Investigation of road accident severity

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The objective of this study is to investigate road accident severity and likelihood in urban areas by analyzing real-time traffic data. In order to achieve the objective of the study, road accident data from a main road axis in Athens, Greece, were collected for the period 2006-2010. Subsequently, traffic data measured real-time were obtained from the Traffic Management Centre of Athens. For that purpose, logistic regression models were developed. Results suggest that road accident severity is influenced by the logarithm of traffic density, the type of vehicle and the type of accident. When data are separated in two groups of peak and off-peak hour accidents, the parameter of traffic density is the only one appearing to be statistically significant. Furthermore, traffic volume is the only parameter having a statistically significant impact on accident likelihood.

INTRODUCTION AND BACKGROUND

Road safety is gaining more attention as transportation activities increase throughout the years and despite efforts, road accidents are still a major contemporary societal problem. The level of complexity in road safety, raises the need for a better understanding of the numerous factors that influence road accident occurrence. Traffic parameters such as flow and speed have gained considerable attention of researchers so far. Recently, the incorporation of real-time traffic data, collected by loop detectors prior to an accident, provided more consistent results and shed some light on predicting crash likelihood and severity on freeways in order to develop proactive safety management and real-time assessment.

The impact of traffic flow on safety is not straightforward and the literature has showed contradictory results. Some researchers proposed linear relationships (Belmont and Forbes, 1953) while others proposed a U-shaped relationship (Leutzbach, 1966; Gwynn, 1967). Power functions were also proposed (Ceder and Livneh, 1978). Dickerson et al. (2000) argues that high accident externalities are associated with high traffic flows, while these externalities appear to be almost zero in light traffic conditions.

Density and occupancy have not been adequately investigated yet. Only a few studies have been found to examine occupancy and accidents (Garber and Subramanyan, 2002). This study suggests that a non-linear relationship (U-shaped) exists. Ivan et al. (2000), estimated Poisson regression models for single and multi-vehicle highway crash rates. The natural logarithm of the segment volume to capacity ratio (which reflects density) was found to have a negative relationship with single-vehicle crash rates, but to be insignificant for multi-vehicle crashes.

Speed is a very important factor in road safety. Theoretically speaking, high speeds result in more severe accidents since the momentum and the kinetic energy increase. Moreover, high speeds make vehicles' maneuvers more difficult and it is harder for drivers to compensate for errors. Literature indicates that increased speeds are associated with high accident occurrence and severity (Nilson, 2004; Elvik et al., 2004). Taylor et al., (2002), showed that a 10% increase in the mean speed may result in a 30% increase in fatal and severe accidents. Aarts and van Schagen (2006), stated that speed and crash rates are found to be related with an exponential or a power function. On the other hand, Baruya (1998), argued that it is not straightforward to deploy a speed-accidents relationship because of the fact that other factors may be present and these factors may affect speed distribution parameters and accidents.

Predicting accident likelihood on freeways by using real-time traffic data has been extensively explored. Ahmed et al. (2012), imply that increased speed variation at any crash segment combined with a decrease in average speed in the respective downstream segment, may be associated with increased likelihood of rear-end crashes. Ahmed and Abdel-Aty (2012), found that the probability of a crash increases when speed variation rises whilst the average speed decreases at the segment of the crash at 5–10 min before (prior to the crash occurrence). However, Kockelman and Ma (2007), found no connection between 30-sec speed changes and accident likelihood.

Martin (2002), examined the relationship between traffic and severity and observed that property-damage accidents as well as injury accidents are maximized when traffic volumes are under 400 vehicles per hour. Milton et al. (2008), argue that it may not be appropriate to assume that the effect of traffic on accident severity to be uniform across geographic locations. Other studies shown that congestion has little or no impact on accident severity (Noland and Quddus, 2005; Quddus et al., 2010). Wang et al., 2013 concluded that increased traffic congestion is associated with more killed and severely injured accidents but has little impact on slight injury accidents. The investigation of accident severity by using real-time traffic data is limited as well. Christoforou et al. (2010), found that the high average traffic volume (measured per lane and over 6 minutes in vehicles) results in less severe accidents. Moreover, average speed under very high traffic conditions (>1120 vehicles/lane/hour) was found to increase severity. Golob et al. (2008), found that traffic conditions had little impact on accident severity. Recently, Yu and Abdel-Aty (2013b), applied Bayesian probit models and found that large variation of speed and low visibility prior

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to an accident increase accident severity.

It is worth noticing that that the large majority of studies investigate the effect of traffic parameters only on freeways and interurban roads. Consequently, there is a lack of studies examining the influence of real-time traffic data on accidents in urban areas.

The objective of this study is two-fold:

a) first, to investigate the factors influencing road accident severity in three regimes: overall, at peak, at off-peak and

b) secondly, to investigate road accident likelihood by using traffic data measured real-time as well as other predictors.

DATA AND METHODOLOGY

Data Collection and Preparation

The study area was a major urban arterial in Athens, namely the Kifisias Avenue which connects the centre of the city with the northern suburbs. In this study two data sets were used.

The first database consists of 5-years of accident data in Kifisias avenue from 2006 to 2010, provided by the Department of Transportation Planning and Engineering of the National Technical University of Athens. A total of 235 accidents with information about the time and position of occurrence were considered. Other related variables such as vehicle type, collision type, weather, lighting conditions were considered as well.

The second database consists of real-time traffic data (flow, speed and occupancy) recorded on 90 second intervals and then aggregated on 5 minute intervals from loop detectors in Kifisias avenue obtained from the Traffic Management Centre of Athens, which operates on a daily basis from July 2004 covering various major arterials in the city of Athens. For each 5-minutes period, a series of flow (veh/h), occupancy (%) and speed (km/h) measurements are provided. Each accident was assigned to the nearest loop detector. This study follows a more macroscopic approach in order to acquire a more wide knowledge of the traffic states at the time of the accident. For that reason, traffic parameters were aggregated to obtain averages for three specific hours: the hour of the accident (Dtacc), 1 hour before the accident (Dtacc-1) and 1 hour after the accident (Dtacc+1). Then the average of these 3 hours was produced.

Regarding severity, the unit of analysis adopted was any person (drivers, passengers or pedestrians) involved in the accident resulting in at least slight injuries. The severity levels considered were SI (slightly injured) and KSI (killed and severely injured). Each observation in the dataset is a record of the level of injury sustained by each vehicle occupant involved in the accident resulting in 301 injured occupants. The database was further split in two subsets. The first concerns the peak period and the second off-peak period. More specifically, accidents which occurred between 7-10am and 3-7pm were classified as peak, while the rest as off–peak. From 301 injured occupants, 123 were injured in peak, while 178 were injured off-peak.

In order to predict accident likelihood, some random non-accident cases were extracted. This methodology is very common in literature as having been followed by many researchers (Abdel-Aty and Pande, 2005; Abdel-Aty et al., 2007; Ahmed and Abdel-Aty, 2012; Yu and Abdel-Aty, 2013a). This study extracted non-crash cases according to the following methodology: A peak and an off-peak period are defined, 7:00-9:00 and 19:00-21:00 respectively. If an accident has occurred outside these two time slices, then traffic data are extracted for these two time slices for the same day and place. If an accident has occurred in any of these time slices, then traffic data only for the other time slice are extracted. For example, if an accident happens on Wednesday 12 August 2009 at 13:00 and is recorded from loop detector MS259, traffic data for the same day for 7:00-9:00 and 19:00-21:00 are going to be extracted from loop detector MS259. If that accident had happened at 19:00, traffic data would have been extracted only for the period 7:00-9:00. Following this approach, 406 non-accident cases were selected.

To the best of our knowledge, this is the first time that accident severity and likelihood are explored with real-time traffic data from urban areas, as in international literature only freeways and urban expressways have been considered yet. The considered independent variables are illustrated in Table 1.

Table 1: List of independent variables

Variable	Abbreviation	Description
traffic volume	Q	continuous in veh/h
mean speed	V	continuous in km/h
occupancy	O	continuous in %
lighting conditions	LightCond	0=bad lighting conditions, 1=good lighting conditions, 2=unknown
weather	WeatherCond	0=adverse weather, 1=good weather
accident type	AggrAccType	0=with pedestrian, 1=other, 2=run-off-road, 3=rear-end, 4=with fixed object, 5=sideswipe, 6=side
vehicle type	AggrTypeVA	0=car, 1=uknown vehicle, 2=moped/motorcycle, 3=truck/bus
number of lanes	LaneNo	continuous
time of day	TimeOfDay	0=night/dusk, 1=day
age of driver	AgeDriverVA	continuous in years
gender of driver	Gender DriverVA	0=female, 1=male
travel direction	AccDir	0=from the centre, 1=to the centre

Table 2: Summary statistics for continuous variables

Variable	Minimum	Maximum	Mean	Standard Deviation
age of driver	0	86	33.70	15.54
occupancy	0.71	50.39	16.11	10.74
traffic flow	85.81	4091.50	1994.54	860.56
mean speed	15.00	77.88	47.74	16.49
number of lanes	2	5	2.94	0.43

Table 3: Summary statistics for discrete variables

Variable		Frequency	Percentage %
travel direction	from the centre	92	30.56
	to the centre	209	69.44
gender	male	255	10.30
	female	31	89.70
time of day	night/dusk	115	38.21
	day	186	61.79
weather	adverse	22	7.31
	good	279	92.69
accident type	with pedestrian	85	28.24
	other	12	3.99
	run-off-road	19	6.31
	rear-end	76	25.25
	with fixed object	32	10.63
	sideswipe	52	17.28
	side	25	8.31
vehicle type	car	190	63.12
	unknown	5	1.66
	moped/motorcycle	100	33.22
	truck/bus	6	1.99
lighting conditions	bad	15	5.00
	good	87	28.90
	unknown	199	66.10

Table 2 and Table 3 provide basic summary statistics for the 301 records of injured persons in the database.

Analysis Method

In order to explore accident severity and likelihood four separate binary logit models are developed. One for exploring severity, two separate models for severity at peak and off-peak periods respectively and one model for predicting accident likelihood.

We search for the best fitting model which describes the linear relationship between a binary (dichotomous) dependent variable and a number of explanatory variables.

If the 'utility function' is $U = \beta o + \beta i^* Xi$ (Eq. 1)

then the probability P is: $P = e^U/(e^U + 1)$ (Eq. 2)

The goodness-of-fit of the model can be assessed with the likelihood ratio test. The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (Lf) over the maximized value of the likelihood function for the simpler model (L0). The likelihood-ratio test statistic equals:

$$-2\log(L_o/L_f) = -2\,[\log(L_o) - \log(L_f)] = -2\,(L_o - L_f) \qquad \text{(Eq. 3)}$$

The backward LR (log-likelihood ratio) method was selected, which is a straightforward method, according to which the all independent variables are put in the initial model and one by one is eliminated provided that the change in the -2Log¬likelihood is not significant for 1 degree of freedom at 95%.

Another indicator of the goodness of fit of the model is the Hosmer-Lemeshow statistic test (Hosmer and Lemeshow, 1980). In Hosmer-Lemeshow test, a non¬significant value in the chi square suggests a good fit.

The following criteria were used to determine the variables' importance in the model:

a) If the Wald ratio is higher than approximately 1.7, then the variable is significant ($P < 0.05$).

b) If a variable is added and the change in –2Log-likelihood is higher than 3.84, then the variable is significant at a 95% level of confidence (1 degree of freedom for each variable). c) If a variable is removed and the change in –2Log-likelihood is higher than 3.84, then the variable is significant at a 95% level of confidence.

In order to estimate the relative influence of each independent variable, the elasticity was used. In logistic regression models, point elasticities may be estimated for the continuous variables as follows (Washington et al. 2003):

$$E^{P(i)}_{x_{ink}} = \frac{P_n(i)}{x_{ink}}\frac{x_{ink}}{P_n(i)} = \frac{\ln P_n(i)}{\ln x_{ink}} = [1 - \sum_{i=1}^{I} P_n(i)]\, x_{ink}\beta_k \qquad \text{(Eq. 4)}$$

Where P(i) is the probability of alternative (i) and x_{ink} the value of variable (k) for alternative (i) of individual (n) and I the number of alternatives including x_{ink}.

In logistic regression models, pseudo-elasticities may be calculated for the discrete variables (Shankar & Mannering, 1996) and they reflect the change in the estimated probability resulting from the transition to one discrete value of a variable to another. The next formula shows how they can be estimated for binary variables (Ulfarsson & Mannering, 2004):

$$E^{P(i)}_{x_{ink}} = e^{\beta_k}\frac{\sum_{i=1}^{I} e^{\beta'_i x_n}}{\sum_{i=1}^{I} e^{\Delta(\beta'_i x_n)}} - 1 \qquad \text{(Eq. 5)}$$

I is the number of possible outcomes, $\Delta(\beta' x_n)$ is the value of the function determining the outcome when xnk has changed from 0 to 1, while $\beta' x_n$ is the related value when xnk is 0, and ik is the parameter estimate of xnk.

The above disaggregate elasticities are estimated for each observation (i) of each individual (n) in the sample. In order to calculate the aggregate elasticity for logistic regression models, the following formula is applied (Ben-Akiva and Lerman, 1985):

$$E^{P(i)}_{x_{ink}} = e^{\beta_k}\frac{\sum_{i=1}^{I} e^{\beta'_i x_n}}{\sum_{i=1}^{I} e^{\Delta(\beta'_i x_n)}} - 1 \qquad \text{(Eq. 5)}$$

RESULTS

Accident Severity

The results of the binary logistic regression showed that accident severity is influenced by traffic volume, mean speed, accident type and vehicle type. The Hosmer and Lemeshow value was insignificant ($p=0.069>0.05$). The summary of the model is illustrated in Table 3a.

The logarithm of the volume to speed (Q/V) has a negative coefficient, meaning that an increase in this ratio results in a lower severity level. By analyzing the logarithm of this ratio, the model shows that the combined effect is a positive relationship between speed and severity and a negative relationship between traffic volume and severity. In simple words, increased speed results in more severe accidents while increased traffic volume in less severe accidents.

The vehicle type is statistically significant with negative sign for the PTWs (moped and motorcycles), implying that mopeds and motorcycles are involved in less severe accidents than cars (which is the reference level), while other categories were found to be insignificant. More specifically, cars are almost 5 times likely to be involved in severe accidents than PTWs. This may seem counterintuitive, but it seems that most accidents in Kifisias avenue that involve PTWs are not severe. This finding was attributed to the fact that 97 from 100 PTWs accidents were not severe. Another explanation could be the fact that an ambulance may be called even if there are no injuries. Consequently, the number of accidents with slight injures may be slightly over reported.

The last significant variable was found to be the accident type. The negative signs of the coefficients of rear-end and run-off road crashes, show that these types of accidents lead to reduced severity levels. On the other hand, collisions with pedestrians and other type of accidents lead to increased severity.

Variable	Estimated Coefficient	Standard error	Wald	Odds ratio
log(Q/V)	-0.510	0.207	6.071	0.680
car*	-	-	-	-
unknown	n.s.	-	-	-
moped/motorcycle	-1.525	0.562	7.357	0.218
truck/bus	n.s.	-	-	-
with pedestrian*	-	-	-	-
other	n.s.	-	-	-
run-off-road	-2.056	1.055	3.802	0.128
rear-end	-1.751	0.590	8.801	0.174
with fixed object	n.s.	-	-	-
sideswipe	n.s.	-	-	-
side	n.s.	-	-	-

LL(f)=152.895

n.s.=non-significant at 95% level

*=reference category

Table 3a: Summary of the logistic model for accident severity

Table 4: Estimated elasticities for the severity model

Variable	Estimated coefficient	Relative elasticity	
		ei	ei*
log(Q/V)	-0.510	-0.556	-1.000
moped/motorcycle	-1.525	-0.718	-1.291
run-off-road	-2.056	-0.829	-1.490
rear-end	-1.751	-0.771	-1.387

Table 5: Summary of the peak model

Variable	Estimated Coefficient	Standard error	Wald	Odds ratio
log(Q/V)	-1.309	0.184	50.656	0.270
LL(f)=80,666				
n.s.=non-significant at 95% level				
*=reference category				

Table 6: Summary of the off-peak model

Variable	Estimated Coefficient	Standard error	Wald	Odds ratio
log(Q/V)	-1.454	0.184	50.656	0.234
LL(f)=116,073				
n.s.=non-significant at 95% level				
*=reference category				

The elasticity analysis of the model showed that rear-end and run-off road collisions have the greatest effect in the model, followed by moped/motorcycle and by the logarithm of volume to speed ratio. For example, run-off-road crashes reduce severity 1.5 times more than the logarithm of volume to speed ratio.

Tables 5 and 6 present peak and off-peak models respectively. All models had non¬significant Hosmer and Lemeshow chi-squares indicating statistical fit. As it can be observed, the only statistically significant variable was the logarithm of volume to speed ratio, having the same negative effect and having very similar value in the coefficient as well. Results indicate that there is no significant variation of the effect of traffic flow on accident severity between peak and off-peak periods of day.

Accident Likelihood

Since the traffic variables of the first accident likelihood models were not found to be significant and also in order to improve statistical fit and prediction, the traffic volume was transformed to a discrete variable. It was attempted to capture any potential non-linear effects of traffic flow on accident likelihood. Table 7 shows the basic summary statistics of the new traffic volume variable (coded as Qcat).

Table 8 shows the results of the accident likelihood model. The Hosmer and Lemeshow test was non-significant in this model as well ensuring the statistical fit.

The model predicted correct 47.4% of accident cases and 71.7% of the non-accident cases. Overall, the model predicted 62.8% of the cases.

Table 7: Summary statistics of traffic volume as a discrete variable

Variable	Categories	Frequency	Percentage %
Qcat	0-100	50	7.81
	1001-2000	176	27.50
	2001-3000	290	45.31
	>3000	124	19.38

Table 8: Summary of the accident likelihood model

Variable	Estimated Coefficient	Standard error	Wald	Odds ratio
Qcat(0)*	-	-	-	-
Qcat(1)	0.897	0.344	6.812	2.452
Qcat(2)	0.749	0.246	9.232	2.115
Qcat(3)	n.s.	-	-	-
Constant	-0.817	0.195	17.581	0.442
LL(f)=152,895				
n.s.=non-significant at 95% level				
*=reference category				

In contrast to the previous models, a constant is included in the final model. The only statistically significant variable in the model is traffic flow having a non-linear effect. More specifically, Qcat(1) and Qcat(2) (reflecting flow categories of <1000veh/h and 1001-2000veh/h respectively) have positive signs, indicating higher probability of accident occurrence compared to the reference category (>3000veh/h). More specifically, these two categories are 2.452 and 2.115 times more likely to result in an accident than the reference category, while flow values between 2001veh/h and 3000veh/h do not statistically differ from the reference category.

Taking into account the results of the accident likelihood model, it can be concluded that below 500veh/h, any increase in the traffic flow leads to a marginal (not statistically significant) change in the probability of an accident occurrence. Changes in flows ranging from 500veh/h to 1500veh/h have also little effect on accident probability because of the fact that under flee flow there are not many interactions between vehicles. It can be observed that as the flow increases, there is a strong decrease in accident probability. A possible explanation is that in this flow state, vehicle speeds are starting to decrease compared to free flow state. Another explanation is that as more interactions begin to take place, drivers are more cautious. When traffic flow is higher than 2500veh/h, accident probability is almost fixed at a constant value. When capacity is reached, then there is little space for interactions and speeds are low. In this traffic state, rises in traffic volume does not influence accident probability.

CONCLUSIONS

The impact of traffic parameters on traffic safety is a complicated phenomenon and has gained considerable attention of researchers. This paper investigates accident likelihood and severity in urban areas. To the best of our knowledge, this is the first time that accident severity and likelihood are explored with real-time traffic data in urban arterials, since international literature has focused only on freeways and urban expressways.

The binary logistic models had sufficient statistical fit and revealed several factors affecting accident severity and likelihood. The logarithm of the ratio of flow to speed, the type of vehicle and the type of accident significantly influenced accident severity. When the analysis is separated to peak and off-peak periods, the only significant variable is the logarithm of the ratio of flow to speed. In all severity models it can be concluded that an increase in this ratio results in decrease in the level of accident severity.

Accident likelihood is affected only by traffic flow when coded as discrete variable, implying a strong nonlinear relationship. Changes in low traffic flows have little or no effect on accident probability, while changes in medium traffic flows leads to significant reduction. After a threshold (2500veh/h), the probability of an accident is held almost constant.

Thus, it can be inferred that traffic flow seems to have the same effect on both severity and crash likelihood. These findings could be attributed to the fact that in increased flows, vehicle maneuvers are more difficult to be performed and interactions are less risky as speeds are lower. This may result to a lower number of accidents which would be less severe if they occur. This finding is consistent with some studies (Christoforou et al., 2010), but inconsistent with other studies (Golob et al., 2008; Noland and Quddus, 2005; Quddus et al., 2010), which shown that traffic parameters and congestion seem to have little or no impact on accident severity through referring on traffic on urban freeways. Consequently, there is a strong need to further investigate the effect of traffic parameters on accident severity.

Of course, the study has some limitations. Traffic data were extracted only from the closest loop detectors (on average every 300 meters). As a result, potential different effect of traffic parameters upstream or downstream could not be grasped. Moreover, more microscopic data could also be used, for example 90-seconds series of traffic parameters. Lastly, in order to estimate the accident likelihood, more non-crash cases could be extracted from days where no accidents occurred in order to have a more rich database.

Nonetheless, this study is a first attempt to explore this complex phenomenon in urban areas, and the findings of this study can be used to improve road safety management, but must be treated carefully when applied in different road environments. For example, speed control measures could be applied on specific time periods, especially in road segments where traffic flow is low, mainly by using variable message signs or by speed enforcement. There is also need for specific focus on low traffic situations which are more risky in both peak and off peak periods.

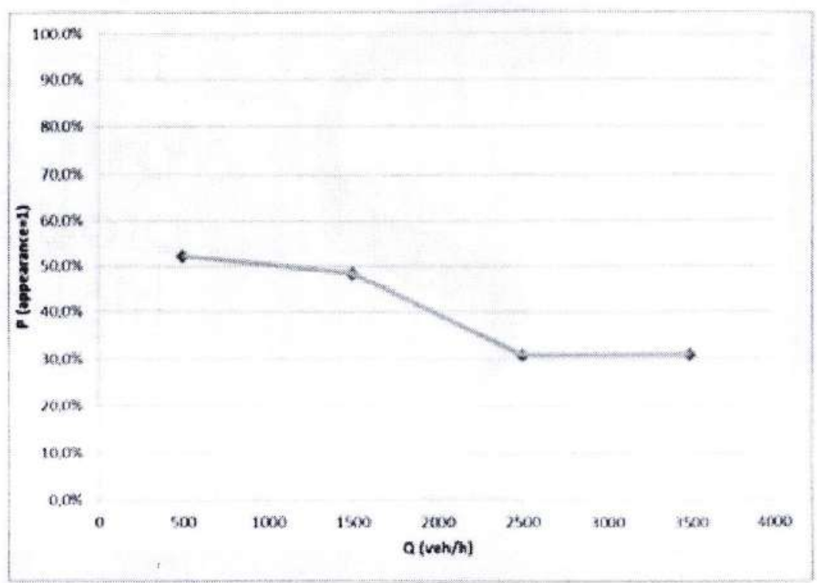

Figure 1: Graphic illustration of the relationship between traffic flow and appearance of an accident

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