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Evaluation of the Predictive Capabilities of Simulated Peak Hour conflict Based Crash Prediction Models

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EVALUATION OF THE PREDICTIVE CAPABILITIES OF SIMULATED PEAK HOUR CONFLICT BASED CRASH PREDICTION MODELS

By

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Abstract

Road traffic crashes are one of the major causes of deaths worldwide. A safety prediction model is designed to estimate the safety of a road entity and in most cases these models link traffic volumes to crashes. A major problem with such models is that crashes are rare events and that crash statistics do not take into account everything that may have contributed to the crashes. The use of traffic conflicts to measure safety can overcome these problems as conflicts occur more frequently than crashes and can be easily estimated using micro simulation. For the purpose of this thesis, simulated peak hour conflict based crash prediction models are developed for 113 Toronto signalized intersections and their predictive capabilities are evaluated. The effects of a hypothetical left turn treatment on crashes and conflicts are also explored and compared to the study conducted by Srinivasan et *al* (2012). Lastly, the transferability of SSAM prediction models is evaluated to explore how well the models predict crashes for Toronto intersections.

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List of Acronyms

3SG	Three Legged Signalized Intersection
4SG	Four Legged Signalized Intersection
AADT	Annual Average Daily Traffic
CURE	Cumulative Residuals
DRAC	Deceleration Rate to Avoid Collision
ET	Encroachment Time
GLM	Generalized Linear Modeling
GOF	Goodness-Of-Fit
GT	Gap Time
HEO	Head On
HTA	Highway Traffic Act
IAPET	Initially Attempted Post Encroachment Time
K	Over Dispersion Parameter
MAD	Mean Absolute Deviation
MPB	Mean Prediction Bias
MSPE	Mean Squared Prediction Error
MPE	Mean Prediction Error
NB	Negative Binomial

PDO	Property Damage Only Collisions
PET	Post Encroachment Time
Pr	Significance Level (p-value)
PSD	Proportion of Stopping Distance
RTOR	Right Turn on Red
SAS	Statistical Analysis Software
SPF	Safety Performance Function
SSAM	Surrogate Safety Assessment Model
TCT	Traffic Conflict Technique
TTC	Time to Collision

1. Introduction

Road traffic crashes are one of the major causes of deaths and injuries around the world. Approximately 1.2 million people (2.1% of all deaths) are killed every year and over 50 million are injured or disabled worldwide due to road traffic crashes (WHO, 2004). Furthermore, the WHO data shows that road traffic crashes are the second leading cause of injury, death, or disability after HIV/AIDS worldwide for the people in the age group of 15-44 years (WHO, 2004). The WHO Global Burden of Disease model also predicts that by 2020, road traffic deaths could rise to 2.34 million/year worldwide, with under developed countries seeing an increase of approximately 80% and developed countries seeing a reduction of about 30% (WHO, 2004). The decrease in road traffic deaths in developed countries can be attributed to many factors such as increased awareness amongst people and strict government policies.

According to *Transport Canada's Road Safety Vision 2010*, Canadian roads are amongst the top 10 safest roads in the world (Transport Canada, 2006). Even after having one of the safest roads in the world, everyday there are approximately 8 deaths, 600 injuries, 1,600 crashes on Canadian roads costing a whopping $27 million to the society (Transport Canada, 2006). Between 1984 and 2006, Canadian roads saw a decrease of 33% in deaths resulting from traffic collisions and a decrease of 35% in the serious injuries resulting from traffic collisions (Transport Canada, 2006). The implementation of the Road Safety Vision aims at reducing the number of deaths and serious injuries by a further 30% through implementation of various different recommendations (Transport Canada, 2006). Roads in Ontario are amongst the safest in both Canada and North America (Patterson, B. 2009). Latest statistics show that the fatality rates in car crashes in Ontario have dropped to 0.87 per 10,000 licensed drivers (Patterson, B. 2009). Even though the roads in Ontario are amongst the safest in Canada, the collisions still generate high numbers in social costs.

According to Transport Canada's report *Analysis and Estimation of the Social Cost of Motor Vehicle Collisions in Ontario*, motor vehicle collisions in Ontario in 2004 generated about 30% of social costs of all Canadian collisions or about 3.5% of Ontario's 2004 GDP (Transport Canada, 2007). Breaking down the social costs of collisions in Ontario by collision severity it can be noted that fatal collisions represented less than 1% of the reported collisions in 2004 but accounted for 64% of the total social costs. Similarly, injury collisions made up 27% of the reported collisions and 28% of the social costs, whereas property damage only (PDO) collisions made up 73% of the collisions but only 8% of the social costs (Transport Canada, 2007).

1.1 Background & Motivation

Generally, the research and measures aimed at evaluating/improving traffic safety of roadways are based on historical crash data/statistics. A safety prediction model is most commonly designed to estimate the expected number of crashes per year for a given intersection/arterial using variables such as the average annual daily traffic (AADT), geometric features (such as intersection skew and presence of exclusive turning lanes), and traffic control features. The generalized linear model used to correlate these variables produces expected number of crashes by taking these variables as explanatory variables.

In most cases, the basic models that relate the traffic volumes to crashes give good results but the same cannot be said for every such model. In a study conducted for 205 rural intersections in California and Michigan, it was found that correlation between the predicted and actual crash frequencies expressed in term of R-squared (coefficient of determination) averaged about 0.41 across all intersections (FHWA, 2008). This result shows a considerable degree of unexplained variance in the prediction of crashes. This also shows that while representative crash prediction models can be fairly capable at times , in some cases they can also be fairly variable (FHWA, 2008).

The main issue with models relating traffic volumes to crashes is that the crash statistics do not take into account all the elements that may have contributed to the collision occurrence. Furthermore, the historical crash records maybe incomplete and may not be representative of the real crash history. For example in Ontario many minor crashes can go unrecorded if the damage does not fall over the minimum damage threshold as identified in the Highway Traffic Act (HTA). In some rare cases, the parties involved in a major crash may decide to solve the issue with mutual consent rather than involving the police and risking a bad driver's record alongside increased insurance premiums.

The use of traffic conflicts to measure the safety of an entity and diagnose the accident risk can overcome some of the problems associated with the incomplete databases. Conflicts have distinct advantage over crashes as they occur much more frequently, thus providing a larger database, and can be recorded easily using micro simulation instead of waiting for a crash to happen and then reported to be entered in the database.

1.2 Objectives

The main purpose of this thesis is to evaluate the predictive capabilities of peak hour conflict based crash prediction models. For this investigation a total of 113 4-legged signalized intersections (4SG) located in City of Toronto were used. Peak hour conflicts are estimated using micro simulation (using VISSIM) whereby the peak hour traffic is simulated and the results of simulation are processed using the Surrogate Safety Analysis Model (SSAM). Since this thesis aims at modelling the peak hour conflicts against the crashes/year, an extra variable is introduced to the model in addition to the variables capturing the geometric features to capture the ratio between the peak hour vehicular traffic and the average daily traffic.

As far as the crash prediction models are concerned, models are developed for total crashes and total conflicts alongside models for other crash types against their relevant conflict type, e.g. rear end crashes against rear end conflicts.

The objectives of this thesis are as follows:

- Identifying the link between crashes/year and the peak hour conflicts for a group of 113 4-legged signalized intersections in the City of Toronto.
- Evaluating the predictive capabilities of the peak hour conflict based crash models.
- Comparing the predictive capabilities of the peak hour conflict based crash models against the more traditional volume based crash models.
- Exploring the effects of a hypothetical left turn treatment and its comparison with the results of a similar study conducted by Srinivasan *et al* (2012).
- Evaluating the model transferability of SSAM's linear and non-linear conflict based crash prediction models.

1.3 Thesis Structure

This thesis consists of a total of seven chapters. This first chapter gave a brief introduction about the current situation of road safety in Canada followed by the background and motivation behind the thesis. It also lists the objectives of this thesis before this final section on the thesis structure.

Chapter 2 focuses on the literature review done prior to choosing the topic for this thesis. This chapter is divided into four subsections. The first subsection talks about collision modelling, followed by discussions about surrogate safety measures, micro simulation and traffic conflict technique. The last subsection of this chapter gives a brief overview of the software packages that are being used for this thesis.

Chapter 3 focuses on the data being analysed. It talks about the general study area and the criteria used to select the sites. It further provides information about the availability of traffic and collision data and also provides summary statistics of the data being used.

Chapter 4 focuses on the methodology used for the analysis. It outlines the way in which the simulations were run, how the conflicts were estimated, and how the crash prediction models were developed.

Chapters 5 and 6 focus on data analysis. In these chapters, all the crash prediction models developed are shown alongside the comparison between different models and the evaluation of the models predictive capabilities. The models are first evaluated for their capabilities in predicting crashes for sites grouped by volumes, conflicts and turn lanes. Then the effects of a hypothetical left turn treatment were explored followed by an evaluation of the transferability of other similar models.

Lastly, Chapter 7 concludes this thesis providing a brief summary of accomplishments of research.

2. Literature Review

This chapter provides a brief summary of the extensive literature review done in regards to collision modelling, surrogate safety measures, micro simulation, and the traffic conflict technique.

2.1 Collision Modelling

The concept of collision modelling to predict collisions has been supported by various researchers. Safety analysts use the collision prediction models to estimate the level of safety at different locations in order to identify the unsafe locations and the problems there that need to be addressed. In the past years, many collision prediction models have been developed by different researchers to evaluate the effects of different variables on safety. The most common collision prediction model uses the traffic volume as the main explanatory variable to predict collisions. Persaud and Dzbik (1993) used a generalized linear model that shows positive relationship between collision data and traffic flow. Many other variables can also be added to the models to take into account various other aspects and details about the infrastructure, vehicles and human behavior.

Elbasyouny (2011) classifies the methods of collision modelling into two main categories; conventional analysis and probabilistic analysis. Conventional analysis assumes that the observed collisions at a specific site can be considered as an unbiased estimate of the true level of safety at the site. Probabilistic analysis on the other hand defines the true collision frequency or any other parameter as a random variable with a probability distribution. Probabilistic methods account for the stochastic effect in collision data and recognize that collisions are rare random events and the mean collision frequency is never known (as in the conventional methods) but estimated. Thus due to large statistical uncertainty and the failure to acknowledge the effect of various aspects the conventional method is no longer used by researchers.

The most common approach used within the probabilistic approach to model collisions is the use of Generalized Linear Regression Models. GENMOD statement in SAS is specifically designed for fitting generalized linear models. The GENMOD statement can be used to model data using a variety of probability distribution such as the Poisson, Negative Binomial (NB), Poisson Lognormal, and many others.

Milton *et al* (2008) investigated the statistical properties of different regression models by using Poisson and NB regression models instead of the linear regression model to estimate the collision frequency over a period of time. The effects of low sample mean values and small sample size on the estimation of the fixed dispersion parameter using NB model were also investigated in the study carried out by Lord (2006).

A model for injury and PDO collisions at urban intersections in Canada was developed by Persaud *et al* (2002) describing the relationship between the collision risk and traffic attributes. The time series collision data from the study explicitly revealed the temporal changes in safety conditions and enabled a comparison of the safety performance of junction types across different cities. Lyon *et al* (2006) described the development safety performance functions (SPFs) for urban signalized intersections in Toronto. They developed different models based on crash types and crash severity for both three- and four-legged signalized intersections. Barred *et al* (2003) compared the safety performance of single point and tight diamond intersections. They found significant differences in frequencies of fatal and injury accidents between the two types of intersections with single point intersections apparently being safer than the tight diamond intersections.

Various other researchers have also investigated the effects of a variety of other factors (other than the traffic volumes) on safety. For example, Shankar *et al* (1996) investigated the relationship between collisions, weather and geometric features. The type and quality of pavement and the presence of parking and turning lanes were investigated by Matthew *et al* (2002). Similarly, Lyon *et al* (2006) evaluated the effects of left turn priority treatments on intersection safety.

2.2 Surrogate Safety Measures

Surrogate safety measures are events that can be correlated with the rate of collisions. Many factors are proposed by different studies (FHWA, 1981; Tarko *et al,* 2009) to be used as potential surrogates for measuring safety. These include:

- Speed,
- Headways,
- Accepted Gaps,
- DRAC (deceleration rate to avoid collision),
- Lane Merging,
- Running Red Lights,
- Traffic Conflicts.

Since all of these events occur more frequently as compared to crashes they can be a better predictor of safety for locations with insufficient or limited collision data. For example, traffic conflicts are events in which a collision is imminent if corrective actions are not taken in time. Conflicts occur more frequently than the crashes and can provide a good estimate of safety. A study conducted by Sayed and Zein (1999) described the application of traffic conflict technique to estimate traffic safety at intersections. They established standards for traffic conflict frequency and severity for intersections allowing for relative comparison of conflict risk at various intersections.

2.3 Traffic Conflict Technique

The traffic conflict technique (TCT) was first developed by two General Motors engineers in the 1960s (Perkins and Harris, 1967). They developed TCT to identify safety problems related to vehicle construction. Their study related conflict patterns to accident types and they found the occurrence of conflicts as a more useful measure of risk as compared to the accident rate. Hyden (1975) defined conflicts as situation where two road users would have collided had neither of them made any kind of aversive maneuver. Hyden used the time to collision (TTC) values together with speeds to determine conflict severity and depicted the relationship between the safety critical events in his safety pyramid as can be seen in Figure 2.1. The safety pyramid indicates that collisions are the last resort and that their numbers are much less when compared to the conflicts.

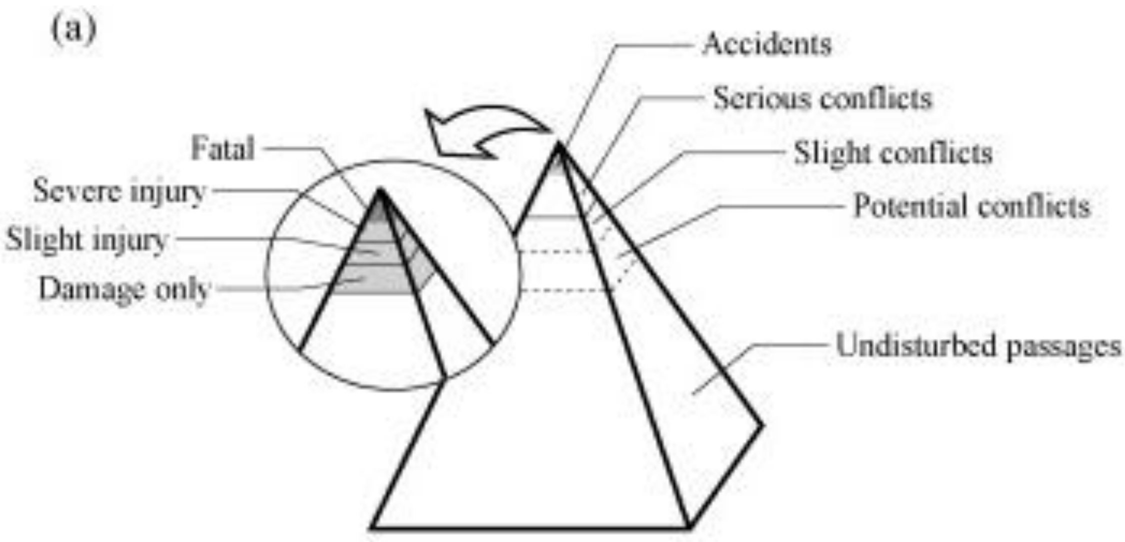

Figure 2.1: Hyden's Safety Pyramid

(Source: http://www.hupferingenieure.de/html/diss_ch_engl.htm)

Elbasyouny (2006) reviewed various TCT measures other than the TTC;

- Gap Time (GT): time lapse between completion of encroachment by turning vehicle and the arrival of the crossing vehicle.
- Encroachment time (ET): time duration during which the turning vehicle infringes upon the right of way of the through vehicle.
- Post Encroachment Time (PET): time lapse between the end of encroachment and the arrival of the through vehicle at the potential point of conflict.
- Initially Attempted Post Encroachment Time (IAPET): time lapse between the start of encroachment plus the expected arrival of the through vehicle and the completion of encroachment by the turning vehicle.
- Proportion of Stopping Distance (PSD): ratio of distance available to maneuver to the distance remaining to the projected location of collision.

There are several studies that relate conflicts (by using them as surrogates to traffic collisions) to collision frequency and volumes. For example, Spicer (1973) and Hyden (1975) in their studies correlated serious conflicts with the reported injury collisions. Sayed (1997) in his study estimated the safety at unsignalized intersections using the TCT. Similarly, Sayed and Zein

(1998, 1999) examined traffic conflict models and standards for signalized and un-signalized intersections.

2.3.1 Micro Simulation

The collection of data pertinent to all of the TCT measures would require extensive field calculations and the presence of field observers or cameras to record data. This process can become time consuming and gruesome. Thus a much easier technique has been developed in the form of micro simulation. A variety of micro simulation programs are available in the market namely VISSIM, SIMTRAFFIC, PARAMICS, INTEGRATION, etc. All of these programs use TCT as a safety measure and provide results in a much easier and faster way. Researchers such as Sayed *et al* (1994) and Mehmood *et al* (2001) have proposed the use of micro simulation as a tool to assess traffic safety.

Sayed *et al* (1994) in their study developed a traffic conflict model to identify the values of different critical traffic parameters at the time of conflict. Their analysis focused on un-signalized intersections and they found reasonable correlations with actual conflicts observations. Mehmood *et al* (2001) evaluated car following simulation models using system dynamics to investigate the mechanisms leading to collisions.

According to Elbasyouny (2006), micro simulation provides valuable insights into the changes brought about by various safety measures, but the concept of micro simulation is still not fully developed and has its limitations. Most of the research conducted on the topic of micro simulation has been using special purpose simulations with the level of details and the variety of model variables being limited or study specific. Furthermore, most of the simulation models do not account for the diverse and less predictable driver behaviour in real road traffic and also captures little or no lateral vehicle movement.

2.4 Software Overview

For the purpose of this study three main software packages were used; SYNCHRO, VISSIM & SSAM. Following is a brief overview of each.

2.4.1 SYNCHRO (Trafficware, 2012)

SYNCHRO is a macroscopic traffic signal model that can be used to optimize signal timing parameters for isolated intersections and to generate coordinated traffic signal timing plans for arteries and networks. It is based on methodologies presented in Highway Capacity Manual and utilizes a graphical user interface to build the network. SYNCHRO is designed to optimize cycle lengths, splits, offsets and phase orders. It also provides the features for signal actuation, progression between signals, and impacts of traffic queue. Additionally, SYNCHRO provides an interface to SIMTRAFFIC, which can be used to view real-time simulation of traffic operations.

2.4.2 VISSIM (PTV America, 2012)

VISSIM is a leading microscopic simulation program for traffic flow modeling. With its unique high level of detail it accurately simulates urban and highway traffic including pedestrians, cyclists and motorized vehicles. VISSIM also provides options for exporting the simulation results in various different formats to be analyzed in other software packages

2.4.3 SSAM (Siemens, 2012)

SSAM combines micro simulation results and automated conflict analysis to analyze the frequency and characteristics of narrowly averted vehicle-vehicle collisions in traffic to assess the safety of traffic facilities.

3. Summary of Data

This section provides information about the data used for the analysis. The study area, guidelines for data assembly and summary statistics of the data used are also discussed.

3.1 Study Area

For the purpose of this study, a group of 113 4-legged signalized intersections in the City of Toronto were used. Figure 3.1 is a map showing the limits of the City of Toronto.

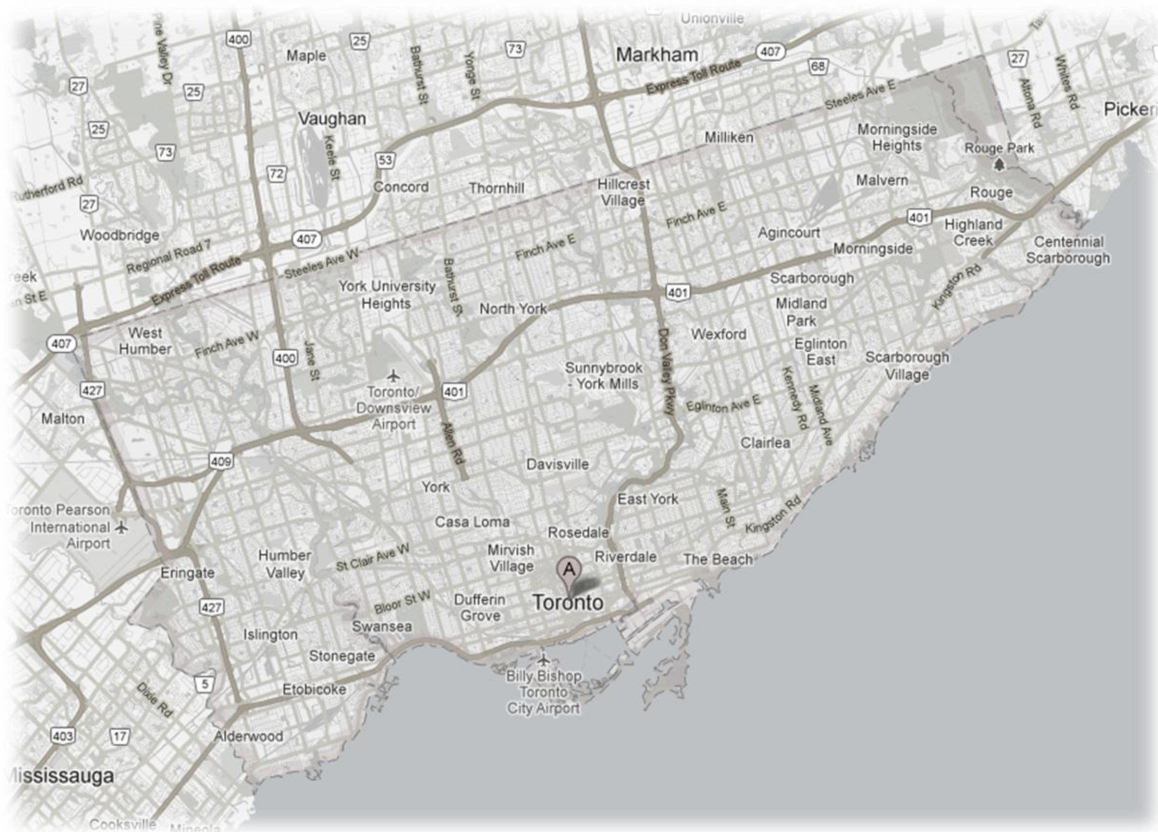

Figure 3.1: Map showing limits of City of Toronto

(Source: https://maps.google.ca/)

The data for this study were provided by the City of Toronto's Traffic Control Centre. A master list of signalized intersections provided by the Traffic Control Centre consisted of both 3-legged and 4-legged signalized intersections. Amongst the sites available, 155 were 3-legged signalized (3SG) and 1786 were 4-legged signalized (4SG).

The data were received in raw format in three files. The first file consisted of the signalized intersection listings, the second one consisted of the traffic volumes at these sites, whereas the third one was the master collision database with a record of each collision. Data were retrieved from these files and matched with the appropriate sites to create a compiled database consisting of an intersection identifier, volumes, and collisions.

3.2 Guidelines for Data Assembly

Some guidelines were set to classify the sites that were to be used for this study. The main challenge in setting these guidelines was that the number of sites to be used and the number of crashes at these sites should be sufficient to yield a good model.

The following guidelines were followed to identify the filtered data:

- The intersections used should not have any degree of skewness.
- The intersections used should not have advanced left turn phasing (presence of left turn lane is permitted).
- The intersections used should have the intersecting roads classified as either major arterial or minor arterial or a combination of the two.

The guidelines used yielded a total of 127 signalized intersections of which 14 were 3SG and 113 were 4SG intersections. The 14 3SG intersections had very few crashes to model and the sample size was also very small to develop a statistically significant model for these intersections.

Hence, the 3SG intersections were omitted and for the purpose of this study only the 113 4SG intersections were used. These intersections were spread all over City of Toronto with about half of them being in the downtown.

Table 3.1 lists the number of intersections by their location/area within the City of Toronto.

Table 3.1: Intersections Classified According to their Location/Area

Locations of the 113 Filtered Intersections	
Location/Area	*No. of Intersections*
Downtown	64
East York	15
North York	11
Scarborough	23

3.3 Traffic Data

The database compiled from the traffic data provided by the Toronto Traffic Control Centre consisted of the major, minor, and the entering AADT (available for 5 years) for the intersections alongside their peak hour traffic counts. The peak hour traffic counts for each intersection included the peak hour left, through and right turning movements for each direction.

Table 3.2 shows the summary statistics of the traffic data for both the filtered and the unfiltered 4SG intersection data.

Table 3.2: AADT Statistics for City of Toronto Data

4-Legged Signalized Intersections				
Data	*All 4-Legged*		*113 Filtered 4-Legged*	
AADT	*MAJOR AADT*	*MINOR AADT*	*MAJOR AADT*	*MINOR AADT*
Mean	13960	4102	12669	6453
Minimum	1322	14	5048	78
Maximum	37495	27936	23807	15772

As can be seen from the above summary, the filtered data is very much representative of the unfiltered data in that the mean values for the major and minor AADT are very close to each other.

3.4 Crash Data

The crash data used for the purpose of this study consisted of 5 year data from the period of 2006-2010. Data was available for all crashes and the crashes during the peak hour. The categories of crashes defined in the database extracted from the raw data were as follows:

1. Total,
2. Injury,
3. PDO,
4. Angle,
5. Head On (HEO),
6. Rear End,
7. Side Swipe,
8. Turning.

The data available in the raw crash database listed the times of the crashes and hence in identifying the peak hour crashes, the peak hour traffic timings for each individual intersection (normally one hour between the timings of 4:00 pm and 6:30 pm) were filtered. The peak hour timings were taken from the available turning movement counts.

Table 3.3 and 3.4 below show the summary statistics of the total crash data and the peak hour crash data for the filtered group respectively.

Table 3.3: Crash Statistics for the filtered 4-Legged Intersections

Filtered 4-Legged Signalized Intersections (2006-2010)				
Collisions	**Mean**	**Minimum**	**Maximum**	**Percentage**
TOTAL	75.593	6	225	100.00%
INJURY	18.283	3	49	24.19%
PDO	57.239	2	190	75.72%
HEO	2.053	0	9	2.72%
ANGLE	14.345	0	37	18.98%
REAR END	23.920	0	85	31.64%
SIDE SWIPE	11.221	0	63	14.84%
TURNING	12.080	0	44	15.98%

Table 3.4: Peak Hour Crash Statistics for the filtered 4-Legged Intersections

Filtered 4-Legged Signalized Intersections - Peak Hour Only (2006-2010)				
Collisions	**Mean**	**Minimum**	**Maximum**	**Percentage**
TOTAL	10.894	0	36	100.00%
INJURY	2.265	0	9	20.80%
PDO	8.628	0	27	79.20%
HEO	0.230	0	2	2.11%
ANGLE	1.858	0	8	17.06%
REAR END	4.195	0	19	38.51%
SIDE SWIPE	1.566	0	12	14.38%
TURNING	1.770	0	7	16.25%

As can be seen from the above tables, the percentage of crashes in the peak hour and the percentage of crashes over all times are fairly similar to each other. As shown the number of crashes in the peak hour is less than the number of crashes in Table 3.3. For instance, the average total crashes over five years for all of the intersections is ~76 as compared to only ~11 during the peak hours.

4. Methodology

4.1 Drawing Intersections using SYNCHRO

During the first part of the study, all of the intersections were modelled using SYNCHRO. Modelling of intersections could also have been done using VISSIM (the micro simulation software used in this study) but due to the simplicity of modelling intersections and entering the related data, SYNCHRO was used.

4.1.1 Data Input in SYNCHRO

The data input in SYNCHRO consisted of the general intersection geometry alongside other traffic data. Following is a list of items that were entered in SYNCHRO:

- Number of lanes in each direction including any presence of exclusive right or left turn lanes.
- In case of presence of turning lanes, the storage lengths and the number of these lanes.
- Presence of channelized right turns and their mode of control (e.g. stop or yield).
- The posted speed limit of the crossing roadways.
- Peak hour traffic volumes along with the peak hour pedestrian flows.
- Traffic signal timings and their mode of control.
- Lane widths.
- Allowance of Right Turn on Red (RTOR).
- Presence of any adjacent parking lanes.

4.1.2 Output from SYNCHRO

Once the data was entered, the files were saved in comma delimited form (.csv) in order to export them to VISSIM. Figure 4.1 and 4.2 shows the intersection of Yonge Street and King Street (one of the intersections used in the study) as drawn in SYNCHRO.

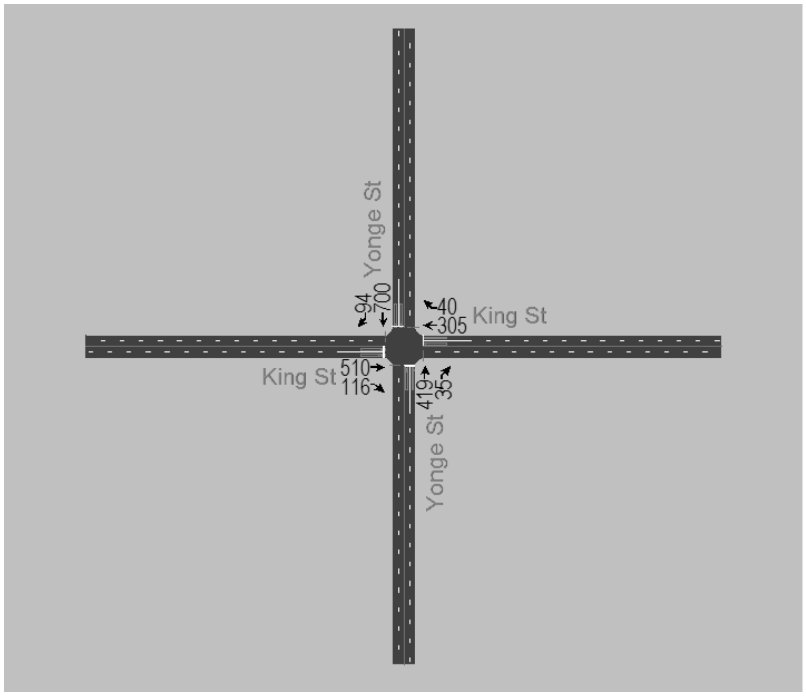

Figure 4.1: SYNCHRO drawing of the Intersection of Yonge St and King St

LANE SETTINGS	EBL	EBT	EBR	WBL	WBT	WBR	NBL	NBT	NBR	SBL	SBT	SBR
Lanes and Sharing (#RL)		↑↱			↑↱			↑↱			↑↱	
Traffic Volume (vph)	0	510	116	0	305	40	0	419	35	0	700	94
Street Name	King St			King St			Yonge St			Yonge St		
Link Distance (m)	—	200.0	—	—	200.0	—	—	200.0	—	—	200.0	—
Links Speed (km/h)	—	50	—	—	50	—	—	50	—	—	50	—
Set Arterial Name and Speed	—	EB	—	—	WB	—	—	NB	—	—	SB	—
Travel Time (s)	—	14.4	—	—	14.4	—	—	14.4	—	—	14.4	—
Ideal Satd. Flow (vphpl)	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900
Lane Width (m)	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6
Grade (%)	—	0	—	—	0	—	—	0	—	—	0	—
Area Type CBD	—	☑	—	—	☑	—	—	☑	—	—	☑	—
Storage Length (m)	0.0	—	0.0	0.0	—	0.0	0.0	—	0.0	0.0	—	0.0
Storage Lanes (#)	—	—	—	—	—	—	—	—	—	—	—	—
Right Turn Channelized	—	—	None	—	—	None	—	—	None	—	—	None
Curb Radius (m)	—	—	—	—	—	—	—	—	—	—	—	—
Add Lanes (#)	—	—	—	—	—	—	—	—	—	—	—	—
Lane Utilization Factor	—	0.95	—	—	0.95	—	—	0.95	—	—	0.95	—
Right Turn Factor	—	0.972	—	—	0.983	—	—	0.988	—	—	0.982	—
Left Turn Factor (prot)	—	1.000	—	—	1.000	—	—	1.000	—	—	1.000	—
Saturated Flow Rate (prot)	—	3096	—	—	3131	—	—	3147	—	—	3128	—
Left Turn Factor (perm)	—	1.000	—	—	1.000	—	—	1.000	—	—	1.000	—
Right Ped Bike Factor	—	1.000	—	—	1.000	—	—	1.000	—	—	1.000	—
Left Ped Factor	—	1.000	—	—	1.000	—	—	1.000	—	—	1.000	—
Saturated Flow Rate (perm)	—	3096	—	—	3131	—	—	3147	—	—	3128	—
Right Turn on Red?	—	—	☑	—	—	☑	—	—	☑	—	—	☑
Saturated Flow Rate (RTOR)	—	48	—	—	25	—	—	15	—	—	25	—

Figure 4.2: Example of Data Input in SYNCHRO for the Intersection of Yonge St and King St

4.2 Micro Simulation using VISSIM

The intersections modelled in SYNCHRO were exported to VISSIM using the .csv file format. Figure 4.3 shows the imported intersection in VISSIM. The figure shows the routing decisions available for the drivers at the intersection alongside pedestrian routes.

4.2.1 Model Calibration

In this study, model calibration results from the Wiedemann 99 car-following model for right-side motorized rule traffic behaviour were used (Menneni *et al*, 2008). These calibrated values are pre-set in VISSIM as one of the default models that can be chosen. A study conducted by Cunto and Saccomanno (2008) found out that amongst the available variables in the Wiedemann 99 model, three variables are the most sensitive and are the best representation of traffic operation at signalized intersections. These parameters and their calibrated values according to the Wiedemann 99 model are:

1. *Desired Deceleration:* It is used in achieving a predefined desired speed. The calibrated value according to Wiedemann 99 model is -2.8m/s^2.
2. *CCO (Standstill Distance):* It is the desired distance between two stopped cars. The calibrated value is 1.5m.
3. *CC1 (Headway Time):* It is the desired time the following vehicle driver should keep behind the leading vehicle. The calibrated value is 0.90 sec.

For the purpose of simulation, the length of the approach was taken as 200 m for all legs since each intersection was analysed individually. This might not be true in some cases in real life because if the intersections are considered in a network the distance between some intersections could have been less than 200 m. However, conflicts were filtered to ensure that the length of approach is consistent with the area used to attribute crashes to the intersections.

4.2.2 Simulation Runs

For each intersection, simulations were run for the whole peak hour (i.e. 3600 sec). In order to capture the randomness in traffic, 10 simulation runs with 10 random seeds were used. The procedure in VISSIM allows for a selection of a random starting seed and then incrementing that by a pre-defined value. In this case, the starting random seed was incremented by the value of 10 for the subsequent runs. VISSIM also offers two modes for simulation; one with visualization and the other with no visualization. Simulations, if run in the visualization mode, take a lot of time since all of the traffic is shown visually. While running the simulations, for the first few intersections, visualization mode was used to see if the traffic behaviour is simulated correctly. The subsequent intersection simulations were then run using the no visualization mode.

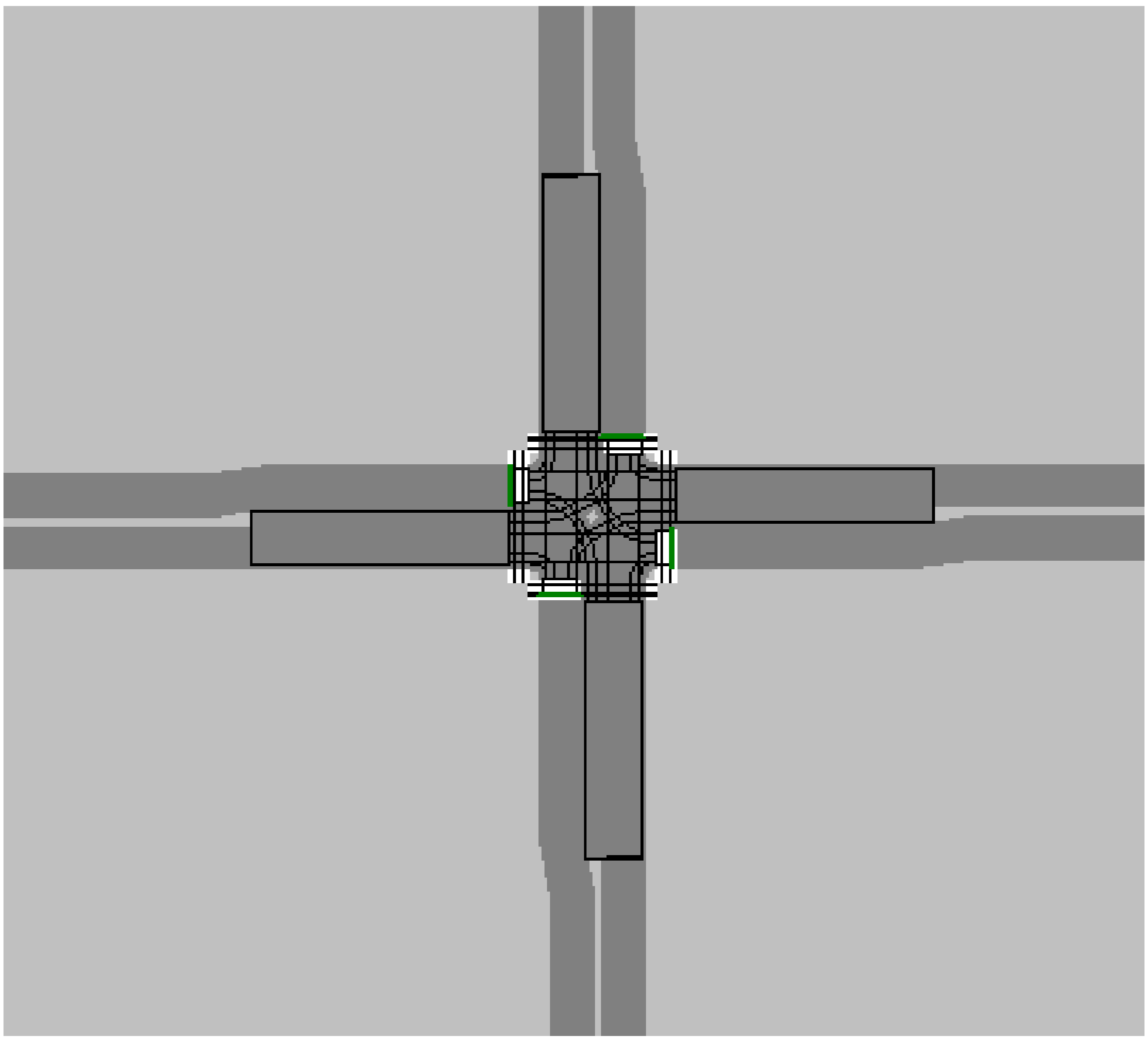

Figure 4.3: Intersection of Yonge St and Jarvis St imported in VISSIM

4.2.3 Simulation Outputs

VISSIM gives an option to save the simulation results in multiple formats for export to different software packages for analysis. For this study, the SSAM trajectories were saved for each simulation run to be analyzed in SSAM.

4.3 Estimation of Conflicts using SSAM

4.3.1 Analyzing the SSAM Trajectories

The SSAM Trajectories available from VISSIM for all ten simulation runs for each intersection were analyzed. The analysis in SSAM yielded conflict results for each simulation and also a total for the ten simulations combined. Eventually the conflicts that will be used in the crash prediction models will be the average of the conflicts over ten simulation runs i.e. the total of conflicts from 10 simulation runs divided by 10.

4.3.2 Types of Conflicts

SSAM classifies conflicts into five main categories. They are:

- Rear End
- Lane Change
- Crossing
- Unclassified
- Total

Figure 4.4 shows the conflict angle diagram used by SSAM in evaluating the conflicts.

As can be seen, any conflicts with angles of less than 30° are classified as rear end, between 30° and 85° are classified as lane change, and between 85° and 180° are classified as crossing. Conflicts with angles greater than 180° are shown as unclassified conflicts. In most cases the number of unclassified conflict was zero.

Normally, while doing modelling the unclassified conflicts should not be taken into account and they should be omitted. The total conflicts count used for this study does not reflect the unclassified conflicts.

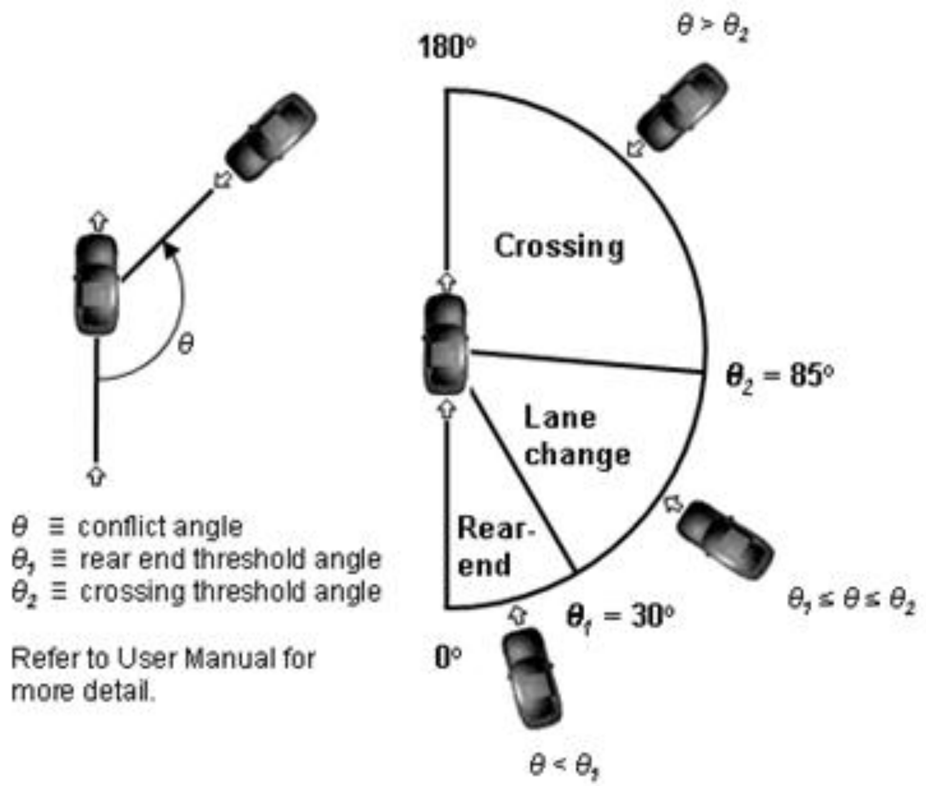

Figure 4.4: Conflict Angle Diagram Used by SSAM

(Source: SSAM Software)

4.3.3 Filtering the Conflicts

Once the conflict analysis was completed, the conflicts were filtered out to remove any uncertainties. The first step was filtering out the conflicts with any values of TTC and PET equal to zero. Zero values of TTC and PET indicate some problems with simulation and as such should be filtered out. Instances with zero values of TTC and PET were very few.

The second thing that was filtered out is the pedestrian-pedestrian conflicts and the vehicle-pedestrian conflicts. The reason for leaving out the pedestrian conflicts is that in this study, vehicle-vehicle conflicts and vehicle-vehicle crashes are being modelled. Furthermore, no data are available for pedestrian-pedestrian crashes and, even so, the number of vehicle-pedestrian crashes is likely much too small to develop reliable models for this crash type. SSAM does not identify pedestrian conflicts separately, but according to the SSAM release notes, filtering out conflicts with speeds of less than 5 mph or 7.3 ft. /sec would basically get rid of all the pedestrian conflicts. This is because 5 mph is over the natural walking pace of pedestrians (SSAM Release Notes, 2011).

Lastly, the intersection coordinates were filtered to only give conflicts within 50m radius of the intersection. This is because the crash data available for the intersections relate crashes within the 50m radius of the intersection as intersection crashes. Thus, filtering the conflicts within 50m radius of the intersection will ensure unity in the way the crashes and conflicts are estimated for the intersections.

4.4 Crash Prediction Models

Consistent with state-of-the-art methods, generalized linear modeling, with the specification of a negative binomial (NB) error structure, was used to develop the Crash Prediction Models (Persaud *et al*, 2012). In turn, the specification of an NB error structure allows for the direct estimation of the over dispersion parameter (one of the parameters used to assess the models) since this is a parameter of the NB distribution. Over dispersion occurs when the data have larger variance than what is expected under the assumption of a Poisson distribution.

Possible model variables include:

- Conflicts – Total number of conflicts by type.
- Entering AADT – Total entering average annual daily traffic at an intersection
- Major AADT – Major road average annual daily traffic at an intersection
- Minor AADT - Minor road average annual daily traffic at an intersection
- Peak Hour Ratio – Ratio of peak hour traffic to average daily traffic

- Presence of right-turn lanes at intersections
- Presence of left-turn lanes at intersections

Different models were developed linking different crash types to their relevant conflict types and different crash types to the average daily traffic. The general form of crash prediction models used is as follows:

$$Crashes = e^{\alpha} \times Variable\ 1^{\beta_1} \times Variable\ 2^{\beta_2} \times --- \times Years \qquad \text{(Equation 4-1)}$$

Where;

Crashes = Type of crash modeled (e.g. Total, Injury, Rear End, etc.),

α = Intercept estimate,

β_1, β_2, etc. = Coefficient estimates for the explanatory variables,

Years = No. of years of crash data used.

Several goodness-of-prediction measures were used to assess the predictive capabilities of each model. These include:

- Plots of the cumulative residuals (observed minus predicted crash frequencies) graphed versus each variable in the model (called “CURE” plots).
- Mean absolute deviation (absolute value of sum of observed minus predicted crash frequencies divided by sample size)
- Mean squared prediction error—MSPE (sum of squared differences between observed and predicted crash frequencies divided by sample size).
- Mean prediction error (square root of the sum of squared differences between observed and predicted crash frequencies divided by sample size).

Prior to assessing the goodness-of-fit of the models the calibration factors were derived. Because the model fitting process is actually fitting the logs of crashes and the independent variables, the sum of observed to fitted crashes is never exactly equal. Although the differences are small, in order to make equal comparisons between models these differences were eliminated by applying calibration factors to each model as a multiplicative factor. The calibration factor is derived by dividing the sum of observed crashes by the sum of predicted crashes.

Comparing the predictive capabilities of the volume based models against the peak hour conflict based models is one of the objectives of this study. Alternative models were compared using standard measures of goodness-of-fit such as the mean residuals (observed minus predicted) and the value of the over dispersion parameter which is estimated as part of the modeling process and is in itself a reliable goodness-of-fit measure, with a smaller over dispersion parameter indicating a model that better captures the over dispersion in the data.

It is important to not only evaluate a model based on overall measures but also to evaluate how it performs over the range of covariates. This evaluation makes use of cumulative residual (CURE) plots (See Figure 4.5).

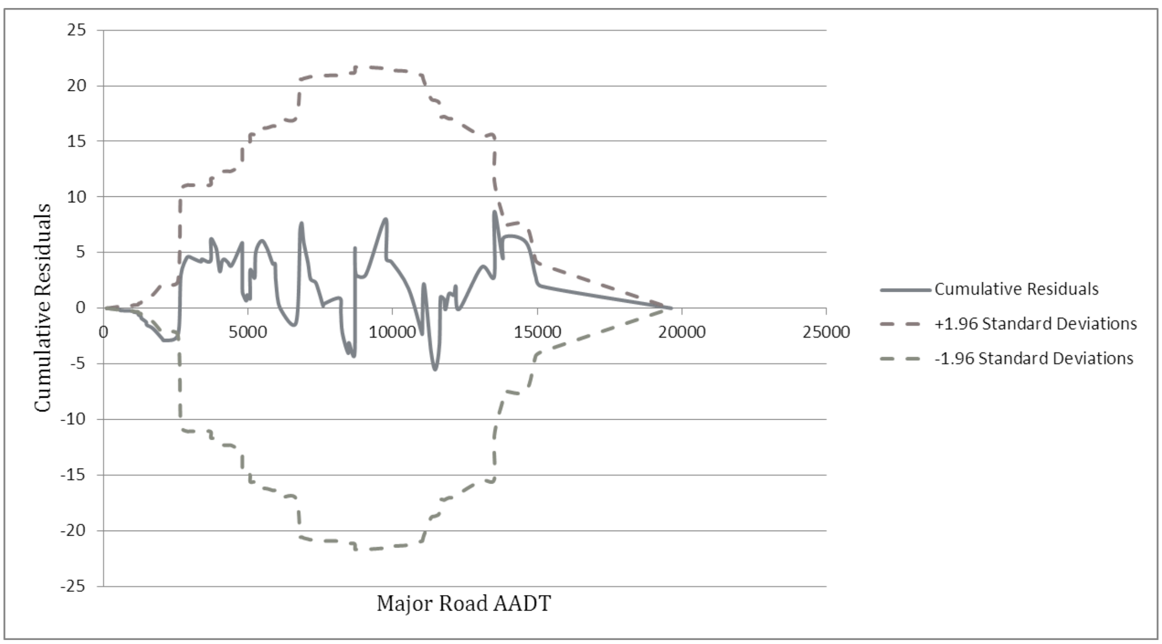

Figure 4.5: Example of a CURE Plot

In the Cumulative Residuals (CURE) method the cumulative residuals (the difference between the observed and predicted values for each site) are plotted in increasing order for each covariate separately. Also plotted are graphs of the 95% confidence limits. If there is no bias in the model, the plot of cumulative residuals should oscillate without systematic over or under-prediction, and stay inside of these confidence limits. The graph shows how well the model fits the data with respect to each individual covariate.

Figure 4.5 illustrates an example of the CURE plot for the Major Road AADT covariate. The indication is that the fit is very good for this covariate in that the cumulative residuals oscillate around the value of zero and lie between the two standard deviation boundaries.

5. Simulated Conflicts

5.1 Conflicts Estimated for all Sites

As discussed before in Chapter 4, the simulation results were exported to SSAM where the vehicle trajectories were translated into possible conflicts. Table 5.1 summarizes the estimated conflicts for all of the 113 intersections.

Table 5.1: Estimated Conflicts Summary Statistics

Conflicts Estimation Statistics				
Collisions	**Mean**	**Minimum**	**Maximum**	**Percentage**
TOTAL	140.327	10	448	100.00%
CROSSING	9.050	0	48	6.45%
REAR END	122.239	6	416	87.11%
LANE CHANGE	9.029	1	37	6.43%

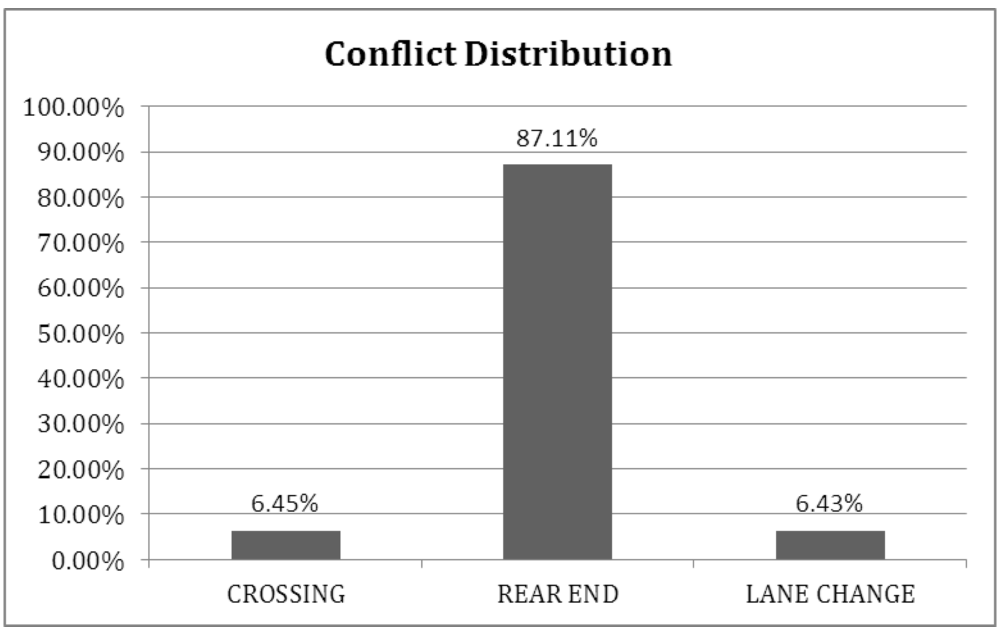

Figure 5.1: Distribution of Conflicts by Type

As can be seen in Table 5.1, Rear End conflicts dominate the conflicts estimated from the simulation results. About 87% of all the conflicts are rear end, whereas only about 6% each are crossing and lane change. Though the Rear End conflicts maybe on the high side in reality, the high estimations in SSAM can be explained by two factors. The first factor that can define the high estimates is the method used in SSAM for the estimation of conflicts. Figure 4.3 in Chapter 4 shows the conflict angle diagram used by SSAM in the estimation of conflicts. It can be seen that any conflicts with angles of less than 30° are classified as rear end, whereas conflicts between angles of 30° and 85° are classified as lane change conflicts. Though it is certain that rear end conflicts occur at smaller angles, a better practice would be to use conflict angles of less than 15° to classify rear end conflicts. This is because any conflict occurring at an angle greater than 15° can be a result of the beginning of a lane change maneuver. The second factor that can define the high estimates is the area used to attribute conflicts to the intersection. Although simulations were run for a 200 m radius, only those conflicts that occurred within 50 m radius of the intersection were attributed to the particular intersection analysed in order to be consistent with the area used to attribute crashes to an intersection. In reality, few vehicles will be changing lanes within 50 m of an intersection unless the traffic light is green. Thus, the idea of using the rear end conflict angle to be less than 15° could have a minor effect on the estimated rear end conflicts, but could change results substantially if a larger portion of a roadway is considered.

5.2 Conflicts Estimated by Site Type

Amongst the 113 intersections used for this study, 33 intersections had no turning lanes on any approaches to the intersection while 80 intersections had a presence of a turning lane on at least one approach.

Table 5.2 shows some AADT statistics for sites with and without the turning lanes.

Table 5.2: AADT Statistics for Sites With and Without the Turning Lanes

Data	*Sites with Turn Lanes*		*Sites without Turn Lanes*	
AADT	*MAJOR AADT*	*MINOR AADT*	*MAJOR AADT*	*MINOR AADT*
Mean	13453	6481	10769	6383
Maximum	21937	15772	23807	11020
Minimum	5061	78	5048	3954

Tables 5.3 and 5.4 summarize the estimated conflicts for sites with and without turning lanes.

Table 5.3: Estimated Conflicts for Sites with Turning Lanes

Conflicts Estimation Statistics (Sites With Turning Lanes)				
Collisions	**Mean**	**Minimum**	**Maximum**	**Percentage**
TOTAL	148.310	14	448	100.00%
CROSSING	9.648	1	48	6.51%
REAR END	128.419	6	416	86.59%
LANE CHANGE	10.223	1	37	6.89%

Table 5.4: Estimated Conflicts for Sites without Turning Lanes

Conflicts Estimation Statistics (Sites Without Turning Lanes)				
Collisions	**Mean**	**Minimum**	**Maximum**	**Percentage**
TOTAL	117.000	10	262	100.00%
CROSSING	7.739	0	28	6.61%
REAR END	102.509	7	242	87.61%
LANE CHANGE	6.761	1	24	5.78%

As can be seen from Tables 5.3 and 5.4, the percentage of crossing conflicts is roughly the same for both the sites with and without turning lanes while minor differences exist in the percentages of rear end and lane change conflicts. The estimates suggest a higher percentage of rear end conflicts for sites without turning lanes and a higher percentage of lane change conflicts for sites with turning lanes. To be certain of a trend in the estimation of conflicts of sites with or without the turning lanes, the number of sites used for each criterion should be about the same. In this study, the much smaller number of sites without turning lanes (when compared to sites with turning lane) can potentially result in an under prediction of the effects of the presence of turning lanes on the conflicts.

6. Model Fitting and Evaluation

This section is divided into three parts. The first part summarizes the different models developed to estimate crashes from traffic volumes and conflicts and also discusses their predictive capabilities. The second part looks at the possible effects of providing protected left turn phasing at a sample of intersections (chosen from the 113 intersections used in this study) that previously had left turn lanes and for which the volumes and the level of service (LOS) for left turn movements justifies the protected-permissive left turn movements. The third part discusses how well the models developed perform in comparison with the SSAM's linear and non-linear models for predicting crashes from conflicts.

6.1 Crash Prediction Models

Three crash prediction models were developed. One model was developed for estimating crashes from traffic volumes and two models were developed to estimate crashes from the simulated peak hour conflicts. The first model estimates crashes from the average daily traffic (using the average daily traffic as the explanatory variable). The second model developed uses the peak hour simulated conflicts to estimate crashes, whereas the third model incorporates the peak hour traffic ratio into the conflict based model in order to better capture the effect of peak hour conflicts on the crashes.

The purpose of developing these models is to compare the predictive capabilities of the volume and conflict based crash prediction models at predicting crashes for all sites and sites grouped by the following:

- Various ranges of AADT (for the volume based models).
- Various ranges of conflicts (for the conflict based models).
- Various combinations of right and left turn lanes.

6.1.1 Crash – AADT Models

The model form used for developing the Crash – AADT models was as follows:

$$Crashes = e^{\alpha} \times Entering\ AADT^{\beta_1} \times Years \qquad \text{(Equation 6-1)}$$

Where;

Crashes = Number of Crashes by Type (e.g. Total, Injury, Rear End, etc.),

α = Intercept estimate,

Entering AADT = Sum of the major & minor AADT's for the intersection,

β_1 = Coefficient estimate for entering AADT,

Years = No. of years of crash data used.

Another possible model form was to use the major and minor AADT's as separate explanatory variables. The models developed using this form did not yield significant coefficient estimates for minor AADT and thus entering AADT was used. The reason behind this might be the lack of variation in the minor AADT values with 66 (of 113) intersections having minor AADT values between 4000 and 7000. Among these 66 intersections, 32 had minor AADT values between 4000 and 5500. This problem with the lack of variation in the minor AADT values at majority of intersections could be eliminated with the use of a higher number of sites with less homogeneity with respect to road characteristics. Also, the major AADT is better correlated with the total crashes as compared to the minor AADT. The Pearson correlation coefficient between major AADT and total crashes is 0.678 compared to 0.143 between minor AADT and total crashes. The correlation between major and minor AADT is 0.173. This indicates a stronger linear relationship between major AADT and total crashes as compared to minor AADT and total crashes.

Table 6.1 on the following page shows the coefficient estimates for each model alongside their significance (p-value) and the dispersion parameter (k). Tables 6.2 shows the calculations for the goodness of prediction estimates and CURE plots for all of these models can be seen in Figures 6.1 and 6.2.

Table 6.1: Coefficient Estimates and Dispersion Parameters for Crash – AADT Models

Crash Type	**Total**		**Injury**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-6.2850	0.0001	-7.3140	<0.0001
β1	0.9133	<0.0001	0.8739	<0.0001
K	0.224		0.181	
Crash Type	**Property Damage Only**		**Angle**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-6.6803	0.0001	-3.9787	0.0454
β1	0.9252	<0.0001	0.5114	0.0115
K	0.253		0.286	
Crash Type	**Head On**		**Rear End**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-3.0356	0.3418	-12.3555	<0.0001
β1	0.2183	0.5015	1.4101	<0.0001
K	0.398		0.252	
Crash Type	**Side Swipe**		**Turning**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-8.3235	0.0017	-10.9798	<0.0001
β1	0.9265	0.0006	1.2026	<0.0001
K	0.524		0.300	

As can be seen from Table 6.1, coefficient estimates for all models are highly significant except for the Head-On crash model. The main reason behind this is possibly the small number of Head-On crashes, with only 232 over five years.

The goodness of prediction measures shown in Table 6.2 shows that the MAD/year/site and the MPE/year/site for all the models are small when compared to the average observed crashes per year per site. For example, for total crashes the MAD/year/site is 0.048 compared to average observed total crashes of ~15 per year per site. Similarly, the MAD/year/site for rear end cashes is 0.018 compared to ~5 rear end crashes per year per site. The CURE plots (Figures 6.1 and 6.2) for all of the Crash – AADT models show that the cumulative residuals lie between the 95% confidence boundaries and that they oscillate consistently, showing little or no bias. Both the goodness of prediction measures and the CURE plots for the models are an indicator of good predictions by the AADT only models.

Table 6.2: Goodness of Prediction Measures for Crash – AADT Models

Crash Type	***Total***	***Injury***	***PDO***	***Angle***
Avg. Obs. Crashes/Year/Site	15.1185841	3.65663717	11.4477876	0.41061947
MAD	26.966	7.017	21.853	1.477
MAD/Year/Site	0.048	0.012	0.039	0.003
MSPE	1256.304	77.185	829.763	3.741
MPE	35.444	8.785	28.806	1.934
MPE/Year/Site	0.063	0.016	0.051	0.003
Crash Type	***HEO***	***Rear End***	***Side Swipe***	***Turning***
Avg. Obs. Crashes/Year/Site	2.86902655	4.7840708	2.24424779	2.4159292
MAD	6.195	10.134	6.672	5.689
MAD/Year/Site	0.011	0.018	0.012	0.010
MSPE	63.683	161.974	94.521	60.041
MPE	7.980	12.727	9.722	7.749
MPE/Year/Site	0.014	0.023	0.017	0.014

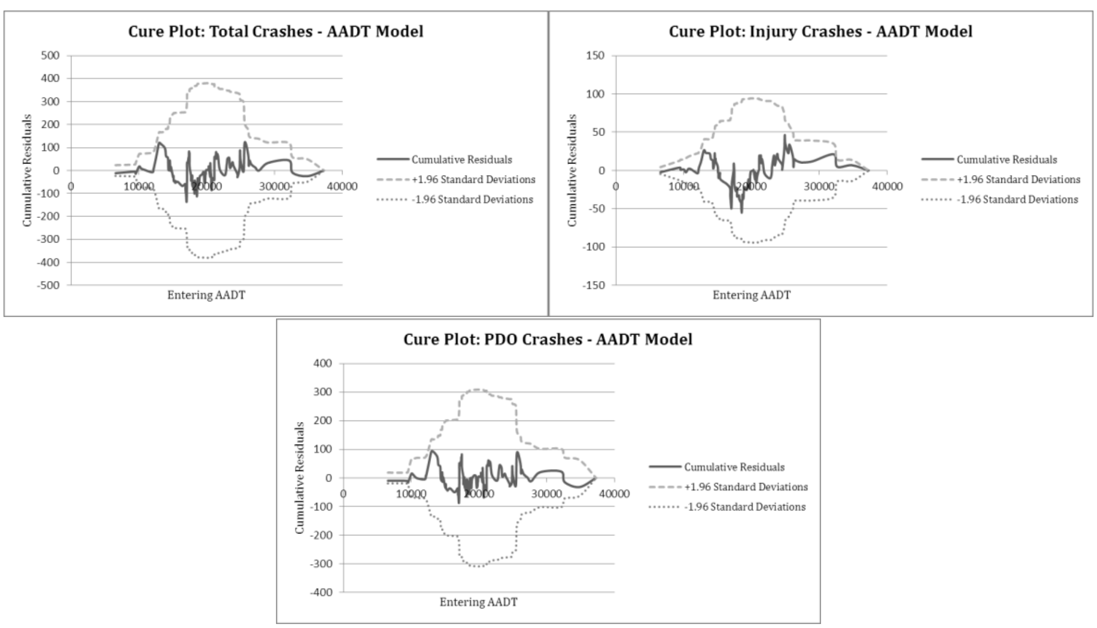

Figure 6.1: CURE Plots for Total, Injury & PDO Crashes (AADT Model)

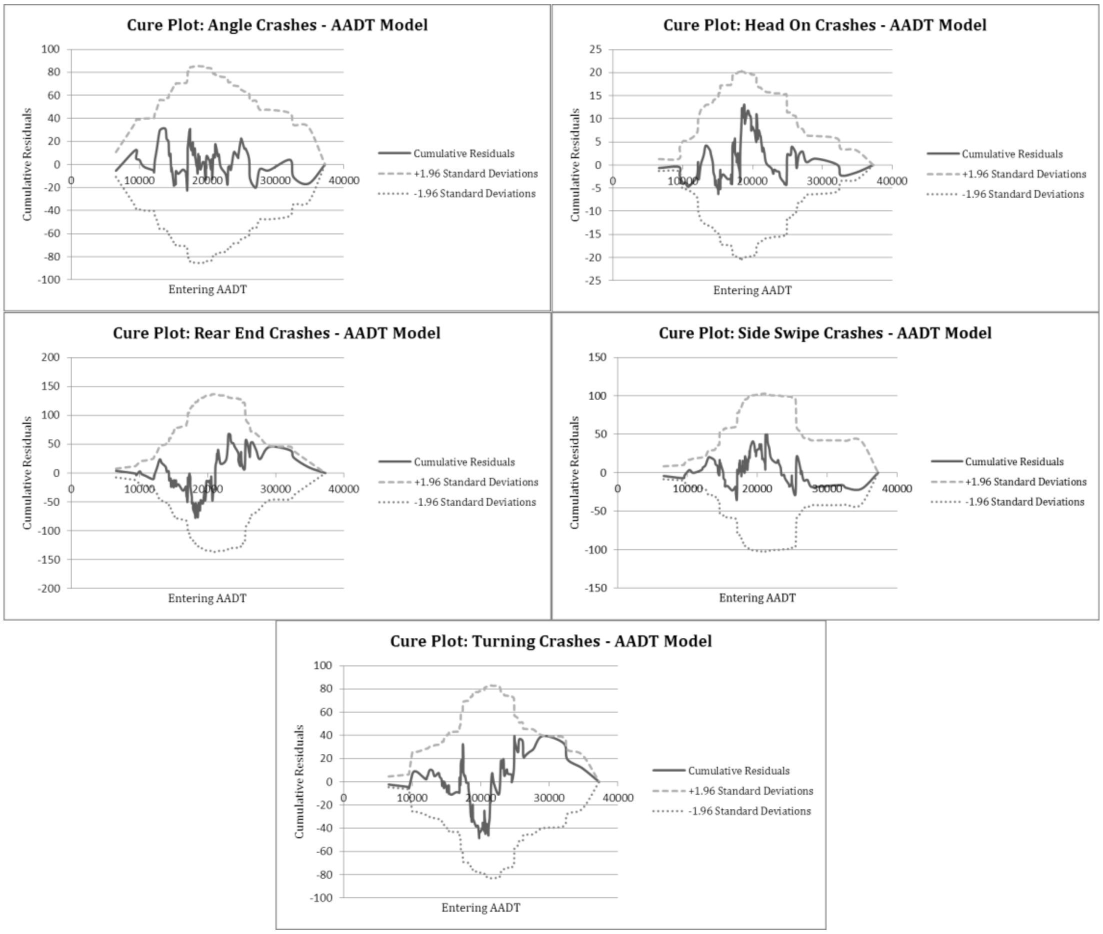

Figure 6.2: CURE Plots for Other Crash Types (AADT Model)

6.1.2 Crash – Peak Hour Conflict Models

For the peak hour conflict based crash models, two different types of models were developed. The first model was a baseline model using the peak hour conflicts as the only explanatory variable. In the second model, an extra variable was added to capture the ratio between the peak hour traffic and the average daily traffic.

The purpose of developing two different peak hour conflict based prediction models is to find whether the introduction of the peak hour ratio into the model improves the capture of the effect of peak hour conflicts on yearly crashes. The effect of peak hour ratio wouldn't have been important in case the model was predicting only the peak hour crashes from the peak hour conflicts. But since the model is used to predict the yearly crashes it could act as a link that leads to better predictions by introducing the average daily volumes into the equation.

The reason that yearly crashes were modelled instead of the peak hour crashes is that from the safety management point of view the safety of a road entity cannot be judged only by the crashes in the peak hour. Though peak hour traffic data are used when designing a roadway, when it comes to measuring safety performance of the same roadway, one should consider crashes at all times rather than just the peak hour. This is because there are likely more crashes in the non-peak hours than there are in the peak hour (Tables 3.3 and 3.4 attest to this fact by showing that for the 113 intersections used, the crashes in the peak hour are only about ~20% of the crashes in the non-peak hour period).

For both model types, 16 different models were developed. The models developed included models linking total, injury and PDO crashes to total, crossing, rear end, and lane change conflicts as well as models linking specific crash types to their relevant conflict types. These models include;

- Angle crashes – Crossing conflicts,
- Rear End crashes – Rear End conflicts,
- Side Swipe crashes – Lane Change conflicts,
- Turning crashes – Crossing conflicts.

6.1.2.1 Models Based on Peak Hour Conflicts

The model form used for developing the models with peak hour conflicts as the only explanatory variable was as follows:

$$Crashes = e^{\alpha} \times Conflicts^{\beta_1} \times Years \qquad \text{(Equation 6-2)}$$

Where;

Crashes = Number of Crashes by Type (e.g. Total, Injury, Rear End, etc.),

α = Coefficient estimate for intercept,

Conflicts = Number of Simulated Conflicts by Type (e.g. Total, Crossing, etc.),

β_1 = Coefficient estimate for Conflicts,

Years = No. of years of crash data used.

Table 6.3 shows the coefficient estimates and the dispersion parameters for models distinguished by their specific crash – conflict types, whereas Table 6.4 shows the goodness of prediction measures for all the model types. The CURE plots for all the crash – conflict models can be seen in Figures 6.3 – 6.6.

Table 6.3: Coefficient Estimates and Dispersion Parameters for Peak Hour Conflict Models

Crash - Conflict	**Total - Total**		**Total - Crossing**		**Total - Rear End**		**Total - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	1.6245	<0.0001	2.2152	<0.0001	1.7761	<0.0001	2.3266	<0.0001
β1	0.2282	0.0004	0.2440	0.0001	0.2036	0.0006	0.1969	0.0025
K	0.255		0.257		0.257		0.262	
Crash - Conflict	**Injury - Total**		**Injury - Crossing**		**Injury - Rear End**		**Injury - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	0.3116	0.3245	0.7150	<0.0001	0.4350	0.1289	0.9093	<0.0001
β1	0.2063	0.0017	0.2830	<0.0001	0.1869	0.0024	0.1954	0.0016
K	0.213		0.201		0.215		0.213	
Crash - Conflict	**PDO - Total**		**PDO - Crossing**		**PDO - Rear End**		**PDO - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	1.3031	<0.0001	1.9568	<0.0001	1.4666	<0.0001	2.0474	<0.0001
β1	0.2372	0.0005	0.2344	0.0005	0.2103	0.0009	0.1976	0.0050
K	0.284		0.290		0.287		0.294	
Crash - Conflict	**Angle - Crossing**		**Rear End - Rear End**		**Side Swipe - Lane Change**		**Turning - Crossing**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	0.6247	0.0004	0.2919	0.3677	0.4342	0.0414	0.3094	0.1241
β1	0.2145	0.0086	0.2742	<0.0001	0.1896	0.0647	0.2859	0.0024
K	0.286		0.344		0.568		0.356	

Table 6.4: Goodness of Prediction Estimates for Peak Hour Conflict Models

Crash-Conflict	***Total - Total***	***Total - Crossing***	***Total - Rear End***	***Total - Lane Change***
Avg. Obs. Crashes/Year/Site	15.119	15.119	15.119	15.119
MAD	29.397	30.320	29.513	29.268
MAD/Year/Site	0.052	0.054	0.052	0.052
MSPE	1414.618	1517.488	1426.835	1506.738
MPE	37.611	38.955	37.773	38.817
MPE/Year/Site	0.067	0.069	0.067	0.069
Crash-Conflict	***Injury - Total***	***Injury - Crossing***	***Injury - Rear End***	***Injury - Lane Change***
Avg. Obs. Crashes/Year/Site	3.657	3.657	3.657	3.657
MAD	7.563	7.550	7.574	7.603
MAD/Year/Site	0.013	0.013	0.013	0.013
MSPE	86.339	90.570	86.975	87.702
MPE	9.292	9.517	9.326	9.365
MPE/Year/Site	0.016	0.017	0.017	0.017
Crash-Conflict	***PDO - Total***	***PDO - Crossing***	***PDO - Rear End***	***PDO - Lane Change***
Avg. Obs. Crashes/Year/Site	11.448	11.448	11.448	11.448
MAD	23.287	24.313	23.027	23.390
MAD/Year/Site	0.041	0.043	0.041	0.041
MSPE	919.847	987.109	942.761	986.504
MPE	30.329	31.418	30.704	31.409
MPE/Year/Site	0.054	0.056	0.054	0.056
Crash-Conflict	***Angle-Crossing***	***Rear End-Rear End***	***Side Swipe-Lane Change***	***Turning-Crossing***
Avg. Obs. Crashes/Year/Site	2.869	4.784	2.244	2.416
MAD	6.320	11.214	6.983	6.133
MAD/Year/Site	0.011	0.020	0.012	0.011
MSPE	65.554	199.915	101.516	67.653
MPE	8.097	14.139	10.076	8.225
MPE/Year/Site	0.014	0.025	0.018	0.015

As can be seen from Tables 6.3 and 6.4, the coefficient estimates for all of the conflict based crash estimation models are significant and the dispersion parameters are very similar to the volume based crash models shown in Section 6.1.1. The MAD/year/site and MPE/year/site values for the models are also small compared to the average observed crashes per year per site. These values are also very close to the MAD and MPE values for the volume based crash models. These results collectively suggest that the crash predictions from the conflict based models can be as good to those from the volume based models. Even though the conflict based models are not superior to the AADT models, there are other benefits of using micro simulation such as the ability to better capture the effects of different geometric features and the potential to evaluate the effects of different hypothetical alternatives.

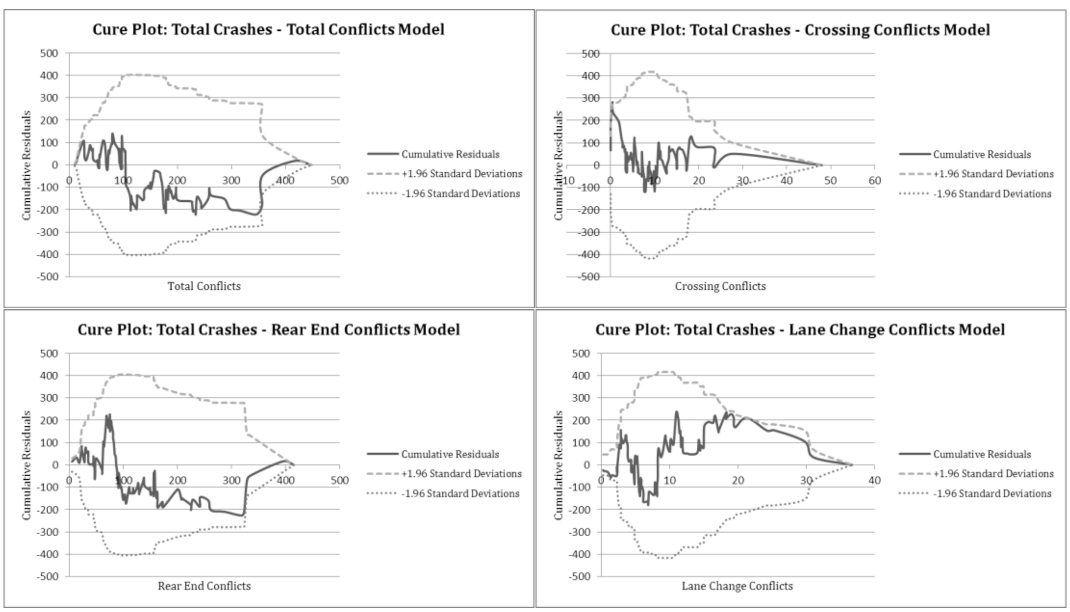

Figure 6.3: CURE Plots for Models Estimating Total Crashes

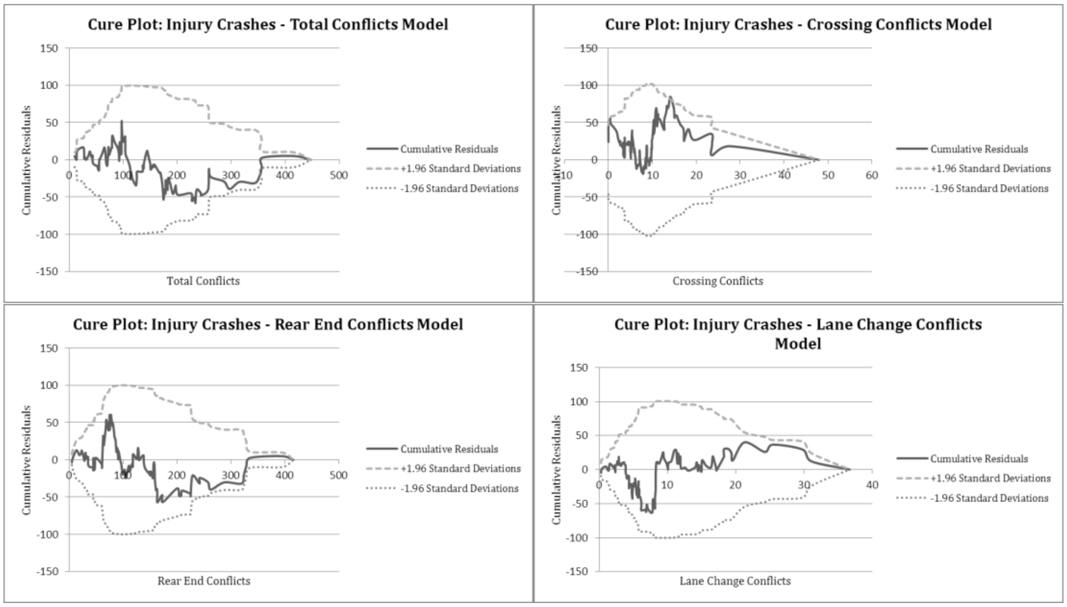

Figure 6.4: CURE Plots for Models Estimating Injury Crashes

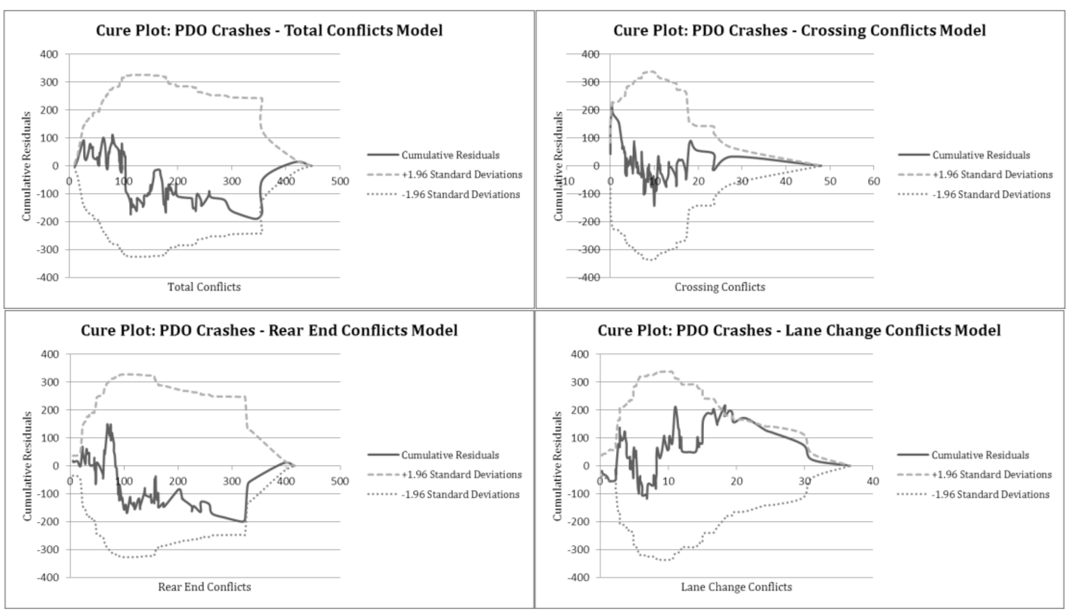

Figure 6.5: CURE Plots for Models Estimating PDO Crashes

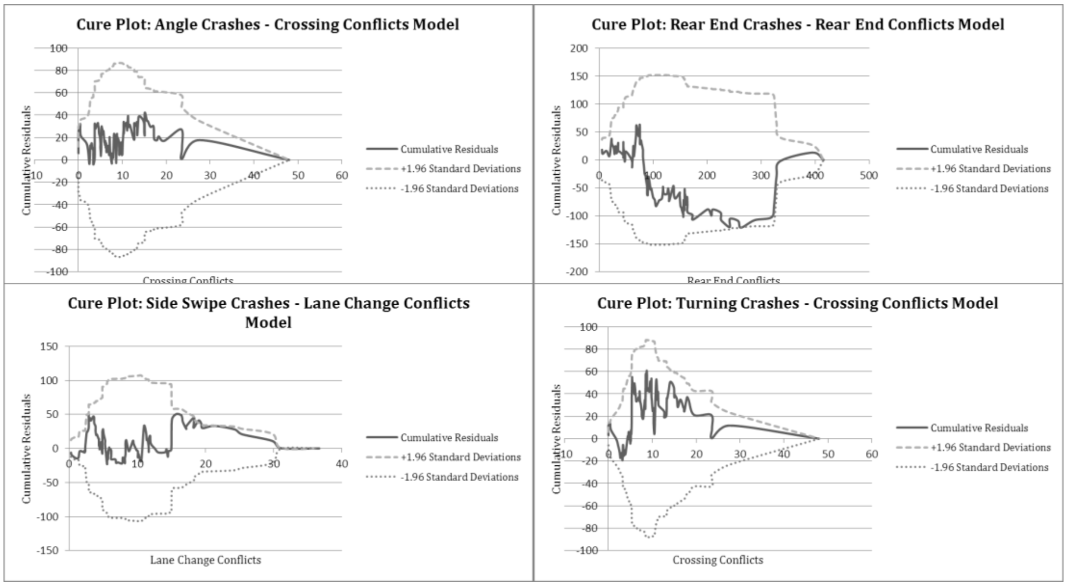

Figure 6.6: CURE Plots for Models Estimating Crash Types from their Pertinent Conflict Type

The CURE plots (Figures 6.3 – 6.6) show that the cumulative residuals in all cases lie within the 95% confidence boundaries and that they oscillate consistently in most cases showing little or no bias in predictions. In some cases, at higher conflict values (see Figures 6.3 and 6.5, Total Crash – Lane Change Conflicts and PDO Crashes – Lane Change Conflicts) the models are under predicting at higher conflict levels. But even in these cases, at lower numbers of conflicts the cumulative residuals oscillate, suggesting a good fit.

It can be seen that the crash predictions from the volume based models and the peak hour conflict based models are very similar in that the MAD/year/site and MPE/year/site are very similar for both models and also that the CURE plots for both models show similar trends. The only thing to be noticed between the two models is that the coefficient estimate for peak hour conflicts, though highly significant, is small compared to the coefficients for the entering AADT in the volume based models. This suggests that conflicts depend less strongly on traffic volumes and more so on other factors than crashes.

6.1.2.2 Models based on Peak Hour Conflicts and the Peak Hour Traffic Ratio

These models were developed in addition to the peak hour conflicts only models (Section 6.1.2.1) to incorporate the variable for the peak hour traffic ratio to see how it will affect the crash predictions.

The model form used for developing the models with peak hour conflicts and the peak hour traffic ratio as the explanatory variables was as follows:

$$Crashes = e^{\alpha} \times Conflicts^{\beta_1} \times Peak\ Hour\ Ratio^{\beta_2} \times Years \qquad \text{(Equation 6-3)}$$

Where;

Crashes = Number of Crashes by Type (e.g. Total, Injury, Rear End, etc.),

α = Coefficient estimate for intercept,

Conflicts = Number of Simulated Conflicts by Type (e.g. Total, Crossing, etc.),

β_1 = Coefficient estimate for Conflicts,

Peak Hour Ratio = Ratio of Peak Hour Traffic to the Average Daily Traffic,

β_2 = Coefficient estimate for the Peak Hour Ratio,

Years = No. of years of crash data used.

Table 6.5 shows the coefficient estimates and the dispersion parameter for models distinguished by their specific crash – conflict types, whereas Table 6.6 shows the goodness of prediction measures for all the model types. The CURE plots for all the crash – conflict models can be seen in Figures 6.7 – 6.10.

Table 6.5: Coefficient Estimates and Dispersion Parameters for Conflict Models (w/ PKHR Ratio)

Crash - Conflict	**Total - Total**		**Total - Crossing**		**Total - Rear End**		**Total - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-0.9722	0.2771	1.0620	0.1047	-0.6492	0.4536	1.0071	0.1437
β1	0.3461	<0.0001	0.2741	<0.0001	0.3065	<0.0001	0.2450	0.0003
β2	-1.0775	0.0023	-0.5788	0.0730	-1.0334	0.0035	-0.6489	0.0520
K	0.235		0.250		0.239		0.254	
Crash - Conflict	**Injury - Total**		**Injury - Crossing**		**Injury - Rear End**		**Injury - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-1.7527	0.0543	-0.0934	0.8837	-1.4876	0.0910	-0.2630	0.7012
β1	0.3030	<0.0001	0.3043	<0.0001	0.2720	0.0001	0.2402	0.0003
β2	-0.8498	0.0164	-0.4059	0.1939	-0.8117	0.0217	-0.5746	0.0823
K	0.201		0.198		0.203		0.207	
Crash - Conflict	**PDO - Total**		**PDO - Crossing**		**PDO - Rear End**		**PDO - Lane Change**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-1.4144	0.1346	0.7333	0.2928	-1.0782	0.2391	0.7129	0.3288
β1	0.3593	<0.0001	0.2655	<0.0001	0.3170	<0.0001	0.2451	0.0008
β2	-1.1303	0.0025	-0.6148	0.0742	-1.0871	0.0038	-0.6574	0.0635
K	0.262		0.282		0.266		0.285	
Crash - Conflict	**Angle - Crossing**		**Rear End - Rear End**		**Side Swipe - Lane Change**		**Turning - Crossing**	
Coefficient	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***	***Estimate***	***Pr > ChiSq***
α	-0.8015	0.2791	-1.2676	0.2341	-1.6218	0.1494	-0.7851	0.3321
β1	0.2549	0.0020	0.3423	<0.0001	0.2608	0.0159	0.3158	0.0009
β2	-0.7117	0.0485	-0.6609	0.1264	-1.0133	0.0639	-0.5477	0.1643
K	0.274		0.336		0.550		0.349	

Table 6.6: Goodness of Prediction Estimates for Conflict Models (w/ PKHR Ratio)

Crash-Conflict	***Total - Total***	***Total - Crossing***	***Total - Rear End***	***Total - Lane Change***
Avg. Obs. Crashes/Year/Site	15.119	15.119	15.119	15.119
MAD	28.842	30.698	28.975	29.016
MAD/Year/Site	0.051	0.054	0.051	0.051
MSPE	1345.643	1517.131	1359.113	1475.647
MPE	36.683	38.950	36.866	38.414
MPE/Year/Site	0.065	0.069	0.065	0.068
Crash-Conflict	***Injury - Total***	***Injury - Crossing***	***Injury - Rear End***	***Injury - Lane Change***
Avg. Obs. Crashes/Year/Site	3.657	3.657	3.657	3.657
MAD	7.395	7.543	7.403	7.536
MAD/Year/Site	0.013	0.013	0.013	0.013
MSPE	84.411	91.353	85.011	86.868
MPE	9.188	9.558	9.220	9.320
MPE/Year/Site	0.016	0.017	0.016	0.016
Crash-Conflict	***PDO - Total***	***PDO - Crossing***	***PDO - Rear End***	***PDO - Lane Change***
Avg. Obs. Crashes/Year/Site	11.448	11.448	11.448	11.448
MAD	22.820	24.388	22.984	23.004
MAD/Year/Site	0.040	0.043	0.041	0.041
MSPE	871.943	982.989	880.872	965.130
MPE	29.529	31.353	29.679	31.067
MPE/Year/Site	0.052	0.055	0.053	0.055
Crash-Conflict	***Angle-Crossing***	***Rear End-Rear End***	***Side Swipe-Lane Change***	***Turning-Crossing***
Avg. Obs. Crashes/Year/Site	2.869	4.784	2.244	2.416
MAD	6.319	11.217	6.878	6.095
MAD/Year/Site	0.011	0.020	0.012	0.011
MSPE	65.358	197.895	100.320	67.807
MPE	8.084	14.068	10.016	8.235
MPE/Year/Site	0.014	0.025	0.018	0.015

As can be seen from Table 6.5, the coefficient estimates for both the peak hour conflicts and the peak hour traffic ratio are significant and the dispersion parameters are slightly lower than the conflicts only models (Section 6.1.2.1). Another thing that can be noticed here is that the addition of the peak hour traffic ratio has led to a higher coefficient estimate for the peak hour conflicts, suggesting a better effect of conflicts on crash predictions. The goodness of prediction measures in Table 6.6 show that the MAD/year/site and MPE/year/site for all models are similar to the peak hour conflict only models, with a difference of ± 0.001 in most cases.

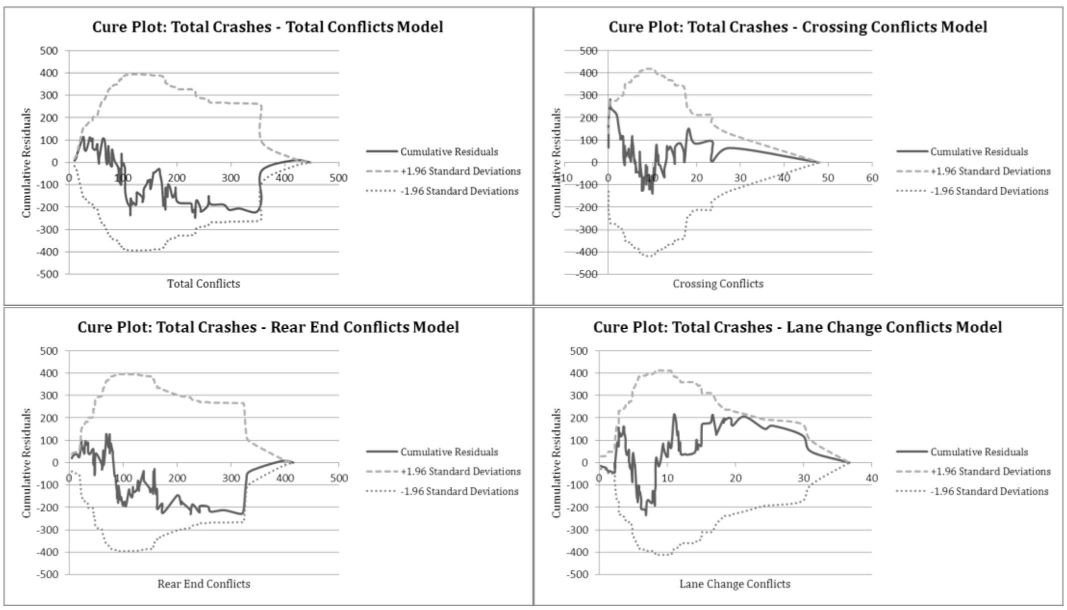

Figure 6.7: CURE Plots for Models (with PKHR Ratio) Estimating Total Crashes

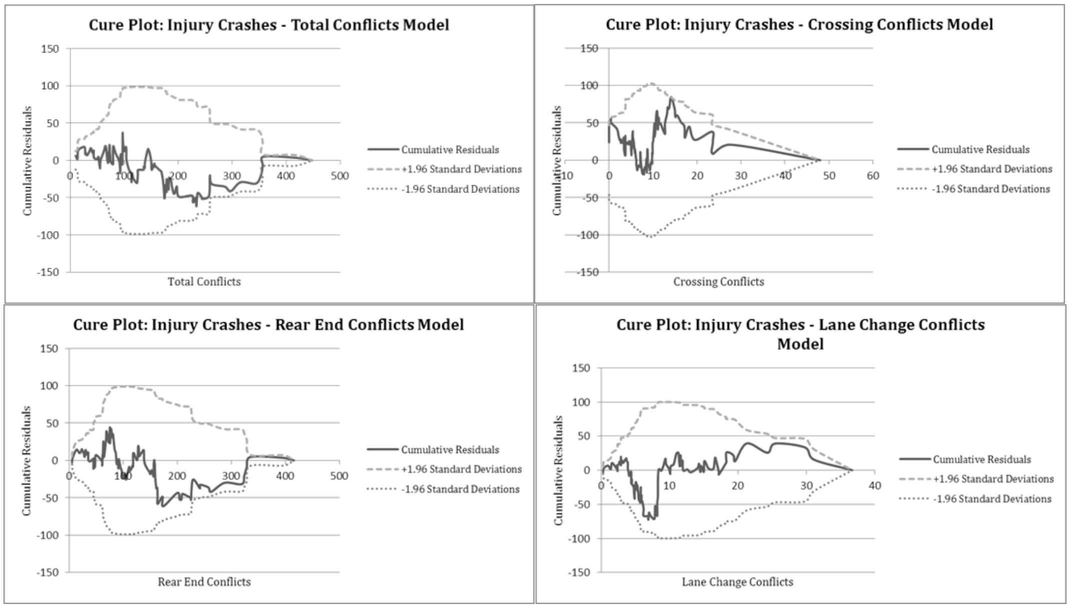

Figure 6.8: CURE Plots for Models (with PKHR Ratio) Estimating Injury Crashes

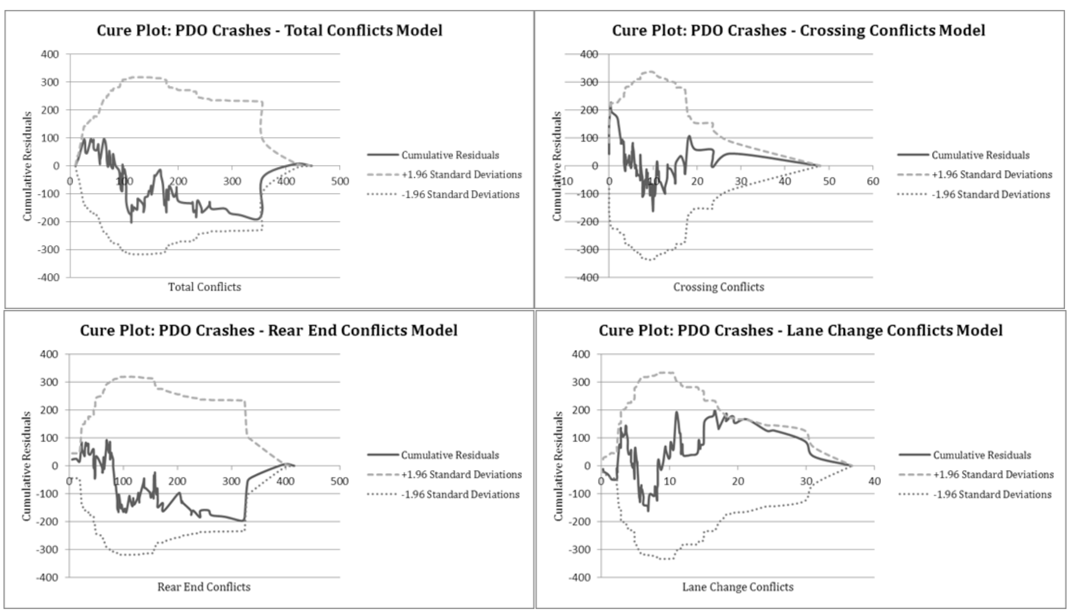

Figure 6.9: CURE Plots for Models (with PKHR Ratio) Estimating PDO Crashes

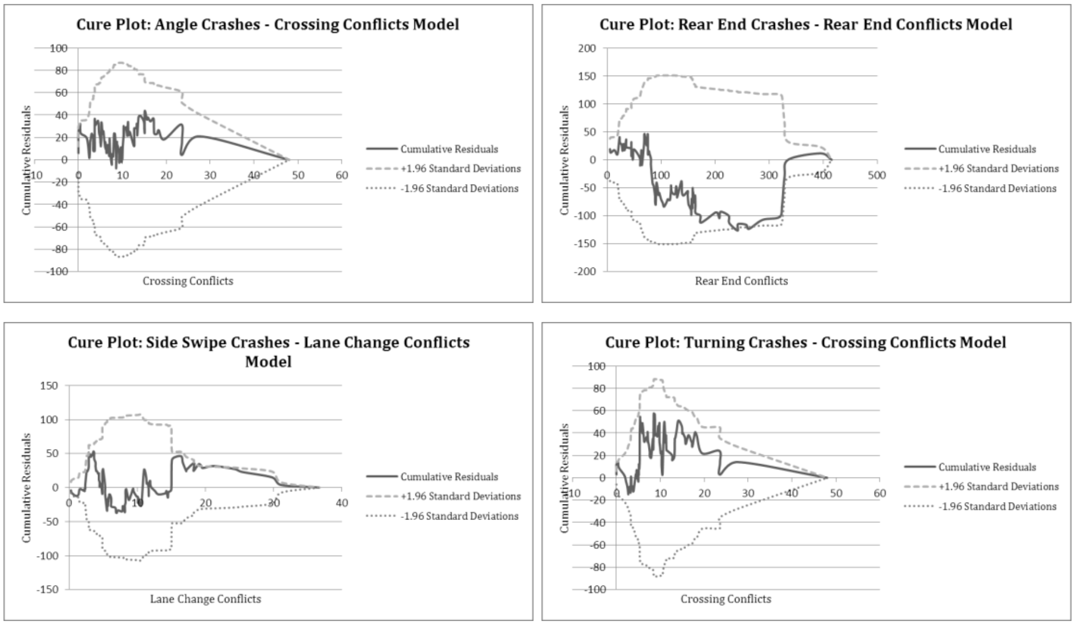

Figure 6.10: CURE Plots for Models (with PKHR Ratio) Estimating Crash Types from their Associated Conflict Type

The CURE plots (Figures 6.7 – 6.10) show that the cumulative residuals in all cases lie within the 95% confidence boundaries and that they oscillate consistently in most cases, showing little or no bias in predictions. In some cases, the models are under predicting for a small range of conflicts at higher levels. But even in these cases, at lower number of conflicts the cumulative residuals oscillate consistently, suggesting of a good fit.

It can be seen that the crash predictions from the peak hour conflict based models and the peak hour conflict based models including a variable for the peak hour traffic ratio are very similar in that the MAD/year/site and MPE/year/site are about the same for both models and also that the CURE plots for both models show similar trends. The only thing that distinguishes the two models is that the coefficient estimate for peak hour conflicts is larger than the estimate from the conflict only models, suggesting of a better effect of the conflicts on the crash predictions.

After looking at the two models, it can be concluded that when predicting the yearly crashes from the peak hour conflicts, it is better to introduce the variable of the peak hour traffic ratio into the model in order to better capture the relationship between the peak hour traffic and the average daily traffic.

6.1.3 Comparison of Predictions by the Volume and Conflict Based Models

6.1.3.1 Comparison of Observed and Predicted Crashes vs. Total Entering AADT

Table 6.7 shows the comparison of observed and predicted crashes for different ranges of total entering AADT in order to see how well the Crash – AADT model (Section 6.1.1) predicts crashes for sites grouped by different ranges of the entering AADT.

Table 6.7: Comparison of Observed and Predicted Crashes Grouped by Total Entering AADT

Entering AADT	Intersections	Ratio: Observed Crashes/Predicted Crashes			
		Total	***Injury***	***PDO***	***Head On***
0 - 15000	22	1.013	1.042	1.002	0.896
15000- 30000	87	1.003	0.999	1.003	1.031
> 30000	4	0.936	0.900	0.948	0.853
Entering AADT	**Intersections**	**Ratio: Observed Crashes/Predicted Crashes**			
		Angle	***Rear End***	***Side Swipe***	***Turning***
0 - 15000	22	0.989	0.952	1.065	0.991
15000- 30000	87	0.999	1.024	0.972	1.033
> 30000	4	1.065	0.787	1.232	0.589

It can be seen that the Crash – AADT model is predicting all the crashes very well even for ranges of total entering AADT. The ratio of observed to predicted crashes in most cases is ~ 1 which shows that the observed and the predicted crashes for each particular reference group are approximately the same.

6.1.3.2 Comparison of Observed and Predicted Crashes vs. Peak Hour Conflicts

Tables 6.8 to 6.11 shows the comparison of observed and predicted crashes for different ranges of peak hour conflicts (by type) in order to see how well the Crash – Peak Hour Conflict model behaves for different ranges of conflicts. The model form used for this comparison is the peak hour conflict based model including the peak hour traffic ratio (Section 6.1.2.2).

Table 6.8: Comparison of Observed and Predicted Crashes Grouped by Total Peak Hour Conflicts

Total Peak Hour Conflicts	Intersections	Ratio: Observed Crashes/Predicted Crashes		
		Total	***Injury***	***PDO***
0 - 150	68	0.980	1.005	0.973
> 150	45	1.021	0.993	1.030

Table 6.9: Comparison of Observed and Predicted Crashes Grouped by Crossing Peak Hour Conflicts

Crossing Peak Hour Conflicts	Intersections	Ratio: Observed Crashes/Predicted Crashes				
		Total	***Injury***	***PDO***	***Angle***	***Turning***
0 - 15	96	1.026	1.063	1.014	1.039	1.047
> 15	17	1.024	0.861	1.077	0.916	0.852

Table 6.10: Comparison of Observed and Predicted Crashes Grouped by Rear End Peak Hour Conflicts

Rear End Peak Hour Conflicts	Intersections	Ratio: Observed Crashes/Predicted Crashes			
		Total	***Injury***	***PDO***	***Rear End***
0 - 150	77	0.979	0.986	0.977	0.963
> 150	36	1.036	1.023	1.040	1.067

Table 6.11: Comparison of Observed and Predicted Crashes Grouped by Lane Change Peak Hour Conflicts

Lane Change Peak Hour Conflicts	Intersections	Ratio: Observed Crashes/Predicted Crashes			
		Total	***Injury***	***PDO***	***Side Swipe***
0 - 15	93	1.010	1.003	1.012	0.989
> 15	20	0.954	0.985	0.944	1.021

As can be seen from Tables 6.8 to 6.11, the comparison was done for crash types models were developed using the related conflict type. All of the models predict crashes very well for different ranges of peak hour conflicts with the ratio of observed to predicted crashes being ~ 1 in most of the cases.

Tables 6.12 show the crash predictions from the peak hour conflict based model including the peak hour traffic ratio (Section 6.1.2.2) for intersections grouped by different ranges of entering AADT.

Table 6.12: Comparison of Observed and Predicted Crashes Grouped by Total Entering AADT (Predicted by the Conflict Based Model)

Entering AADT	**Intersections**	**Ratio: Observed Crashes/Predicted Crashes (By Crash - Conflict Type)**			
		Total - Total	***Total - Crossing***	***Total - Rear End***	***Total - Lane Change***
0 - 15000	22	0.784	0.715	0.777	0.775
15000- 30000	87	1.030	1.087	1.031	1.028
> 30000	4	1.274	1.215	1.330	1.350
Entering AADT	**Intersections**	**Ratio: Observed Crashes/Predicted Crashes (By Crash - Conflict Type)**			
		Injury - Total	***Injury - Crossing***	***Injury - Rear End***	***Injury - Lane Change***
0 - 15000	22	0.811	0.759	0.805	0.812
15000- 30000	87	1.027	1.078	1.027	1.025
> 30000	4	1.243	1.132	1.287	1.284
Entering AADT	**Intersections**	**Ratio: Observed Crashes/Predicted Crashes (By Crash - Conflict Type)**			
		PDO - Total	***PDO - Crossing***	***PDO - Rear End***	***PDO - Lane Change***
0 - 15000	22	0.775	0.701	0.767	0.762
15000- 30000	87	1.031	1.090	1.032	1.029
> 30000	4	1.095	1.494	1.719	0.856
Entering AADT	**Intersections**	**Ratio: Observed Crashes/Predicted Crashes (By Crash - Conflict Type)**			
		Angle-Crossing	***Rear End-Rear End***	***Side Swipe-Lane Change***	***Turning-Crossing***
0 - 15000	22	0.816	0.604	0.806	0.612
15000- 30000	87	1.057	1.062	0.998	1.111
> 30000	4	1.095	1.494	1.719	0.856

As can be seen from Table 6.12, the crash predictions from the conflict based models for sites grouped by different ranges of total entering AADT show a variable trend. The model predicts crashes very well for entering AADT's between 15000 and 30000 with the ratio of observed to predicted crashes being ~ 1. For entering AADT's lower than 15000, the model is over predicting the crashes by roughly 20% in most cases, whereas, for entering AADT's higher than 30000, the model is under predicting the crashes. This trend can be explained by the two things, first that the conflict based models were calibrated using conflicts and as such they do predict crashes well for sites grouped by the number of conflicts (see Tables 6.8 – 6.11). The second reason behind the under and over prediction at lower and higher ranges of entering AADT can be the small number of sites, 22 and 7 respectively, compared to 87 sites for entering AADT's between 15000 and 30000, for which the conflict model predicts as well as the volume model.

At this point it can be seen that the peak hour conflict models are predicting as well as the volume based models when it comes to grouping the sites into different groups of AADT (for volume based models) and conflicts (for peak hour conflict based models).

6.1.3.3 Comparison of Observed and Predicted Crashes vs. No of Left and Right Turn Lanes

Tables 6.13 and 6.14 give the comparison of the observed and predicted crashes as predicted using the total entering AADT and the peak hour conflicts. The comparison is grouped by the various combinations of approaches to the intersection with left and right turn lanes (as allowed by the data). The purpose of this comparison is to see whether the conflict based model can predict crashes at sites with and without turn lanes better than the volume based model without the use of variables for geometric features in the models.

Following is a description of what conflicts were used to estimate the crashes (by type) as they are shown in the comparison:

- Total Conflict: Total, Injury and PDO Crashes.
- Crossing Conflicts: Angle and Turning Crashes.
- Rear End Conflicts: Rear End Crashes.
- Lane Change Conflicts: Side Swipe Crashes.

Table 6.13: Comparison of Observed and Predicted Crashes vs. No. of Turn Lanes

Approaches with Right Turn Lanes	Approaches with Left Turn Lanes	Intersections	Ratio: Observed Crashes/Predicted Crashes													
			Total		*Injury*		*PDO*		*Angle*		Rear End		Side Swipe		Turning	
			AADT Model	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*
0	0	33	1.202	1.131	1.159	1.093	1.216	1.144	1.306	1.307	1.071	0.974	1.357	1.262	1.030	0.964
1	0	5	1.578	1.480	1.293	1.236	1.669	1.559	1.134	1.066	1.632	1.590	2.333	2.614	1.114	1.090
0	1	3	0.964	0.817	0.992	0.844	0.956	0.809	0.370	0.311	0.896	0.683	1.229	1.123	1.177	0.836
2	0	2	0.608	0.745	0.446	0.526	0.660	0.817	0.420	0.870	1.060	1.235	0.638	0.618	0.215	0.419
1	1	7	0.747	0.814	0.613	0.667	0.790	0.862	0.470	0.467	0.900	1.087	1.138	1.027	0.622	0.642
0	2	16	0.949	0.852	0.969	0.884	0.938	0.840	0.927	0.857	0.851	0.781	1.058	1.081	0.774	0.721
1	2	7	0.779	0.793	0.848	0.858	0.754	0.770	0.540	0.578	0.838	0.825	0.612	0.619	1.266	1.328
0	3	4	0.760	0.790	0.829	0.845	0.739	0.770	1.037	1.177	0.940	0.892	0.466	0.492	0.559	0.611
2	2	4	0.534	0.536	0.651	0.642	0.497	0.501	0.700	0.809	0.503	0.448	0.366	0.323	0.770	0.815
0	4	11	1.008	0.980	1.072	1.044	0.987	0.959	1.145	1.101	1.056	1.012	0.721	0.730	1.085	1.025
2	3	1	0.722	1.065	0.703	1.010	0.728	1.087	0.570	0.690	1.205	2.016	0.531	0.634	0.407	0.579
1	4	6	0.856	0.926	0.897	0.987	0.841	0.908	1.019	1.057	0.814	0.994	0.523	0.555	1.274	1.503
2	4	7	0.807	0.919	0.921	1.043	0.771	0.881	0.913	1.023	0.889	1.071	0.395	0.438	1.097	1.368
3	4	2	0.525	0.679	0.613	0.755	0.497	0.651	0.832	0.972	0.443	0.530	0.374	0.460	0.534	0.607
4	4	5	1.388	1.714	1.458	1.768	1.366	1.697	1.259	1.253	1.493	2.022	1.096	1.129	1.762	1.868

Table 6.14: Comparison of Observed and Predicted Crashes vs. Grouped No of Turn Lanes

Approaches with Right Turn Lanes	Approaches with Left Turn Lanes	Intersections	Ratio: Observed Crashes/Predicted Crashes													
			Total		*Injury*		*PDO*		*Angle*		Rear End		Side Swipe		Turning	
			AADT Model	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*	*AADT Model*	*Conflict Model*
0	0	33	1.202	1.131	1.159	1.093	1.216	1.144	1.306	1.307	1.071	0.974	1.357	1.262	1.030	0.964
1 or 2	0	7	1.319	1.319	1.066	1.074	1.400	1.399	0.937	1.037	1.487	1.512	1.881	2.023	0.881	0.990
1, 2, 3, or 4	1	10	0.799	0.815	0.706	0.719	0.830	0.847	0.443	0.420	0.899	0.965	1.160	1.050	0.747	0.700
1, 2, 3, or 4	2	27	0.852	0.800	0.897	0.848	0.835	0.783	0.797	0.786	0.807	0.750	0.857	0.855	0.895	0.871
1, 2, 3, or 4	3	5	0.752	0.837	0.800	0.874	0.736	0.824	0.937	1.078	1.004	1.062	0.481	0.522	0.523	0.605
1, 2, 3, or 4	4	31	0.964	1.049	1.038	1.126	0.940	1.025	1.065	1.095	1.005	1.142	0.646	0.684	1.210	1.310

As can be seen from Tables 6.13 and 6.14, the crash predictions by both the volume and conflict based models for sites grouped by the number of left and right turn lanes are very similar to each other since the ratio of observed and predicted crashes are similar (or in similar range) in almost all the cases. But one thing that can be noticed here is that in almost of the cases the ratio is slightly closer to 1 for the conflict based models as compared to the volume based models. This shows that the predictions by the conflict based are closer to the observed crashes at the grouped sites than the predictions from the volume based models. Also to be noted is that the ratio of observed to predicted crashes, both in case of grouped and non-grouped number of turn lanes, as predicted by the conflict based prediction model suggest that the ratio is oscillating around 1, with little or no bias. This shows that in all cases the conflicts and the conflict models appear to be capturing the effect of the number of turn lanes on crashes reasonably well.

6.1.4 Discussion

The results show that the peak hour conflict based models can predict crashes that are very similar to the predictions by the volume-based models. For all of the models, the MAD/year/site and the MPE/year/site values were low compared to the average crashes/year/site and the CURE plots also showed that cumulative residuals lie between the 95% confidence intervals and that they oscillate consistently, suggesting of little or no bias in most cases.

The incorporation of the peak hour traffic ratio variable into the peak hour conflict based models further enhances the models predictive capabilities. This can be seen in Section 6.1.2.1 and 6.1.2.2 where the models using the peak hour traffic factor had lower dispersion parameters as compared to the peak hour conflict only models and also the coefficient estimate for the peak hour conflicts was higher indicating that the model better captures the effects of conflicts on crashes.

Furthermore, the conflict based models predicted crashes for sites grouped by number of turn lanes better than the volume based models, in that the predictions were closer to the observed crashes.

6.2 Effects of Changing Left Turn Phase from Permissive to Protected-Permissive on Conflicts and Crashes

This part of analysis aims at exploring whether the models can reasonably estimate the effects of providing left turn movement protection at signalized intersections. The conflict type of interest for this part is the crossing conflicts and this analysis will help in finding out how the numbers of crossing conflicts and its pertinent crash types (angle and turning) will change if the left turn phasing at some intersections in the sample were to be changed from permissive to protected-permissive. Effects of this treatment on other conflict and crash types will also be looked at. The estimated effects will then be compared to those estimated in a before-after study conducted by Srinivasan *et al* (2012) for a group of similar Toronto intersections that actually underwent a change from permissive to protected-permissive left turn phasing.

The criteria used for selecting intersections for applying the hypothetical treatments was that the intersections should have at least one approach with an exclusive left turn lane and that the level of service (LOS) and traffic volumes would permit the installation of a protected-permissive signal. A total of 20 intersections out of the 113 intersections used in this thesis were selected for the hypothetical treatment. The LOS for the left turning traffic at these 20 intersections was C or worse, and the left turning traffic volume was more than 50 vehicles per hour. Of the 20 intersections, 1 approach was treated at 1 intersection, 2 approaches were treated at 7 intersections, 3 approaches were treated at 3 intersections, and 4 approaches were treated at 9 intersections. Signal timings (including the protected-permissive left turns) were optimized using SYNCHRO and the traffic was then simulated in VISSIM.

6.2.1 Simulated Conflicts Before and After the Treatment

Table 6.15 shows a summary of the number of peak hour conflicts at the 20 sites before and after the hypothetical treatment was applied.

Table 6.15: Mean Conflict Estimation Statistics (Before & After Treatment)

Mean Conflicts Estimation Statistics			
Collisions	**Before Period**	**After Period**	**% Change**
TOTAL	163.505	99.88	-38.91%
CROSSING	9.815	4.75	-51.60%
REAR END	143.355	88.42	-38.32%
LANE CHANGE	10.335	6.71	-35.07%

The average total conflicts at these sites would be reduced by about 39% from ~164 to ~100. Amongst the specific conflict types, crossing conflicts would have the largest reduction (51.60%) after the treatment was applied. Rear end conflicts would be reduced by ~ 38% and lane change conflicts would be reduced by ~ 35%.

The results of simulated conflicts indicate the largest potential benefit for the turning vehicles (the target vehicles) as they will get involved in only about half of the conflicts they would have been involved in without the treatment.

6.2.2 Predicted Crashes Before and After the Treatment

Table 6.16 provides crash predictions from the peak hour conflict based model (with the peak hour traffic ratio) shown in Section 6.1.2.2. The table also shows the percentage of each crash type with respect to the total predicted crashes.

The crash predictions shown in table were calculated on the basis of the following crash-conflict combinations:

- Total Crashes form Total Conflicts.
- Angle and Turning Crashes from Crossing Conflicts.
- Rear End Conflicts from Rear End Conflicts.
- Side Swipe Crashes from Lane Change Conflicts.

Table 6.16: Crash Predictions Before and After the Hypothetical Treatment was Applied

Crash Type	Before Treatment		After Treatment		% Change in After Period
	Predicted Crashes	% of Total	Predicted Crashes	% of Total	
Total	1646.565	100.00%	1368.255	100.00%	-16.90%
Angle	304.821	18.51%	250.729	18.32%	-17.75%
Rear End	519.356	31.54%	433.158	31.66%	-16.60%
Side Swipe	240.194	14.59%	203.448	14.87%	-15.30%
Turning	259.954	15.79%	204.239	14.93%	-21.43%

Similar to the conflict results (Section 6.2.1), there would be a reduction in the all of the predicted crashes at the 20 sites where the treatment was applied. Angle and turning crashes would be reduced by ~ 18% and 22% respectively, while both the rear end and side swipe crashes would be reduced by ~ 16%. At the same time it can be seen that the percentages of rear end and lane change crashes when compared to the total crashes in the after period would be increased slightly. The results indicate that the treatment would be beneficial in reducing the number of angle and turning crashes (the target crash types).

6.2.3 Discussion

Analysis of the effects of treating 20 intersection by changing the left turn phasing from permissive to protected-permissive indicate that there would be a decrease in the target conflict and crash types.

These results are similar to the study conducted by Srinivasan *et al.* (2012) in which 55 intersections in the City of Toronto were evaluated for change in crashes after changing the left turn phasing from permissive to protected-permissive. The results of the study also indicate that the crashes involving a left turning vehicle would decrease, but this decrease would come at an expense of increased crashes of other types. That study also concluded that changing the left turn phasing from permissive to protected-permissive may result in an increase in the rear end crashes. Table 6.17 compares the percentage reduction in the crashes from this study and Section 6.2.2.

Table 6.17: Comparison of Crash Reductions Predicted from Simulated Conflicts with those from Srinivasan *et al.'s* (2012) Before-After Crash Evaluation

Crash Type	**% Change in Crashes based on Simulated Conflicts**	**Srinivasan *et al* (2012)**	
		% Change	**Standard Error**
Total	-16.90%	3.30%	2.30%
Angle + Turning	-19.44%	-14.20%	5.60%
Rear End	-16.60%	6.30%	3.80%
Side Swipe	-15.30%	N/A	N/A

As can be seen from the Table 6.17, the sum of target crashes (Angle + Turning) reduced by about 19% which is comparable to the reduction achieved by Srinivasan *et al* (2012) of about 14% with an error of about 5%. The study by Srinivasan *et al* (2012) found statistically insignificant increases in total and rear end crashes, whereas the results of the conflict-based analysis show a decrease in both of them of about 16%. This may be because the samples for the two analyses are different.

6.3 Transferability of the SSAM's Linear and Non-Linear Models

This section looks into evaluating the predictive capabilities of the peak hour conflicts based model (with the peak hour traffic ratio) against the rescaled versions of the SSAM's linear and non-linear models for evaluating crashes from conflicts. Comparisons were done for three different crash – conflict types; total crashes from total conflicts, angle crashes from crossing conflicts and rear end crashes from rear end conflicts. SSAM's linear and non-linear models can be seen below in Equation 6-4 and 6-5, respectively. (FHWA, 2008).

$$\log(Crashes) = 1.09 \times \log(Conflicts) - 0.98 \qquad \text{(Equation 6-4)}$$

$$Crashes = 0.119 \times Conflicts^{1.419} \qquad \text{(Equation 6-5)}$$

Rescaling of the SSAM model was done by adjusting one parameter in each case (0.98 and 0.119) such that the sum of predicted crashes by the rescaled models equalled the sum of observed crashes over all of the 113 Toronto sites.

6.3.1 Transferability of SSAM's Linear Model

6.3.1.1 Estimation of Total Crashes from Total Conflicts

The SSAM linear model before rescaling predicted 47306 total crashes from total conflicts against the observed 8542 total crashes. This high prediction by the SSAM's linear model suggest that even after recalling it may behave poorly when predicting crashes for Toronto intersections. The rescaled model for calculating total crashes is as follows:

$$\log(Crashes) = 1.09 \times \log(Conflicts) - 2.692 \quad \text{(Equation 6-6)}$$

The MAD/year/site value for the rescaled SSAM linear model was 0.071 slightly higher than the value of 0.051 achieved by the conflict based model (Section 6.1.2.2). Similarly, the MPE/year/site value for the SSAM rescaled model was 0.092 as compared with 0.065 achieved by the conflict based model.

The CURE plot for the SSAM linearized model (as shown in Figure 6.11) also shows that the cumulative residuals are constantly outside the 95% confidence boundaries and are oscillating very rarely. The goodness of prediction measures alongside the CURE plot show that the rescaled SSAM linear model provides poor results.

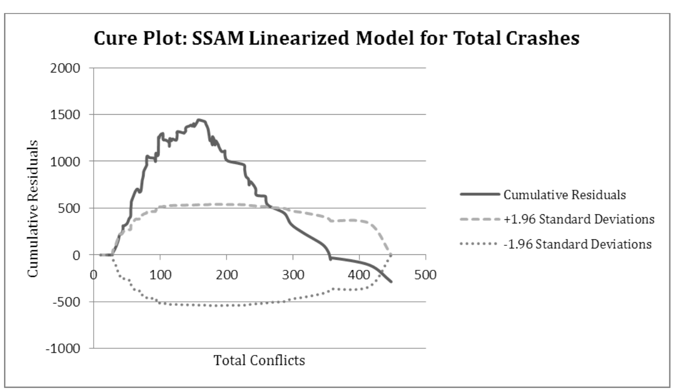

Figure 6.11: CURE Plot for SSAM Linear Model for Total Crashes

6.3.1.2 Estimation of Angle and Rear End Crashes

The SSAM linear model before rescaling predicted 2392 angle crashes from crossing conflicts and 40790 rear end crashes from rear end conflicts against the observed 1621 angle and 2703 rear end crashes. These high predictions by SSAM's linear model once again suggest that the model is quite poor at prediction crashes at Toronto intersections. The rescaled models for calculating angle and rear end crashes are shown in Equation 6-7 and 6-8 respectively.

$$\log(Crashes) = 1.09 \times \log(Conflicts) - 1.369 \qquad \text{(Equation 6-7)}$$

$$\log(Crashes) = 1.09 \times \log(Conflicts) - 3.694 \qquad \text{(Equation 6-8)}$$

The MAD/year/site and the MPE/year/site values for angle crashes estimated from the SSAM rescaled model were 0.015 and 0.038 respectively. These values were slightly larger than 0.011 and 0.014 respectively as achieved from the calibrate model (Section 6.1.2.2). Similarly the MAD/year/site and MPE/year/site values for rear end crashes as achieved by the rescaled SSAM model were 0.0203 and 0.0309 compared to 0.020 and 0.025 achieved from the calibrated conflict model (Section 6.1.2.2).

The CURE plots for the SSAM linearized models for angle and rear end crashes as shown in Figures 6-12 and 6-13 also show very little oscillation and the cumulative residuals mostly lie outside of the 95% confidence boundaries. The results show that the rescaled SSAM linear model provides poor results for both angle and rear end crash predictions.

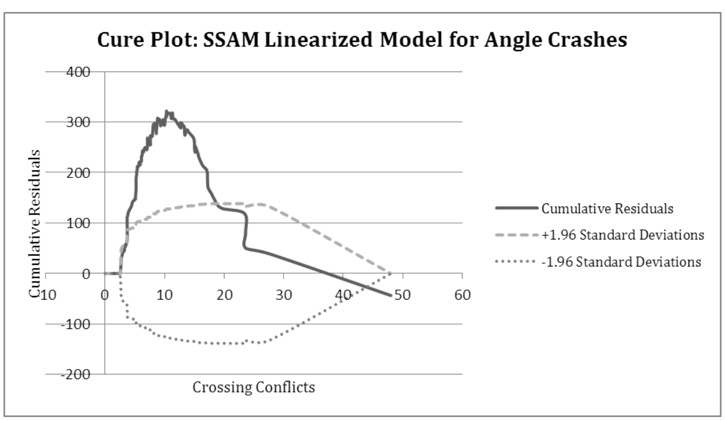

Figure 6.12: CURE Plot for SSAM Linear Model for Angle Crashes

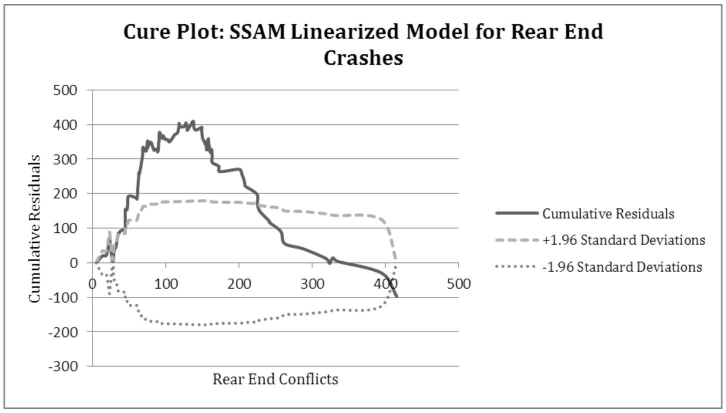

Figure 6.13: CURE Plot for SSAM Linear Model for Rear End Crashes

6.3.2 Transferability of SSAM's Non-Linear Model

6.3.2.1 Estimation of Total Crashes from Total Conflicts

The SSAM non-linear model before rescaling predicted 83426 total crashes against the observed 8542 crashes. The high prediction shows that like the linear model, the non-linear model also predicts crashes poorly for Toronto intersections. The rescaled model for calculating total crashes is as follows:

$$Crashes = 0.012 \times Conflicts^{1.419} \quad \text{(Equation 6-10)}$$

The MAD/year/site value for the rescaled SSAM linear model was 0.082 slightly higher than the value of 0.051 achieved by the conflict based model (Section 6.1.2.2). Similarly, the MPE/year/site value for the SSAM rescaled model was 0.085 as compared with 0.065 achieved by the conflict based model.

The CURE plot for the SSAM non-linearized model (as shown in Figure 6.14) also shows that the cumulative residuals are constantly outside the 95% confidence boundaries and are oscillating very rarely. The goodness of prediction measures alongside the CURE plot show that the rescaled SSAM non-linear model provides poor results.

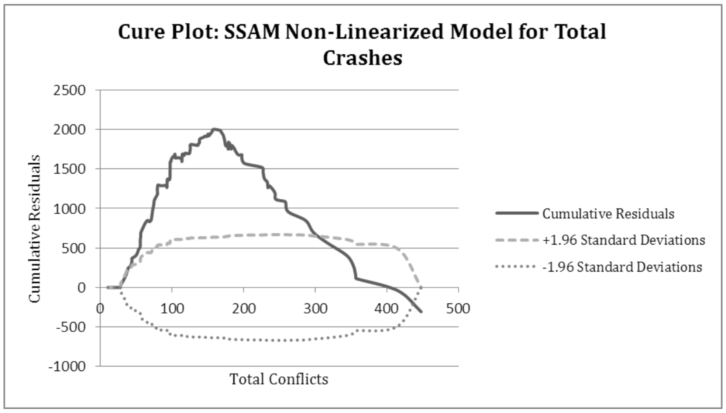

Figure 6.14: CURE Plot for SSAM Non-Linear Model for Total Crashes

6.3.2.2 Estimation of Angle and Rear End Crashes

The SSAM linear model before rescaling predicted 1740 angle and 69482 rear end crashes against the observed 1621 and 2703 crashes, respectively. These high predictions by SSAM's non-linear model again suggest that the SSAM model is poor at predicting crashes at Toronto intersections. The rescaled models for calculating angle and rear end crashes are shown in Equation 6-11 and 6-12 respectively.

$$Crashes = 0.111 \times Conflicts^{1.419} \qquad \text{(Equation 6-11)}$$

$$Crashes = 0.005 \times Conflicts^{1.419} \qquad \text{(Equation 6-12)}$$

The MAD/year/site and the MPE/year/site values for angle crashes estimated from the SSAM rescaled model were 0.018 and 0.028 respectively. These values were slightly larger than 0.011 and 0.014 respectively as achieved from the calibrate model (Section 6.1.2.2). Similarly the MAD/year/site and MPE/year/site values for rear end crashes as achieved by the rescaled SSAM model were 0.0307 and 0.0402 compared to 0.020 and 0.025 achieved from the calibrated conflict model (Section 6.1.2.2).

The CURE plots for the SSAM non-linearized models for angle and rear end crashes as shown in Figures 6-15 and 6-16 also show very little oscillation and the cumulative residuals mostly lie outside of the 95% confidence boundaries. The results show that the rescaled SSAM non-linear model provides poor results for both angle and rear end crash predictions.

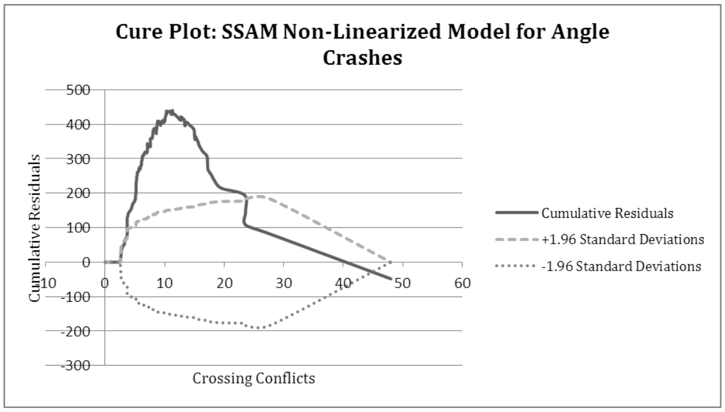

Figure 6.15: CURE Plot for SSAM Non-Linear Model for Angle Crashes

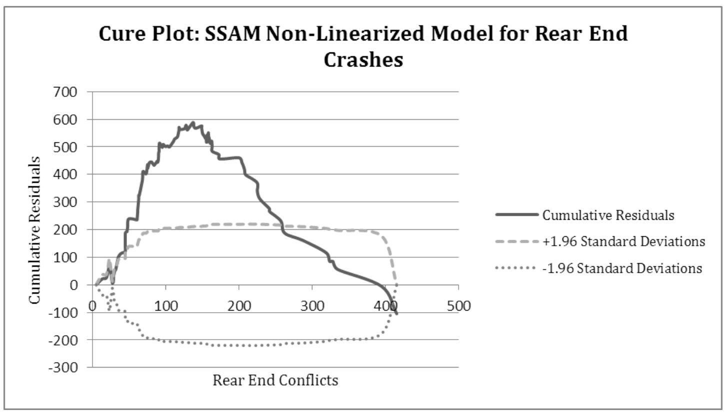

Figure 6.16: CURE Plot for SSAM Non-Linear Model for Rear End Crashes

6.3.3 Summary

The rescaled SSAM linear and non-linear models for estimating crashes from conflicts gave poor results for all of the three crash types evaluated. The poor performance of the SSAM linear and non-linear models also suggests that these conflict based crash prediction models are not readily transferable for use in other jurisdictions.

7. Conclusions

The analysis of the peak hour crash prediction models was divided into three parts. The first part compared the predictive capabilities of the peak hour conflict based crash models against the traditional volume based crash prediction models. Two peak hour conflict based prediction models were developed, one using the peak hour conflicts as the only explanatory variable, and the other using the peak hour traffic ratio as an additional explanatory variable.

All of the models developed showed that the coefficients estimates for the variables were statistically significant in almost all cases to the 10% level. The MAD/year/site and the MPE/year/site values are also very small when compared with the average crashes/year/site. The dispersion parameters for both the volume and conflict based models are small and similar to each other. The CURE plots for some peak hour conflict based models do suggest slight under fitting for at higher values of conflicts but since the residuals stay well within the 95% confidence boundaries the model predictions are still good and valid. The analysis also shows that the conflict based model using peak hour conflicts and the peak hour traffic ratio as explanatory variables is better than only using the peak hour conflicts for predicting yearly crashes. The peak hour conflict based models, however, yield a significant coefficient estimate for the conflicts but the effect of conflicts is weak as can be seen by lower coefficient estimates. The coefficient estimates for conflicts increase when extra variables for the peak hour traffic ratio are included in the models but they are still low when compared to the estimates of the volume based models. The weak effect of conflicts on the crashes can be explained partially by the number of sites used in the study. A higher number of sites with more homogeneity with respect to geometric features might have yielded different results.

Both the volume based and conflict based models provide good crash predictions for sites grouped over a range of entering AADT (volume based models) and conflicts (conflict based models). Comparison between the two for predicting crashes for sites grouped by various combinations of right and left turn lanes show that both the volume and conflict based models predict crashes well but the predictions from the conflict based models were slightly closer to the observed values. After comparing the two models, it can be said that the conflict based models can predict crashes as well as the volume based models and that it does reasonably capture the effects of the number of turn lanes on crashes.

The second part of the analysis looked at the possible effects of changing the left turn phasing to protected-permissive. 20 sites were chosen for the application of this treatment and the conflicts and crashes before and after the treatment were compared. The estimated effects were also compared to those estimated in a before-after study conducted by Srinivasan *et al* (2012) for a group of similar Toronto intersections that actually underwent a change from permissive to protected-permissive left turn phasing. The result shows that changing the left turn phasing to protected-permissive does benefit the users by reducing the percentage of target conflicts and crashes (Crossing conflicts, Angle and Turning Crashes). This reduction was comparable with the result for the same crash type from the Srinivasan *et al.*'s study. The conflict-based crash prediction models suggested a reduction in the total and rear end crashes as well, whereas, the study by Srinivasan *et al* found insignificant increases in both crashes. This difference could be attributed to the different samples being analysed.

The third part of the analysis looked at the transferability of the SSAM linear and non-linear models to the data set used for this thesis. The SSAM models were rescaled such that the prediction by the model would equal the observed crashes. The rescaled SSAM models gave poor results, and from this it becomes evident that this conflict based crash prediction model may not be transferable for use in other jurisdictions.

To conclude, it can be said that conflict based crash prediction models provide a good alternative to the volume based models. They can be used to evaluate the safety of a road entity comparably to volume-based models and can, with caution, be used to estimate crashes from simulated conflicts at signalized intersections for cities/jurisdictions with similar characteristics to the City of Toronto.

In future research, a single model could be investigated for estimating crashes from simulated conflicts for signalized and unsignalized intersections and road segments by using a variable to classify the different site types. Additionally, more work could be done on calibrating the model to capture features of real life traffic such as the differences in reaction times between people of different age groups, and the effect of the traffic stoppage created by streetcars when loading/ unloading passengers.

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