International Journal of Latest Trends in Engineering and Technology
Special Issue SACAIM 2017, pp. 499-505
e-ISSN:2278-621X

PREDICTING SEVERITY AND ROAD TRANSPORT SAFETY THROUGH EFFECTIVE TRANSPORT PLANNING USING PREDICTIVE ANALYSIS

Mr. Suman Lasrado[1], Nikhil DevendraNaik[2] & RensonRolifSerrao[3]

Abstract - This paper introduces a model framework to anticipate seriousness and term of car crashes by utilizing Requested Probit model and Risk show, individually. The models are assessed utilizing auto collision information gathered in Jilin region, in 2010. With the created models, three seriousness markers, in particular, number of fatalities, number of wounds, and property harm, and also mishap term, is anticipated, and the essential impacts of related factors are distinguished. The outcomes show that the decency of-attack of Requested Probit display is higher than that of SVC demonstrate in seriousness displaying. Moreover, mischance seriousness is ended up being a critical determinant of term; that is, more fatalities and wounds in the mishap prompt longer length. Study results can be connected to forecasts of mischance seriousness and length, which are two fundamental strides in mishap administration process. By recognizing those key influences, this study also provides suggestive results for government to take effective measures to reduce accident impacts and improve traffic safety.

1. INTRODUCTION

Auto collisions are a huge wellspring of passings, wounds, property harm, and a noteworthy worry for general wellbeing furthermore, activity wellbeing. Mishaps are likewise a noteworthy reason for movement blockage and postponement. Successful administration of mishap is urgent to alleviating mishap impacts and enhancing activity wellbeing and transportation framework productivity. As two noteworthy ventures of the mishap reaction program (appeared in Figure 1), seriousness expectation and term estimation are, in this way, of incredible significance. Exact expectations of seriousness and length can give pivotal data to crisis responders to assess the seriousness level of mishaps, appraise the potential effects, and actualize productive accidentmanagement methodology. To the creators' learning, the vast majority of the past investigations. The rest of this paper is composed as takes after. In Area 2, we introduce the writing survey on expectations of seriousness and span as a rule. The information are portrayedin Area 3. Following is mishap seriousness demonstrating in Area 4 and length anticipating in Segment 5. The paper finishes up with an outline and bearings for future research.

2. LITERATURE SURVEY

As two main considerations in mischance investigation, seriousness and length have for some time been imperative subjects for look into. Most of the past investigations analyzed just a single of seriousness and length. For instance, as for seriousness examination, Chang and Mannering [1] contemplated the connection between damage seriousness and vehicle inhabitance usingWashington State mishap data.ManneraandW¨unsch-Ziegler [2] explored mishap seriousness and decided the imperative impacts of related variables. As for duration, Chung [3] modeled accidentduration with freeway accident data collected in Korea. Anastasopouloset al. [4] presented a Bayesian network model thatcan be used to learn emerging patterns and predict accidentclearance time. Nevertheless, accident severity was found tohave influence on duration time by some researchers. Forinstance,Nam andMannering [5] revealed thatwhether thereis fatality or injury in accident impacts accident duration.Besides, as shown in Figure 1, severity prediction and durationestimation are connected procedures in the accidentmanagement system. Therefore, the two indicators should beconsidered together and combined in one model system.Concerning severity analysis, which includes mainlythree aspects, that is, number of fatalities, number of injuries,and property damage, most of the existing researchersinvestigated it as one comprehensive indicator; for example,Mannera and W¨unsch-Ziegler [2]took accident severity asone independent variablewith four alternatives, namely, fatal,severe injury, light injury, and property damage. Miltonet al. [6] defined severity levels as property damage only,possible injury, and injury. Malyshkina and Mannering [7]modeled severity by using three alternatives, that is, fatality,injury, and property damage only. In addition, a number ofresearchers considered only one or two of the three aspectsof severity. For instance, Stone and Broughton [8] and Szeand Wong [9] considered only the aspect of fatality bydefining two levels of severity, that is, fatal and nonfatalaccident. Delen et al. [10] defined injury severity levels asno injury, probable injury, nonincapacitating, incapacitatingand fatality. Similarly, Ballesteros et al. [11] and Roudsarietal. [12] considered only number of fatalities and

[1] Assistant Professor, Department of M. Sc (ST), AIMIT, St. Aloysius College, Mangaluru– 575022, Karnataka, India
[2] Student, MCA 5th Semester, Department of MCA, AIMIT, St. Aloysius College, Mangaluru– 575022, Karnataka, India
[3] Student, MCA 5th Semester, Department of MCA, AIMIT, St. Aloysius College, Mangaluru– 575022, Karnataka, India

injuries butnot property damage. In fact, different types of losses as wellas the amount of losses lead to different response measuresand last possibly for disparate

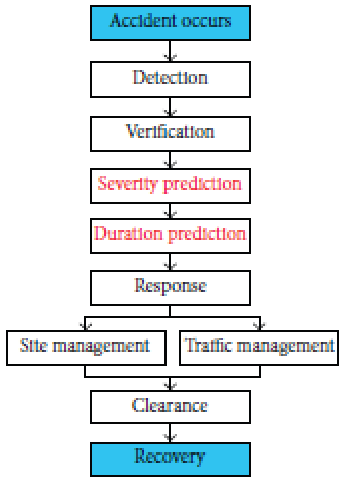

Figure 1: Accident response procedure.

amount of time. For example,either an accident resulting in $167–5000 property damage oran accident leading to 1–3 injuries will be defined as level 2accident in Zhang's study [13]. However, the latter one needsrescue services but the former one does not. This indicatesthat any of the three indicators, that is, number of fatalities,number of injuries, and property damage, is crucial tomakingaccident response decision and is therefore recommendedto be modeled separately in order to provide more detailedinformation about accident management.As mentioned above, most of the previous studies examinedaccident severity and duration separately, although theywere found to have correlation between each other.Moreover,only one or two of the three aspects of accident severity,that is, number of fatalities, number of injuries, and propertydamage, were investigated by the existing studies.Therefore,the present work is aimed at developing a model system toestimate both accident severity and duration. Furthermore,three indicators for accident severity will be investigated,which represent number of fatalities, number of injuries, andproperty damage, respectively.

3. DATA MODELLING FRAMEWORK

The dataset for the examination contains police-announced activity mishap records for Jilin region, China, in 2010. With records containing missing esteems wiped out, our last dataset comprises of 3,914 cases, in which, 1,280 (32.70%) cases were person on foot included mishaps and 387 (9.89%) cases were non-engine vehicle-included mischances. Also to seriousness data, the information contains data with respect to term, mischance qualities (vehicle fire, crash sort, mischance event time, and number of paths influenced), crisis administrations (police administrations, fire what's more, safeguard administrations, tow administrations, and crisis restorative administrations), vehicle attributes (vehicle sort included, trash included, risky material included, and incapacitated

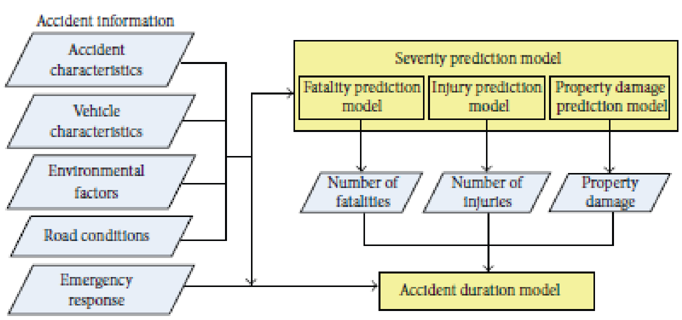

Figure 2: Accident severity and duration modeling framework.

vehicles included), natural components (climate conditions and perceivability separation) and street conditions (number of paths, asphalt condition, street geometrics, and roadway surface condition, and so forth).Based on a preliminary correlation test, 4 independent variables and 26-candidate dependent variables were selectedfrom the dataset, as shown in Table 1.With Nof, Noi, and Pd as independent variables, threeseparate severity prediction models will be developed.Then,duration modeling will be conducted by taking accidentseverity as input. The modeling framework is shown inFigure 2.

4. SEVERITY MODELLING

Other than the Requested Probit show [14], which is regularly utilized in discrete decision demonstrating, SVM will be presented in this paper and be contrasted and the Requested Probit show as indicated by the expectation correctnesses. 4.1. Requested Probit Demonstrate. As shown in Table 1, the alternativesof the severity related dependent variables are allordered. Since multinomial logit (MNL) model, which iscommonly used in discrete choice modeling, would fail toaccount for the ordinal nature of the dependent variableand have the problem of Independence from irrelevant alternatives(IIA) [15], this study will employ Ordered multiplechoice model for severity modeling.TheOrderedmultiple choice model assumes the relationship:

$$\sum_{j=1}^{J} P_n(j) = F\left(\alpha_j - \beta_j X_n, \theta\right), \quad j = 1, \ldots, J-1,$$
$$P_n(J) = 1 - \sum_{j=1}^{J} P_n(j), \qquad (1)$$

where $Pn(j)$ is the probability that alternative j happensin accident n (n = 1, . . . , N), αj is an alternative specificconstant, Xn is a vector of the attributes of accident n, βj isa vector of estimable coefficients, and θ is a parameter thatcontrols the shape of probability distribution F. Therefore,, can have various shapes of distribution based on differentvalue of θ.The Ordered Probit model, which assumes standard normaldistribution for F is the most commonly used Orderedmultiple choice model [16]. The Ordered Probit model hasthe following form:

$$P_n(1) = \Phi\left(\alpha_1 - \beta_j X_n\right),$$
$$P_n(j) = \Phi\left(\alpha_j - \beta_j X_n\right) - \Phi\left(\alpha_{j-1} - \beta_j X_n\right), \quad j = 2, \ldots, J-1, \qquad (2)$$
$$P_n(J) = 1 - \sum_{j=1}^{J-1} P_n(j),$$

where $Pn(j)$ is the cumulative standard normal distributionfunction. For all the probabilities to be positive, wemust have$\alpha 1$ <$\alpha 2$ <⋅⋅⋅<αJ−1.4.2. Support Vector Machine Model. Support vector machine(SVM) is a type of learning algorithms based on statisticallearning theory, which can be adjusted to map the inputoutputrelationship for the nonlinear system [17–19]. SVMhas been widely used in transportation modeling; for example,Bolbol et al. [20] employed SVM classification in travelbehavior analysis, Apatean et al. [21] used it in road obstacleclassification, and Abdel-Aty and Haleem [22] applied it toanalyze angle crashes at unsignalized intersections. Previousstudies indicate that SVM can conduct discrete choice modelingwith acceptable accuracy. Therefore, it is chosen to beemployed to model accident severity in this paper.Given a set of input-output data pairs D =($x1$, $y1$), ($x2$, $y2$), . . . , (xl, yl) ($xi \in X \subseteq Rm$, $yi \in Y \subseteq Rn$, and$l$ being the number of training samples, that are randomlyand independently generated from an unknown function,SVM estimates the function using the following equation[23]:

f (x) = $w \cdot \Phi(x)$ + bw,$x \in Rm$, $b \in Rn$, (3)

Table 1: Variables and statistics based on survey data.

Factors	Variables	Values	Percentage (%)	Variables	Values	Percentage (%)
Accident severity	Number of fatalities: Nof	0	89.59	Number of injuries: Noi	0	9.86
		[1, 2]	10.38		[1, 3)	85.89
		More than 3	0.03		[3, 11)	4.14
	Property damage (yuan): Pd	Less than 1000	61.18		Over 11	0.11
		[1001, 30000)	37.19			
		Over 30000	1.63			
Duration	Duration (Continuous value)	Mean (min) 192.95	Standard deviation 111.63			
Accident characteristics	Motor-vehicle-only accident: Mvoa	Yes	57.41	Vehicle fire: Vf	Yes	8.93
		No	42.59		No	91.07
	Head-on type collision: Hotc	Yes	8.93	Weekend or festival: Wof	Yes	38.60
		No	91.07		No	61.40
	Rear-end type collision: Retc	Yes	19.64	Vehicle rollover: Vr	Yes	26.79
		No	80.36		No	73.21
	Time of day: Tod	[00:00, 6:00)	6.24	Number of lanes blocked: Nolb	0	3.57
		[6:00, 18:00)	69.12		1	62.50
		[18:00, 24:00)	24.64		over 1	33.93
Vehicle characteristics	Bus involved: Bi	Yes	16.07	Hazardous material involved: Hmi	Yes	1.79
		No	83.93		No	98.21
	Truck involved: Ti	Yes	89.29	Disabled vehicles involved: Dvi	Yes	27.27
		No	10.71		No	72.73
	Debris involved: Di	Yes	53.57			
		No	46.43			
Environmental factors	Weather conditions: Wc	Sunny	89.48	Visibility distance (meter): Vd	Less than 50	8.90
		Fog	0.23		[50, 100)	22.70
		Sleet	5.97		[100, 200)	19.86
		Other	4.32		Over 200	48.54
Road environment factors	Number of lanes in each direction: Nol	2	33.92	Accident location (horizontal): Alh	Motor vehicle lanes	71.68
		3	51.79		Bike lane	6.60
		Over 3	14.29		Shared motor vehicle and bike lane	13.71
	Pavement condition: Pc	Asphalt	96.95		Sidewalk	2.22
		Cement	2.85		Crosswalk	3.42
		Sand and gravel	0.07		Other	2.37
		Soil	0.07	Accident location (vertical): Alv	Regular road section	60.01
		Other	0.06		Four-way intersection	20.43
	Roadway surface condition: Rsc	Dry	85.16		Other road sections (narrow carriageway and tunnel, etc.)	1.09
		Wet	6.38		Other intersections	18.47
		Slippery (snowy or icy conditions)	6.76	Road geometrics: Rg	Flat and straight	98.57
		Other	1.70		Hill or bend	1.43
	Traffic signal control: Tsc	Yes	17.46			
		No	82.54			
Emergency services	Police services: Ps	Yes	71.43	Fire and rescue services: Frs	Yes	16.07
		No	28.57		No	83.93
	Tow services: Ts	Yes	98.21	Emergency medical services: Ems	Yes	33.93
		No	1.79		No	66.07

5. ACCIDENT DURATION MODELLING

5.1. AFTModel and KMEstimator.

As recommended by Nam and Mannering [5] and Stathopoulos andKarlaftis [29], hazardbasedlength models have preference in that they permit the express investigation of length impacts of mischances (i.e., the connection between to what extent a mishap has endured and the probability of it finishing soon).Thus, hazard-based durationmodels, in particular the accelerated failure time (AFT)metric, were utilized in this study to model the accidentduration. The reason that we choose AFT model is that,compared with other forms of hazard-based model, AFTmodel is predominately fully parametric; that is, a probabilitydistribution is specified and it is also less affected by thechoice of probability distribution [30, 31], and the results ofAFT model are easily interpreted [32].Let T be a nonnegative random variable representing theaccident duration. The hazard at time t on the continuoustime-scale $h(t)$ is defined as the instantaneous probabilitythat the duration under study will end in an infinitesimaltime period Δt after time t, given that the duration has notelapsed until time t. A mathematical definition for the hazardfunction is as follows:

$$h(t) = \lim_{\Delta \to 0^+} \frac{P(t \le T < t + \Delta \mid T > t)}{\Delta}. \quad (8)$$

Let $(\cdot)$ and $(\cdot)$ be the density and cumulative distribution function for T, respectively.Then the probability of ending in an infinitesimal interval of range Δt, after time t is$(t)\Delta t$. And the probability that the process lasts for at least $t$is given by the survival equation

$S(t) = (T>t) = 1 - (t)$. (9)

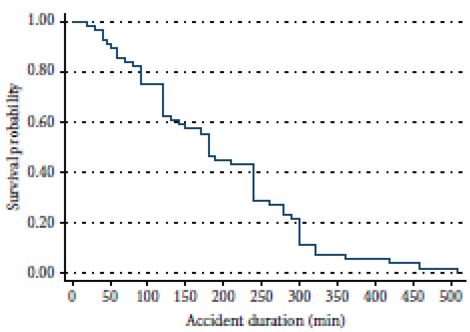

FIGURE 3: Survival curve of accident duration.

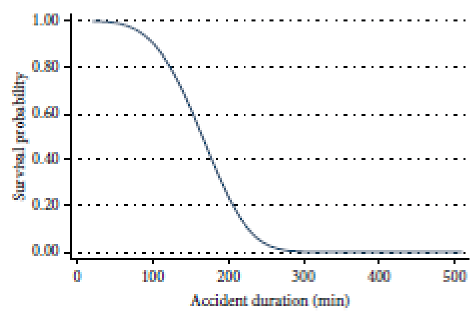

FIGURE 4: The estimated survival curve of accident duration.

Thus, the hazard function can be further expressed as

$$h(t) = \frac{f(t)}{S(t)} = \frac{dF(t)/dt}{S(t)} = \frac{-dS(t)/dt}{S(t)} = \frac{-d \ln S(t)}{dt}. \quad (10)$$

The distribution of the hazard can be assumed to be oneof many parametric forms or to be nonparametric. Because the distribution of the accident duration is unknown, one ofthe nonparametricmethods, theKaplan-Meier (KM) productlimit estimator, is conducted to explore the covariates effectsand the potential distribution.As a nonparametric method, the KM estimator, producesan empirical approximation of survival and hazard but hardlytakes any covariate effects into consideration. It is similar toan exploratory data analysis. Denoting the distinct failuretimes of individuals n as $t1 < t2 < \cdots < tm$, the KMestimator of survival at time $ti$is computed as the productof the conditional survival proportions:

$$S_{KM}(t_i) = \prod_{k=1}^{i} \frac{r(t_k) - d(t_k)}{r(t_k)}, \quad (11)$$

where $r(tk)$ is the total number of accidents at risk for endingat $tk$and $d(tk)$ is the number of accidents stopping at tk.By using the KM estimator, the survival function curvesof the accident duration are estimated, which are shown inFigure 3. The results indicate that the survival probabilitydecreases with duration, which implies an accelerated failuretime model with Weibull or Exponential distributionshould be employed.Therefore, the AFT model is developedto examine the linkages between duration and covariatesrelative to accident information.

The AFT model permits the covariates to affect theduration dependence. Its survival function is given as

$S(t) = S0\,[t \cdot \exp(-\beta\square X)]$, (12)

where$S0(\cdot)$ is the baseline survival function.Thecorrespondinghazard function is

$$h(t) = \frac{-\partial S(t)/\partial t}{S(t)} = h_0\left[t \cdot \exp\left(-\beta' X\right)\right] \exp\left(-\beta' X\right). \quad (13)$$

The AFT model can be expressed as a log-linear model:

$$\ln t = \beta\square X + \varepsilon. \tag{14}$$

Assuming that the random error ε follows either a Weibull distribution or an Exponential distribution, one can get twokinds of AFT models, and both of them are often used induration analysis.5.2. Estimation Results. Assuming that the random errorin (14) follows a Weibull distribution and an Exponentialdistribution, respectively, the accident duration models areestablished. The models are estimated by employing maximumlikelihoodestimation (MLE), and the estimation resultsare shown in Table 3.The Mean absolute percentage error (MAPE), whichlooks at the average percentage difference between predictedvalues and observed ones, is adopted to examine the accuracyof the developed duration predication model. MAPE iscalculated as

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right|, \tag{15}$$

where $A_i$is the observed value and $P_i$is the predicted valuefor observation i.The MAPE value of Weibull distribution (0.22) is lessthan that of the Exponential distribution (0.23), indicatingthat the values predicted by the AFT model with theWeibulldistribution is more close to the actual accident duration [3].Therefore, theWeibull distribution function is chosen.The estimation results indicate that most of the resultswere consistent with the theoretical expectation. Accordingto the results, the variables with respect to accident severitysignificantly affect accident duration: the more fatalities andinjuries occur in the accident, the longer duration it will leadto. This supports the necessity of combining predictions ofaccident severity and duration in one model system. Besides,accident type is revealed to be crucial to duration: comparingwith other types of accidents, the duration of rear-end typecollision is 37% shorter, while that of rollover is 28% longer.The results also show that the duration of accident involvingbus, truck, debris, or hazard material is 60%, 58%, 55%,

Table 2: Estimation results of severity prediction models.

Variables	Fatality model			Injury model			Property damage model		
	SVM	Ordered Probit		SVM	Ordered Probit		SVM	Ordered Probit	
		Coef.	Z-stat.		Coef.	Z-stat.		Coef.	Z-stat.
Dvi	—	—	—	—	—	—	√	0.23	1.99
Bi	√	0.75	8.82	√	0.28	4.37	—	—	—
Ti	√	0.64	7.93	√	0.29	4.61	—	—	—
Di	—	—	—	—	—	—	√	0.11	2.00
Hmi	√	0.04	1.34	√	0.04	1.65	√	0.21	1.96
Tod	√	0.12	2.94	√	0.04	1.21	—	—	—
Wc	√	0.12	2.3	√	−0.05	−2.3	√	0.04	2.46
Vd	—	—	—	—	—	—	√	0.10	5.92
Tsc	√	0.03	2.31	√	−0.02	−1.56	—	—	—
Alh	√	−0.03	−1.44	√	0.04	2.71	√	−0.03	−2.12
Alv	√	−0.11	−6.88	√	0.06	5	√	−0.13	−12.16
Rsc	—	—	—	√	0.11	4.03	—	—	—
Rg	√	−0.26	−1.71	—	—	—	√	−0.18	−2.01
Pc	—	—	—	—	—	—	√	−0.18	−2.09
Vf	√	0.73	7.70	—	—	—	√	0.13	1.98
Vr	√	0.04	1.32	—	—	—	—	—	—
Mvoa	—	—	—	—	—	—	√	0.45	11.66
α_1	—	0.63	—	—	−0.68	—	—	0.06	—
α_2	—	2.79	—	—	2.36	—	—	1.99	—
α_3	—	—	—	—	3.71	—	—	—	—
Hit ratio (%)	89.21	89.59		86.50	86.89		59.57	62.66	

Table 3: Estimation results of accident duration model.

Variables	Weibull distribution		Exponential distribution	
	Coef.	z-stat.	Coef.	z-stat.
Constant	5.12	13.99	4.71	11.76
Nof	0.51	4.14	0.51	1.43
Noi	0.33	4.45	0.34	1.28
Pd			−0.13	−1.01
Retc	−0.37	−2.62	—	—
Vr	0.28	2.06	—	—
Nolb	0.24	4.48	0.25	1.64
Bi	0.60	4.01	0.41	1.07
Ti	0.58	3.12	—	—
Di	0.55	5.28	0.45	1.35
Hmi	0.88	2.89	—	—
Wof	−0.14	−1.49	—	—
Alv	−0.57	−4.55	−0.43	−1.06
Nol	−0.18	−2.81	—	—
Ts	0.38	1.35	—	—
γ (shape parameter)	0.26	—	—	—
Prob > χ^2	0		0.0067	

Table 4: Goodness of fit index and estimated distribution statistics of accident duration model.

Model statistics	Mean (min)	Variance	Maximum (min)	Minimum (min)	MAPE value
Observed value	192.95	111.63	510	20	0.22
Predicted value	188.38	84.52	327.14	53.03	

or, on the other hand 88% longer than that of different mischances, separately. In addition, as indicated by the, the mischance which happens in end of the week or celebration is observed to be related with shorter duration.The reason is that the movement volume in nonworking day is lower than that inworkingday.As for accident location,the results reveal that the accident occurs at regular roadsection or 4-way intersection results in longer duration thanthat occuring at other locations. The reason may be that thetraffic volume is higher at regular roadsectionor intersection.As to administrations, the mishap which needs tow administrations has longer length. In addition, as the quantity of paths possessed in the mischance expands, length increments. By utilizing the mischance term show, the survival bend of term is estimated,which is appeared in Figure 4. Contrasting with watched esteem, the forecast exactness of mishap term display is appeared in Table 4.

6. CONCLUSION

In this paper, a seriousness forecast show framework was built by utilizing Requested Probit show, and a span expectation display was set up by applying Danger demonstrate. Mishap seriousness, including number of fatalities, number of wounds, and property harm, and in addition mishap length was estimated with the models.Study results can be connected to seriousness and span forecast, which are basic strides in mishap reaction process. By contrasting SVM and Requested Probit show, it additionally makes a methodological commitment in upgrading forecast precision of seriousness estimation. In addition, byidentifying the key effects of related factors on accidentseverity and duration, the results provide useful clues forgovernment to take effective measures in order to reduceaccident impacts and improve traffic safety.One limitation of current study is that some factors, suchas characteristics of the driver, passenger and pedestrian, andtraffic condition, which have potential effects on accidentseverity and duration, are not considered because of the lackof suitable data. Further study should be done to collectthe related information and investigate the impacts of thesefactors.

7. REFERENCES:

[1] [1] L.-Y. Chang and F. Mannering, "Analysis of injury severity andvehicle occupancy in truck- and non-truck-involved accidents,"Accident Analysis and Prevention, vol. 31, no. 5, pp. 579–592,1999.

[2] [2] H. Mannera and L.W¨unsch-Ziegler, "Analyzing the severity ofaccidents on the German Autobahn," Accident Analysis andPrevention, vol. 57, no. 8, pp. 40–48, 2013.

[3] [3] Y. Chung, "Development of an accident duration predictionmodel on the Korean Freeway Systems," Accident Analysis andPrevention, vol. 42, no. 1, pp. 282–289, 2010.

[4] [4] P. C. Anastasopoulos, V. N. Shankar, J. E. Haddock, and F. L.Mannering, "A multivariate tobit analysis of highway accidentinjury-severity rates," Accident Analysis and Prevention, vol. 45,pp. 110–119, 2012.

[5] [5] D. Nam and F. Mannering, "An exploratory hazard-based analysisof highway incident duration," Transportation Research A,vol. 34, no. 2, pp. 85–102, 2000.

[6] [6] J. C. Milton, V. N. Shankar, and F. L. Mannering, "Highwayaccident severities and the mixed logit model: an exploratoryempirical analysis," Accident Analysis and Prevention, vol. 40,no. 1, pp. 260–266, 2008.

[7] [7] N. V. Malyshkina and F. L. Mannering, "Markov switchingmultinomial logit model: an application to accident-injuryseverities," Accident Analysis and Prevention, vol. 41, no. 4, pp.829–838, 2009.

[8] [8] M. Stone and J. Broughton, "Getting off your bike: cyclingaccidents in Great Britain in 1990–1999," Accident Analysis andPrevention, vol. 35, no. 4, pp. 549–556, 2003.

[9] [9] N. N. Sze and S. C. Wong, "Diagnostic analysis of the logisticmodel for pedestrian injury severity in traffic crashes," AccidentAnalysis and Prevention, vol. 39, no. 6, pp. 1267–1278, 2007.

[10] [10] D. Delen, R. Sharda, and M. Bessonov, "Identifying significantpredictors of injury severity in traffic accidents using a seriesof artificial neural networks," Accident Analysis and Prevention,vol. 38, no. 3, pp. 434–444, 2006.

[11] [11] M. F. Ballesteros, P. C. Dischinger, and P. Langenberg, "Pedestrianinjuries and vehicle type in Maryland, 1995–1999," AccidentAnalysis and Prevention, vol. 36, no. 1, pp. 73–81, 2004.