across the three incident types, developing a single duration model (as considered in existing literature) can potentially result in biased and incorrect parameter estimation.

3.1 Independent Variables

The incident management dataset is augmented with several exogenous variables. These variables are sourced from American Community Survey, Florida Geographic Data Library, FDOT and Florida Automated Weather Network databases. Exogenous variables considered can be classified into six broad categories: incident characteristics, traffic characteristics, roadway characteristics, weather conditions, built environment and socio-demographic characteristics. <u>Incident characteristics</u> include number of responders, first responder and notified agency. <u>Roadway characteristics</u> considered include location in terms of intersection and interchange, roadway's functional class, geometric characteristics, average annual daily traffic (AADT). <u>Traffic characteristics</u> include time of the day to accommodate hourly variation of traffic and weekday/weekend. <u>Weather condition</u> include season and rain. <u>Built environment characteristics</u> include land-use mix variable, number of business centers, commercial establishment, recreational establishment, restaurants and other establishments in 0.5mile buffer area of each incident. Socio-demographic characteristics include population and median income in the 0.5mile buffer area. Built environment and socio-demographic variables are computed for the 0.5 miles buffers area of each incident location by using ArcGIS. The descriptive statistics of exogenous variables found significant in the final specified model are presented in Table 1.

TABLE 1 Description of Model Estimation Sample

Variable	**Variable Description**	**Freq.**	**Percentage (%)**
Dependent Variable for Incident Type Component			
Crash		2044	17.033
Debris		2197	18.308
Others type of incidents		7759	64.658
Dependent Variable for Incident Duration Component			
Incident duration category 1 -T1	>0-5minute	4353	36.275
Incident duration category 2 -T2	>5-10minute	1523	12.692
Incident duration category 3 -T3	>10-15minute	1025	8.542
Incident duration category 4 -T4	>15-20minute	747	6.225
Incident duration category 5 -T5	>20-25minute	507	4.225
Incident duration category 6 -T6	>25-30minute	357	2.975
Incident duration category 7 -T7	>30-50minute	880	7.333
Incident duration category 8 -T8	>50-80minute	798	6.65
Incident duration category 9 -T9	>80-120minute	542	4.517
Incident duration category 10 -T10	>120minute	1268	10.567
Independent Variables (Categorical)			
Incident Characteristics			
First responder			
Road Ranger	First responder is the Road Rangers	10417	86.808
Other agencies	First responder is Other agencies	1583	13.192
Notified Agency			
Road Ranger (RR)	Incidents were notified to the Road Rangers	5248	43.733
Other agencies	Incidents were notified to the Other agencies	6752	56.267
Roadway Characteristics			
At interchange or not			
At interchange	Incident was identified on an interchange	1323	11.025
Non-interchange	Incident was not identified on an interchange	10677	88.985
At intersection or not			
At intersection	Incident was identified on an intersection	3055	25.458
Non-intersection	Incident was not identified on an intersection	8945	74.542
Functional Classification			
Rural Highway	Incident was identified on rural highway	803	6.692
Rural Arterial	Incident was identified on rural arterial	485	4.042
Rural Local	Incident was identified on rural local road	53	0.442

Urban Interstate	Incident was identified on urban interstate	3535	29.458
Urban Freeway	Incident was identified on urban freeway	2980	24.833
Urban Arterial	Incident was identified on urban arterial	2065	17.208
Urban Local	Incident was identified on urban local road	2079	17.325
Posted speed limit			
Speed limit<55	Posted speed limit is less than or equal to 55mph	4913	40.942
Speed limit>55	Posted speed limit is higher than 55mph	7087	59.058
Traffic Condition			
Weekend/Weekday			
Weekday	Monday - Friday	9196	76.633
Weekend	Saturday and Sunday	2804	23.367
Time of the day			
6am – 9am		1822	15.183
9am – 4pm		5151	42.925
4pm – 6pm		1877	15.642
6pm – 9pm		1826	15.217
9pm – 6am		1325	11.042
Weather Condition			
Season			
Spring	March, April and May	2910	24.25
Summer	June, July and August	3193	26.608
Fall	September, October and November	3124	26.033
Winter	December, January and February	2773	23.108
Independent Variables (Ordinal)			
Variable		**Mean**	**Min/Max**
Incident Characteristics			
No. of responders	No. of responders involved in clearance	1.175	1.000/8.000
Time elapsed	Time since 2012 in year	2.500	0.000/5.000
Independent Variables (Continuous)			
Roadway Characteristics			
AADT	Ln(AADT/10000)	1.421	0.030/3.033
Inside shoulder	Ln(Inside shoulder width in ft)	2.056	0.693/3.611
Outside shoulder	Ln(Outside shoulder width in ft)	2.009	0.693/3.045
Median width	Ln(Median width in ft)	3.698	1.099/5.889
Weather Condition			
Rain	Amount of rain in inch at the hour of incident occurrence	0.006	0.000/1.617
Built Environment			
Business	Ln(No. of business establishments in 0.5mile buffer)	0.101	0.000/1.609
Commercial	Ln(No. of commercial establishment in 0.5mile buffer)	0.095	0.000/1.792
Recreational	Ln(No. of recreational establishment in 0.5mile buffer)	0.271	0.000/2.565

Restaurant	Ln(No. of restaurants in 0.5mile buffer)	1.111	0.000/4.357
CBD distance	Ln(Distance from central business district in miles)	1.754	-2.182/3.444
Land-use mix	Land-use in computed as $\frac{-\Sigma_k(p_k(\ln p_k))}{ln\, N}$, where $\boldsymbol{k}$ is the category of land-use, $\boldsymbol{p}$ is the proportion of the developed land area, $\boldsymbol{N}$ is the number of land-use categories within a buffer	0.377	0.000/0.963
Socio-demographic Characteristics			
Population	Ln(Total population in 0.5mile buffer)	6.805	2.652/8.721
Median income	Ln(Average median income in 0.5mile buffer in thousand)	4.211	3.488/4.997

4. MODEL SELECTION

The empirical analysis involves the estimation of models by using six different copula structures: a) FGM, b) Frank, c) Gumbel, d) Clayton, e) Joe and f) Gaussian copulas. A series of models have been estimated in the current study context. First, an independent copula model (separate SMNL and GGOL models) is estimated to establish a benchmark for comparison. Second, 6 different models that restricted the copula dependency structure across the three incident types and incident duration models to be the same are estimated. Third, based on the copula parameter significance for each incident type, copula models that allow for different dependency structures for different incident type and incident duration combinations are estimated (for example Frank copula for the first two incident types and Clayton copula for other incident type). Fourth, joint models with different copula profiles are further augmented by parameterizing the copula profiles. Finally, to determine the most suitable copula model (including the independent copula model), a comparison exercise is undertaken. The alternative copula models estimated are non-nested and hence, cannot be tested using traditional log-likelihood (LL) ratio test. We employ the Bayesian Information Criterion (BIC) to determine the best model among all copula models without parameterization.

The computed BIC (LL, Number of parameters) value of the independent model is 62434.01 (-30709.80, 108). With single copula dependency structure, the best model fit is obtained for Frank with BIC value of 62336.31 (LL = -30698.50, No. of parameters = 100). However, the lowest BIC value is obtained for a combination model of Frank-Clayton-Frank copulas (Frank copula structure for crash and other incident types and Clayton dependency structure for debris) and the BIC value is found to be 62335.11 (LL = -30697.92, No. of parameters = 100). Subsequently, the copula profile for the Frank-Clayton-Frank model has been parameterized. The copula model with and without parameterizations are nested within each other and can be compared by employing log-likelihood ratio test. The LL value for the parameterized Frank-Clayton-Frank copula model is found to be LL = -30693.72 (No. of parameters = 101, BIC = 62336.10). The log-likelihood ratio test yields a test statistic value of 8.40 which is substantially larger than the critical chi-square value (6.635) with 1 degrees of freedom at 99% level of significance. Thus, the comparison exercise confirms the importance of allowing the dependency profile to vary across different records. In presenting the effects of exogenous variables in the joint model specification, we will restrict ourselves to the discussion of the Frank-Clayton-Frank specification with parameterization.

5 MODEL RESULTS

5.1 Incident Type Model Component

Table 2 provides parameter estimates of incident type model component. A positive (negative) value of the parameters in Table 2 indicates higher (lower) propensity of the corresponding incident category compared to the base category.

5.1.1 Roadway Characteristics

Among roadway characteristics, interchange variable impact indicates that at interchange locations, the likelihood of debris incidence is higher while at intersections, the likelihood of crashes is higher. Incidents on rural highways are more likely to be crashes while less likely to be debris. The relationship is reversed for rural arterials. For rural local roads, crash incidences are found to be higher. On urban interstate, the results indicate higher possibility for crash and a lower possibility for debris incidents. The relationship is reversed for urban freeways. On urban arterials, the possibility of crash incident type is likely to be higher.

Estimation result for posted speed limit indicates that the roadway speed limit being greater than 55 has a negative impact on the likelihood of crash incidence and positive influence on debris incidence. Parameter estimate for AADT indicates that increasing AADT is likely to reduce the possibility of Debris incidences. Shoulder width and median width variables have significant impacts on incident types. Specifically, with the increase in inside shoulder width, the probability of crash incidence is found to be higher. On the other hand, increasing width of the outside shoulder is likely to reduce the possibility of crash and debris incidents. This is expected because with increasing outside shoulder width more space for disabled or abandoned vehicles is available (a major share of the Other alternative). Median width variable is negatively associated with crash and positively associated with debris incidents.

5.1.2 Traffic Characteristics

Traffic characteristics prior to the occurrence of incident might affect the potential incident type. However, it is not feasible to generate detailed traffic information across all the incident records considered in our analysis. Hence, as potential surrogates reflecting traffic conditions, we considered the time period and day of the week. The results indicate that all time periods from 6 am – 9 pm are less likely to result in crash. The possibility of crashes is particularly lower in the time period 9 am – 4 pm. At the same time, the results indicate that debris incidences are more likely to occur during the 6 am – 9 pm time period. The probability is particularly higher for debris during time period 6 am – 4 pm. Finally, the day of the week parameters indicate that the likelihood of debris incidence is lower on weekdays (relative to weekends).

5.1.3 Weather Conditions

The variables tested for seasonality resulted in a significant parameter for spring. The result indicates lower propensity for crash during spring season. The results for Rain variable indicate that in the presence of rain, crash incidences are likely to be higher. The result is expected in Florida with tropical weather where heavy showers appear in short time frame affecting overall road safety.

5.1.4 Built Environment

Incident type is affected by crash proximity to central business district (CBD). Specifically, as the distance of the incident location to CBD increases the likelihood of crash and debris increases. Several land-use variables affect incident type likelihood. Business and restaurant land use contribute to lower debris incidence while recreational land use contributes to higher debris incidence. Commercial and restaurant land use contribute to higher crash possibilities. Finally, overall land-use mix variable is found to have a positive effect on debris variable.

5.1.5 Socio-demographic Variables

Population density and median income in the proximity of incident are found to be significant predictors of incident type. Higher population density increases probability of an incident being debris and reduces the likelihood of an incident being crash relative to other incidents. The result is reflective of the enhanced safety in highly populated areas. Similarly, incidents occurring in high income areas are less likely to be a crash.

5.1.6 Scale parameter

To accommodate for difference in incident type with time, we generated the time elapsed variable (time since 2012). The estimated model result indicates that the variance of the error term for the time elapsed variable increases with time highlighting the impact of unobserved time specific factors.

TABLE 2 Parameter Estimates for Incident Type Component (SMNL Model Results)

Variable	**Crash**		**Debris**		**Other Incidents**	
	Est.	**t-Stat**	**Est.**	**t-Stat**	**Est.**	**t-Stat**
Constant	7.6596	9.9390	-5.9350	-10.2680	--	--
Roadway Characteristics						
At Interchange or not (Base: Non-interchange)						
At interchange	--[1]	--	0.9211	9.9460	--	--
At intersection or not (Base: Non-intersection)						
At intersection	0.1787	2.176	--	--	--	
Function class of roadway (Base: Urban Local)						
Rural highway	0.4979	2.601	-0.5990	-2.048	--	--
Rural arterials	-1.2389	-4.3970	0.9905	4.5440	--	--
Rural local	2.2113	4.3770	--	--	--	--
Urban interstate	0.8258	5.7170	-0.8513	-5.122	--	--
Urban Freeway	-0.5846	-3.7250	1.5622	11.709	--	--
Urban arterials	0.4458	4.5400	--	--	--	--
Posted speed limit (Base: Speed limit<55)						
Speed limit>55	-0.4219	-3.8180	0.3847	3.6670	--	--
AADT	--	--	-0.2971	-4.8940	--	--
Inside shoulder	0.1585	2.1560	--	--	--	--
Outside shoulder	-0.1880	-2.3040	-0.4233	-5.878	--	--

Median width	-0.5487	-8.7420	0.1502	1.9980	--	--
Traffic Condition						
Time of the day (Base: 9pm – 6am)						
6am – 9am	-0.2782	-2.3850	1.5825	7.0290	--	--
9am – 4pm	-0.6918	-7.2730	1.5318	7.1820	--	--
4pm – 6pm	-0.2568	-2.3760	1.1637	5.1630	--	--
6pm – 9pm	-0.4600	-4.2390	0.9021	3.9670	--	--
Weekend/ Weekday (Base: Weekend)						
Weekday	--	--	-0.4261	-5.4610	--	--
Weather Conditions						
Season (Base: Other seasons)						
Spring	-0.2338	-3.1960	--	--	--	--
Rain	2.2397	4.1600	--	--	--	--
Built Environment						
CBD Distance	0.3397	6.9950	0.3598	5.1390	--	--
Business	--	--	-1.1775	-7.3720	--	--
Commercial	0.6877	5.8180	--	--	--	--
Recreational	--	--	0.3336	4.0340	--	--
Restaurants	0.1346	4.4310	-0.1513	-3.9760	--	--
Land-use mix	--	--	0.4499	2.6560	--	--
Socio-demographic						
Population	-0.4200	-8.4150	0.3749	6.7340	--	--
Median income	-1.1809	-9.2630	--	--	--	--
Scale Parameter						
Time elapsed	Estimate = 0.0895 (t-stat = 10.4950)					

[1]-- = Attributes insignificant at 90% confidence level

5.2 Incident Duration Model Component

Table 3 provides parameter estimates of the duration model for crash, debris and other incident type categories considered in the study. A positive (negative) value of the parameter in Table 3 indicates propensity for higher (lower) duration.

5.2.1 Incident Characteristics

Several incident characteristics such as number of responders, category of the first responder and notified agency are found to influence incident duration. In terms of number of responders, the incident duration is found to be higher with the increased number of responders for all duration models. The result might seem counterintuitive. However, the increase in the number of responders is representative of the seriousness of the incident. Thus, based on incident notification, for more serious incidents, a large number of responders are likely to arrive at a scene for assisting in incident clearance. Several agencies are involved in the incident notification and clearance activities. The results indicate that if Road Ranger is the notified agency then the incident durations are likely to be lower for debris and other incidents (see (Laman *et al.*, 2018) for similar result). Incident durations are also found to be lower for all incident categories if Road Ranger is the first responder.

5.2.2 Roadway Characteristics

The roadway characteristics are found to have no impact on incident duration for crashes. The result is a reflection of the emphasis on crash incident clearance. The emphasis is warranted given the potential savings of life in the event of crash. For debris, the duration is likely to be longer on rural arterials. For other incidents, the roadway classification of rural arterials and urban freeways are found to have negative impact on the duration component. The results from our models are different from earlier research (Ghosh *et al.*, 2014; Laman *et al.*, 2018) and warrant further investigations. Roadway geometric characteristics are found to have no effect on incident duration for any incident categories.

5.2.3 Traffic Characteristics

For crash and debris, the model estimation results indicate that incident durations are likely to be higher during 9 pm to 6 am (see (Chung, 2010) and (Laman *et al.*, 2018) for similar findings). On the other hand, for disabled vehicles duration is likely to be longer in the 6 am to 9 am time period. For the time period between 9 am to 9 pm, the disabled vehicles incidence is likely to have shorter incident duration. On weekdays, duration of crash incidence is likely to be shorter (as is supported by earlier research (Laman *et al.*, 2018). On the other hand, duration is longer for debris on weekdays. Overall, the results are an indication of infrastructure readiness for crash incident clearance and reduced emphasis on debris clearance during the daytime and weekdays.

5.2.4 Weather Effects

Only seasonal effects are found to affect incident duration. Specifically, the results indicate that incident duration for debris is likely to be of longer duration in summer.

5.2.5 Built Environment

As the distance from CBD increases, the time for clearance for crash incidences are found to be higher. The result is indicative of the presence of more incident clearance infrastructure around CBD.

5.2.6 Socio-demographic Variables

While several socio-demographic variables were considered in the model only two variables offered statistically significant results in the incident duration component. As population increases, the model results indicate a reduction in duration for crash and other incidents. For debris incidents, the reduction in duration is associated with higher median income. Overall, the results indicate that the incident management authorities are likely to prioritize highly populated areas.

5.2.7 Alternative specific constants

The proposed duration model also allows for alternative specific effects on various duration categories. In our incident duration estimation, we consider various alternative specific constants based on model fit and sample sizes across each duration category. The estimation results of these parameters are reported in the second-row panel of Table 3. These constants are similar to constant in discrete choice models and do not have an interpretation after incorporating other variables.

5.2.8 Variance Components

As described in the methodology section, the variance of the GGOL model components are estimated as a function of observed exogenous variables. The parameter estimates of these components are presented in the third-row panel of Table 3. From the results, it can be found that the exogenous variables that contribute to the variance profile of duration model of crash incidences include notified agency is Road Rangers and number of responders. The only exogenous variable that contributes to the variance profile of duration model of debris is outside shoulder width. The exogenous variables that contribute to the variance profile of duration model of other incidents include AADT, at intersection, first responder is Road Rangers and the incident was notified to Road Rangers. Thus, these results highlight the presence of heteroscedasticity in the data.

5.2.9 Dependence Effects

As indicated earlier, the estimated Frank-Clayton-Frank copula based SMNL-GGOL model with parameterization provides the best fit in incorporating the correlation between incident type and incident duration. The result of the dependency profile is presented in the last row panel of Table 3. The results clearly highlight the presence of common unobserved factors affecting incident type and incident duration. The Frank copula dependency structure is associated with the crash and other incident categories, while the Clayton dependency structure is associated with the debris category. For the crash incident type, the Frank dependency is negative indicating that the unobserved factors that are likely to increase crash likelihood are likely to reduce the incident duration. The Frank dependency for other incidents offers similar results. The reader would note that for other incident type, the dependency parameter varies by season. Finally, for debris incident, Clayton copula parameter indicates that the unobserved factors affecting debris incident and its associated duration have a strong lower tail dependency.

TABLE 3 Parameter Estimates for Incident Duration

Variables	**Crash**		**Debris**		**Other Incidents**	
	Est.	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**
Propensity components						
Constant	104.2761	12.9790	-12.6649	-0.6340	78.3892	4.5180
Incident characteristics						
No. of responders	9.7250	10.0730	24.5795	4.4010	25.9121	4.4290
First responder (Base: Other agencies)						
Road Ranger	-9.2166	-4.6170	-27.5312	-4.7480	-37.0589	-4.0290
Notified agency (Base: Other agencies)						
Road Ranger	--[1]	--	-36.8587	-6.4270	-49.5242	-8.0620
Roadway Characteristics						
Functional class (Base: Other classes)						
Rural arterial	--	--	13.2396	2.8060	-102.6595	-9.5910
Urban freeway	--	--	--	--	-27.8564	-4.4550
Traffic characteristics						
Time of the day (Base: 9pm – 6am)						

6am – 9am	-11.1390	-3.8540	-24.2698	-3.2280	14.5904	2.2610
9am – 4pm	-10.7558	-4.6140	-21.5290	-3.0470	-40.7983	-7.3300
4pm – 6pm	-5.8756	-2.1250	-25.9414	-3.4110	-36.9026	-5.6730
6pm – 9pm	-7.8879	-2.8990	-20.1242	-2.7090	-22.5256	-3.5450
Weekend/ Weekday (Base: Weekend)						
Weekday	-3.9172	-2.0310	6.0762	2.1960	--	--
Weather condition						
Season (Base: Other Seasons)						
Summer	--	--	5.4717	2.1250	--	--
Built Environment						
CBD distance	4.0977	3.7370	--	--	--	--
Socio-demographic Characteristics						
Population	-5.2669	-5.7490	--	--	-6.7246	-4.0450
Median income	--	--	-8.2901	-2.1660	--	--
Category-specific constants						
Constant for T1	19.7306	7.3080	14.6056	9.6070	122.1130	27.4130
Constant for T2	8.7898	5.5190	--	--	73.8363	23.8800
Constant for T3	--	--	--	--	40.8383	19.5830
Constant for T4	--	--	--	--	16.4859	13.5050
Constant for T5	--	--	--	--	--	--
Constant for T6	--	--	--	--	--	--
Constant for T7	--	--	--	--	--	--
Constant for T8	--	--	--	--	--	--
Constant for T9	18.8899	14.1380	24.0710	7.2220	--	--
Variance components						
Constant	3.3264	57.6220	3.2171	42.1950	3.8284	53.9040
No. of responders	-0.1324	-5.5390	--	--	--	--
First responder (Base: Other agencies)						
Road Ranger	--	--	--	--	0.5878	8.4000
Notified agency (Base: Other agencies)						
Road Ranger	0.4490	6.4160	--	--	-0.0711	-2.3800
At intersection or not (Base: Non-intersection)						
At intersection	--	--	--	--	0.1458	2.8510
AADT	--	--	--	--	0.0323	2.1030
Outside shoulder	--	--	0.0594	2.1690	--	--
Dependence Effects						
Constant	-2.5268	-4.5610	4.8241	4.4080	-1.5917	-3.7590
Season (Base: Other seasons)						
Summer	--	--	--	--	-0.8163	-2.8940

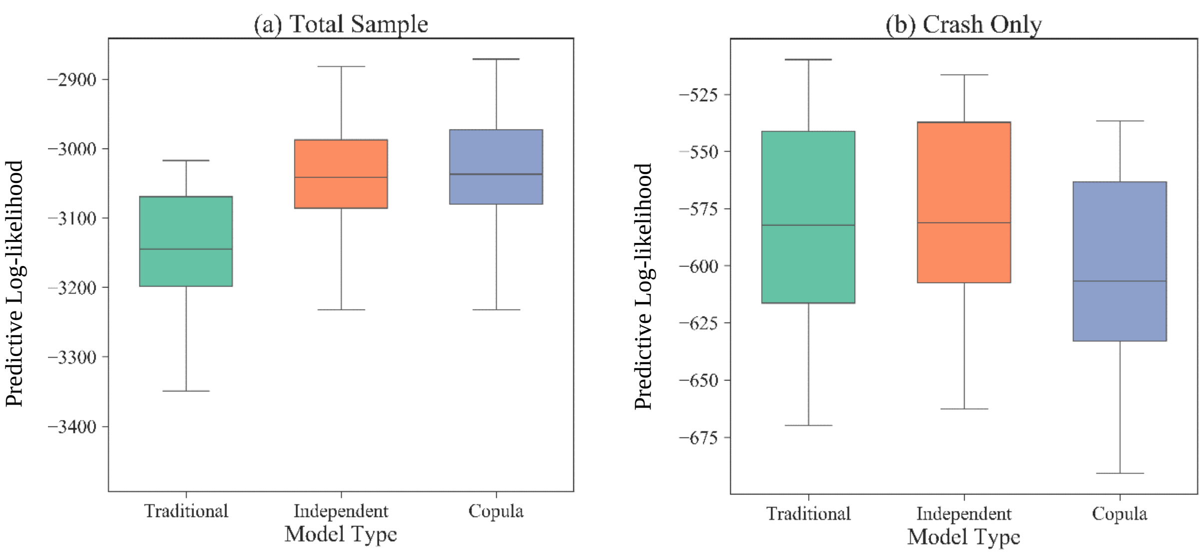
[1]-- = Attributes insignificant at 90% confidence level

6 MODEL PERFORMANCE AND APPLICATION

6.1 Validation Analysis

To test the predictive performance of the estimated model, a validation exercise with holdout sample is performed. For this validation test, 2500 records from each year are drawn randomly from the unused data resulting in a validation dataset of 15,000 records. For testing the predictive performance of the models, 25 data samples, of about 1000 records each, are randomly generated from the hold out validation sample consisting of 15,000 records. The average log-likelihood and BIC score for the copula model are -3046.67 [(-3089.91, -3003.44)] and 6792.93 [(6705.32, 6880.54)], respectively. The average log-likelihood and BIC score for the independent model are -3050.62 [(-3092.55, -3008.69)], and 6849.30 [(6764.22 ,6934.38)], respectively. The average log-likelihood and BIC score for the traditional model (single duration model using incident type as an independent variable) are -3150.97 [(-3193.39, -3108.55)], and 6800.64 [(6714.99, 6886.30)], respectively. For every individual sample, the predicted log-likelihood and BIC value for the copula model are better than the corresponding log-likelihood and BIC value for the independent and the traditional model. The validation result clearly reflects the superiority of joint model over independent and traditional model.

We also examine predictive performance by incident type: (a) All incidents, (b) crash, (c) debris and (d) other incidents. The predictive LL value box plots for the three models by these four categories are presented in Figure 2. For the overall sample comparison reflected in the first box plot comparison, it is clear that a single model that ignores duration profiles by incident type is outperformed by the two models that consider duration profiles by incident type (independent and copula models). Among incident type specific comparison, the models developed in our study out-perform the traditional model for debris and other incident types. However, for crash incident records, the traditional model marginally outperforms the proposed models.



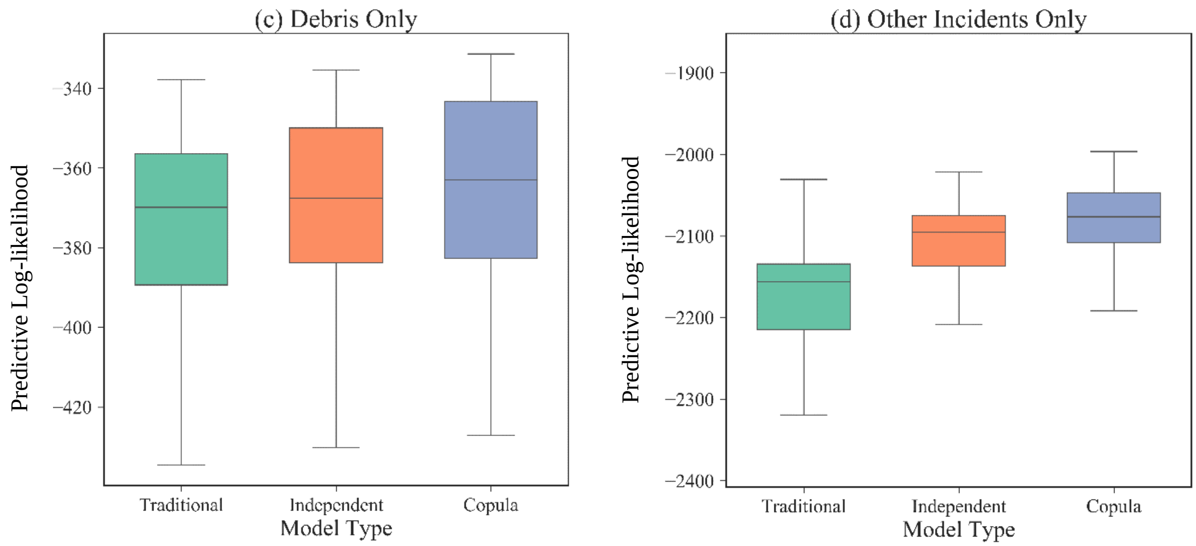


FIGURE 2 Comparison of Predictive Log-likelihood of the Three Models

6.2 Elasticity Analysis

The parameter estimates of developed copula-based incident model can be utilized to identify whether an independent variable increases or decreases the probability of higher/lower order incident duration categories. But parameter estimates do not directly identify the magnitude of the change on the probability of a duration category. Therefore, elasticity effects for all independent variables with regard to incident duration were calculated. For the sake of brevity, we restrict ourselves to the presentation of elasticity values of the highest duration category in Table 4. Values presented in Table 4 reflect the percentage change in aggregate probability of the highest duration category due to the change in independent variables. From the elasticity analysis results, it is found that an increase in the number of responders increases the probability of higher ordered incident duration categories significantly. On the other hand, Road rangers being the first responder and the incident being notified by the Road Rangers reduce the probability of higher ordered duration categories. In case of traffic characteristics variables, crashes and debris occurring 6am to 9pm and other incidents occurring 9am to 9pm have lower duration compared to nighttime from 9am to 6am. With increasing CBD distance, duration of crashes increases significantly. With increased population in close proximity of crashes and other incidents, incident duration decreases significantly. Another socio-demographic characteristic, median income significantly influences duration of debris type of incident. Increase of median income decreases the probability of higher order duration category. Overall, the elasticity analysis results can be helpful to the incident management agencies to identify the dominant factors affecting incident duration.

TABLE 4 Elasticity Analysis for Incident Duration

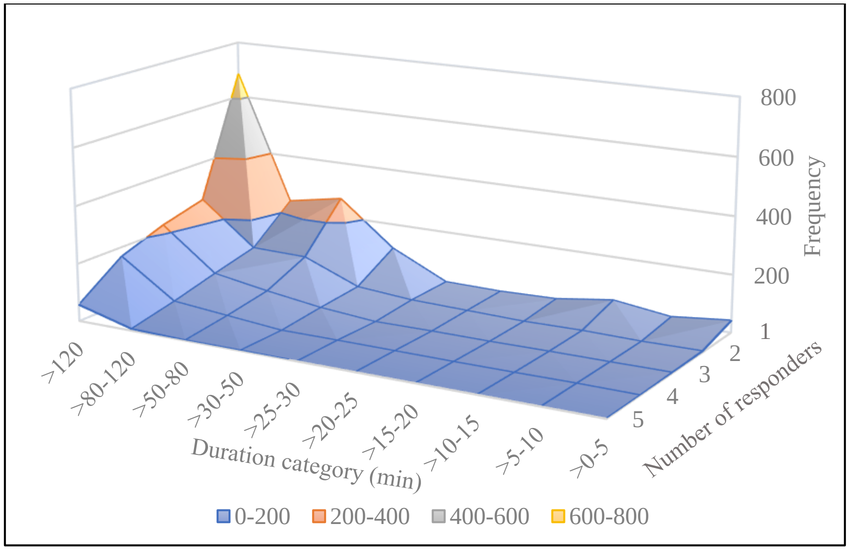
Variables	Crash	Debris	Other Incidents
Incident characteristics			
No. of responders	3.06799	6.83959	0.84843
First responder (Base: Other agencies)			
Road Ranger	-14.82945	-104.78980	-4.92734
Notified agency (Base: Other agencies)			
Road Ranger	0.26746	-65.26592	-16.50839
Roadway Characteristics			
Functional class (Base: Other classes)			
Rural arterial	--	41.09485	-23.75875
Urban freeway	--	--	-8.087557
Traffic characteristics			
Time of the day (Base: 9pm – 6am)			
6am – 9am	-17.55639	-56.43968	4.531904
9am – 4pm	-16.94333	-61.75876	-12.17580
4pm – 6pm	-9.287986	-55.22964	-10.54608
6pm – 9pm	-12.47041	-43.79461	-6.61213
Weekend/ Weekday (Base: Weekend)			
Weekday	-6.18817	15.51287	--
Weather condition			
Season (Base: Other Seasons)			
Summer	--	14.96467	--
Built Environment			
CBD distance	4.10584	--	--
Socio-demographic Characteristics			
Population	-5.64136	--	-1.37324
Median income	--	-8.72836	--

* Values indicate the percentage changes of aggregated probability of the highest duration category

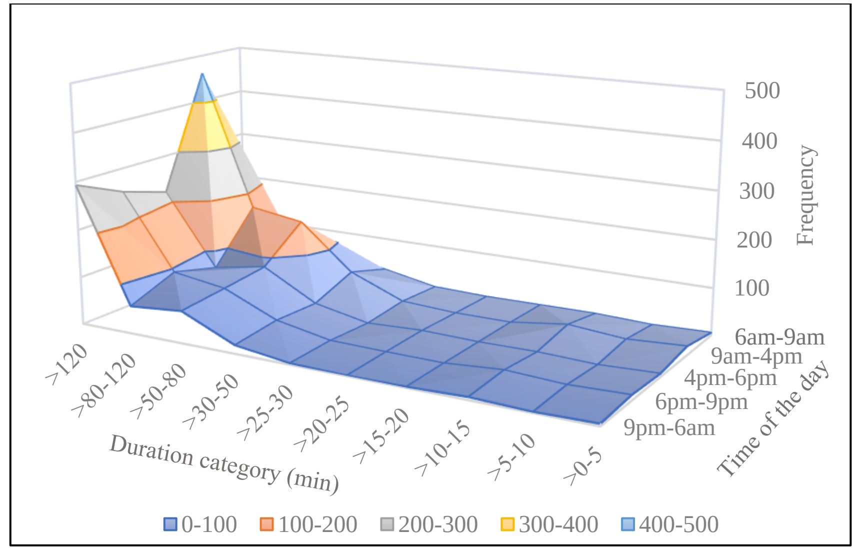
6.3 Model Illustration

To demonstrate the applicability of the developed model, the final model was applied to generate response surface using duration categories, incident frequencies and selected independent variables for different incident types. In generating the values for plotting the response surface, the incident duration categories are identified based on probabilistic assignment by using predicted probabilities computed from the final copula model (Frank-Clayton-Frank parameterized). The probabilities are appropriately aggregated across categories to identify the corresponding incident frequencies. For example, incident frequencies of crashes are plotted against duration categories and number of responders in Figure 3a. The plotted surface shows that crash incidents are typically associated with longer clearance times and are likely to involve increased number of responders compared to other incident types. Figure 3b presents crash incident frequencies by time of the day and indicates that crash frequency is the highest between 9am to 4pm compared to other time of the day. Similar to Figure 3a, crash incident frequencies are higher for longer duration levels.

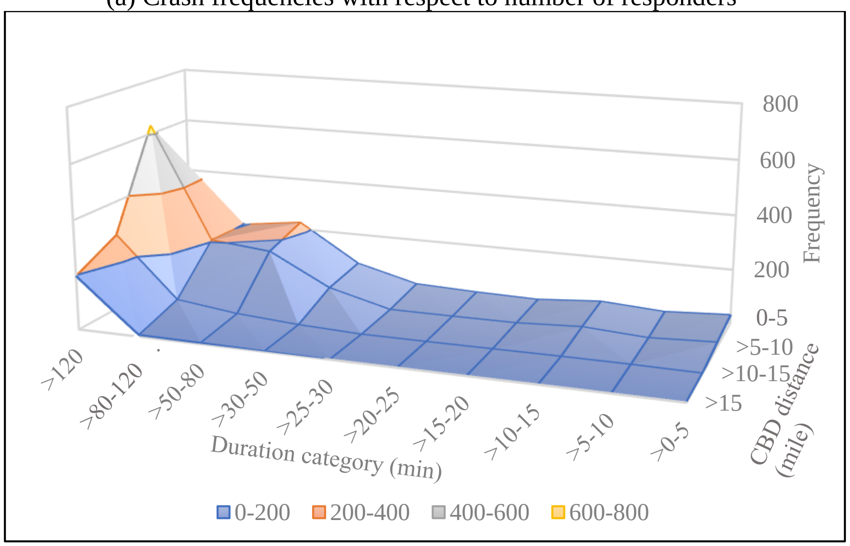
Figure 3c indicates that the likelihood of crash incidents is higher for locations between 5 to 10 miles from central business district. Figure 3d presents other incident frequencies by duration category and time of the day. The reader would note that the plots provided are only a sample of the various illustrations that can be generated based on the independent variables in the models. The development of such response surface could be helpful for the incident management agencies to allocate their resources based on the reported incident scenarios.



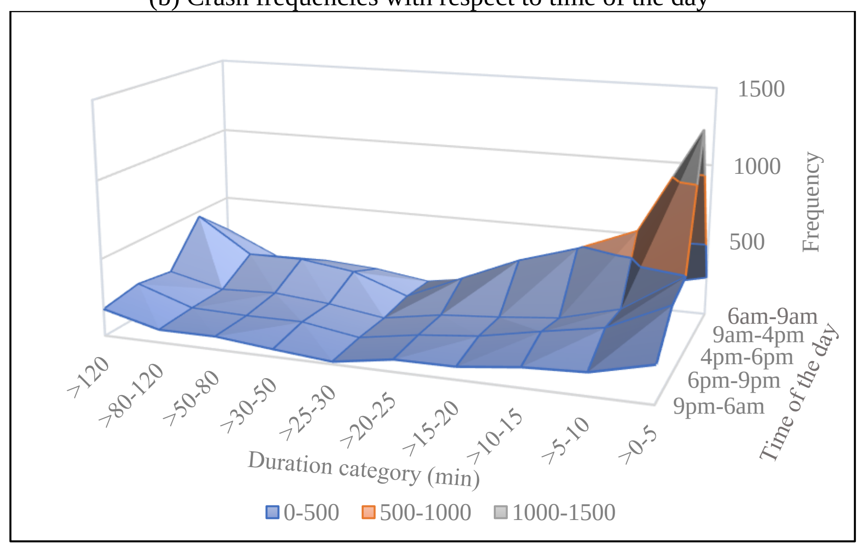
(a) Crash frequencies with respect to number of responders



(b) Crash frequencies with respect to time of the day



(c) Crash frequencies with respect to CBD distance



(d) Other Incidents frequencies with respect to time of the day

FIGURE 3 Response Surface for Predicted Incident Frequencies

7 CONCLUSION

To understand the impact of observed and unobserved effects on incident type and incident duration, this paper formulated and estimated a copula-based joint model with a scaled multinomial logit model (SMNL) system for incident type and a grouped generalized ordered logit (GGOL) model system for incident duration. The proposed model is estimated using FDOT's incident management data from Greater Orlando region, with a host of independent variables including incident characteristics, roadway characteristics, traffic condition, weather condition, built environment and socio-demographic characteristics. The current study contributes to incident duration literature in multiple ways. First, the current study posits that incident duration is strongly influenced by incident type and allows for distinct incident profile regimes. Further, the study accommodates for common unobserved factors affecting incident type and incident type within a closed form copula-based model structure. Second, the study using data from multiple years, develops a framework that accommodates for observed and unobserved temporal effects on incident type and incident duration. Finally, the proposed model system is estimated using a comprehensive set of exogenous variables.

The empirical analysis involves the estimation of models by using six different copula structures: 1) FGM, 2) Clayton, 3) Gumbel, 4) Frank, 5) Joe and 6) Gaussian. The parameterized Frank-Clayton-Frank copula system (Frank copula structure for crash and other incident type and Clayton dependency structure for debris) offered the best data fit for our empirical context. The model estimation results presented in the current paper suggest that the impact of exogenous variables vary (for some variables) in magnitude as well as in sign across incident types. To further understand the performance of the developed model, a comprehensive model performance evaluation and applicability exercise was conducted. The results from the exercise illustrate the value offered by the proposed model system.

The enhanced duration model can be employed by planning agencies to guide incident clearance as well as traffic congestion management. To elaborate, based on the model system, planning agencies can generate guidelines on incident duration times for important variables such as incident type, location and time of day. These guideline durations for incident clearance can allow agencies to identify the appropriate messaging signs (such as what is targeted demand for diversion) for route detours at the occurrence of an incident.

ACKNOWLEDGEMENT

The authors would like to acknowledge Florida Department of Transportation to provide access to their incident management dataset.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Naveen Eluru, Shamsunnahar Yasmin, Sudipta Dey Tirtha; data collection: Sudipta Dey Tirtha, Shamsunnahar Yasmin, Naveen Eluru; model estimation: Sudipta Dey Tirtha, Shamsunnahar Yasmin, Naveen Eluru; analysis and interpretation of results: Sudipta Dey Tirtha, Naveen Eluru, Shamsunnahar Yasmin; draft manuscript preparation: Sudipta Dey Tirtha, Naveen Eluru, Shamsunnahar Yasmin. All authors reviewed the results and approved the final version of the manuscript.

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