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Exploring the relationship of conflict characteristics and consequent crash severity

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Abstract

This paper outlines the development of a modelling approach to measure the occupant injury severity of two vehicle crashes based on the characteristics of the conflict. A combination of statistical analysis and numerical analysis based on Newtonian Mechanics is utilised to develop this modelling framework. The Australian Crash In-Depth Study (ANCIS) database is used to estimate and validate the model. Three sequential steps were undertaken to develop the model. In the first step, the driver reaction before a crash was determined according to the type of conflict, weather condition, driver's gender and speed limit of the vehicles. A Binary Probit Model was utilised to measure the driver reaction before the crash. In the second step, the speed change of the subject vehicle (ΔV_s) was estimated using conflict characteristics and driver reaction in conflict. A Log-Gamma regression model was used to estimate ΔV_s. Newtonian mechanics was used to estimate the kinetic energy applied to the subject vehicle according to the mass and estimated ΔV_s. In the third step, a Log-Gamma regression model was used to estimate the Injury Severity Score (ISS) of the conflict based on estimated kinetic energy of the subject vehicle, the impact type of the crash, presence of airbag, presence of seat belt and age of the occupant. The modelling approach can be incorporated into a micro simulation model to provide more accurate safety assessment of road locations based on conflict analysis.

Keywords: driver reaction, kinetic energy, conflict characteristics, crash severity

1. Background of the research:

The literature of road safety evaluation has shown that modelling of safety evaluation in the past have generally focused on two distinct directions, primarily focusing on either the vehicle or the transport system. In both cases, the driver is the centre of the system, making decisions and bearing the consequences of these decisions.

Considerable research has been directed at modelling vehicles and the severity of collisions between vehicles and other objects. These models tend to focus on the interaction between vehicles and/or vehicles and roadside objects. Newtonian mechanics, which duplicates the physical dynamics of a crash, has been used to develop numerical models to explore the relationship of crash characteristics and crash severity. They describe the vehicle-to-vehicle interaction in considerable detail. Researchers like Wood and Simms (2002) and Buzeman et al. (1998) focus on crash information as the main predictor of the crash severity outcome.

Other researchers have approached the safety issue from the traffic system side, considering crash involvement, as opposed to crashworthiness. Initially traffic system models focused on the traffic flow in particular directions and determined the level of conflict. Studies (Golob et al., 1988; Turner et al., 1998) have been carried out to look at the level of vehicle interaction at intersections, relating the approach volume to the number of accidents.

Along a similar line Chin and Quddus (2003) and Abdel-Aty and Keller (2005) used regression and/or ordered probit models for analysing driver injury severity level at intersections. Researchers have used statistical models to explore the relationship of the main factors affecting safety with the number and severity of crashes. Lord, et al. (2005) and Li et al.(2008) developed models to investigate crash number or occurrence. Other researchers (Caliendo et al., 2007 , Wong et al., 2007) analysed the severity of crashes. Ma et al. (2008) and Naderan and Shahi (2010) investigated the relationship of the road and environmental factors to the number of crashes for each severity level.

Another approach to replicating crash outcomes uses traffic micro-simulation analysis. The previous approaches have tended to use crash data as the basis of their analysis. The lack of such data, its slowness in being collected and the difficulty in observing some accident situations, encouraged researchers to look at other approaches.

Recently, Archer and Young (2009) and the Federal Highway Administration (2008) have made significant steps towards incorporating the traffic conflict approach into traffic simulation models in order to estimate the number and type of crashes. Archer and Young (2010) studied the application of surrogate safety measures for intersection safety assessment and their application in micro-simulation modelling. They used a probability approach for developing a gap acceptance model for unsignalised T intersections in order to determine the number and severity of conflicts. In this research, the probabilistic gap acceptance model is developed using a binary logistic regression model. The severity of the conflicts is measured, using Hyden's (1996) definition regarding the required braking rate (RBR) for each conflict. The Federal Highway Administration (2008) undertook further research, which considers intersection safety evaluation. They developed Surrogate Safety Assessment Model (SSAM) for assessing the safety performance of different types of intersections. In order to do this they developed software, which supports traffic simulation models including VISSIM, AIMSUN, PARAMICS and TEXAS. The SSAM model can determine the number and severity of conflicts in each conflict point at an intersection. Based on the assumption that the severe conflicts will lead to accidents, they measured the severity of accidents by calculating the speed difference of vehicles in the accident (ΔV).

In summary, the research studies carried out using the three preceding approaches (See Sobhani et al. (2010) for further details) to investigate the level of safety of roads all contribute to a better understanding of safety evaluation. In this paper, the relationship of conflict characteristics and the consequent crash severity is investigated. This paper aims at developing a model of crash severity, which can be incorporated into a discrete event simulation model of conflict outcome prediction.

In this paper, the next section outlines the proposed model to estimate the crash severity based on conflict characteristics. After that, the database used for model estimation is explained and the model estimation process is outlined.

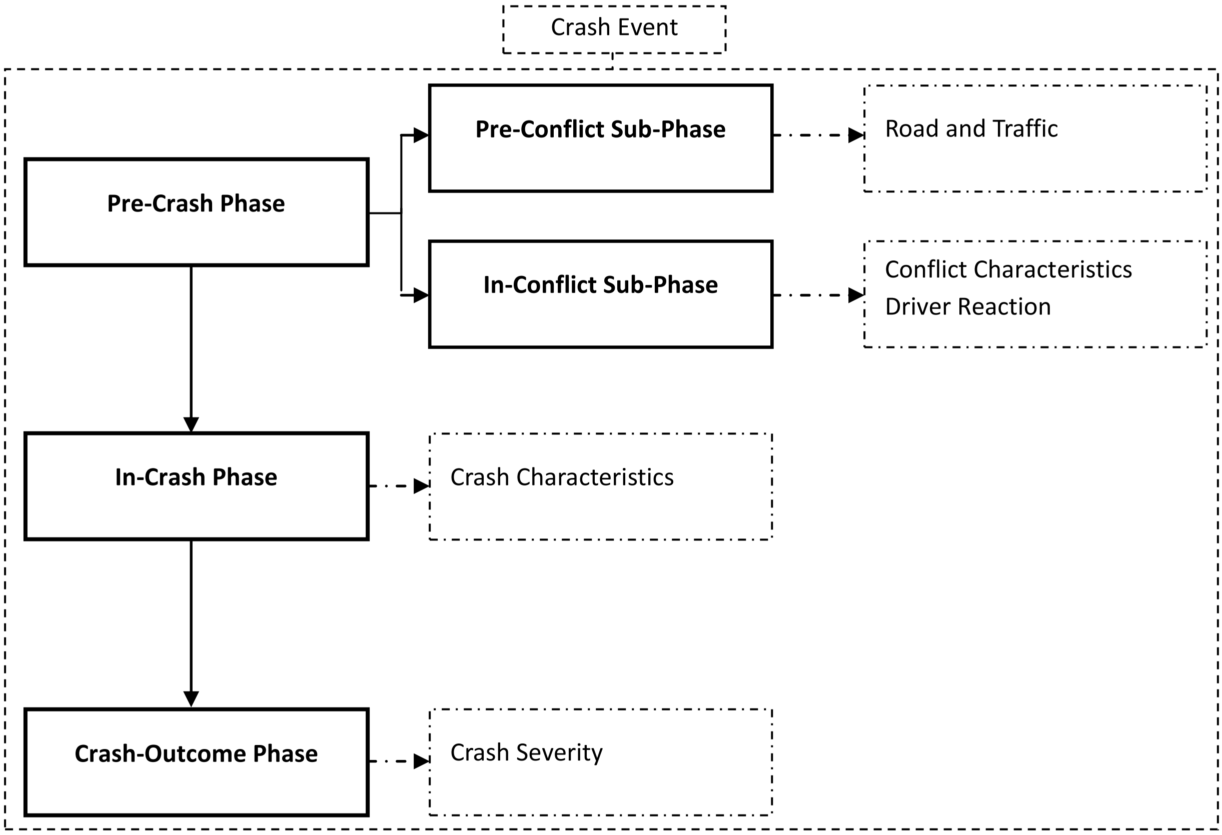
2. Methodology:

In the previous section, the need for developing a model to link conflict characteristics and crash severity was highlighted. Figure 1 shows different phases of a crash event. In this Figure, a crash event is divided into three phases, which are pre-crash, in-crash and crash-outcome phases. The pre-crash phase includes two sub-phases, which are pre-conflict and in-conflict.

The in-crash phase deals with crash characteristics and the crash-outcome phase is related to the variables associated with crash severity. As outlined in the literature above statistical modelling approaches have been developed to investigate the relationship of crash-outcome phase with pre-crash phase and in-crash phase. Researchers have also utilised numerical analysis based on Newtonian Mechanics to explore the link between in-crash phase and crash-outcome phase. The relationship between the pre-conflict sub-phase and in-conflict sub-phase has been investigated using micro simulation models. In this study, the relationship between in-conflict sub-phase and crash-outcome phase is investigated using a combination of statistical analysis and Newtonian Mechanics. Latter studies will incorporate this approach into the simulation models of traffic.

Figure 2 outlines the general framework to estimate the crash severity based on characteristics of a conflict.

Figure 1: Different phases of a crash event



The pre-conflict sub-phase is related to the traffic, road and environmental characteristics. The in-conflict sub-phase is related to conflict characteristics and driver reaction in a conflict.

2.1 . Crash severity

This sub-section introduces the measure of crash severity used in the study as well as the approach utilised to estimate the measure of crash severity.

2.1.1. Measure of crash severity

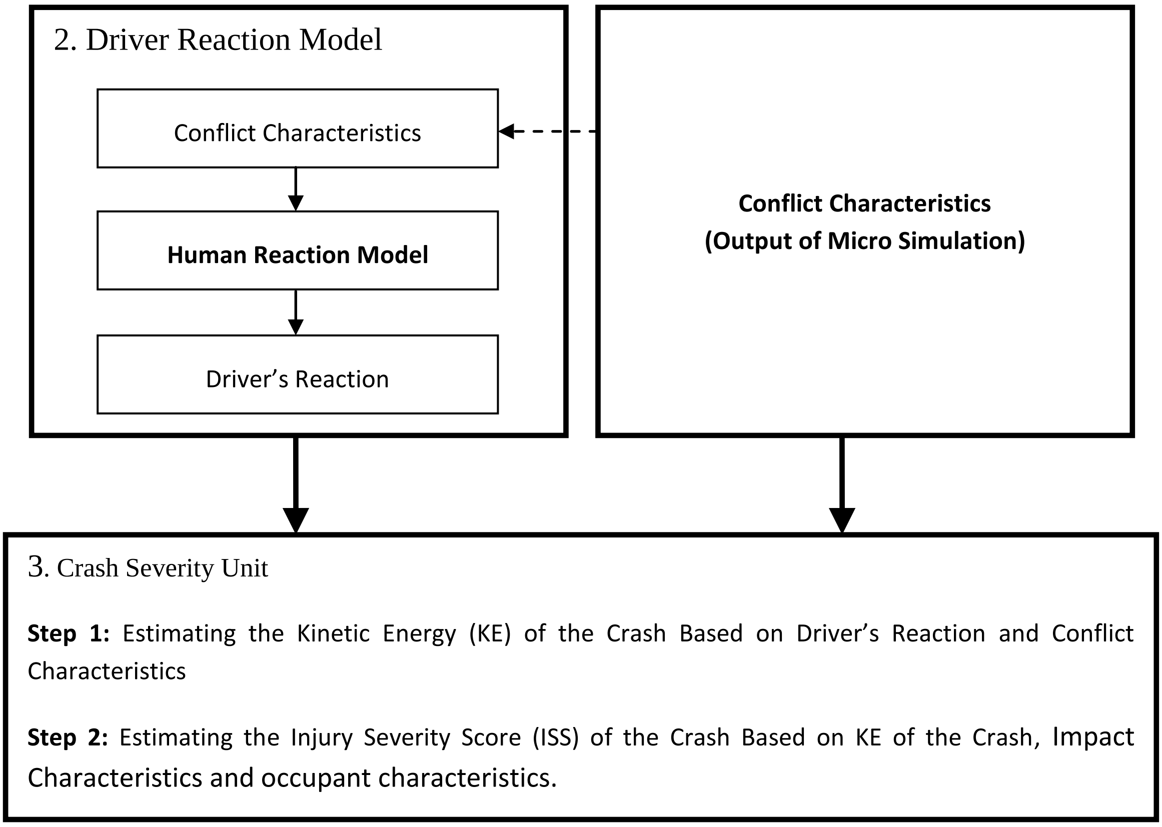
A commonly used measure of the severity of a crash is the Abbreviated Injury Severity Scale (AIS). The AIS is a measure constructed in 1971 to indicate the level of occupant injury for crashes. While the AIS provides an indication of the threat-to-life of individual injuries, it does not provide any indication of overall injury severity or survival probability. The Injury Severity Score (ISS) is based on the AIS and was developed to measure the overall injury severity based on the combination of the AIS levels of different body regions. The body regions considered for the ISS calculation are head or neck, face, thorax, abdomen, extremities and external. ISS is calculated by sum of the squares of highest AIS for three most injured body regions.

$$ISS = AIS_1^2 + AIS_2^2 + AIS_3^2 \quad (1)$$

Where, the subscripts 1 to 3 show the highest AIS for three most injured body regions.

Since the ISS has been shown to be a good indicator of mortality risk (Sampalis et al., 1995) of the occupant and is relatively simple to evaluate, it was chosen as the primary measure of occupant injury severity in this study.

Figure 2: General modelling framework



2.1.2. The crash severity model

The ISS provides a measure of injury severity to the occupant. The development of a relationship between the conflict characteristics and the ISS (injury severity) is now required.

The kinetic energy (KE) of each vehicle is related to the mass and the speed of the vehicle in the form:

$$K = \frac{1}{2} \times m \times v^2 \quad (2)$$

K : Kinetic energy of the object

m : Mass of the object

v : Velocity of the object

Some of the kinetic energy transferred between the vehicles involved in a crash is transferred to the vehicle occupant. This transferred energy results in injuries to the people in the car if it exceeds a certain threshold. Greater kinetic energy transferred to the vehicle occupant generally results in higher Injury Severity Scores (ISS).

The kinetic energy transferred to the vehicle occupant is correlated with the crash characteristics. In turn, the crash characteristics are related to the characteristics of the conflicts leading to the crash.

The modelling of crash severity is carried out in two steps. In the first step, the expected kinetic energy transferred to the subject vehicle in crash was estimated. The transferred kinetic energy to the subject vehicle is calculated using the following equation:

$$KE_s = \frac{1}{2} \times m_s \times \Delta V_s^2 \qquad (3)$$

KE_s: Kinetic energy transferred to the subject vehicle in crash

m_s : Mass of the subject vehicle

ΔV_s : Speed change of the subject vehicle before and after the crash

In the second step, the Injury Severity Score (ISS) of the Crash is estimated Based on the kinetic energy of the Crash, Impact Characteristics and occupant characteristics.

3. Data used in model development:

To develop the models outlined above, a data set that contains the appropriate variables is required. The Australian Crash In depth Study (ANCIS) database (Logan et al., 2006) was used to develop the statistical relationship between conflict characteristics, driver reaction and crash injury severity. ANCIS is a research program in which in-depth data on passenger vehicle crashes since 2000 in Victoria and New South Wales was collected. The occupants recruited to this study are those who have been hospitalised because of the crash. In this study, the participants are interviewed using a structured questionnaire, the vehicle they were travelling in is inspected and the site of the crash is visited.

Medical records of the victims are examined to determine their injuries. Photographs of the vehicles involved in the crash were taken to measure the damage of the crash and a variety of crashworthiness measures evaluated. The total number of available cases in ANCIS database is 700 crashes; however, the information required for model development reduces the number of cases used in this study. The reason is that the required information of the dependent and explanatory variables for the models was not available for all 700 crashes.

4. Model Estimation:

Figure 2 introduces the various levels of modelling. This section estimates the driver reaction, ΔV_s and ISS models. Nonlinear regression modelling and different generalised linear modelling techniques (Agresti, 2002) are examined to develop the Driver reaction, ΔV_s and ISS models in this study. Generalised linear regression models fits better than nonlinear regression models for ΔV_s and ISS models, which have continuous output variables. Also generalised linear regression models with binary output variables are examined to measure the driver reaction before the crash.

4.1. Driver reaction model:

The model development of driver reaction before crash is outlined in this part. This model represents the second part of the Figure 2. The driver reaction considered in this study is a binary output variable. Binary Logistic Regression and Binary Probit Models (BPM) were examined to estimate driver reaction before crash. The conducted statistical analysis showed that the goodness of fit for the BPM was verified; therefore, this model is adopted in this study to estimate driver reaction before crash. BPM is a type of GLM in which the random component is normal distribution and the link function is Probit function. The mathematical equation of the BPM is:

$$P_n(j) = \phi(a_0 + \sum_{i=1}^{n} a_i x_i) \qquad (4)$$

$$P_n(J) = 1 - P_n(j) \qquad (5)$$

where:

$P_n(j)$: Dependent variable (1= reaction, 2= no reaction).
i : Subscribe showing the number of independent variables.
j : The first level of the dependent variable (i.e., no reaction).
J : The second level of the dependent variable (The reference level), i.e., reaction.
x_i : Independent variable (see Table 1).
a_0 : Intercept
a_i : Coefficient calculated for each of the independent variables.
ϕ : Denote the standardised cumulative density function (CDF) of normal distribution.

Level J is the reference level of the dependent variable. In the Equations (4) and (5), a_0 and a_i are calculated in calibration process of the BPM.

The ANCIS database was used to develop model. The dependent variable of this model is the probability of driver reaction. The levels of driver reactions considered are “no reaction” and “reaction”. The “reaction” level is considered as the reference level (level J). The explanatory variables considered for the model are summarised in Table 1. The levels of the definition for classifying accidents (DCA) used in ANCIS are shown in Figure 3.

The goodness of fit of the model was tested using Omnibus test comparing the performance of the estimated and “Null” model. The contribution of each of the explanatory variables to the model was tested using Wald statistics with 5% level of significance. The goodness of fit criterion for the model are summarised in Table 2. The model variables and parameters are explained in Table 3. The results of the estimation show that the model fits well based on the preceding goodness of fit criterion.

The variables, which were significant in the model, are the speed limit at the scene of the crash, and the combination of “Definitions for Classifying Accidents (DCA)”, “weather condition” and “gender”.

As can be seen in Table 3, the model parameters show that as the speed limit at the scene of the crash increases the probability of “no-reaction” behaviour decreases. This value gives an estimation of average speed of the vehicles moving on the road.

Table 3 shows that only the clear weather condition is presenting the model. The DCA of a crash shows the crash type. In general, the interaction of “weather condition”, “DCA” and "gender" has positive impact on "no-reaction" behaviour. However, this influence is different for different interaction levels of type of crash and gender.

Figure 3: Crash configurations used (from definitions for classifying accidents)

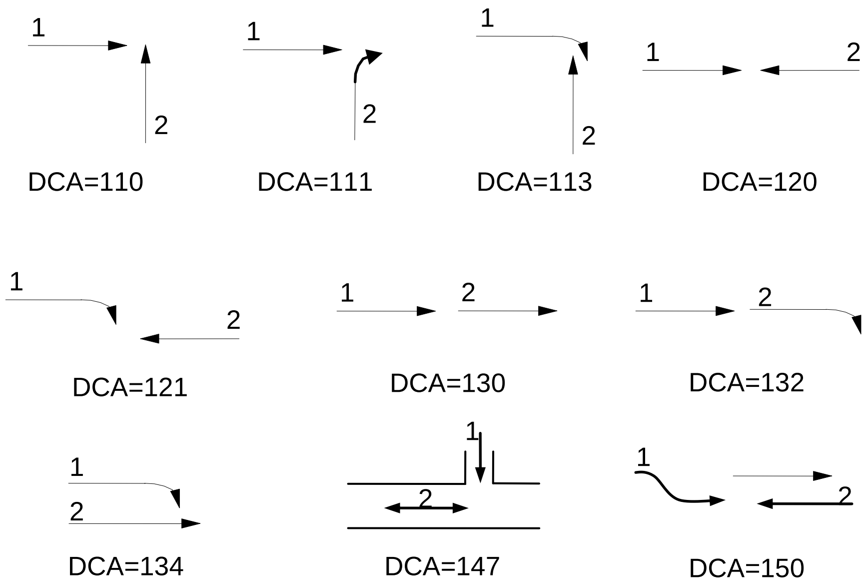


Table 1: Variables considered for developing the model

dependent variable	Independent variable	Description	Defined levels
Driver Behaviour (2 levels: 1= Reaction; 2=No-reaction)	I_1	Speed limit at the scene of the crash	Numerical
	I_2	Weather condition	2 levels: 0= weather is not clear; 1= weather is clear.
	I_3	Definitions for Classifying Accidents (DCA)	5 levels: 1= Side crashes (110); 2= right near crashes (113); 3= head on crashes (120); 4= right through crashes (121); 5= other crashes.
	I_4	Gender	2 levels: 0= female; 1=male.

Table 2: Significance of the model parameters and goodness of fit criterion

Tests of Model Effects	
Variable	**Significance**
Speed limit at the scene of the crash	< 0.001
Interaction of weather condition, DCA and gender	0.002
Fitness Criteria	**P value of Hypothesis Testing**
Omnibus Test	< 0.001

The probability of "no-reaction" for side crashes is more than right turn against, head-on and right near crashes. This is reasonable as side crashes usually happen at intersections and it is harder to see the other vehicle in a side crash. For frontal crash, the probability of reaction is more than other crashes. This makes sense as both drivers can generally see each other more easily in a frontal crash.

Table 3: Binary Probit model parameters

Level of The Dependent variable*	Independent Variable	Parameters	Significance Level (Wald Statistic)	S.E.
No-Reaction	I_1	-0.031	< 0.001	0.0077
	$I_2(1) * I_3(1) * I_4(0)$	3.431	< 0.001	0.9155
	$I_2(1) * I_3(1) * I_4(1)$	2.413	0.002	0.7751
	$I_2(1) * I_3(2) * I_4(0)$	2.088	0.050	1.0257
	$I_2(1) * I_3(3) * I_4(0)$	1.783	0.015	0.7333
	$I_2(1) * I_3(3) * I_4(1)$	2.113	0.002	0.6874
	$I_2(1) * I_3(4) * I_4(0)$	2.310	0.001	0.6705
	$I_2(1) * I_3(5) * I_4(0)$	2.680	< 0.001	0.6428
	$I_2(1) * I_3(5) * I_4(1)$	3.089	< 0.001	0.7307

The model presented in Table 3 is used to find the probability of "no-reaction" behaviour in a crash situation. A cut off value of 50% is defined to indicate the marginal value that if the probability exceeded that value the "no reaction" behaviour is occurred. The result of BPM is used as an independent variable in the ΔV_s model.

4.2. ΔV_s model

Various modelling functions with continuous outcome (dependent variable) such as linear regression models, non-linear regression models and generalized linear regression models were examined to estimate ΔV_s of the crash. The Log-Gamma regression model, which is a type of generalized linear regression models (GLRM), provided the best fit for predicting the ΔV_s of the subject vehicle in the crash. It was adopted in this study. In this model the random component of the dependent variable is estimated using a Gamma distribution. The Log function is selected as the link function of the model. The mathematical equation of the model is shown below:

$$f_3 : Y = EXP(\beta_0 + \sum_{i=1}^{i} \beta_i \times x_i') \tag{6}$$

Where

Y : Dependent variable
i : Subscribe showing the number of independent variables
x_i' : Independent variable
β_0 : Constant, calculated in calibration process
β : Coefficient of the independent variable, calculated in calibration process of the model.

The conflict characteristics considered as independent variables in the ΔV_s model is indicated based on the crash characteristics affecting the value of ΔV_s (Sobhani et al., 2010). The conflict characteristics considered to estimate expected ΔV_s for each conflict is outlined in Table 4. Different levels of DCA are shown in Figure 3.

The significance of the conflict characteristics was determined using statistical analysis (Levine et al., 2008). The variables included in the model, their parameter estimates, and the significance of the parameters (5% level) are summarised in Table 5.

Table 4: Variables considered for developing the model

dependent variable	Independent variable	Description	Defined levels
ΔV_s	P_1	Speed limit at the scene of the crash	Numerical
	P_2	Driver reaction	2 levels: 1= reaction; 2= no reaction.
	P_3	Definitions for Classifying Accidents (DCA)	10 levels: 1= Side crash (110; 2= Right far crash (111); 3= right near crash (113); 4= head on crash (120); 5= right through crash (121); 6= Rear end crash (130); 7= Right rear crash (132); 8= Lane change right crash (134); 9= Emerging from driveway-lane crash (147); 10= Head on (overtaking) crash (150).
	P_4	Mass ratio (Mass of bullet vehicle* over mass of target vehicle**)	Numerical

* Bullet vehicle is the striking in a two-vehicle crash
** Target vehicle is the struck vehicle in a two-vehicle crash

The variables which are significant for the model are m_b / m_s and the interaction of driver reaction and definitions for classifying accidents (DCA). The Omnibus test and likelihood ratio Chi-Square test statistics, examined the significance of each independent variable in the model, were used to test the model goodness of fit. The goodness of fit criterion for the model are summarised in Table 6. The results of the goodness of fit tests of the model show the model fits the data well,

The mathematical equation of the kinetic energy of crash is:

$$f_1 : KE_s = \frac{1}{2} \times m_s \times (EXP(\sum_{i=1}^{i} \beta_i \times x_i'))^2 \tag{7}$$

Where:

β_i and x_i are the parameters and independent variables of the ΔV_s model respectively (see Table 5). KE_s is the kinetic energy transferred to the subject vehicle.

The estimated parameters of ΔV_s model show that the ratio of mass of bullet vehicle over mass of target vehicle influences the ΔV_s in positive way. This makes sense since according to the law of conservation of momentum this parameter has a positive correlation with ΔV_s. Table 5 shows that there are 15 different interactions between the DCA and human behaviour. This interactive variable is very important because these variables influence vehicles situation before and after the crash. Therefore, the value of ΔV_s is affected by these parameters. The estimated parameters of the model show that the ΔV_s for the crashes with DCA levels 7, 8 and 9 are lower than other type of crashes. This is reasonable as these levels of DCA are related to rear-end, sideswipes and "Emerging from driveway-lane" crashes which are generally less severe than other types of crashes.

Table 5: Characteristics included in the ΔV_s model

Dependent variable	Independent variable	Average Value (Numerical)	Proportion of crashes involving interaction ($P_2()*P_3()$) (Categorical)	Significance level	Parameters	S.E.
ΔV_s of The Subject Vehicle	$P_2(1)*P_3(1)$		4.9 (%)	< 0.001	3.168	0.2737
	$P_2(2)*P_3(1)$		14.8 (%)	< 0.001	3.110	0.1693
	$P_2(2)*P_3(2)$		1.6 (%)	< 0.001	3.469	0.3349
	$P_2(2)*P_3(3)$		4.9 (%)	< 0.001	3.109	0.2417
	$P_2(1)*P_3(4)$		8.2 (%)	< 0.001	3.576	0.2041
	$P_2(2)*P_3(4)$		31.1 (%)	< 0.001	3.520	0.2252
	$P_2(1)*P_3(5)$		8.2 (%)	< 0.001	3.369	0.2261
	$P_2(2)*P_3(5)$		6.6 (%)	< 0.001	3.371	0.2326
	$P_2(1)*P_3(6)$		6.6 (%)	< 0.001	3.161	0.2209
	$P_2(2)*P_3(6)$		3.3 (%)	< 0.001	3.602	0.3110
	$P_2(2)*P_3(7)$		1.6 (%)	< 0.001	2.342	0.5588
	$P_2(1)*P_3(8)$		1.6 (%)	< 0.001	2.719	0.3272
	$P_2(2)*P_3(9)$		3.4 (%)	< 0.001	2.315	0.4345
	$P_2(1)*P_3(10)$		1.6 (%)	< 0.001	3.554	0.3357
	$P_2(2)*P_3(10)$		1.6 (%)	< 0.001	3.709	0.3414
	P_4	1.1521		0.021	0.347	0.1508

Table 6: Goodness of fit criteria for Log-Gamma regression model

Tests of Model Effects	
Variable	**Significance**
Ratio of mass of bullet vehicle over mass of target vehicle	0.027
Interaction of driver reaction and DCA	< 0.001
Fitness Criteria	**P value of Hypothesis Testing**
Omnibus Test	< 0.001

In addition, the parameter estimation of the model shows that there is not a large difference among the other estimated parameters associated with interaction of different levels of the preceding variable. Thus, the interactions, which have more frequency in the data, have more effect on the model. The ANCIS database shows that the proportion of frontal crashes, side crashes and right turn against crashes are more than other cases. These are among the most severe type of crashes in the road network (Abdel-Aty and Keller, 2005)·

4.3. ISS model:

The next step in the model process is the relationship between the ISS of the crash and the kinetic energy of the crash. The independent variables of this model are shown in Table 7.

The Log-Gamma regression model is used to estimate ISS of the model since it provides the best fit of all statistical models tested. Equation 8 shows the general formula of the model.

$$f_2 : Y' = EXP(\alpha_0 + \sum_{i=1}^{i} \alpha_i \times x_i'') \tag{8}$$

Where

Y' : Dependent variable
i : Subscribe showing the number of independent variables
x_i'' : Independent variable
α_0 : Constant, calculated in calibration process
α : Coefficient of the independent variable, calculated in calibration process of the model.

The Omnibus test and Wald statistics, examined the significance of each independent variable in the model, were used to test the fitness of the model. The results of the fitness of the model show that the model fits well based on the preceding fitness criterion (Sobhani, et al., 2010). The goodness of fit criterion for the model are summarised in Table 8. It should be noted that the model, which included a constant variable, was estimated and does not fit well; therefore, the constant parameter was excluded from the model in Table 8.

Table 7: Crash characteristics considered for ISS **model (Sobhani et al., 2010)**

Model	Independent variable	Description	Defined levels
ISS	KE_s	Kinetic Energy Applied to Subject Vehicle	Numerical
	I_6	Near side/ Far side/Front/Rear Impact	5 levels: (1=struck on near side; 2= struck on far side; 3= none; 4= front; 5= rear)
	I_7	Gender of the occupant	2 levels: (1=male; 2= female)
	I_8	Age of the occupant	5 levels: (1=Less than 18 years old; 2= 19-30; 3= 31-60; 4= 60-70; 5= More than 70 years old)
	I_9	Presence of airbag	2 levels: (0=no; 1= yes)
	I_{10}	Presence of seat belt	2 levels: (0=no; 1= yes)

Table 8: Goodness of fit criterion for ISS **model (Sobhani et al., 2010)**

Tests of Model Effects	
Variable	**Significance**
Energy	0.007
Interaction of impact type, presence of airbag, presence of seat belt and age of the occupant	< 0.001
Fitness Criteria	**P value of Hypothesis Testing**
Omnibus Test	< 0.001

The kinetic energy transferred to the subject vehicle and a variable representing the interaction between the type of impact, presence of airbag, presence of seat belt and age of the driver are considered as independent variables of this model. The model characteristics are summarised in Table 9.

Table 9 shows that the predictors of the ISS model include the kinetic energy applied to subject vehicle (KE_s) and the interaction of impact type, presence of airbag, presence of seat belt and age of the occupant.

The results of parameter estimate of the model show that the KE_s affect the ISS in a positive manner. This is reasonable since a part of this kinetic energy transfers to human body and cause injuries and fatalities (Sobhani et al., 2010; Corben et al., 2004; Elvik, 2004).

As shown in Table 9, there are 25 interactions between the impact type, presence of airbag, presence of seat belt and age of the occupant. The following observations are made based on the estimated parameters of these interactions:

- The crash injury severity is higher for crashes where airbags and seat belts are present for struck-side impact cases than non-struck side and frontal crashes. This makes sense because in struck on far side and frontal impact types a larger amount of kinetic energy is absorbed by the vehicle body structure than the struck on near side impact type. However, the results show that the crash injury severity is lower for crashes where airbags and seat belts are not present for struck on near side than struck on far side and frontal crashes (Sobhani et al., 2010).
- In general, the presence of air bag and seat belts reduce the crash injury severity. However, this is not the case for occupants aged between 18 and 60 years old in near side impacts. Also for very old occupants (more than 70 years old) the presence of airbag increases the injury severity of crashes (Sobhani et al., 2010).
- In addition, the model parameters show that the injury severity of different age groups varies based on the impact type and presence of airbag. For the near side struck crashes, the injury severity of the occupants aged between 60 and 70 years old is more than the injury severity of others. For far side struck crashes in absence of airbag the injury severity of middle aged occupants (between 30 and 60 years old) is higher in comparison with others; while, in presence of airbag the injury severity of young occupants aged between 18 and 30 years old is more than others. For the frontal impact type crashes in absence of airbag, the injury severity of young occupants (18 to 30 years old) is higher than the other occupants; however, in presence of airbag very old occupants (more than 70 years old) suffer more than the other occupants (Sobhani et al., 2010).

The mathematical equation representing the relationship of the ISS and crash characteristics can therefore be defined by:

$$f_2 : ISS = EXP\left[(2.011\times10^{-7})\times(0.5\times m_s \times(EXP(\sum_{i=1}^{i}\beta_0+\beta_i x_i'))^2)+\sum_{i=2}^{i}\alpha_0+\alpha_i\times x_i'') \right] \quad (9)$$

Where the estimates of $\beta_0, \beta_i, x_i', \alpha_0, \alpha_i$ and x_i'' are shown in Table 5 and Table 9.

5. Conclusion:

This paper explained the development of a modelling approach to measure the severity of two vehicle crashes based on conflict characteristics. The developed modelling approach can be incorporated in a micro simulation model to provide more accurate safety analysis based on conflict simulation. Three steps were undertaken to develop a sequential modelling framework. In the first step, the driver reaction in crash was determined according to the type of conflict, weather condition, gender of the driver and speed limit of the vehicles.

Table 9: Characteristics included in ISS model (Sobhani, Young et al., 2010)

Dependent Variable	Independent Variable	Average Value (Numerical)	Significance Level	S.E.	Parameters
ISS	KE_s	126124.49 (J)	0.007	< 0.001	2.011×10^{-7}
	$I_6(1)*I_9(0) *I_{10}(0) *I_8(2)$		< 0.001	0.6740	2.684
	$I_6(1)*I_9(0) *I_{10}(1) *I_8(1)$		0.021	0.4781	1.103
	$I_6(1)*I_9(0) *I_{10}(1) *I_8(2)$		< 0.001	0.3155	2.070
	$I_6(1)*I_9(0) *I_{10}(1) *I_8(3)$		< 0.001	0.2551	2.108
	$I_6(1)*I_9(0) *I_{10}(1) *I_8(4)$		< 0.001	0.4779	3.115
	$I_6(1)*I_9(0) *I_{10}(1) *I_8(5)$		< 0.001	0.4753	1.899
	$I_6(1)*I_9(1) *I_{10}(1) *I_8(2)$		< 0.001	0.3962	2.698
	$I_6(1)*I_9(1) *I_{10}(1) *I_8(3)$		< 0.001	0.4790	2.635
	$I_6(1)*I_9(1) *I_{10}(1) *I_8(4)$		< 0.001	0.6947	2.814
	$I_6(1)*I_9(1) *I_{10}(1) *I_8(5)$		0.022	0.6722	1.544
	$I_6(2)*I_9(0) *I_{10}(1) *I_8(2)$		< 0.001	0.5184	2.200
	$I_6(2)*I_9(0) *I_{10}(1) *I_8(3)$		< 0.001	0.4121	2.792
	$I_6(2)*I_9(0) *I_{10}(1) *I_8(5)$		< 0.001	0.5277	2.417
	$I_6(2)*I_9(1) *I_{10}(0) *I_8(3)$		0.004	0.6787	1.934
	$I_6(2)*I_9(1) *I_{10}(1) *I_8(2)$		0.003	0.6787	2.038
	$I_6(2)*I_9(1) *I_{10}(1) *I_8(3)$		0.001	0.4117	1.339
	$I_6(2)*I_9(1) *I_{10}(1) *I_8(4)$		0.029	0.6737	1.470
	$I_6(2)*I_9(1) *I_{10}(1) *I_8(5)$		0.004	0.4772	1.379
	$I_6(5)*I_9(0) *I_{10}(1) *I_8(2)$		< 0.001	0.5000	2.585
	$I_6(5)*I_9(0) *I_{10}(1) *I_8(3)$		< 0.001	0.2317	2.143
	$I_6(5)*I_9(0) *I_{10}(1) *I_8(5)$		< 0.001	0.4800	1.892
	$I_6(5)*I_9(1) *I_{10}(1) *I_8(2)$		< 0.001	0.5256	1.991
	$I_6(5)*I_9(1) *I_{10}(1) *I_8(3)$		< 0.001	0.2636	1.900
	$I_6(5)*I_9(1) *I_{10}(1) *I_8(4)$		< 0.001	0.3447	2.221
	$I_6(5)*I_9(1) *I_{10}(1) *I_8(5)$		< 0.001	0.6721	3.114

The second step was to estimate the kinetic energy applied to the subject vehicle according to conflict characteristics and the driver reaction. In the third step the Injury Severity Score (ISS) of the crash was predicted using the estimated kinetic energy of the subject vehicle, the impact type of the crash, presence of airbag, presence of seat belt and occupants' age.

A Binary Probit Model was developed to measure the driver reaction in the crash. The measured driver reaction was used as predictor in the ΔV_s model.

A Generalized Log-Gamma regression model is utilised to find out the relationship of the ΔV_s of the subject vehicle with driver reaction and conflict characteristics. Newtonian Mechanics was used to determine the main crash characteristics affecting the ΔV_s of the subject vehicle. Those conflict characteristics, which have influence on the determined crash characteristics were used as independent variables of ΔV_s model. The kinetic energy of the subject vehicle was calculated using the ΔV_s and mass of the subject vehicle.

A Generalised Log-Gamma linear regression model utilised to make a relationship of ISS of the crash to calculated kinetic energy of the subject vehicle, impact type of the crash, presence of airbag, presence of seat belt and age of the occupant.

The results showed that ratio of mass of bullet vehicle over mass of subject vehicle had positive effect on the ISS of the crash. Also, the interactions of different levels of definitions for classifying accidents (DCA) and driver reaction affected the crash injury severity in a positive way. Those interactions, which are associated with right turn against, frontal and side crashes, had more influence on crash injury severity.

The modelling approach outlined in this paper enhances the modelling process of road safety evaluation based on conflicts as it enables the researchers to estimate the severity of expected crashes for each conflict determined using micro-simulation modelling approach. Furthermore, the modelling framework uses a combination of, statistical and numerical analysis to link the conflicts with crash severity to provide more accurate safety assessment of road network based on conflict simulation.

There are, however, some areas of this research, which are needed to be improved in future studies. Different conflict characteristics and conflict severity levels should be considered as an important factor affecting the crash severity. This issue was not investigated in this study. In terms of the transferability of the results, the model theory is transferable as is the finding related to the variables included in the model. However, the data used in estimating the model parameters was collected in Australia. As such it will have certain characteristics, which are peculiar to design standards, behaviour and road conditions in that country. Estimation of the parameter values for similar models in other countries will verify the transferability of the model and improve our understanding of different conditions in different constituencies.

References:

Abdel-Aty, M. and J. Keller (2005). "Exploring the overall and specific crash severity levels at signalised intersections." *Accident Analysis and Prevention* **37**(3): 417-425.

Agresti, A. (2002). "*Categorical Data Analysis*". Hoboken, New Jersey, John Wiley & Sons, Inc.

Archer, J. and W. Young (2009). "Signal treatments to reduce heavy vehicle crash risk at metropolitan highway intersections." *Accident Analysis and Prevention* **41**: 404-411.

Archer, J. and W. Young (2010). "The measurement and modelling of proximal safety indicators." *Proceedings of the Institute of Civil Engineers (ICE)* **163**(TR4): 191-201.

Buzeman, D. G., D. C. Viano and P. Lovsund (1998). "car occupant safety in frontal crashes: A parameter study of vehicle mass, impact speed, and inherent vehicle protection." *Accident Analysis and Prevention* **30**(6): 713-722.

Caliendo, C., M. Guida and A. Parisi (2007). "A crash-prediction model for multilane roads." *Accident Analysis and Prevention* **39**(4): 657-670.

Chin, H. C. and M. A. Quddus (2003). "Applying the random effect negative binomial model to examin traffic accident occurrence at signalised intersections." *Accident Analysis and Prevention* **35**(2): 253-259.

Federal Highway Administration (2008). Surrogate safety assessment model and validation: Final Report. Mclean, Virginia, U.S. Department of Transportation

Golob, T. F., B. Ruhl, H. Meurs and L. V. Wissen (1988). "An ordinal multi variate analysis of accident counts as functions of traffic approach volumes at intersections." *Accident Analysis and Prevention* **20**(5): 335-355.

Levine, D. M., D. F. Stephan, T. C. Krehbiel and M. L. Berenson (2008). "*Statistics for managers using microsoft excel*". New Jersey, Pearson Education, Inc.

Li, X., D. Lord, Y. Zhang and Y. Xie (2008). "Predicting motor vehicle crashes using Support Vector Machine models " *Accident Analysis and Prevention* **40**(4): 1611-1618.

Logan, D. B., J. Scully, L. N. Sharwood, V. Xafis and B. Fildes (2006). ANCIS - Progress Report, July 2003 - December 2005. Melbourne, Monash University Accident Research Centre (MUARC). **Report #247**.

Lord, D., S. P. Washngton and J. N. Ivan (2005). "Poisson, poisson-gamma and zero inflated regression models of motor vwhicle crashes: balancing statistical fit and theory." *Accident Analysis and Prevention* **37**(1): 35-46.

Ma, J., K. M. Kockelman and P. Damien (2008). "A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods." *Accident Analysis and Prevention* **40**(3): 964-975.

Naderan, A. and J. Shahi (2010). "Aggregate crash prediction models: Introducing crash generation concept." *Accident Analysis and Prevention* **42**(1): 339-346.

Sobhani, A., W. Young, D. Logan and S. Bahrololoom (2010). "A kinetic energy model of two vehicle crash injury severity." *Accident Analysis and Prevention* **DOI:10.1016/j.aap.2010.10.021**.

Turner, S. and A. Nicholson (1998). "Intersection Accident Estimation: The role of intersection location and Non-Collision flows." *Accident Analysis and Prevention* **30**(4): 505-517.

Wong, S. C., N. N. Sze and Y. C. Li (2007). "Contributary factors to traffic crashes at signalised intersections in Hong Kong." *Accident Analysis and Prevention* **39**(6): 1107-1113.

Wood, D. P. and C. K. Simms (2002). "Car size and injury risk: a model for injury risk in frontal collisions." *Accident Analysis and Prevention* **34**(1): 93-99.