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ANALYSIS OF TRAFFIC ACCIDENT OCCURRENCE AT HAZARDOUS ROAD LOCATIONS: A CASE STUDY IN TUNISIA

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ABSTRACT

The main objective of this study was to investigate the impact of factors linked to the geometric, roadway and traffic flow characteristics on traffic accident occurrence at Hazardous Road Locations (HRL) in the region of Sousse, Tunisia using longitudinal data of 52 HRLs for an 11-year monitoring period from January 1, 2004 to December 31, 2014. The results of estimation of Negative Binomial model and the Random Effects Negative Binomial model reported that the different variables representing the presence of rural segment, the curved alignment, the visibility, the average daily traffic volume, the presence of public lighting, the number of lane, the presence of vertical/horizontal sign, the presence of drainage system, the presence of paved shoulder, the roadway surface condition, and the presence of major road were the main significant variables influencing accident occurrences. Therefore, the results could be useful for deciders in the transport sector in order to implement effective measures to improve road safety by adopting proper sound use practices, establishing efficient transportation systems and formulating appropriate traffic policies and legislation.

Contribution/Originality: This is one of the few studies which have investigated the occurrence of traffic accidents at Hazardous Road Locations in the region of Sousse (Tunisia) as a function of various explanatory factors linked to the geometric characteristics, roadway characteristics and traffic flow characteristics.

1. INTRODUCTION

The accidents caused by road traffic are a very common cause of admission to the hospital around the world, especially in developing countries. Disability, loss of days of work as consequence of the road traffic accidents lead to further socioeconomic deprivation in the society. Road traffic collisions lead to massive social and economic costs. Thus, traffic safety is an important issue especially in Tunisia. According to Hillier (2002) road accidents are the results of the human, vehicle and environmental related factors. Precautions regarding these three aspects are essential to take care from road accidents (Van Raemdonck & Macharis, 2014). Nowadays, road traffic safety is considered as the most studied subjects in the field of transportation engineering. Every year, approximately 1.2 million deaths and about 50 million injuries are caused by road accidents (World Health Organization, 2013). The mortality rates are highest in the eastern Mediterranean and in the African region. More than 90 per cent of road deaths occur in low- and middle-income countries (World Health Organization, 2013). For example in Tunisia, 1443 persons were killed in 2016 and 11035 were injured in traffic-related crashes on the roads (National Observatory of Informatiol, 2010). The fatality rate on Tunisian roads is 24.4, 154.4 deaths per 100 000 inhabitants and 100 000 motors vehicles respectively (World Health Organization, 2015). In 2016, the proportion of injuries and deaths on national Highways were the highest in Tunisia, compared to any other highways (National Observatory of Informatiol, 2010). In spite of the considerable impact of traffic accidents and fatality rate, the magnitude of the consequences must be reduced (Erdogan, 2009). There is a need to investigate traffic accident occurrence at Hazardous Road Locations "HRL" in Tunisia. Several studies have addressed crash-injury frequency. A detailed review is given by Lord and Mannering (2010) and Mannering and Bhat (2014). There is an abundant literature presenting the relation between accident frequency and roadway characteristics, traffic characteristics, built environment characteristics, geometric characteristics and environmental characteristics. In all modeling efforts, crash frequency and crash rate were the most common response variable used in accident frequency modeling. Overall, the previous findings are consistent. The factors, that most commonly found to increase frequency of accidents, are Section length (Abdel-Aty & Radwan, 2000; Anastasopoulos, 2016; Anastasopoulos & Mannering, 2009; Caliendo, De Guglielmo, & Guida, 2013; Caliendo., De Guglielmo, & Guida, 2016; Carson & Mannering, 2001; Malyshkina, Mannering, & Tarko, 2009; Naznin, Currie, Logan, & Sarvi, 2016; Qin, Ivan, & Ravishanker, 2004; Singh, Sachdeva, & Pal, 2016; Venkataraman, Ulfarsson, & Shankar, 2013; Wang, Quddus, & Ison, 2011) number of lanes (Caliendo et al., 2013; Chang, 2005; Gomes, 2013; Venkataraman., Ulfarsson, Shankar, Oh, & Park, 2011) and the presence of work zone (Chen. & Tarko, 2014; Eustace, Aylo, & Mergia, 2015; Roshandeh, Agbelie, & Lee, 2016). The factors, that most commonly found to decrease frequency of collisions, are the presence of sidewalk (Caliendo et al., 2013; Caliendo. et al., 2016) the presence of stop signs (Agbelie, 2016b) angle of intersection (Dong, Clarke, Nambisan, & Huang, 2016; Dong, Clarke, Yan, Khattak, & Huang, 2014) and the presence of paved shoulder (Bullough, Donnell, & Rea, 2013; Singh et al., 2016). However, some researchers report conflicting results. Abdel-Aty and Radwan (2000) concluded that number of lanes is associated with decreased frequency, while Caliendo et al. (2013); Chang (2005); Venkataraman. et al. (2011); Gomes (2013) and Wang. and Abdel-Aty (2006) reported the opposite. Carson and Mannering (2001) and Bullough et al. (2013) concluded that posted speed limit are associated with decreased frequency, while Dong et al. (2014) and Agbelie (2016a) concluded that posted speed limit less than 55 mph are associated with increased frequency. Kumara and Chin (2003) concluded that the existence of surveillance camera is associated with decreased frequency, while Chin and Quddus (2003) reported the opposite. Kumara and Chin (2003) found a decreased frequency of accident with sight distance. Nevertheless, Kumara and Chin (2005)reported that Sight distance<100 meters are associated with increased frequency. Interestingly, in most studies, shoulder width (both left, right and median shoulder) was found to decrease frequency (Abdel-Aty & Radwan, 2000; Agbelie, 2016a; Chen. & Tarko, 2014; Dong et al., 2016; Qin et al., 2004; Venkataraman et al., 2013; Venkataraman. et al., 2011) still, various authors claimed the opposite (Anastasopoulos, 2016; Carson & Mannering, 2001). Adverse road conditions such as depressed median configuration (Bullough et al., 2013; Malyshkina et al., 2009) defected pavement surface (Roshandeh et al., 2016) found to increase frequency of accidents.

Abdel-Aty and Radwan (2000); Kumara and Chin (2003); Agbelie (2016a) and Anastasopoulos (2016) showed how horizontal curved road are linked to increased risk of accidents while Carson and Mannering (2001); Chang (2005); Anastasopoulos and Mannering (2009) and Venkataraman. et al. (2011) showed that the presence of horizontal curved road presents a diminished risk of accidents. Malyshkina et al. (2009) and Anastasopoulos and Mannering (2009) showed that vertical curved road is associated with decreased frequency, while Venkataraman. et al. (2011) and Venkataraman et al. (2013) reported the opposite. Furthermore, Carson and Mannering (2001); Bullough et al. (2013); (Agbelie, 2016b) and Agbelie (2016a) reported that the existence of urban segment was related to increased risk of accidents, while Venkataraman. et al. (2011) and Chen. and Tarko (2014) reported that urban segment present a low risk of accidents. Eustace et al. (2015) found that driver age< 21years and age > 65 years was linked to a reduced number of accidents.

Because the number of accidents on a given road section consists of a nonnegative integer and often infrequent and random, models of Poisson regression and Negative Binomial (NB) are commonly employed. Abdel-Aty and Radwan (2000) reported that road accidents data are dispersed such that the variance is superior the mean ($E[y_i] < VAR[y_i]$). Therefore, biased estimates of parameters are obtained. The NB model is often used to resolve the problem of over-dispersion. Once accidents data are obtained from L_i (1, ..., L) locations for T_i (1,.., T) time-periods, the NB model presumes that there are L_i*T_i independent observations (Naznin et al., 2016). The NB model does not consider the time variant nature in accidents data and thus the estimated standard errors may be underestimated. In order to surpass this constraint, we use longitudinal accidents (panel) data with L_i groups and T_i periods. Panel data models can be Fixed Effect model and Random Effect model that is called a Variance Components model. Fixed Effects models permit the estimation of a large number of parameters Chen. and Tarko (2014). As opposed to Fixed Effects model, Random Effects model is generally widely estimated for repeated accident data (Chen, Ma, & Chen, 2014; Chen. & Tarko, 2014; Chin & Quddus, 2003; Ma et al., 2017; Naznin et al., 2016; Wang. & Abdel-Aty, 2006). We estimate here the Random Effects Negative Binomial (RENB) model and the NB model. (Naznin et al., 2016) identified the RENB model as more appropriate than NB. (Chin & Quddus, 2003) applied RENB model to investigate the relationship between accident occurrence and the characteristics of signalized intersections in Singapore. Wang. and Abdel-Aty (2006) employed the RENB model and spatial and temporal correlation models to investigate rear-end crash frequencies at signalized intersections in Florida. Ma et al. (2017) used RENB model and NB model to predict 50-km long expressway crash frequency in China. Their results clearly indicated that the RENB model surpasses the NB model. Both of the previous research efforts reported that the RENB model is more appropriate for the geometric features and traffic volume variables (Chin & Quddus, 2003; Ma et al., 2017; Naznin et al., 2016). In addition, RENB model can offer some advantages in terms of handling temporal correlation (Lord & Mannering, 2010). Previous studies found that the length of road segments affects the description of the frequency of accidents (Thomas, 1996). The length of each HRL is determined by dangerous distribution of local risk factors, which increase the risk of an accident. In Tunisia, according to a NOITDRS, a HRL is a part of the road having 1000 meters of length and recording 10 serious and fatal accidents during 5 consecutive years (National Observatory of Informatiol, 2010).

In this context, the main objective of this study is to model traffic accidents occurrence at HRL in the region of Sousse, Tunisia, as a function of various explanatory factors linked to the geometric characteristics, roadway characteristics and traffic flow characteristics. For this purpose, we employ the database of an 11-year monitoring period obtained from NOITDSRS. Accidents data were obtained from 52 HRL for an 11-year monitoring period from January 1, 2004 to December 31, 2014. The data used are panel data with L_i locations groups and T_i periods. With this respect, the RENB model is employed in this study, which includes locations as individual random effects to model the relationship between the expected frequency of accidents per year as dependent variable and the covariates. All HRL investigated were mainly located at majors and minors highways including Expressways, National, Regional and Local Highways. Highways data were obtained from the Ministry of Equipment, Housing and Territorial Development in Tunisia (MEHTD). In this research, both non-severe and severe crashes were jointly examined (Qin et al., 2004).

There are three major motivations for justifying this research. Firstly, the necessity to assess the effects on the crash frequency at HRL as a function of various explanatory variables related to the geometric characteristics, roadway characteristics and traffic flow characteristics. Secondly, we want to determine the main significant variables that affect accident frequency at HRL. Thirdly, despite the multitude of research initiatives on the topic of accident frequency modeling, earlier researches did not identify any sort of study dealing with the same aspect of our research. The purpose of this work is to contribute to filling that gap. We are reasonably confident that this kind of analysis presents a helpful guide for the engineers in designing highways in Tunisia.

2. MATERIALS AND METHODS

In order to construct a theoretical model that relates accident frequencies occurred in HRL in Tunisia to its determinant factors, we consider a set of dangerous sections, which have various geometric features and traffic characteristics. The study area centers on the region of Sousse, Tunisia. Located in east of the country, the region of Sousse is bounded by the governorate of Nabeul in North, Kairouan in West and Monastir and Mahdia in South. It covers 2669 Km^2, which represent 1.7 % of total area of the country. Administratively, Sousse is divided into 15 delegations and 16 municipalities. According to 2014 Census, it has a population of 674,971 inhabitants with a density of 253 inhabitants / Km^2.

There were two sets of data used: accidents data and highways data. Accidents data were obtained from the NOITDSRS in Tunisia. Highways data were obtained from MEHTD in Tunisia. The different highways considered here are Local Highways (LH), National Highways (NH), Regional Highways (RH) and Motorway (A1). The Municipal Highways and railways that are shown in grey colors in Figure 1.a are excluded from our analysis. Knowing the geographical location of accidents permits to determine their causal factors. In the region of Sousse, accidents are uniformly and spatially distributed see Figure 1.b.

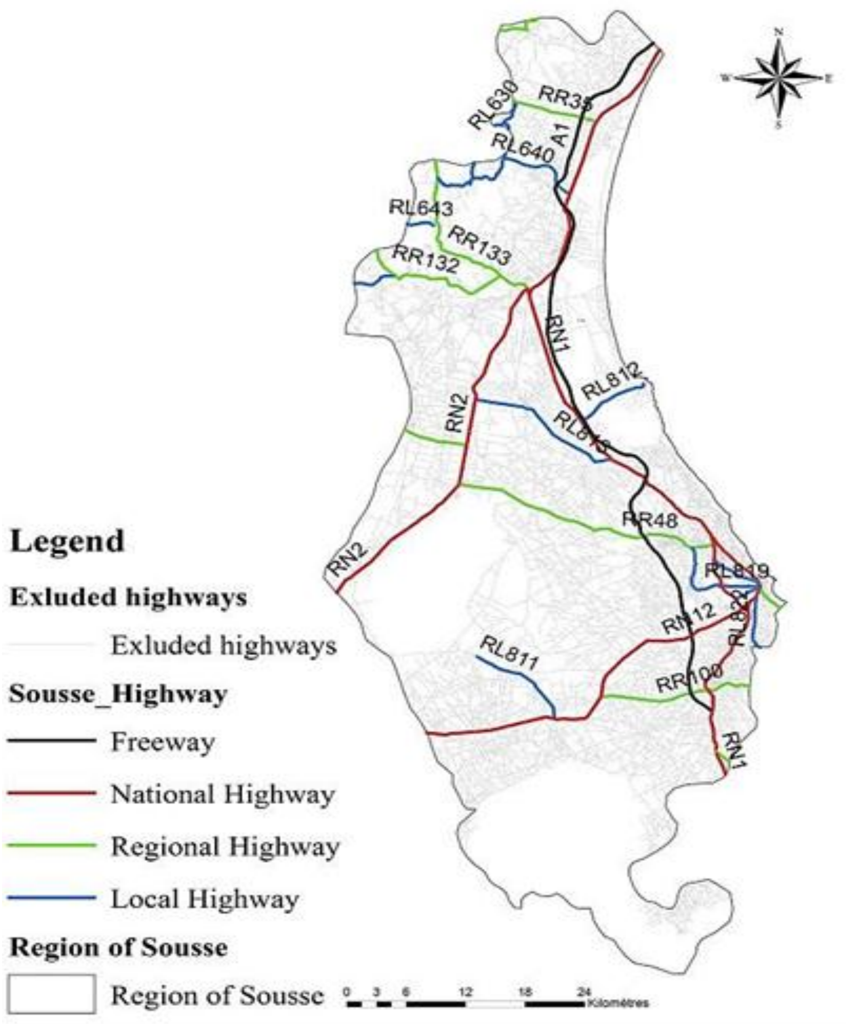

Figure-1(a). Road network in the regions of Sousse.

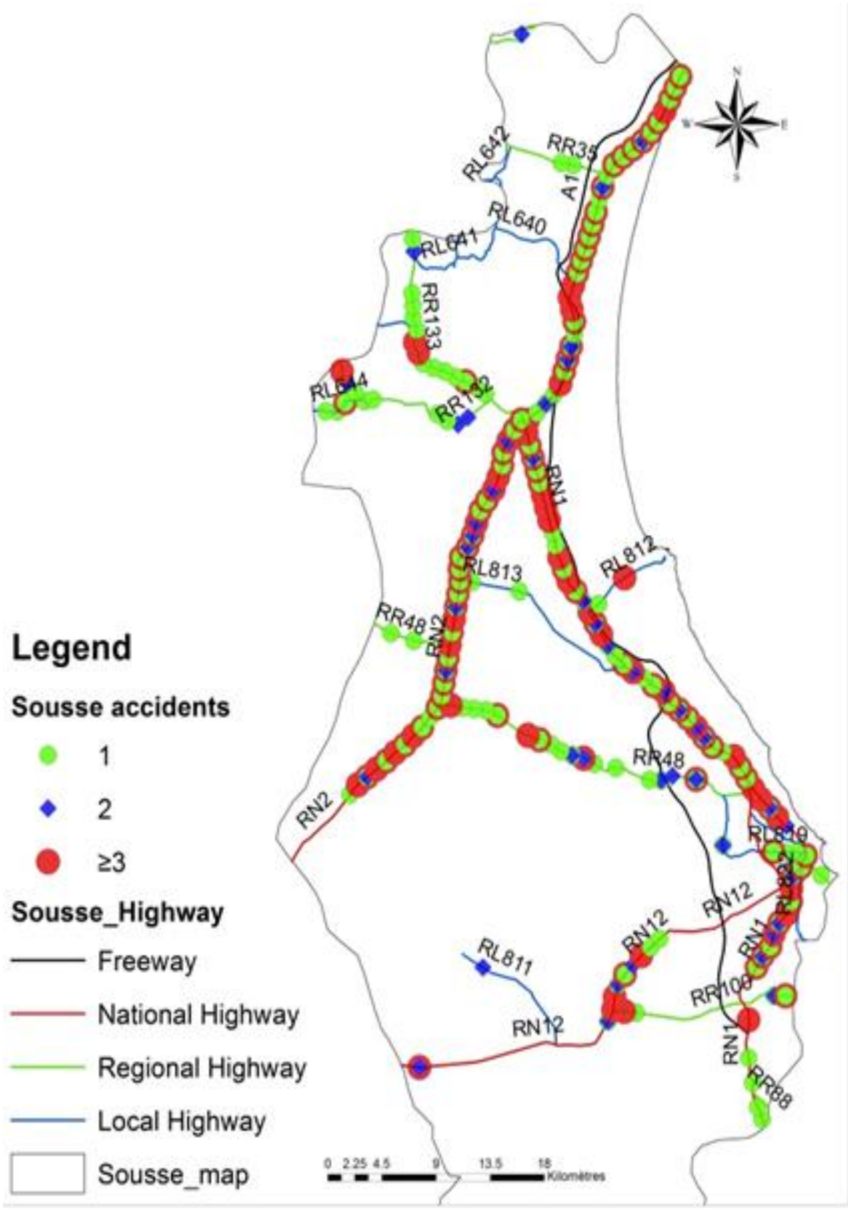

Figure-1(b) Distribution of road traffic accidents in the region of Sousse.

In our case, our proposed prediction model is based on all severe and non-severe accidents (Caliendo et al., 2013). Accidents with only property damage are not considered. Figure 1.b indicated that accidents were concentrated on NH-1, NH12, RH100 and the A1 motorway. Thus, the study of HRL should be based on 1000-meters-long road segments (National Observatory of Informatiol, 2010). Therefore, the links considered were divided into 1000-meters-long fixed segments for which the geometric characteristics, roadway characteristics and traffic flow characteristics were registered. On the other hand, the accidents frequency for each HRL in each year is considered as an observation for the 52 HRL, generating 1397 crash records. There are 10 HRL that are identified in A-1, 25 in NH-1, 12 in NH-12, 2 in NH-2, 2 in RH-100 and 1 in LH-819. Given the complexity of the phenomenon and the need for cooperation between the different actors of road safety, knowledge of the main determinant factors of accident frequency at HRL present advantageous insights on HRL for Tunisian decision makers.

Table 1 reported the various descriptive statistics regarding primary variables used in the modeling process. It is shown that the mean, standard deviation and the maximum of frequency of accidents per year are 2.44, 2.46 and 11, respectively. The mean of curved alignment and number of lane are 0.38 and 0.80 respectively.

Table-1. Descriptive statistics.

Variables description	Mean	Std. Dev.	Min	Max
Frequency of accidents per year	2.44	2.46	0	11
Average Daily Traffic volume (ADTV)	15119.35	7944.79	788	29770
Curved alignment (1 if curved , 0 otherwise)	0.38	0.48	0	1
Presence of public lighting (1 if present; 0 otherwise)	0.3	0.46	0	1
Visibility (1 if clear; 0 otherwise)	0.74	0.43	0	1
Number of lane (1 if 2 lane; 0 otherwise)	0.8	0.39	0	1
Presence of vertical/horizontal sign (1 if present; 0 otherwise)	0.64	0.47	0	1
Urban segment (1 if urban; 0 otherwise)	0.78	0.4	0	1
Drainage system (1 if present; 0 otherwise)	0.56	0.49	0	1
Roadway surface condition (1 if good; 0 otherwise)	0.6	0.48	0	1
Paved shoulder (1 if paved; 0 otherwise)	0.46	0.49	0	1
Presence of major road (1 if present; 0 otherwise)	0.94	0.23	0	1

Many previous researches have used count data models for predicting road traffic accidents. Among these models, there is the Poisson model, which is extensively employed in the literature based on the study of Lord (2006) and successors that consider the NB and zero-inflated models (Anastasopoulos & Mannering, 2009). For the basic Poisson model known as a Log-Linear model, the Poisson distribution gives the likelihood of an event count yi, given the vector of covariates Xi, as follows:

$$P(y_i) = \frac{\exp(-\lambda_i)\lambda_i^{(y_i)}}{y_i!} \qquad (1)$$

Where $P(y_i)$ is the likelihood of HRL *i* having y_i accidents per year, λ_i is the Poisson parameter which is HRL i's expected number of accidents $E[y_i]$ in some predetermined period (Carson & Mannering, 2001). The Poisson regression models the Poisson parameter λ_i as a function of explanatory variables using a log-linear form as follow (Anastasopoulos & Mannering, 2009):

$$\lambda_i = \exp(\beta X_i) \qquad (2)$$

Where β is a vector of parameters that can be estimated by standard maximum likelihood methods and X_i is a vector of explanatory variables describing geometric characteristics, roadway characteristics and other relevant road segment feature that affect accident frequency.

(Lord & Mannering, 2010) reported that in Poisson model, the conditional variance is equal to conditional mean ($E[y_i] = VAR[y_i]$). In the case of non-equality, crash frequency data are under-dispersed ($E[y_i] > VAR[y_i]$) or over-dispersed ($E[y_i] < VAR[y_i]$) (Anastasopoulos & Mannering, 2009). Therefore, biased estimates of parameters are obtained. To overcome the over-dispersion or under-dispersion, we use the NB model.

The NB regression model (based on a Gamma-distributed error term) is a form of count data model. It is derived as follows:

$$\lambda_i = \exp(\beta X_i + \varepsilon_i) \qquad (3)$$

Where $\exp(\varepsilon_i)$ is a Gamma-distributed error term that is assumed uncorrelated with X_i, with mean one and variance α. The addition of this term allows the flexibility of the variance to vary from the mean as (Anastasopoulos & Mannering, 2009):

$$VAR[y_i] = E[y_i]\,[1 + \alpha E[y_i]] = E[y_i] + \alpha E[y_i]^2 \qquad (4)$$

Where $VAR[y_i]$ is the variance of observed collisions y at HRL *i* and $E[y_i]$ is the expected annual collisions frequency at HRL *i*. The Negative Binomial Probability Density Function (NBPDF) has the form:

$$P(y_i)=\frac{\Gamma[(1/\alpha)+y_i]}{\Gamma(1/\alpha)y_i!}\left[\left(\frac{1/\alpha}{1/\alpha+\lambda_i}\right)^{1/\alpha}\right]\left[\left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{1/\alpha}\right] \quad (5)$$

Where $\Gamma[.]$ represents the gamma function.

The Poisson model is a limiting one of the NB model as α (often referred to as the dispersion parameter of the Poisson-gamma distribution) approaches to zero ($i.e., \alpha \rightarrow 0$), the variance equals the mean and the NB collapses to the standard Poisson regression model (Gomes, Geedipally, & Lord, 2012). Thus, if α is different from zero, the NB model is suitable. Therefore, the NB model is more flexible than other models (Washington, Karlaftis, & Mannering, 2003).

For the current study, accidents data were collected at 52 HRL from January 1, 2004 to December 31, 2014, which means that we have panel accidents data (Naznin et al., 2016). We used the RENB model for this research, which includes random location specific effects to estimate the effects of different explanatory factors on expected frequency of accidents per year. RENB model offer advantages in terms of handling temporal correlation (Lord & Mannering, 2010).

Therefore, the RENB model that was estimated is presented by the following equation:

$$\lambda_{it}= \exp\,(\beta X_{it}+ \varepsilon_{it}+ U_i) \quad (6)$$

Where λ_{it} represents the expected frequency of accidents along HRL i in year t, β represents the vector of coefficients, X_{it} represents the explanatory variables for HRL i in year t, ε_{it} is the residual error term for HRL i in year t, U_i indicates the specific random effects across HRL, and $\exp(U_i)$ is a Gamma-distributed term with mean 1 and variance α_i where α_i is also the over-dispersion parameter. In addition $1/(1+\alpha_i)$ is randomly distributed as a beta variable *Beta (r,s)* (Hausman, Hall, & Griliches, 1984). Based on the outcomes of Hausman et al. (1984)+ the RENB density function for the i^{th} HRL can be written as follows (Ma et al., 2017):

$$f(y_{it}|X_{it}) = \frac{\Gamma(r+s)\Gamma(r+\sum_t \lambda_{it})\Gamma(s+\sum_t y_{it})}{\Gamma(r)\Gamma(s)\Gamma(r+s+\sum_t \lambda_{it}+\sum_t y_{it})} \quad (7)$$

With y represents the frequency of accidents along HRL. All parameters r and s, and the coefficient vector β were estimated by maximizing the likelihood function (Ma et al., 2017; Naznin et al., 2016).

In order to check if the model fits better for the data used, we compute the Goodness of fit tests can be conducted to show how well the model fits the data. To assess the overall fit of the model is possible to compare the model's Log-likelihood at convergence LL (β) with the model's Log-likelihood at zero LL (0) which is the model with the constant as the only explanatory variable. In order to check if the model fits better for the data used, we compute ratio index ρ^2, which is defined as following:

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \quad (8)$$

Where LL (β) is Log-likelihood for all the vector coefficients β, and LL (0) is the Log-likelihood for β equal to zero. The ratio ρ^2 takes the values from 0 to 1. When the value of ρ^2 is near 1, the model fits well. In general, when ρ^2 is superior 0.1, the goodness fit of the model is accepted (Ulfarsson, Kim, & Booth, 2010).

After a final model was specified, a comprehensive analysis and interpretation of results were performed. Estimated parameters are considered inadequate to explore the ways in which the independent variables might influence the resulting probability. Accordingly, marginal effect represents the change of the dependent variable because of "one unit" change in an explanatory variable Park, Lee, and Jeon (2016). Park et al. (2016) calculated the marginal effects of explanatory variables calculated by the partial derivative $\partial\lambda_i / \partial x_{ik}$, where λ_i is expressed as in Equation 2, 3, or 6 depending on the model being Considered (Anastasopoulos & Mannering, 2009).

The main hypothesis here is to include a significant variable at the 99%, 95% and 90% level that could improve the goodness fit of the model. The primary concern was to not include a highly correlated variable with another one (Naznin et al., 2016). To do this, a Pearson Correlation Coefficient "*PCC*" was used. It has a value between -1 and +1. The formula for *PCC* is (STATA, 2014).

$$PCC = \frac{\sum_{i=1}^{n} w_i(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} w_i(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n} w_i(y_i - \bar{y})^2}} \tag{9}$$

The variables were considered as highly correlated when PCC was more than ± 0.7 (Mukaka, 2012; Naznin et al., 2016).

3. EMPIRICAL RESULTS AND THEIR DISCUSSION

The different results of estimation are presented and sufficiently discussed. Table 2 reflects the matrix of Pearson correlation value for each independent variable along with their significance value. It is shown that no variable is correlated with other because the absolute values of all correlation coefficients are less than 0.7 (Naznin et al., 2016).

Table-2. Estimates of Pearson's correlation coefficients.

Variables	AADT	CURV	PPLH	VISB	NBLA	PVHSG	PUSEG	PDSYS	RSCOD	PAVSH	PMAJ
AADT	1	0.135 [a]	-0.546 [a]	0.460 [a]	0.432 [a]	-0.148 [a]	-0.272 [a]	-0.082 [b]	-0.286 [a]	-0.372 [a]	-0.021
CURV	0.135[a]	1	0.10 [c]	0.067	0.385 [a]	0.086 [b]	-0.171 [a]	-0.419 [a]	-0.535 [a]	0.531 [a]	0.533 [b]
PPLH	-0.546 [a]	0.10 [c]	1	0.150 [a]	0.115 [a]	0.087 [b]	0.207 [a]	-0.370 [a]	-0.346 [a]	0.053	0.165 [a]
VISB	0.460 [a]	0.067	0.150 [a]	1	0.664 [a]	-0.288 [a]	-0.225 [a]	-0.218 [a]	-0.447 [a]	-0.601 [a]	0.024
NBLA	0.432 [a]	0.385 [a]	0.115 [a]	0.664 [a]	1	-0.363 [a]	-0.252 [a]	-0.429 [a]	-0.391 [a]	-0.525 [a]	-0.120 [a]
PVHSIG	-0.148 [a]	0.086 [b]	0.087 [b]	-0.288 [a]	-0.363 [a]	1.0	0.177 [a]	-0.038 [a]	-0.073 [c]	0.267 [a]	-0.027
PRSEG	0.272 [a]	-0.171 [a]	0.207 [a]	-0.225 [a]	-0.252 [a]	0.177 [a]	1	-0.266 [a]	-0.029	0.197 [a]	0.073 [c]
PDSYS	-0.082 [b]	-0.419 [a]	-0.370 [a]	-0.218 [a]	-0.429 [a]	-0.038 [a]	-0.266 [a]	1.0	0.304 [a]	0.133 [a]	-0.218 [a]
RSCOD	-0.286 [a]	-0.535 [a]	-0.346 [a]	-0.447 [a]	-0.391 [a]	-0.073 [c]	-0.029	0.304 [a]	1	0.242 [a]	0.078 [c]
PAVSH	-0.372 [a]	0.531 [a]	0.053	-0.601 [a]	-0.525 [a]	0.267 [a]	0.197 [a]	0.133 [a]	0.242 [a]	1	-0.266 [a]
PMAJ	-0.021	0.533 [b]	0.165 [a]	0.024	-0.120 [a]	-0.027	0.073 [c]	-0.218 [a]	0.078 [c]	-0.266 [a]	1.0

Note: **AADT** refers to Average Daily Traffic volume, **CURV** refers to curved alignment, **PPLH** refers to the presence of public lighting, **VISIB** refers to visibility, **NBLA** refers to number of lane, **PVHSG** refers to the presence of vertical/Horizontal sign, **PUSEG** refers to the presence of urban segment, **PDSYS** refers to the presence of Drainage system, **RSCOD** refers to road surface condition, **PAVSH** refers to the presence of paved shoulder**, PMAJ** refers to the presence of major roads.
[a] It indicates significance at the 1% level.
[b] It indicates significance at the 5% level.
[c] It indicates significance at the 10% level.

Estimated results for both RENB and NB models and the estimated marginal effects are reported in Table 3 and Table 4, respectively. Estimated coefficients presented in Table 3 indicate the impacts of variables on the frequency of road traffic accidents at HRL. It is indicated that twelve variables were statistically significant including the constant term at the 1% level, 5% level or 10% level by which the signs of their coefficients were either positive or negative based on the impact of each variable. Standard errors of the coefficients were shown in parentheses. The variables that were insignificant are the presence of straight alignment, lane width, posted speed limits, the presence of road bump, the presence of parking area and the presence of guardrail. The dispersion parameter α determined from the NB model appeared to be significant (0.589), which suggests that the NB model was adequate and it was more suitable than the Poisson model. In addition, the beta-distributed $1/(1+\alpha_i)$ had the values of (r =19.401) and (s =21.660). The overall value of LL (β) for RENB model was equal to (−870.21), which confirmed relatively better improvement than the NB model where its LL (β) was equal to (-933, 46). With respect to goodness of fit value, ρ^2 improves from 0.106 in NB model to 0.189 in RENB model.

The estimation results of RENB model are presented and discussed below. The outcomes indicated that Average Annual Daily Traffic Volume (AADTV) causes the increase in the frequency of accidents at HRL (β=0.474). Its positive coefficient implies that the frequency of collisions at HRL increases due to the increase of the Average Annual Daily Traffic Volume. It is well known that traffic volume and congestion could lead to the increase in the number of accidents. The marginal effects estimates showed that when AADTV increased by one unit the crash frequency would increase by 0.474.

Table-3. Estimation results of RENB and NB models.

Variables description	**Negative binomial parameter estimates**					
	RENB model			**NB model**		
	Coefficient	**Standard error**	**t-statistics**	**Coefficient**	**Standard error**	**t-statistics**
Constant	3.401	1.04	3.27***	0.302	0.108	2.79***
Average Annual Daily Traffic volume (AADT)	0.474	0.095	4.96***	0.459	0.095	4.79***
Curved alignment (1 if curved , 0 otherwise)	0.17	0.038	4.43***	0.19	0.039	4.87***
Presence of public lighting (1 if present; 0 otherwise)	0.201	0.060	3.34***	0.205	0.060	3.41***
Visibility (1 if clear; 0 otherwise)	0.2	0.105	1.89*	0.192	0.097	1.98**
Number of lane (1 if 2 lane; 0 otherwise)	-0.441	0.192	-2.29**	-0.521	0.211	-2.47**
Presence of vertical/Horizontal sign (1 if present; 0 otherwise)	-0.206	0.102	-2.02**	-0.167	0.088	-1.89*
Urban segment (1 if Urban; 0 otherwise)	-0.045	0.027	-1.68*	-0.046	0.027	-1.72*
Drainage system (1 if present; 0 otherwise)	-0.484	0.202	-2.39**	-0.507	0.217	-2.33**
Roadway surface condition (1 if good; 0 otherwise)	-0.154	0.058	-2.62***	-0.161	0.058	-2.75***
Paved shoulder (1 if paved; 0 otherwise)	0.557	0.209	2.66***	0.645	0.193	3.33***
Presence of major road (1 if present; 0 otherwise)	0.201	0.060	3.34***	0.207	0.060	3.43***
Dispersion parameter for negative binomial distribution (α)				0.589	0.063	
Parameter r[1]	19,401	7.121				
Parameter s[1]	21.660	8.612				
Number of observations	572			572		
Log-likelihood with constant only LL(0)	-1309.781			-1309.781		
Log-likelihood at convergence LL(β)	-1061.143			-1170.199		
$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}$	0.189			0.106		
Likelihood-ratio test vs. pooled: chibar2 = 16.78: Prob > = 0.000						

Note: Statistical significance of the parameters is indicated as follows: *** It indicates significance at 1% ; ** It indicates significance at 5% ; * It indicates significance at 10% 1 Inverse of one plus the dispersion is assumed to follow a Beta(r, s) distribution in the Random Effects Negative Binomial model (Naznin et al., 2016; STATA, 2014).

The presence curved alignment (1 if curved, 0 otherwise) has a positive parameter (β=0.17), where a unit increase of curved alignment along the HRL for the RENB model results in a 0.189 increase in the annual average of number of accidents. The average marginal effect for the NB model implies that the number of accidents increased by 0.421. Our findings are conform to previous results (Abdel-Aty & Radwan, 2000; Agbelie, 2016a; Anastasopoulos, 2016; Kumara & Chin, 2003; Venkataraman et al., 2013; Venkataraman. et al., 2011).

They are the results of the lack of visibility on curved alignment compared to the straight alignment, which offers a greater visibility and a better judgment capacity of the driving speed. Contrariwise, Carson and Mannering (2001); Lee and Mannering (2002); Chang (2005); Malyshkina et al. (2009) and Anastasopoulos and Mannering (2009) reported a decreased risk of accidents under curved roads. Drivers always tend to drive with higher speeds on the long stretches of straight sections, which increase the risk of an accident. In addition, driving in straight sections has a psychological effect on drivers and promotes a feeling of routine driving.

Table-4. Marginal effects of RENB and NB models.

Variables Description	Marginal effect of RENB model	Marginal effect of NB model
Average Daily Traffic volume (ADTV)	0.474	1.018
Curved alignment (1 if curved , 0 otherwise)	0.189	0.421
Presence of public lighting (1 if present; 0 otherwise)	0.181	0.473
Number of lane (1 if 2 lane; 0 otherwise)	-0.561	-1.37
Presence of vertical/Horizontal sign (1 if present; 0 otherwise)	-0.296	-0.397
Urban segment (1 if Urban; 0 otherwise)	-0.012	-0.103
Drainage system (1 if present; 0 otherwise)	-0.637	-1.342
Visibility (1 if clear; 0 otherwise)	0.294	0.447
Paved shoulder (1 if paved; 0 otherwise)	0.036	1.633
Roadway surface condition (1 if good; 0 otherwise)	-0.042	-0.362
Presence of major road (1 if present; 0 otherwise)	0.052	0.46

The presence of public lighting has a positive parameter (β=0.17), where a unit increase of public lighting along the HRL for the RENB induced a 0.181 increase in the annual average of number of accidents. The average marginal effect for the NB model indicates a 0.473 increase in the number of accidents. The presence of clear visibility has a positive coefficient indicating that a unit increase of clear visibility for the RENB model induced a 0.294 increase in the annual average of number of collisions. This result could be induced by the influence of increased speed when the visibility of roads is clear. This finding is unexpected. Contrariwise, Janoff, Koth, McCunney, Berkovitz, and Freedman (1978) reported that the visibility has a negative impact on the number of accidents. When the road visibility is clear, the number of accidents decreases.

The number of lane (1 if 2 lane, 0 otherwise) has a negative coefficient indicating that an increase of one unit in the number of lane for the RENB model caused a 0.561 decrease in the average annual number of collisions. A unit increase of number of lane for the NB model induced a 1.370 decrease in the average annual number of collisions. Major roads are characterized by a speed limit of 110 km/h, a number of lanes generally greater than four lanes which, increasing thus the risk of road accidents. However, Lord (2006) have shown that by increasing the number of lanes could reduce the effect of the congestion, decreasing thus the risk of accidents.

The empirical results also reported that the Presence of vertical/Horizontal sign were found negatively correlated with crash frequency at HRL (β= -0.206). Marginal effects showed that when the presence of vertical/horizontal sign increased by one unit, the crash frequency would decrease by 0.296. These findings are conform to those obtained by the previous studies that investigated the impact of road signs on crash frequency (Agbelie, 2016b; Chin & Quddus, 2003; Gomes et al., 2012; Mitra & Washington, 2012). For most high road lines, increasing the number of road signs reduces the frequency of collisions, because drivers are likely to compensate for increased number of stops along the route by reducing speed and increasing the alert when approaching an intersection with a stop (Agbelie, 2016b).

The results also showed that HRL located in an urban area has a lower crash frequency than a HRL located in rural area. These results are consistent with previous studies (Agbelie, 2016a; Bullough et al., 2013; Carson & Mannering, 2001). However, various authors claimed the opposite (Chen. & Tarko, 2014; Venkataraman. et al., 2011; Wang. & Abdel-Aty, 2006; Yan, Wang, An, & Zhang, 2012). This may be due to a longer emergency response time and a long distance between accident sites in rural areas (Yan et al., 2012). More other findings were presented by Ouni. and Belloumi (2018); (Ouni.. & Belloumi, 2019) and Belloumi and Ouni (2019).

Roadway drainage is the process of eliminating and maintaining excess surface water within the best way. Drainage quality is an important parameter that influences the highway pavement performance. In our case, the presence of drainage system contribute to decrease the frequency of accidents at HRL (β= -0.484). Its average marginal effect is equal to −0.637. This finding likely reflects that absence of drainage systems can cause premature deterioration of the highway, increasing thus the risk of road accidents.

The road surface condition is another class of genes leading to traffic accidents in Tunisia. Its negative coefficient implied that the frequency of collisions at HRL decreased with the good surface condition. Marginal effects showed that when the presence of good surface condition increased by one unit the crash frequency would decrease by 0.042. These findings were consistent with previous studies (Bullough et al., 2013; Eustace et al., 2015; Malyshkina et al., 2009). Bad surface condition is one of the major causes of road accidents outside built-up areas. This suggests that unforeseen changes in the road surface condition may be particularly dangerous if drivers are unable to adjust their speed to an appropriate level. The public authorities also have a significant share of responsibility for the safety of our roads.

The presence of paved shoulder (1 if present, 0 otherwise) has a positive effect. For example, a one-unit increase of paved shoulder along the HRL for the RENB model induced an increase of 0.036 in the annual average of number of collisions. A unit increase of paved shoulder along the HRL for the NB model results in a 1.633 increase in the average annual number of collisions. This result showed that the presence of paved shoulder induced an increase in pedestrian movements, increasing thus the risk of road accidents. A road without paved shoulder offers parking benefits, as parked cars occupy a part of the roadway and reduce its width reserved for traffic, which may force drivers to slow down their speed. Nevertheless, Bullough et al. (2013) reported a decreased risk of accidents at paved shoulder as it offers a safer zone for vulnerable users. In addition, roads without paved shoulder are mainly located in rural areas, which are generally characterized by low traffic volume.

Regional effects such as the presence of HRL at major roads were found positively correlated with crash frequency (β=0.201). Our findings are conform to those found by Wang et al. (2011); Gomes et al. (2012); Chen. and Tarko (2014) that reported an increased risk of collisions at motorways and major roads. This risk can be justified by the intensive use of different means of transport within the same infrastructure (two wheels, special cars, Heavy trucks, etc.). Marginal effects showed that the presence of major roads induced in average an increase of 0.052 in the number of accidents at HRL.

4. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Through this section, some summary is presented in relation to results and discussion followed by a brief discussion concerning future research directions**.** The main aim of this work was to estimate the RENB and NB models for HRL in the region of Sousse, Tunisia, in order to determine the effects of some factors related to the geometric, roadway and traffic flow features on the expected number of accidents per year using data collected at 52 sections. Despite the multitude of number of studies on the topic of accident frequency modeling, earlier researches did not identify any sort of study dealing with the same aspect of our research. The RENB model was proven to provide superior likelihood compared to NB model. The overall log-likelihood at convergence for RENB confirmed relatively better improvement than the NB model. With respect to goodness of fit value, ρ^2 improves from 0.18 in

NB model to 0.23 in the RENB. The empirical results are of great interest. Our findings showed that that the variables representing the presence of vertical/horizontal sign, presence of public lighting, AADTV, curved alignment, presence of major road, visibility, number of lane, presence of drainage system, roadway surface condition, presence of rural segment, and presence of paved shoulder were the main significant determinants of the number of accidents in the region of Sousse. Therefore, deciders in the transport sector should implement effective measures to improve road safety by adopting proper sound use practices, establishing efficient transportation systems and formulating appropriate traffic policies and legislation.

There are several potentials to carry out further research in this area. For potential researches, it will be interesting to look at the possible applications of RENB model in other traffic safety fields. Moreover, this study mainly focused on accidents frequency at HRL. It can be extended more deeply to future research directions by exploring crash factors that affect injury severity along HRL. In our case, the RENB model was proven to yield better likelihood compared to NB model, the adequacy of other sorts of statistical models to the data collected in this study should be examined, as a way to test better fittings.

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