ESTIMATION OF SIDE IMPACT CRASH RISK AT SIGNALIZED INTERSECTIONS

BY

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ABSTRACT

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Side impact accidents are considered to be the most dangerous of all types of intersection accidents due to their high severity. In-depth investigation of accident occurrence could be a valuable means of mitigating these accidents. Based on the relationship between the distribution of disturbances near intersections and drivers reactions, this study developed a logic for three major types of signalized intersections side impact crashes were considered for this study – right-angle, and left and right-turning crashes. This study developed models to understand the relationship between accident frequency and some explanatory variables that represent driver, vehicle, traffic flow and intersection design characteristics. Negative binomial regression with maximum likelihood estimation of parameters is applied to address the overdispersion usually found in accident count data. The models explain the mechanism of side-impact accident occurrence and could be used to assist safety management agencies to devise countermeasures aimed at drivers, vehicles, and the physical roadway environment.

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CHAPTER 1

INTRODUCTION

1.1 INTERSECTION SAFETY ISSUES

Accidents on the roads and highways cause loss of life and financial loss. Since the invention of the automobile, modern civilization has enjoyed greatly increased mobility which brings not only many benefits, but also a number of negative problems such as air pollution, noise and, the most serious and disturbing, traffic accidents. Urban areas have the highest population-based rates of both injury and property-damage crashes. The number of both injury and collision claims per insured vehicle year increases with urbanization. Research findings indicate that fatality, injury and property damage only crashes all occur at their highest rates in urban areas intersections, even after controlling for vehicle and resident populations. These findings suggest that increased attention should be focused on reducing the number and severity of crashes in urban areas and, especially, at intersections where so many crashes occur.

Safety and efficiency are the two primary objectives of transportation engineering. The extremely high costs associated with traffic accidents make safety improvements an important objective of transportation engineering. Although the number of road accidents continues to rise, in terms of crash rates, road safety continues to improve in most developed countries. In many developed countries over the past two decades, the total number of fatalities has decreased during a period when the number of motor vehicle accidents has doubled.

In contrast, the number of injury and property damage accidents related to intersections in Ontario has increased approximately 6% to 7% per year between 1993 and 2003 (ORSAR 2003). The total number of people killed at intersections has decreased slightly, but several types of fatal intersection crashes have remained unchanged during the 1993 to 2003 period. Overall, accidents at intersections and accidents related to intersections accounts for approximately 48% of the total number of accidents (ORSAR 2003). A quarter of the total accidents occur at signalized intersections (ORSAR 2003). Because of the complexity of the problem and difficulty of providing effective safety countermeasures, more attention needs to be given to traffic safety studies at intersections and the detailed issues involved, especially in the urban environment.

It is recognized that the topic of intersection safety is very broad and includes intersection and signal design standards and guidelines, and federal, state, and local policies. The frequency and type of vehicle-to-vehicle collisions that occur at intersections can vary by location. The most common types of intersection crashes are side impact collisions (where one vehicle strikes the side of another), rear-end collisions, and collisions resulting from improper turning and lane changes.

Side impact crashes are particularly important because of the large number of personal injuries and fatalities associated with this crash type. Overall, the severity of injuries caused by side impact crashes is significantly higher than the severity of injuries associated with types of intersection collisions. These striking issues point to a need to undertsand the nature of the side-impact crash occurrence mechanism at a microscopic level in order to develop appropriate countermeasures to increase safety at signalized intersections.

This study takes a microscopic level approach to side-impact crashes at urban intersections. The study aims to aid traffic safety management and regulatory agencies by developing a new concept for understanding and implementing accident countermeasure techniques. The concept is based on using accident histories and probability estimates of the risk of several major types of vehicle-to-vehicle side impact crashes at four-legged signalized intersections. Data from the City of Toronto are used in the analysis.

The analysis investigates, the relationship between the frequency of collisions and various geometric and traffic related aspects of the intersection environment. The analysis also investigates the interaction between the two drivers involved, including their perceptions, behaviour and reactions.

The results reveal some important factors that cause traffic accidents and the possibility of new cost-effective strategies that are likely to reduce the probability of severe side impact intersection crashes at four-legged signalized intersections.

1.2 BACKGROUND OF THE STUDY

Side impact crashes are considered the most dangerous of all types of intersection accidents due to their high severity. According to data published by by the Ontario Road Safety Annual Report (ORSAR 2003), side impact crashes account for 25% to 40% of all crash types on Ontario roads (Chipman at. el. 2004). In 2003, side impact crashes accounted for 22% of the fatal accidents and 35% of the injury accidents in Ontario. The high number of fatalities and injuries associated with side impact crashes at intersections increases the need to undertsand the microscopic nature of the accident occurrence mechanism as a basis for developing appropriate and advanced countermeasures that will increase safety at signalized intersections.

Between 1984 and 1994, the number of fatal accidents in Ontario consistently exceeded 1,000. After 1994, the number of fatal accidents in Ontario decreased below the 1,000 level seeming to suggest an improvement. At intersections, however, the number of accidents and the number of fatalities remained stable or increased. Overall, the number of fatal accidents has decreased in Ontario, but the total number of accidents has increased. This may indicate that countermeasure designed to reduce the number of fatal accidents are already showing results. Although the cost of fatal accidents has decreased (because of the reduced number of fatal accidents), total direct accident costs remain high. There are also the indirect costs of traffic congestion associated with accidents, and the indirect costs of the mental trauma suffered by the injured persons and their families. The problem of intersection crashes in Ontario, and specifically in Toronto, remains serious and far from an "acceptable" level.

Transport Canada has supported detailed investigations of a sample of side impact crashes since 1988. Previous research developed several important aspects of side-impacts crashes related to vehicle design, nature of fatality and injury, effect of environmental factors. This study intends to investigate the association of side impact crashes at randomly selected signalized intersections in the City of Toronto and determine the factors that may lead effective countermeasure from traffic engineering point of view.

1.2.1 Traffic Safety Studies

The academic background of traffic safety studies at signalized or unsignalized intersections is much more complex than other areas of safety research. The latest developments in intersection safety include the following: the application of improved statistical techniques; the development of an understanding of the human factors operating at intersections; and integrated signal design and safety approaches. In recent years, considerable progress has been made in safety estimation techniques for intersections.

In general, accident counts are influenced by numerous factors other than the risk level (Fridstrom et al., 1995). Firstly, accident counts are subject to random variation. This is the foremost issue. Secondly, they are strongly influenced by (perhaps almost proportional to) exposure levels. Thirdly, they are affected by natural phenomena like weather and daylight. Fourthly, they depend on the accident reporting routines currently in effect and on the changes occurring in these routines over time.

The use of the terms 'random disturbance' and 'probabilistic modeling' has become common in economics and in other social science disciplines. A collection of individuals may very well behave according to certain social or economic laws that are knowable up to a margin of statistical 'error'. This error is, however, epistemic rather than objective.

In the case of road accidents, there seems to be something more to consider. Although accidents are the result of human choices and behaviour, no-one chooses to have an accident. On the contrary, when an accident happens, it is because certain road users (the accident victims) did not succeeded in avoiding the accident, although they certainly want to avoid it. Accidents are the unintentional side effects of certain actions taken for reasons that do not include intending to cause injury or damage. They are random and unpredictable in the striking sense that had they been anticipated, they would most probably not have happened. Each single accident is, in a sense, unpredictable by definition. Within the realm of behavioral science, is there a set of phenomena coming closer than road accidents to being objectively random in character? No matter how much we learn about accident generating mechanisms or countermeasures, according to Fridstrom et al. (1995) we would never be able to predict exactly where, when, and by whom the single accident is going to occur. The best we can hope to achieve and predict is their approximate number.

1.2.2 Previous Safety Studies

Researchers have used three approaches to describe the relationship between accidents and geometric characteristics and traffic related explanatory variables: multiple linear regression, Poisson regression and negative binomial regression.

Research into traffic accidents shows that *multiple linear regression* suffers from some undesirable statistical properties when applied to accident analysis (Jovanis and Chang, 1986). To overcome the problems associated with multiple linear regression models, Jovanis and Chang proposed *Poisson regression* for the modeling of accident frequencies. They argued that Poisson is a superior alternative to conventional linear regression for applications related to highway safety. In addition, Poisson regression could generally be used with smaller sample sizes than linear regression.

The Poisson model, however, also suffers from certain limitations. Joshua and Garber (1990) studied the relationship between highway geometric factors and truck accidents in Virginia using both linear and Poisson regression models. Miaou et al. (1992) used a Poisson regression model to establish the empirical relationship between truck accidents and highway geometry. During Miaou et al.'s modeling, a limitation of the Poisson model was established. Using the Poisson model requires the mean and the variance of the accident frequency variable to be equal. In most accident data, the variance of the accident frequency exceeds the mean and the data are overdispersed. A follow-up study completed by Miaou and Lum (1993) considered four types of model: an additive linear regression model, a multiplicative linear regression model; a multiplicative Poisson regression with exponential function; and a Poisson regression with non-exponential rate function. They found the variance of the estimated model coefficients tended to be underestimated. They attempted to relax the Poisson constraint of the mean being equal to the variance by using Wedderburn's over dispersion parameter.

Several researchers investigated the possible application of the *Negative Binomial model* to encounter the overdispersion issue. Miaou (1994) found that the overdispersion is high using both the Negative Binomial and the zero inflated Poisson regression. For accident data with a high number of zero frequencies, the zero inflated Poisson regression is the better choice. Shankar et al. (1995) also used both Poisson and Negative Binomial distributions for the same purpose and pointed out similar conclusions.

1.2.3. Recent Intersection Safety Studies

The factors found to dominate intersection crashes are greatly influenced by the approach related variables. Previous studies have ignored the approach specific detail in crash model development. However, during last decade several researchers developed new techniques to study intersection crashes in detail.

Poch et al. (1996) conducted a study using an approach-based (assigning variables to all intersection approaches) methodology to predict the accident frequency of intersections of principal arterial and concluded that negative binomial regression is a powerful predictive tool and that the approach-based method reveals many aspects of intersection accident frequency. The Transport Research Laboratory (TRL) in Great Britain also conducted a study using the approach-base methods (Hall 1986 and later Maher et al. 1996) to relate accident frequency to traffic flows and to the geometric and control features of intersections in order to design appropriate improvements and remedial measures.

Urban drivers' psychology at or near intersections adds a new dimension to the complexity of the research effort into establishing the factors that lead to side impact crashes. An experiment that investigated the underlying mechanism of the visual search made by drivers (Miura 1992) showed that in demanding situations, especially in crowded intersections, a driver's functional field of view becomes narrower (between 4^0 to 20^0 at or near intersection approach) and his or her reaction time for detecting relevant objects therefore becomes longer.

Eye-marker studies (Hills 1979) found that drivers average only three fixations per second under 'normal' conditions.

Emergence of 'disturbance' and its distribution near intersection approach is a key issue in side-impact crashes. Disturbance is a term used to quantify numbers of "expected or unexpected points/entity/objects" at intersections. In general, it is a distribution of "fixation points" at or near the intersection. The theory is based on probability logic in that driver's available PRT should be greater than the required PRT (perception reaction time). If the number of fixation points is greater than the standard human capacity (which is around three fixations per second), it is possible to estimate the probability that a driver could miss at least one fixation and thus face the risk of a specific type of accident.

The complex visual tasks required of a driver who is approaching an intersection change the range of perception-reaction time (PRT) depending on the complexity of the solution and the driver's expectancy of the hazard (Bates 1995). Bates defined the PRT as "total time it takes a driver to commence an appropriate response to an impending hazard: this includes detection (is there something that will become a hazard?), identification (what is hazard?), decision (what should I do?) and response execution (for example, moving the foot from the accelerator to brake pedal)". This study adopts Bates definition of PRT (see section 4.3.2 and Figure 4-2). Finally, the combination of unanticipated geometric and traffic related factors increases the drivers' mental load, a problem which may ultimately cause a severe right-angle accident at an intersection.

The selection of the variables used to explain side impact intersection crashes is a controversial issue. It is worth mentioning that an invididual accident is not normally due to a single cause or factor, but is a combination of causes. Hills (1980) reported that an accident occurring in a complex situation (like an intersection) can involve as many as 15 or more independent factors. Thus, the causes of accidents and different types of accident can vary widely, and it is advisable to restrirct the accident types being modeled. If all the major types of intersection crash are taken into account for modeling purposes, a very large number of potential factors must be considered. The issues are further complicated by the finding that human error is believed to contribute to 95% of accidents (Moore 1969 and Tsyganov et al. 2005).

Another issue often ignored by right-angle or red-light-running crash researchers leads to a specification error of angle accidents at signalized intersections. The different vehicles involved in side impact crashes at signalized intersections should be investigated in terms of the set of variables that describes their specific situations. For example, a vehicle which runs the red-light (the 'main or subject vehicle') always has a higher probability of an accident involvement than does the 'cross-street vehicle'.

This study explicitly considers the role of human factors and the role of the microscopic detail that affects the accident occurrence mechanism. The study also develops a 'proportionate probability risk' approach to estimate the probabilities of vehicle-to-vehicle side-impact accidents at four-legged signalized intersections.

1.3 STATEMENT OF THE PROBLEM

The Vehicle Safety Research Team at Ryerson University, Canada, (one of eight teams conducting research on side impact crashes) carried out detailed reconstructions of motor vehicle collisions to assist in determining the efficacy of current Canadian Motor Vehicle Safety Standards. Chipman et al. (2004) identified the characteristics of crash-involved vehicles related to other vehicle observed at the crash site. Using British Columbia data, Chipman et al. (2004) suggested that side impact crashes are less likely to occur in the dark, on one-way streets, and on streets with higher speed limits. Chipman et al. (2005) also compared classic side-impact crashes to non-crashing control vehicles and concluded that vehicle characteristics were associated with crash risk to a different degree for bullet and target vehicles.

These studies, however, neither incorporated the human factors involved in the side-impact crashes nor clarified the microscopic details of the accident occurence mechanism. The location-associated approach can be applied at the level of a geographic area (macro location) or at the site-specific level (micro location). Detailed intersection geometric and signal timing design, traffic safety rules and regulations, road side features and their links to human performance, all remain unexplored in the existing studies.

Many types of accident occur at intersections every year. Of the various types of accident, side-impact accidents are the most critical and the most complex in terms of exploring the mechanism of their occurrence at the microscopic level. For example, right angle accidents, a major type of side impact crash, constitute 16-20% of total crashes at signalized intersections. But it comprises 44% of fatal and 49% of injury accidents at signalized intersections in Toronto, the setting for the data used in this study. In addition, the approach-base model for explaining the phenomena related to angle and turning accidents is not enough to expose in-insight crash occurrence at signalized intersection. It is worth mentioning that the arm-base approach's analysis needs a very large amount of data well integrated in a suitable and manageable database.

1.4 PURPOSE AND OBJECTIVES OF THE STUDY

The purpose of this study is to develop a right-angle accident model that will estimate the expected risk of side impact crashes. The model is based on data obtained from 70 four-legged signalized intersections in the City of Toronto. The main issues investigated are:

- the relationship between the frequency of collisions and the various geometric and traffic related factors; and

- the interaction between the two drivers involved, including their perceptions, behaviour and reactions.

The study focuses mainly on developing a model that estimates the probability of crash risk rather than a model that predicts the number of accidents. The study also suggests how this model of accident risk might be used to identify the different set of variables that affects the probability of severe side-impact accidents at four-legged signalized intersections. In turn, this knowledge could be used to suggest measures for improving intersection traffic safety.

1.5 METHODOLOGY

In order to develop the model's methodology and to achieve the study's objectives, a comprehensive literature review was first conducted. The second step was to understand the mechanism and logic that leads to angle accidents. The third step was to decide on a tentative set of explanatory variables (based on the logic of accident occurrence) to be used in the model's development.

The main concepts underlying the study were adopted from the approach-based method developed by Mannering et al. (1995) and Hall (1986). These researchers explained the mechanism of accident occurrence in detail considering the vehicle(s) involved in an intersection accident in terms of the different approach roads to the intersection.

1.6 SCOPE OF THE STUDY

The scope of the study is as follows:

- Constructing the detailed, microscopic detail of angle (including right-angle), left-turn and right-turn accidents and explaining and modeling the mechanism of accident occurrence;

- Estimating the over-dispersion parameter, relative importance of continuous variables used in the study to explain the variables' influence on accident involvement, and investigating the correlation problem as related to accident modeling; and
- Classifying the explanatory factors into several classes that facilitate the management of the factors and the extraction of information from the accident risk model;

1.7 ORGANIZATION OF THE THESIS

The study is presented in six chapters.

Chapter 1 provides a brief review of traffic accident studies and the intersection accident history of Toronto. The Chapter introduces the objectives and scope of the study.

Chapter 2 presents an overview of recent trends in traffic accidents and the current situation. The Chapter discusses traffic safety facilities available in Canada and their importance to this study's investigation of intersection accidents and to the study's classification process.

Chapter 3 describes the procedures used in the preliminary survey and data collection phase. The Chapter provides a detailed description of the data processing and defines the important indicator variables.

Chapter 4 deals with the analysis methodology. The Chapter discusses the logic underlying the construction and development of four types of side impact crash risk model.

Chapter 5 presents the results. The explanatory factors that significantly affect the risk of angle accidents and turning accidents (right-turn and left-turn accident) are discussed and summarized in tables. The Chapter discusses and interprets the study's findings and compares the findings and interpretation with previous studies. This chapter also presents the fitness of the models.

Chapter 6 discusses the achievements and deficiencies of this study.

CHAPTER 2

THE NATURE OF INTERSECTION TRAFFIC ACCIDENT OCCURRENCE

2.1 INTRODUCTION

Apart from the usual problems resulting from rapid urbanization and a tremendous increase in motorized traffic, all the countries in the world face an acute problem with road traffic accidents. This chapter discusses the road accident situation in the province of Ontario and in Canada in general. The chapter presents past and present trends in traffic collisions, causalities, fatalities, and injuries. Certain road accident characteristics are highlighted and discussed with a view to developing an improved understanding and searching for appropriate ways to deal with the problem. Accident classification techniques are reviewed to determine the appropriate intersection classification for this study's investigation of the accident occurrence mechanism and the corresponding model development. Side impact crashes and their characteristics are discussed separately (in Chapter 3) in relation to signalized intersection collisions.

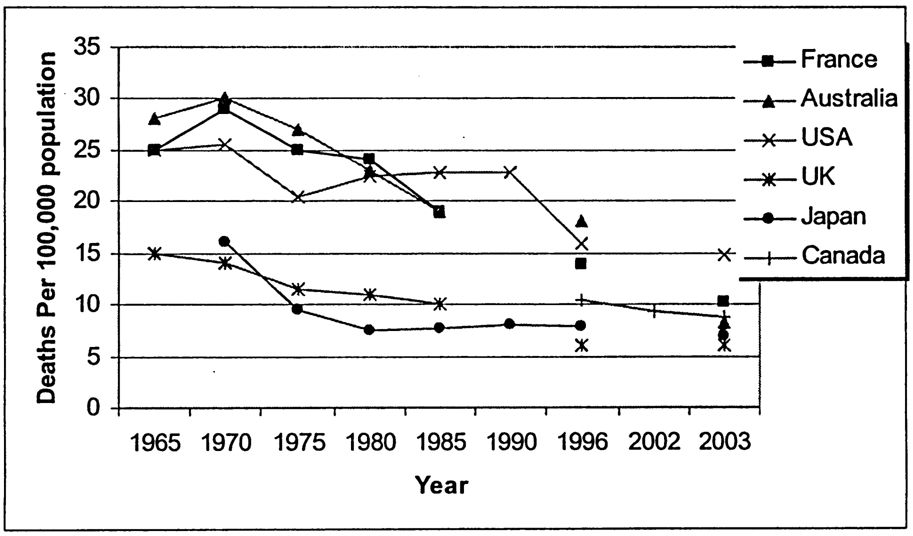
2.2 GENERAL ACCIDENT TRENDS

The following sections describe general accident trends and their common characteristics at the macroscopic level. By looking at long-term trends, it is possible to identify anomalies limited to a single year and better assess the most serious problems. The aim is to target the most dangerous crashes that result in the majority of fatalities and serious injuries in our roadways.

2.2.1 Traffic Accident Trends Around the World

Figure 2-1 compares deaths per hundred thousand population in Canada and five other developed countries for various time periods since 1965 (Karim, 1995). The Figure shows a general tendency for accident fatality rates to decrease. Accident deaths per 100,000 population in Canada have been decreasing over the last five years. Japan and U.K. experienced the lowest rate compared to other countries.

Figure 2-1: International Road Accident Fatalities (Deaths per 100,000 populations)



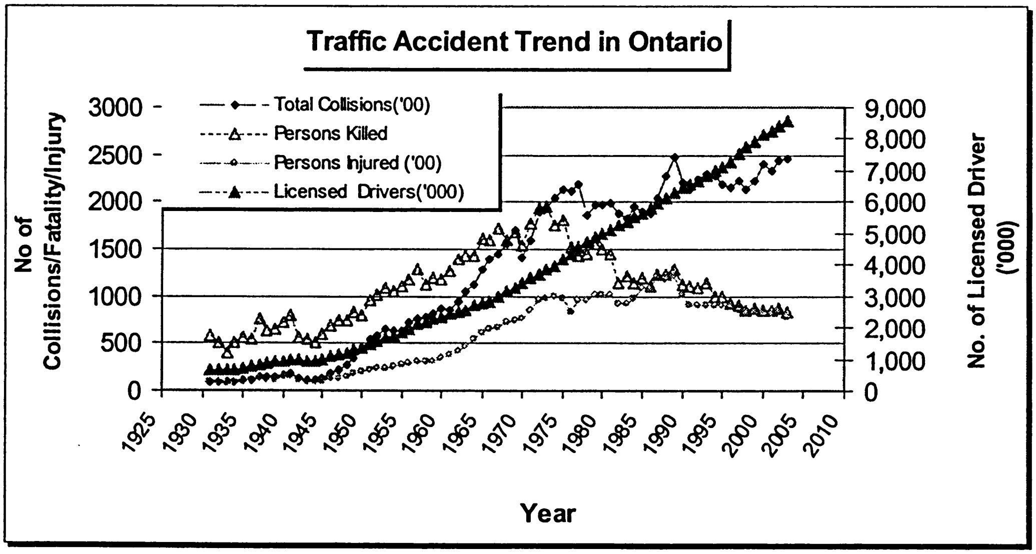
According to the Transport Canada, there were nearly 21.8 million licensed drivers in Canada and 598 vehicles per thousand people in 2003 (Transport Canada, 2003). In 2003, 2,778 fatalities occurred in Canada, a 30% reduction in fatalities compared with 1984. Approximately 72% of the injuries and 38% of the fatalities occurred in urban areas. Canadian roads are some of the safest among the highly motorized countries. Although Ontario is consistently among the top road safety jurisdictions in North America, traffic accidents continue to be a heavy financial burden for the province. For example, the cost of accident in the United States was estimated at $900,000 for a death, $32,800 for a non-fatal disabling injury, and $5,800 for property damage only (Poch et al. 1996).

2.2.2 Nature of Traffic Accident and Causalities in the Province of Ontario

Motorized traffic has increased dramatically. It may be too extreme to expect the number of accidents to drop significantly when motorized traffic has increased dramatically. In fact, one would expect the tremendous increase in motorized traffic to result in an increase in the number of accidents. The important issue, however, is whether the increase in the number of accidents reflects a deterioration in road safety when considered in relation to the increase in traffic.

Accident trends are often indexed to certain exposure variables. Figure 2-2 shows the relationship between level of motorization (in terms of the number of licensed drivers) and the number of traffic collision deaths and injuries in Ontario from 1925 to 2003.

Figure 2-2: Comparison of the Number of Licensed Drivers with the Number of Fatalities, the Number of Injuries and the Total Number of Collisions on Ontario Roads, 1925 to 2003



From 1975 to 2003, the number of licensed drivers doubled and vehicle registrations increased by 85% although the population increased by only 48% during the same period. The increase in the number of licensed drivers and the increase in travel suggest that traffic accidents would increase during this period. The total number of collisions in Ontario increased to 86% (as might be expected), but the number of fatalities decreased by 54% and the number of injuries decreased by 20%.

The number of fatalities has gradually decreased over the last two decades because of improved highway design and improved vehicle design, modern and efficient road-side emergency service and safety standards introduced by the automobile industry in North America. Unfortunately, injuries from road accidents still cost the health care system billions of dollars annually.

2.3 INTERSECTION SAFETY

Traffic accidents at urban intersections result in a huge cost to society in terms of death, injury, lost productivity, and property damage. For example, in 2002, more than 9,000 Americans died and roughly 1.5 million Americans were injured in intersection related crashes. In economic terms, intersection related crashes in the year 2000 cost about $US 40 billion (ITE, 2004). The number of accidents at intersections has increased more than the number of non-junction accidents. (An increase in the number of vehicles on the road is generally accompanied by an increase in the number of multi-vehicle collisions which rise at a faster rate than single vehicle accidents.)

In general, more than 50% of the collisions occur at intersections although intersections occupy only a small portion of total roadway space. Data from a number of countries support the above statement and show that over the years, the number of intersection accidents has increased at a faster rate than other accidents.

Extensive and detailed data analysis (using ORSAR data from 1993 to 2003) was performed to investigate intersection and intersection related accident trends in Ontario. Figures A-1 and A-2 (in Appendix A) reveal an alarming trend in intersection crashes in Ontario: a reverse tendency national fatality trend. According to ORSAR data for 2003, intersection and intersection related crashes accounted for 28.4% of fatalities, 51.2% of personal injuries, 41.7% of property damage crashes and 44% of the total number of crashes. Between 2003 and 1993, crashes at intersections in Ontario increased by 28% and the number of fatalities at intersections increased by 19%.

To avoid giving an intersection a negative public image, the location of intersections with a high number of crashes is not publicized. This approach was challenged in a special workshop organized by the Federal Highway Administration (FHWA) and partnered by the Institute of Transportation Engineers ITE (George 2003). A multidisciplinary approach aimed at reducing intersection crashes by 20% is in progress in both the United States and Canada (Road Safety Vision 2010). This approach offers a great deal of promise for success and will incorporate enforcement and educational components along with engineering solutions to improve intersection safety.

2.3.1 Significance of Intersection Accidents

In 1978, Hakkert et al. reported that single vehicle accidents might, other things being equal, be expected to increase in proportion to traffic volumes, whilst multi-vehicle accidents would be expected to increase in proportion to some higher power of the flow. Hence, as traffic increased, multi-vehicle accidents, i.e. collisions, would be expected to become a higher proportion of the total. Hakkert et al then argued that accidents at intersections are rather more likely to involve two or more vehicles than accidents away from junctions, and that accidents at intersections would therefore be expected to increase relative to those away from intersections, although there might be counter balancing factors.

In support of their argument, the researchers provided data showing annual accident statistics published in various countries. The data clearly show that the trend for an increasing number of accidents at intersection is still continuing suggesting that intersection safety in urban areas remains a problem. For example in the United States, the percentage of personal injury accidents that occurred at intersections was 40% in 1938 and 49% in 1952.

Table 2-1: Intersection Accident Situation in Various Countries

Source: Hakkert A.S., and Mahalel, D., (1978)

Country	Type of Accident	From	To	% Increase
USA	Urban Area—Fatal Accident	40% (1938)	49%(1952)	9
	Rural area—Fatal Accident	10%(1938)	14.5%(1952)	4.5
	Fatalities	23.1(1965)	24.9%(1953)	1.8
UK	Intersection Accident	26% (1933)	37%(1952)	11

Table 2-2: Intersection Personal Injury Accident in~ Various Countries) Note:

*-Holland Statistics from 1964 to 1971

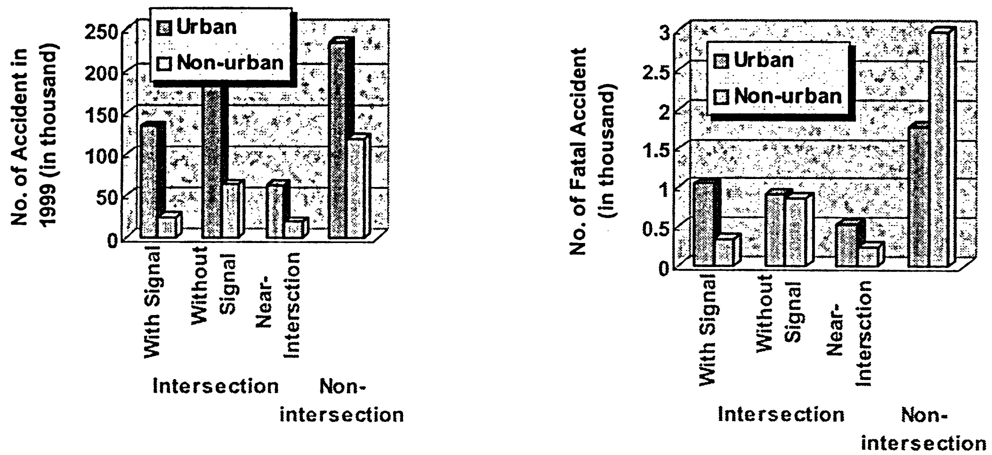
Source: Hakkert A.S., and Mahalel, D., (1978)

Country	From	To	% Increase
Ireland	43%	43.7%	0.7
Israel	31%	39%	8
Denmark	37%	37.9%	8
Holland*	43.3%	43.6%	0.3

Intersection Accidents in Canada and Ontario

As has been mentioned in section 2.3, although various countermeasures have been adopted and although a huge amount of money has been invested in making road transportation safer in Ontario and Canada, intersection safety is still far from satisfactory. Figures A-3 and A-4 (in Appendix A) show intersection safety in Ontario (ORSAR, 1993 - 2003). According to the ORSAR estimates, it appears that intersection and intersection related accidents, particularly side-impact crashes (Figure A-9 and A-10 in Appendix A), in Ontario were either steady or increased in ten year period. Figure A-5 shows the major types of intersection accident on Ontario roads.

Figure 2-3: Intersection Accident and Fatalities in 1999



As about 44% of all traffic accidents and 51% of injury accidents occurred at intersections in 2003, it appears that intersections are accident-prone areas. Most intersection accidents, about 89%, are vehicle-to-vehicle accidents (including accidents involving motorcycles, mopeds and bicycles). Figure 2-3 also shows that in urban areas comparatively more accidents occur without signals, and in rural areas most of the accidents occur away from intersections (ORSAR 2003). The evidence clearly shows the failure of traditional countermeasures to reduce intersection vehicle-to-vehicle accidents. Despite the fact that we have been trying over many years to reduce the number of traffic accidents, we still do not fully recognize clearly the significance of the number of intersection accidents.

To find effective countermeasures against intersection accidents, studies have focused on intersection vehicle-to-vehicle accidents. In-depth psychological studies of driver behaviour at intersections should be investigate in detail. Unfortunately, the elements that affect the frequency of intersection accidents are not well understood and, as a result, it is difficult to predict the effectiveness of specific intersection improvements that are aimed at reducing accident frequency.

2.3.2 Causes of Intersection Accidents

Traffic law violations and the circumstances that lead to lost control are critical to intersection accident modeling because each type of intersection accident is closely related to breaking a traffic law. From Figure A-9 (in Appendix A) and Table 2-3 (below), it is clear that the most frequent traffic violation is failure to yield right of way (29%). This violation is followed by disobeying traffic control (24%), the leading cause of red-light running crashes. Other important intersection related violations are improper turn (7%) and improper passing (7%).

Right-angle or crossing accidents (AG2, according to the intersection accident classification of Hauer 1988 and Wang 1998. Detail are given in section 2.4) are closely related to improper stopping and failure to stop traffic law violations. Violation of proper stopping procedures or disregarding traffic signals at intersections leads to right-angle accidents. (This is an important assumption for the development of side-impact crash risk modeling described in Chapter 4 in detail.) Improper turns, lane infringement and speeding near an intersection leads to right-turn accidents (AG3) and left-turning accidents (AG1).

Losing control of the vehicle is the leading cause of intersection accidents and accounts for 60% of crashes at intersections (Table 2-3). The amount of information that must be processed by the driver at an intersection may exceed human capacity especially in demanding situations. Additional human factors responsible for losing control of the vehicle at or near an intersection include lack of familiarity with the area, driving environment expectance, and poor sign location. In particular, turning accidents are closely related to inattentive driving. These traffic violations, added to the random probability of an accident occurring, lead to intersection accidents and especially to side impact accidents at intersections. A comprehensive investigation of all the possible causes of accidents is helpful in developing the accident model for various types of accident at intersection, as described in Chapter 3.

Table 2-3: Causes of Intersection and Related Accident in Ontario (ORSAR, 1993~2003)

Year	Improper Turn %	Disobey Traffic Control %	Failed to Yield Right of Way %	Improper Passing %	Lost Control %
2003	5.25	22.62	24.92	7.21	40.00
2002	6.23	25.57	21.97	5.90	70.16
2001	9.18	22.62	23.61	5.25	56.07
2000	6.56	23.28	27.21	3.61	67.87
1999	6.89	24.59	30.16	5.90	66.56
1998	9.51	23.28	28.20	7.87	56.72
1997	6.23	20.66	30.49	8.20	62.95
1996	4.59	25.25	31.15	6.89	57.70
1995	7.87	24.92	33.11	6.89	56.72
1994	8.20	21.31	26.56	7.54	58.36
1993	6.56	21.97	36.07	10.16	65.25
Average	7.00	23.28	28.49	6.86	59.85

2.4 CLASSIFICATION OF ACCIDENTS

Efforts to reduce the number and severity of urban crashes have been hampered by a lack of information about the types of crash that predominate in urban environments. Insurance collisions claims data are based predominantly on self-reported information from crash-involved drivers and consequently do not provide useful information on crash circumstances. Many communities have limited resources to process or analyze data on crashes. Police crash reports do include information on the number of vehicles, relative vehicle movements, location of intersection crash, the type of traffic control, and other detailed aspects of the accident.

Table 2-4: Number of Accidents According to Collision Types (in 1999)

Source: Transport Canada Statistics and ORSAR data, 1999

Conflict	Type of Accident	Day/Night Ratio	Day	Night
Pedestrian to Vehicle	While walking facing vehicle	1.24	0.37	0.68
	While walking parallel to vehicle	1.38	0.74	1.23
	While crossing the road	1.72	5.62	7.56
	While playing on the road	7.35	0.19	0.06
	Wile working on the road	2.61	0.19	0.17
	While standing on the road	1.42	0.21	0.34
	Others	2.36	1.29	1.27
Vehicle to Vehicle	Head-on Collision	2.24	3.82	3.95
	Rear-end Collision	2.12	28.84	31.51
	Crossing Collision	3.28	29.42	20.80
	Passing and Overtaking	3.58	1.61	1.04
	Turning Accident	2.31	1.41	1.41
	Passing Each Other	2.66	0.95	0.83
	Left-turn Collision	3.55	5.30	3.47
	Right-turn Collision	1.85	8.98	11.26
	Collision while crossing a road	2.69	1.05	0.91
	U-turn Collision	1.26	0.45	0.82
	Back-up Collision	3.04	1.54	1.18
	Others	2.56	3.82	3.46
Single Vehicle	Collision with Structures	0.92	1.98	4.96
	Collision with Parked vehicle	0.65	0.18	0.64
	Running off the Road	1.36	0.49	0.83
	Turning over	2.30	1.20	1.21
	Others	2.22	0.36	0.38
Train	Train	2.84	0.01	0.01

2.4.1 Traffic Accident and Fatalities by Accident Type

In Ontario, the police categorize intersection accidents according to the initial impact type (such as rear end, angle, turning right, turning left, etc.). For example, "turning left" accidents include rear end accidents that occur while turning left as well as angle accidents that involve opposite through vehicles. This categorization makes it difficult to know the nature of the original configuration that led to the accident, and how the driver failed to make an effective response.

According to Table 2-4, vehicle-to-vehicle accidents account for the great majority of all types of accident (87% in 1999) (Transport Canada Statistics 1999). The next most common types of accident are crossing collision (29%), rear-end (28%), right turning accident (9%), and left turning accident (5%). This classification and the definitions are summarized in Table 2-5.

2.4.2 Previous Studies on Urban Intersection Accident Classification

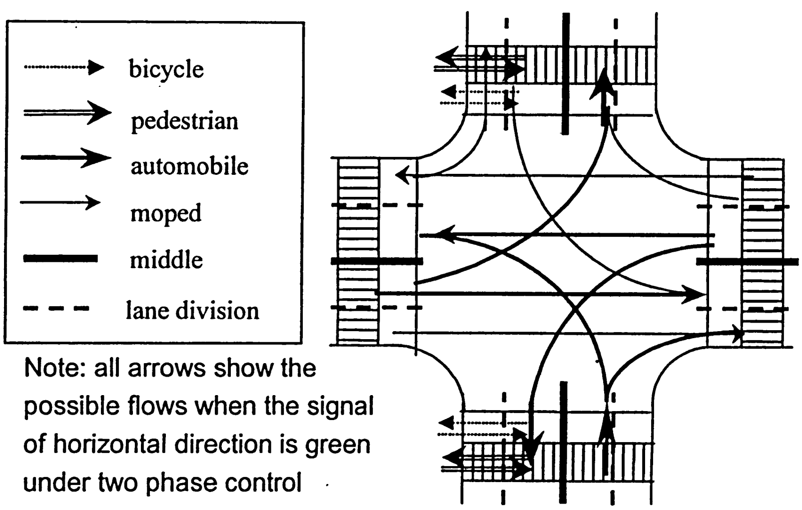
Several researchers have used a number of different approaches in their classifications of urban accidents. The most common approach used in the classification of intersection accidents is to use the initial impact type. To understand and analyze accidents at intersections, it is, however, better to use a classification system that relates the accidents to the intersection flow in which the vehicles that collided were moving.

Accident classification was started by the Electro-Mechanics Department of General Motors Research laboratories in 1968 (Perkins et al.). The Department wanted to analyze the interaction of the driver, vehicle, and roadway at four-way intersections in order to determine which traffic situations could develop into accidents. The Department's classification technique was later modified by Campbell et al. (1970) for Y-type intersections. Campbell et al concluded that conflicts per vehicle were a fairly stable measure that could be verified through time. The researchers' view was that traffic conflicts can and do seem to define potential accident situations and potential accidents. Traffic conflicts can define areas to be investigated, but they do not show the changes necessary to reduce accident potential.

Hauer et al. (1988) classified vehicle-to-vehicle accidents at signalized intersections into 15 patterns according to the movements made by the involved vehicles before the collision. This approach makes it possible to analyze the relationship between the traffic flows along each path and the accident rate on each path. Hauer et al. (1988) concluded that when accidents are categorized by initial impact type, their cause-and-effect relationship with traffic flow is weakened. The logic of attempts to seek an aggregated relationship between accident frequency and some function of all flows (sum of entering flows, sum of products of flows, etc.) is unsatisfactory.

Retting et al. (1995) classified urban crashes on the basis of pre-crash driver/vehicle behavior. Their study was designed to investigate the most common circumstances associated with urban crashes so that planners and policy makers can develop countermeasures aimed at reducing the most prevalent types of crash.

Figure 2-4: Diagram of Traffic Flows in a Typical Toronto Intersection



Note: all arrows show the possible flows when the signal of horizontal direction is green under two phase control

Wang (1998) classified intersection crashes based on the complex traffic situation at an intersection, including a variety of automobile flows, motorcycle and moped flows, bicycle flows and pedestrian flows coming from different directions and frequently conflicting at the intersection (Figure 2-4). This study combines Hauer and Wang's classification and has re-classified side-impact crashes in some detail (Tables 2-4). The variety of flows and conflicts means that intersection accidents are diversified in type and complex in causation. The crash classification (described in section 2.4.3) successfully summarizes the causal factors for different kinds of accidents, and therefore describes the relationship between accident risk and accident causal factors.

2.4.3 Classification of Intersection Accident in This Study

Karim (2005) reclassified urban intersection accidents according to the traffic flows and the movements of the involved vehicles to model vehicle-to-vehicle accidents. The classification of intersection accidents used in this study is shown in Figure 2-5.

The classification is based on the movements of the vehicles before the collision. The ten types of accident shown in Figure 2-9 are the most common accident types. (The frequency of other possible types of accident, is too low to analyze. These accidents are grouped together under "other accidents" in Figure 2-9.)

The rest of this study uses the abbreviated name of each accident type to express clearly which kind of accident is being discussed. . For example, AG1 (angle accident type 1) refers to an accident between a right turning vehicle and an opposite through vehicle, and AG2 (angle accident type 2) refers to an accident between through vehicles traveling from different crossing legs. All the abbreviations and their corresponding meanings are listed in Table 2-9.

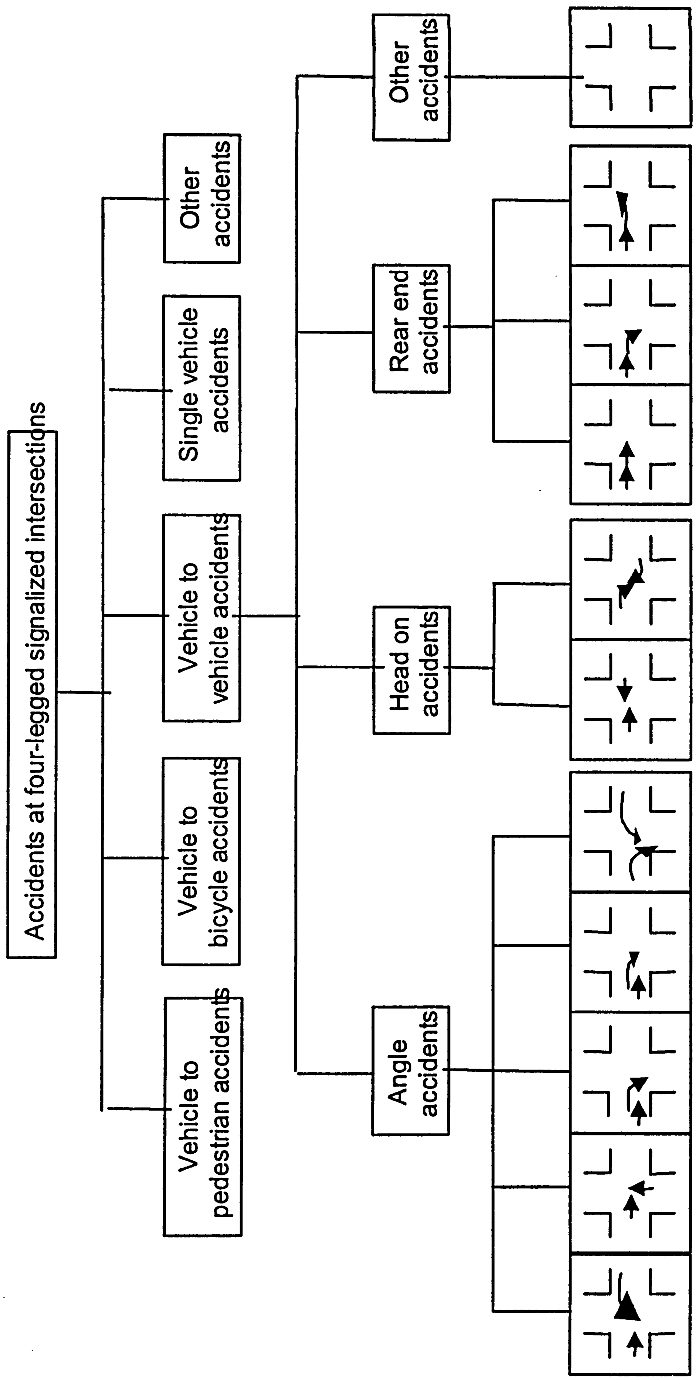


Figure 2-5 Reclassification of accidents at four-legged signalized intersections

Table 2-5: Abbreviations of Accident Types and Their Definition

Abbreviation	Full expression	Description of the accident
AG1	Angle accident type 1	Accident between left turning vehicle and opposite through vehicle. Left-turning vehicle is normally the driver at fault.
AG2	Angle accident type 2	Accident between through vehicles from different crossing legs. Normally it is caused by running red signals.
AG3 (AG3A and AG3B)	Angle accident type 3	Accident between through vehicle and turn oriented vehicle (including those for lane change). Cause is normally turning vehicles disturbed the moving of through vehicles.
AG4	Angle accident type 4	Accident between right turning vehicle and left turning vehicle from opposite leg.
HO1	Head on accident type 1	Accident between through vehicle and a vehicle from opposite direction.
HO2	Head on accident type 2	Accident between two left turning vehicles from opposite directions.
RE1	Rear end accident type 1	Accident between consecutive through vehicles. It is normally caused by the deceleration of leading vehicle and ineffective reaction of the following driver.
RE2	Rear end accident type 2	Accident between consecutive right turning vehicles.
RE3	Rear end accident type 3	Accident between consecutive left turning vehicles.
OT	Other vehicle-to-vehicle accidents	Any other types of accident beyond the above ones. These types of accident are very rare, and generally could not be analyzed separately.

2.5 CHAPTER SUMMARY

This chapter discussed the road accident situation in Ontario and City of Toronto in general. Data collection strategy, methods and preliminary analyses of road accident trends with special emphasis on intersection accident types were presented in this chapter. Certain accident characteristics have been highlighted and contrasted with special emphasis on intersection accidents and their classification. Some important points of signalized intersection crashes were observed that will help understand the real crash occurrence mechanism of major side-impact crash types and its relationship with explanatory variables for model development. An attempt was made to investigate possible relationships between accident number and fatalities and accident exposure variables to provide rough guide to overall accident investigation. These models not only provide a possible explanation of the trends observed but also could be used as a basis of a prediction tool and better understanding of total accidents. A review of accident classification was undertaken.

CHAPTER 3

DATA COLLECTION AND PRELIAMINARY ANALYSIS

3.1 INTRODUCTION

To conduct a microscopic vehicle-to-vehicle side impact accident statistical analysis and modeling, it was necessary to select a sample of intersections with similar intersection characteristics (e.g. four-legged, urban intersection) from a suitable crash database. The City of Toronto maintains a very large crash database that is updated yearly after an intense verification process. The City takes care to ensure that no breakdown or loss of information occurs during data collection and data recording. For each crash, more than 200 variables are used to describe the site and time of the crash, the geometric conditions, the traffic control, the drivers, the vehicles and the pedestrians. The City of Toronto's database includes crashes with a high amount of property damage, an injury, or a fatality. Minor property damage accidents are poorly reported. (This may affect the estimated risk of side impact crashes at the selected intersections.)

This study also developed a detailed crash database based on police reports of accident occurrence. Accident reports are a key issue in any accident database because the reports may contain numerous errors due to the errors that arise during reporting and data processing. Extra care was been taken when data were collected from various agencies and from field inspections.

This chapter discusses the details of the database data collection procedures for data collected from various sources. The chapter also discusses the data analysis process. The analysis of these data was undertaken to develop several models for various types of side impact accidents at intersection. Typical values were used to estimate various parameters of the models that can subsequently be used in various forecasting and prediction applications.

The following sections discuss important issues that arose during intersection sampling, traffic flow and accident data collection, data management and the integration of the crash data with other useful databases. Finally, this chapter demonstrates the importance of data analysis and the visualization of collected data that facilitates the optimization needed for parameter estimation, and confirms the importance of independent variable selection in statistical accident modeling (Details of intersection data were given in Appendix B and C).

3.2 OBJECTIVES OF THE DATA COLLECTION

The objectives of the data collection exercise are as follows

- To reduce the regression-to-mean bias by selecting a group of intersections of having similar characteristics;
- To observe the effects of explanatory variables on side impact crashes at signalized intersections and to establish the cause-effect relationships that are present in the data, but hidden by the randomness in accident counts; and
- To estimate the risk of three major types of side impact crashes (angle accidents, right-angle accidents and left-turn accidents) at four-legged signalized intersections in the City of Toronto.

3.3 DATA COLLECTION

Accidents were considered for analysis if they occurred within 30m of the intersection or were intersection related. In order to increase the homogeneity of the data used, the study investigated only four-legged intersection and two vehicle accidents. Seventy intersections were selected from City of Toronto's database containing 2,827 accidents that met these criteria (depending on the definition of target accident which is discussed in section 2.4). More than 86% of the 2,827 accidents occurred at two-way four-legged signalized intersections compare to 14% in one-way intersections.

3.3.1 Reconnaissance and Sample Selection

To develop a mathematical model that correlates accident frequencies with the intersection's geometric and traffic characteristics, one needs to select a sample of intersections that possess a wide variety of geometric and traffic characteristics. To enhance the chances of success, the intersections were selected on the basis of the homogeneity principle of data collection (Belanger 1995) using similar intersection characteristics to assess homogeneity.

An extensive reconnaissance of about 200 Toronto intersections was conducted to identify a sample of sites suitable for the study. The data collection area extended from Queen's Quay in the south to Lawrence Avenue in the north, and from Islington Avenue in the west to Warden Avenue in the east. An aerial view of the data collection map is provided in Figure B-1 in Appendix B.

The sample selected comprised 70 four-legged, variable-time, signalized urban intersections most of which had two-way traffic on all four approaches. A list of the selected intersections is provided in Table B-1 in Appendix B.

The sample sites were selected to provide a sample that could be stratified according to important variables such as traffic flows and the main features of the intersection layout. Data were assembled from electronic police accident reports, microfilm sketches and written descriptions on the hard copy versions, traffic volume files, and field visits.

Randomly selected data were used to generalize the acceptance of the accident model for all types of intersection, at least in the City of Toronto. It is cumbersome and meaningless to develop separate models for intersections with a low accident frequency and intersections with a high-accident frequency.

The integration of several levels of database makes the model transferable between all types of intersection for future research of model transferability.

3.3.2 Sample Size

Sample size is one of the most critical issues in determining the form of the risk-estimation model and the types of data needed to calibrate it. The high variability of accident data tends to translate into the need for large sample sizes to establish sound statistical relationships. Large sample sizes imply a large database of crash data. There are several ways to overcome the database requirements needed to create a sample large enough for meaningful analysis. One way to make use of a very large accident database is to create a smaller database of the intersections of the type being considered. In this study, the targeted intersections are four-legged urban intersections and the targeted accident are side impact accidents.

Although subsetting (for three major types of side-impact crashes: right-angle, left-turn and right-turn crashes) has the beneficial effect of increasing similarity in the resultant database, it is achieved by extracting a portion of the original database. Thus, it has the disadvantage of reducing the available sample size. According to Bonneson (1994), the amount of subsetting is generally limited to that which will allow the questions of the research to be answered without compromising the analyst's predetermined sample size requirement. The trade-offs between sample size and sample similarities were carefully considered and a proper balance was achieved.

The database used in this study contains targeted accident data from 1999 to 2004. More than 250 variables were collected for each crash record. Tables B-3 and B-4 in Appendix B describes the variables pertaining to subject and target vehicle respectively.

3.3.3 Target Accident Data Selection

The accident databases were derived from computerized versions of police accident reports stored in the City of Toronto's "Traffic Safety Centre" microfilm base database. A comprehensive consistency check was performed on microfilm crash reports to identify the target and bullet vehicles from the police accident description, the vehicles' traveling direction before the accident, and the types of side impact accident to be included in the study. The accident counts used were 24-hour counts from 1999 to 2004. The accidents were divided into several types of side impact collision. (Details of the accident classification and the preliminary analysis are described in the section 3.3.5.).

Figure 3-1 shows the basic statistics for side impact crashes at selected signalized intersections for the six years from 1999 to 2004. Side impact crashes accounted for approximately 35% to 40% of the total number of accidents at the selected intersections. Right-angle crashes accounted for the largest group of side-impact crashes (crash distribution showed that 20% to 48% of the side impact crashes at the selected intersections). Angle crashes (right-angle and other angle crashes combined) show a steady increase over the six years.

All of the distributions are positively skewed and show a major departure from the normal distribution. The detailed distributions and the analysis are discussed in the section 3.6.

Table 3-1: Basic Statistics for Major Types of Side Impact Crash at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

Basic Statistics	Total Number of Crashes	Percent of Side Impact Crashes	Number of Side Impact Crashes	Percent of Right-Angle Crashes	Number of Right-Angle Crashes	Percent of Left-turn Crashes	Number of Left-turn Crashes
Mean	125.6	33.7	40.4	32.0	13.0	19.7	8.1
Standard Error	6.9	1.2	2.2	1.9	1.2	1.1	0.7
Median	110.5	32.2	36.0	33.0	12.0	20.0	7.5
Mode	104.0	33.3	36.0	33.3	12.0	25.0	10.0
Standard Deviation	57.4	10.3	18.7	15.8	9.7	9.6	5.5
Sample Variance	3292.1	107.0	348.2	250.3	94.8	91.4	30.6
Kurtosis	0.0	0.2	0.8	-0.4	10.6	-0.3	8.0
Skewness	0.5	0.7	0.8	0.5	2.6	0.1	2.0
Range	273	47.66	94	67.6	64	40	35
Minimum	24	15.38	4	0.0	0	0	0
Maximum	297	63.04	98	67.6	64	40	35
Sum	8791	2359.11	2830	2241.1	909	1382.4	566
Count	70	70	70	70	70	70	70
Largest(1)	297	63.0	98	67.6	64	40	35
Smallest(1)	24	15.4	4	0	0	0	0
Confidence Level (95.0%)	13.68	2.47	4.45	3.77	2.32	2.28	1.32

3.3.4 Traffic Flow Data Collection

The study's resulting database contained six years of data (1999 to 2004) for the 2,827 accidents recorded at 70 signalized intersections in the City of Toronto. The data included the daily traffic flows for the major and minor road at each intersection. An 8-hr traffic count was available for each of the 12 maneuvers that occur at a four-legged intersection (left-turn, through and right-turn on each approach). Using data collected from permanent traffic counters, these 8 hour counts were converted to average daily traffic flow estimates that are representative of an average day, month and year of the period of analysis. Traffic demand data were estimated and converted.

Table 3-2 shows the basic statistics for entering traffic flows at the 70 intersections. Traffic flow distributions were given in Appendix B from Figure B-

3 to B-6. Through traffic accounted for approximately 64% to 68% of the total traffic flow, right-turn flows for 20% and left-turn flows for 15%.

Table 3-2: Basic Statistics of Entering Traffic Volume at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

Basic Statistics	Left-turn Traffic Volume	Through Traffic Volume	Right-turn Traffic Volume	Total Traffic Volume
Mean	824.0	3665.8	1117.2	4684.8
Standard Error	68.6	140.4	78.8	164.4
Median	484.5	3260.5	674.0	4081.0
Mode	0	0	0	0
Standard Deviation	1148.3	2349.2	1317.9	2751.7
Sample Variance	1318632	5518875	1736918.1	7571863
Kurtosis	18.20	1.22	15.17	0.99
Skewness	3.46	0.96	3.20	0.88
Range	9968	12109	11097	14167
Minimum	0	0	0	0
Maximum	9968	12109	11097	14167
Sum	230713	1026436	312807	1311737
Count	280	280	280	280
Largest(1)	9968	12109	11097	14167
Smallest(1)	0	0	0	0
Confidence Level (95.0%)	135.1	276.4	155.0	323.7

3.3.5 Identification of Types of Side Impact Intersection Crashes

Accidents were considered relevant if they met the definition of side-impact crashes given in Chapter 2. A total of 2,827 accidents met the criteria. Of these, 1,347 accidents were classified as "angle accidents" and 1,480 accidents were classified as "turning accidents" according to police reports. The study required data on the combination of flows that led to the accident and the details of each accident's patterns, but the information coded in the accident files was unreliable. The list of patterns provided on the accident report form is not exhaustive, and codes are often missing or inconsistent. Some of the problems were corrected by analyzing the microfilm for each accident report.

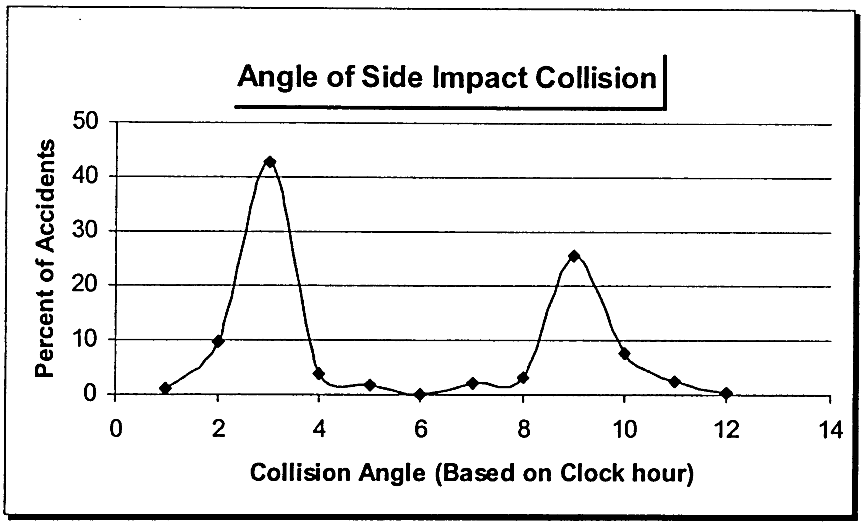
The study analyzed the following major categories of side impact crashes

1. All Side-impact (SI) crashes;
2. Right-Angle accidents (AG2); and
3. Left-turn crashes (AG1).

Some partial results for right-turn crashes and personal injury side impact crashes are also presented in the next section.

Some recent studies have established criteria for the definition of side impact crashes (Chipman et al. 2004, Chipman and Desapriaya 2005, Gandhi and Hu 1996 and Farmer et al. 1997). Eight teams are conducting side impact crash investigations across the country to assist Transport Canada in determining the efficacy of the current Canadian Motor Vehicle Safety Standards.

Figure 3-1: Angle (in Terms of Clock Angle) of Side Impact Crash Accidents



This study investigated side impact crashes which met the following criteria

- The vehicle-to-vehicle crash occurred near 30 m of the selected intersection's centre point;
- The target vehicle was a model from the last ten years;

- The primary direction of force (PDOF) for left side impacts was between 8 and 10 o'clock;
- The PDOF for right-side impacts was between 2 and 4 o'clock; and
- The vehicle damage pattern fell in to one of the following groups (see the detailed definition given by Chipman et al. 2005):
  - T-Bone;
  - L-type (front);
  - L-type (rear); and
  - Other (e.g. damage to the front of both vehicles, damage to the rear of either vehicle, damage to others parts).

The City of Toronto's definitions of angle and turning crashes meet the criteria listed above, but 7% of the crashes in the City's database (see Figure 3-1) were excluded from the study's final database due to inconsistencies with the above criteria and/or the accident classification described in Chapter 2.

Figure 3-2: Extent of Vehicle Damage of Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

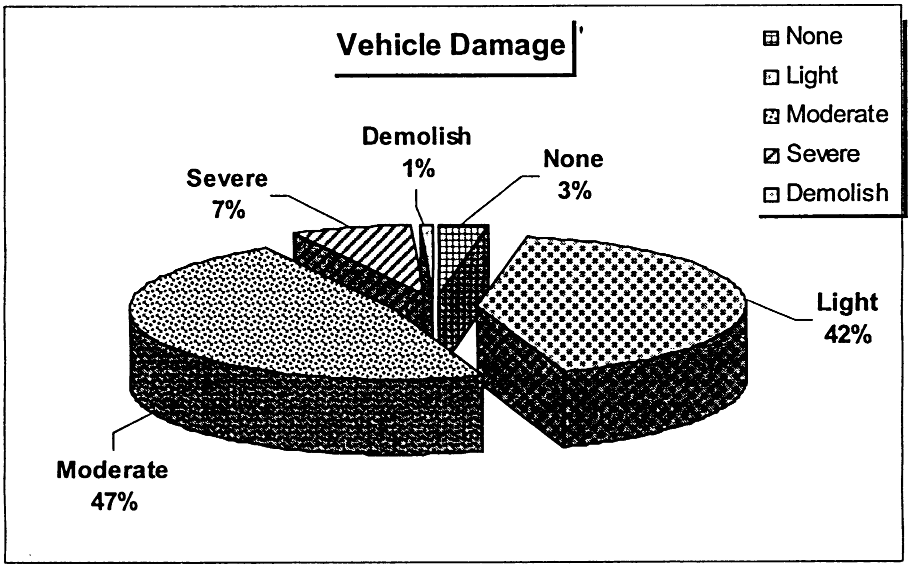


Figure 3-2 shows the extent of vehicle damage suffered after a side-impact occurred at the signalized intersections. Most damage was "moderate" (47%) or "light" (42%). Damage was "severe" in 7% of the side impact crashes. Compared with other types of intersection accident, side impact crashes produced significantly more "moderate" and "severe" vehicle damage.

3.3.6 Identification of Target and Bullet Vehicle

A similar problem occurred during the selection of the vehicles and identification of the drivers involved in the side impact crashes at the 70 signalized intersections. According to the assumptions of the modeling framework, a vehicle-to-vehicle accident must include the emergence of the subject vehicle and the inadequate response of the driver of the target vehicle. Separate factors are logically discerned relevant to the two premises were collected during data collection process. An observation unit in this study is an intersection leg (or arm/bound/approach), and this is a radical departure from most of the previous studies, where the entire intersection is regarded as a single unit.

3.3.7 Traffic Regulation Data Collection

Traffic flows at intersections are very complex. The role of traffic regulations at intersections is usually more significant than along highway sections. Since traffic regulations have significant effects on traffic flows, traffic regulations will definitely affect accident risk. Data on the traffic regulations, in force at the intersections (such as speed limits, signal control patterns, through bans, right-turn bans and left-turn bans) were collected during a series of site surveys conducted in 2006 with the help of an undergraduate student.

Signal control can be divided into three types:

- two-phase control under which turning flows and through flows use the same green interval;

- four-phase control under which an additional left or right turn green phase is added to the usual two-phase control for each direction; and
- Four-phase control under which left turning vehicles are only allowed to proceed during the left turn green interval.

Under two-phase control, conflicts between left turn flows and through flows are inevitable. The two types of four-phase control separate conflicts partially or completely.

3.3.8 Geometric Data Collection

The geometric data related to the selected intersections were collected during extensive field surveys conducted over a five month period. Some geometric data were also collected from Mapquest and Google Earth digital maps.

About 86% of the 70 selected intersections have a regular shape, i.e. the two crossing roads are almost perpendicular to each other (all of the four crossing angles are within 75 to 105 degree). The remaining 14% are irregular shaped intersections.

The study also considered intersection size and the surrounding land use pattern. .The surrounding land use could be a key factor affecting human activities within or near the intersection.

3.3.9 Road Side Data Collection

The initial motivation for collecting data on road-side features was an attempt to understand the safety impact of livable streetscape treatments on urban roadways. Many groups and individuals encourage the design of "livable" streets. These streets attempt to better integrate the needs of pedestrians and local developmental objectives into a roadway's design, but very little is known about the impact of street side features on traffic safety (Dumbaugh 2005). There is considerable disagreement among safety professionals about the impact of "livable" streets on single-vehicle crashes and the negative aspects on safety. Very little information is available on the use of aesthetic streetscape features and much of the existing literature on the application of "AASHTO's clear zone" policies in urban environments problematic is problematic. No literature on the effects of "livable streets" on two-vehicle crashes at signalized intersections was found.

There is, however, a growing body of evidence suggesting that the inclusion of trees and other streetscape features in the roadside environment may actually reduce crashes and injuries on urban roadways. Naderi (2003) examined the safety impacts of aesthetic streetscape enhancements placed along the roadside and medians of five arterial roadways in downtown Toronto. The author found that the inclusion of features such as trees and concrete planters along the roadside resulted in statistically significant reductions in the number of mid-block crashes along all five roadways: the number of crashes decreased from 5% to 20%. The presence of a well defined roadside edge may lead drivers to exercise greater caution and to decrease their speed.

This study attempts to explore the effects of streetscape features on two-vehicle crashes at signalized intersections as a part of the model developed and described in the section 5.6 in detail. Extensive field surveys and CAD diagrams were used to collect and input the roadside variables into the statistical model. The independent variables are listed in Table B-2 of Appendix B.

3.4 DATA ANALYSIS

The analysis of intersection crashes uses different tools than the analysis of city wide crashes. This section analyzes the study's data in detail. The purpose of this section is to explore the crash patterns found in the data and to reveal important relationships within the data as a basis for decisions regarding the selection of the model's independent variables and the format of the dependent variables.

The data collected from the City of Toronto and elsewhere did not include information on traffic volumes' direction. A separate site survey was conducted (by the author) to obtain the necessary leg-wise information.

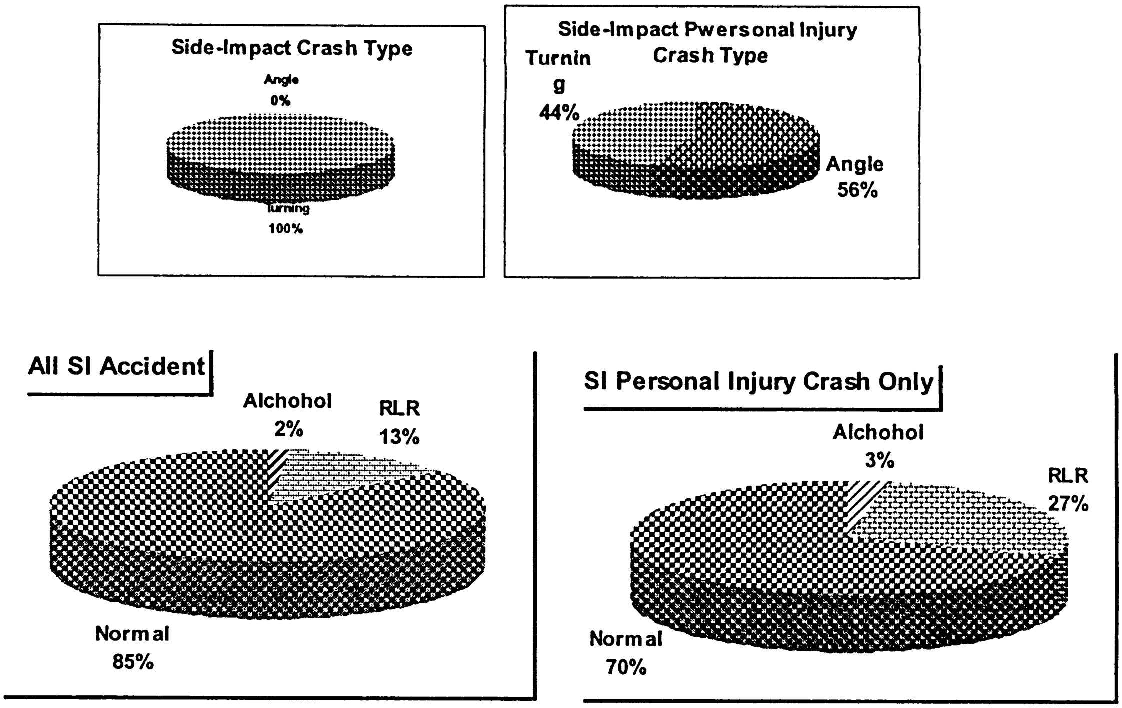
All of the databases were finally combined into a single database which contained all the dependent and independent variables.

3.4.1 Comparative Accident Study

Establishing the correct context for crash data analysis is very important. A comparison of sites can determine where a disproportionate number of crashes suggests special circumstances or road conditions.

The accident percent for each type of side impact accident is shown in Figure 3-3. Turning crashes (i.e. AG1, AG3) are the most frequent type of urban intersection crash. If only personal injury crashes are considered, angle accidents becomes the most common type of crash found at the intersections. While 13% of all side impact crashes involved red-light running (RLR), 27% of severe personal injury accidents involved RLR. This finding suggests that angle accidents are more severe than any other type of intersection accident. This is one of the reasons why side impact accidents represent a special hazard for urban intersection users and one of the reasons why the angle accident occurrence mechanism should be analyzed thoroughly. As the City of Toronto accident classification is different from the classification used in this study, the cause and effect of the accidents analyzed may differ. In this study, the analysis and modeling focuses on three categories of side-impact crashes: total side-impact crashes; right-angle; and left-turn accidents. The number of other side impact crashes was too small to be included in the distribution fitting part of the analysis and model development.

Figure 3-3: Comparison of Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

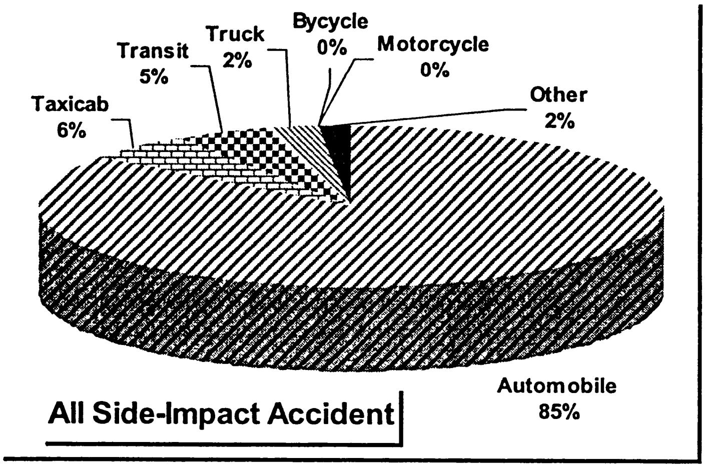


3.4.2 Traffic Accident by Vehicle Type

Figure 3-4 shows the percentage of side impact vehicles attributed to each vehicle type. The percentages were compared with the percentage of each vehicle type found in the province's 1999 vehicle registrations.

Figure 3-2 shows that 85% of the side impact accidents involved ordinary cars, but automobiles account for a lower percentage of vehicle registrations. The unexpectedly high accident involvement might be because automobile drivers spend more time on the road as compared with other drivers. Car drivers might, therefore, be more likely than others to be involved in an accident due to their longer period of exposure on the road. One might also argue that automobile drivers would be more experienced and would be better able to handle a potential accident situation and succeed in avoiding an accident. Other factors such as fatigue, speeding and inattentive driving could, however, be the main factors leading to accidents involving drivers of ordinary cars. A specific in-depth study on this case would be necessary before any concrete understanding can be achieved.

Figure 3-4: Component Ratio of Vehicles Involved in Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004



3.4.3 Nature of Side-Impact Accidents

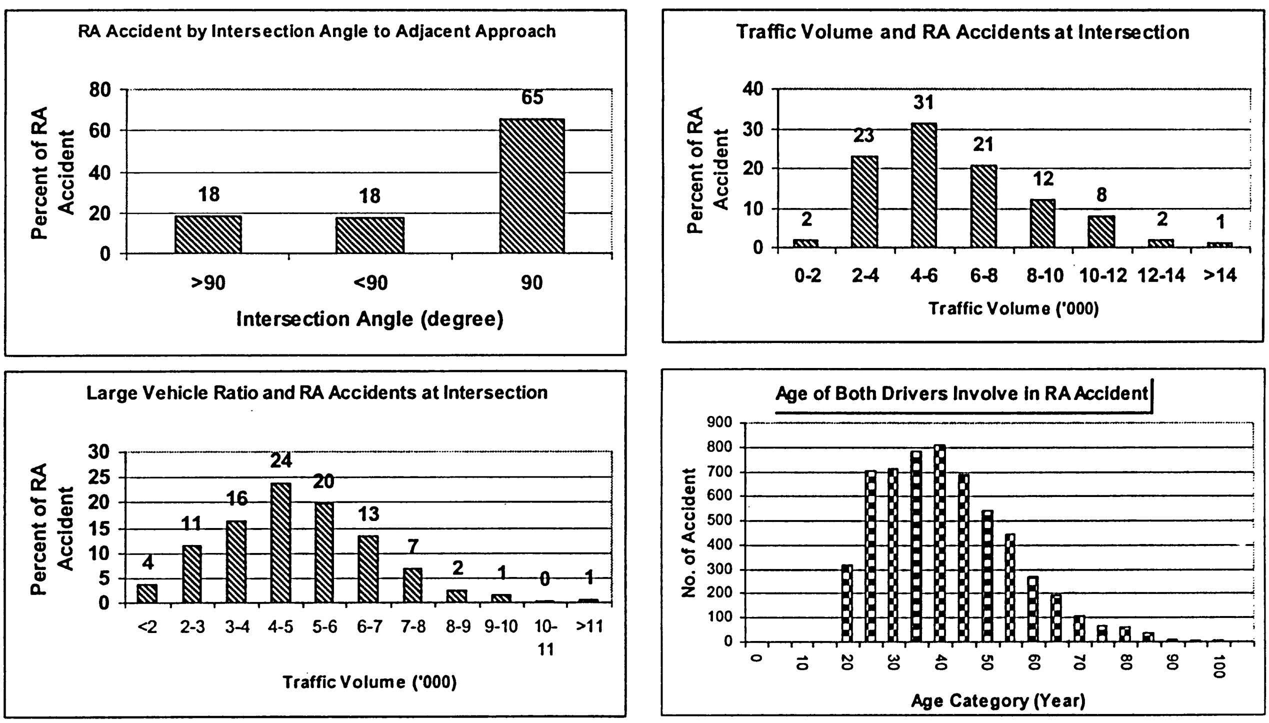
The key criterion for developing a microscopic model is to analyze the data of Side-Impact (SI) accident, which lays the foundation of microscopic details of collision occurrence mechanism. A database of was selected from an initial one of 161 intersections by considering the most dominant intersection geometry (91% accident occurred at four-legged intersections) and number vehicles in right-angle accidents (only 3% are multi-vehicle side-impact accident). For example, 52% SI accidents occur in commercial area compared to 34% in residential areas and 12% industrial zone. This representation was reflected in the database.

Careful review of the data revealed the feasibility of addressing fundamental issues involved in the collision occurrence mechanism for side impact crashes and in the development of a microscopic model development for side-impact accidents. Table 3-3 sets out some of the basic accident characteristics that helped to develop important assumptions and helped to assess the controlling factors involved in side-impact accidents.

Table 3-3: Basic Facts of Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

Signal Control Type	Two-phase 85%	Three-phase 11%	Multi-phase 3%
Road Type	Minor Street 28%	Major Road 70%	Collector 2%
Land Use	Commercial 52%	Residential 34%	Industrial 14%
Intersection Approach Angle	$>90^0$ 18%	$<90^0$ 17%	90^0 65%
Approach Type	Major Road 70%	Minor Road 30%	
Vehicle from	Right 44%	Left 55%	

Figure 3-5: Example of Four Factors that Affects Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004



Most of the SI accidents (85%) occurred at intersections with two-phase signal control. The red-light-running accident rate is not a simple function of the major road's traffic flow (Baguley 1988) and local streets experience a significant proportion of side-impact accidents. The risk for cross street vehicles from the left seems higher than the risk for vehicles from the right. Campbell et al. (1970) reported similar conclusions (they found 60.3% of the vehicles that violated the stop sign approached from the left).

Figure 3-5 is a graphical representation of the basic characteristics of the study's side-impact accidents. The results section (section 5.6) describes the factors associated with the side-impact accidents in detail and interprets the factors in relation to the model outcome.

3.4.4. Effects of Driver Age on Accidents

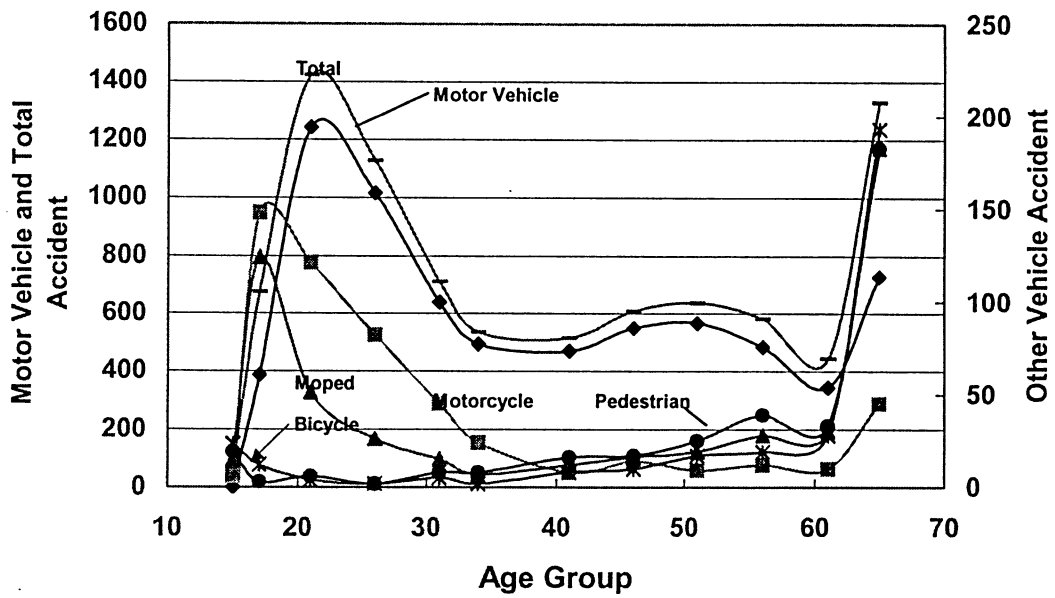
Driving can be seen as an integrated procedure for perceiving the conditions of the environment, taking decisions, making the corresponding maneuvers and implementing all these tasks within a few seconds. As drivers of different age groups have different abilities regarding sight, hearing, information processing and reaction times, drivers from different age groups may have different accident risks.

Elderly drivers may be more experienced, but their declining mental and physical abilities make them poor at perceiving information and quickly implementing the necessary driving maneuvers. Elderly drivers are likely to perceive dangers later than other drivers, react slowly and react less precisely. Elderly drivers are, therefore, more likely to be involved in accidents especially where traffic conditions are complex as at an intersection. It also observed that the ratio of deaths to other age group fatalities is higher (20.5%) for the older age group than for other age groups (Figure 3-6).

There is very little literature on the effect of driver age on intersection crashes. Garber (1991) examined the intersection design and operation parameters that significantly affect the accident involvement of the elderly. He also developed guidelines to reduce the elderly's involvement in accidents. Garber concluded that:

1. the elderly are more prone to traffic violations than are other age groups;
2. the provision of protected left-turn phase with left-turn lanes will help in reducing the accident rates of the elderly at signalized intersections; and
3. longer amber times will be beneficial to the elderly.

Figure 3-6: Fatal Accident Involvement according to Age



Chipman et al. (2005) reported that the mean age of drivers involved in side-impact crashes was a little higher for target vehicle drivers (38.7 years) than for the bullet vehicle drivers (33.5 years).

This study examined the effects of driver age on side impact crashes at signalized intersections in detail. The results are given in Tables 3-4 and 3-5 and in Figures 3-5 to 3-7.

The differences in the age of the target and bullet vehicle drivers were small and not significantly different (Table 3-4). Table 3.5 provides information about the involvement of various age groups in side impact crashes. Since exposure information is unavailable it is difficult to make conclusions from this information.

Table 3-4: Summary of Age of Drivers Involve in Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

Basic Statistics	Both Drivers	Target Vehicle Drivers	Bullet Vehicle Drivers	Both Drivers - - Personal Injury Crashes Only	Target Vehicle Drivers_ Personal Injury Crashes Only	Bullet Vehicle Drivers_ Personal Injury Crashes Only
Mean	39.42	39.98	38.75	38.32	38.98	37.44
Standard Error	0.19	0.26	0.27	0.38	0.52	0.54
Median	38	38	37	36	37	35
Mode	37	38	37	32	32	24
Standard Deviation	14.10	13.83	14.46	13.96	13.73	14.24
Sample Variance	198.86	191.15	209.1	195.12	188.35	202.78
Kurtosis	0.41	0.42	0.451	0.681	0.870	0.60
Skewness	0.754	0.70	0.77	0.867	0.85	0.86
Range	81	81	97	81	81	90
Minimum	16	16	16	16	16	2
Maximum	97	97	97	97	97	92
Sum	226675	117023	109667	52503	27166	25907
Number of Sample	5750	2927	2830	1370	697	692
Largest(1)	97	97	92	97	97	92
Smallest(1)	16	16	16	16	16	17
Confidence Level (95.0%)	0.36	0.50	0.53	0.74	1.02	1.06

Table 3-5: Side Impact Crashes for Age Groups at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

Age Group	Number of Side-Impact Crashes	**Percent of Total**	Minor Injury (MI)	**Percent of Total**	Moderate Injury (MR)	**Percent of Total**	Major Injury (MJ)	**Percent of Total**
>65	149	**5.3**	35	**4.5**	20	**4.9**	0	**0.0**
40-64	1169	**41.4**	275	**35.4**	165	**40.6**	12	**60.0**
21-40	1348	**47.7**	394	**50.8**	191	**47.0**	7	**35.0**
<20	161	**5.7**	72	**9.3**	30	**7.4**	1	**5.0**
Total	2827	**100**	776	**100**	406	**100**	20	**100**

Figure 3-7: Target (Driver 1) and Bullet (Driver 2) Drivers' Age Distribution for All Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

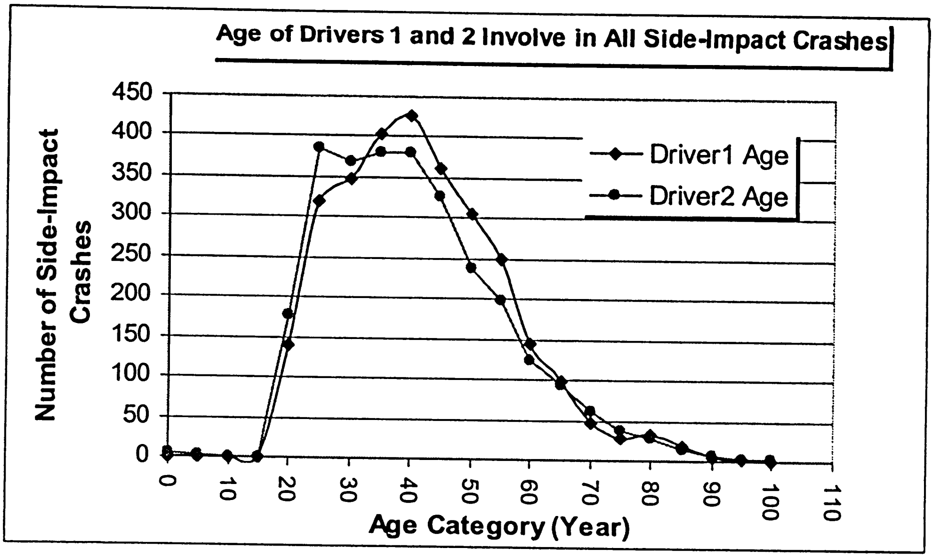


Figure 3-8: Target (Driver 1) and Bullet (Driver 2) Drivers' Age Distribution for Personal Injury Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

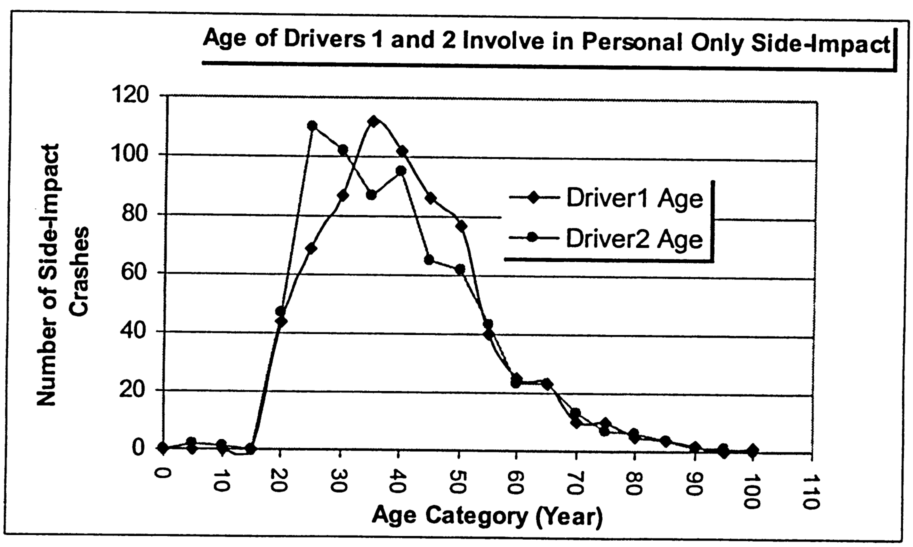
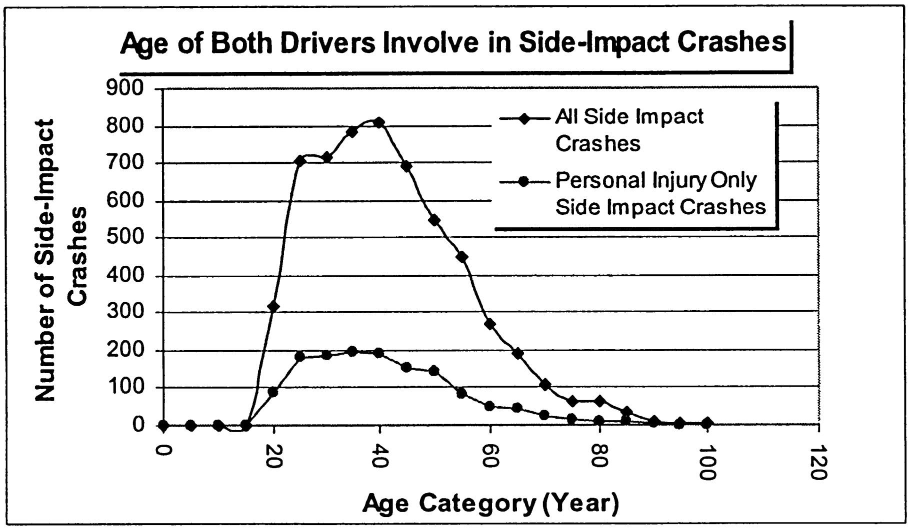


Figure 3-9: Combined Target and Bullet Drivers' Age Distribution for All Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

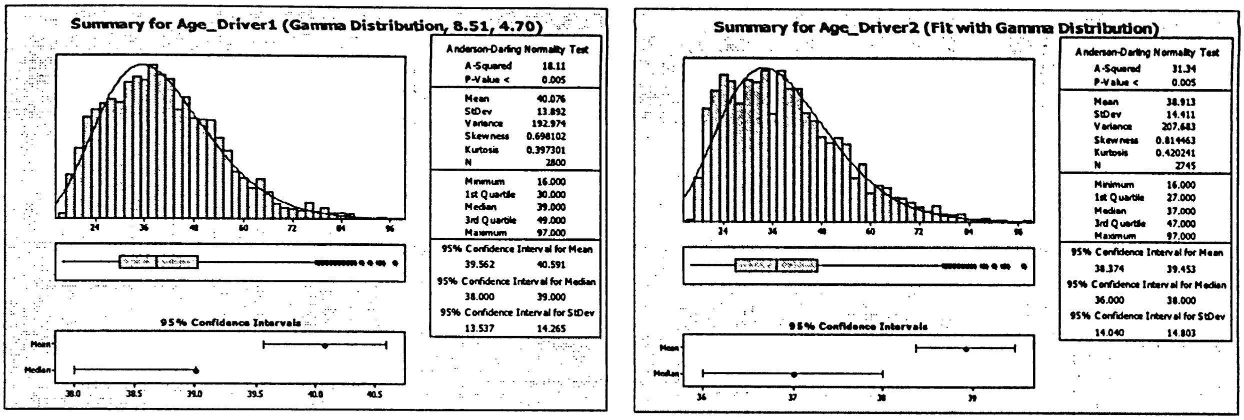


It is commonly thought that younger and older drivers are the major contributors to total accident counts. Figures 3-5 to 3-7 do not support the view for side impact crashes. Drivers aged between 25 and 55 were involved in 82% of the side impact crashes.

Younger or older driver might be thought likely to be involved in a high percentage of other types of intersection accident, particularly rear-end, head-on or side-swipe crashes. However, actual driving force to occur a side-impact collision at intersection probably some other factors which is impossible to avoid in spite of driver age.

Research by Miura (1992) concluded that the demands made on drivers negotiating a signalized intersection can exceed a driver's information processing capacity in the very limited time frame available. Where the information load required for crossing the intersection is higher than a driver anticipates or where there are intersection design problems, the operational requirements become so complex that drivers of any age have difficulty and succumb to the same errors.

Figure 3-10: Fitting Gamma Distribution of Age of Drivers Involved in Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004



The results of these investigations are used to identify the appropriate framework of statistical model, as described in Chapter 4.

3.4.5 Temporal Analysis

The development of a multi-year crash database enables safety professionals to analyze crash trends during extended periods of time. Crash histories for a 5 to 10 year period are helpful in identifying underlying causal factors (ITE 2004).

Figure 3-11 Side Impact Crash Trend at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004

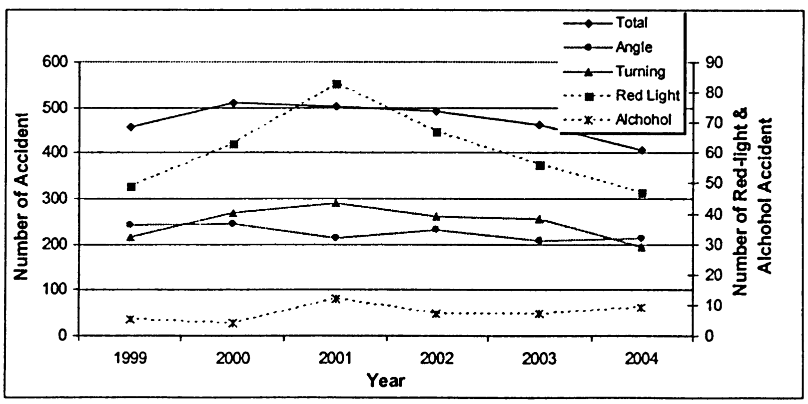


Figure 3-11 shows the accident trends for five major factors between 1999 and 2004. Although national crash trends are tending to decrease (see Section 2.2.2), none of the side impact crash trends shown in Figure 3-9 seems to be decreasing.

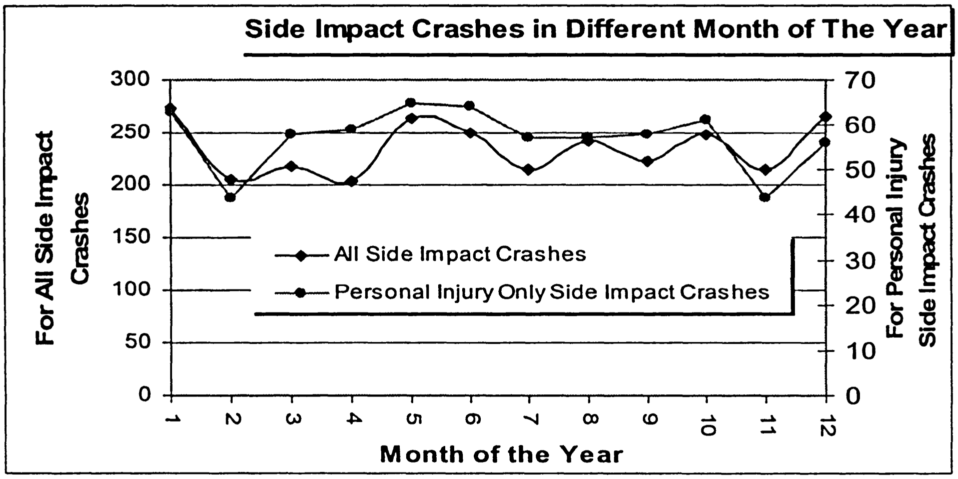


Figure 3-12: Side Impact Crash Variation in Different Month of the Year

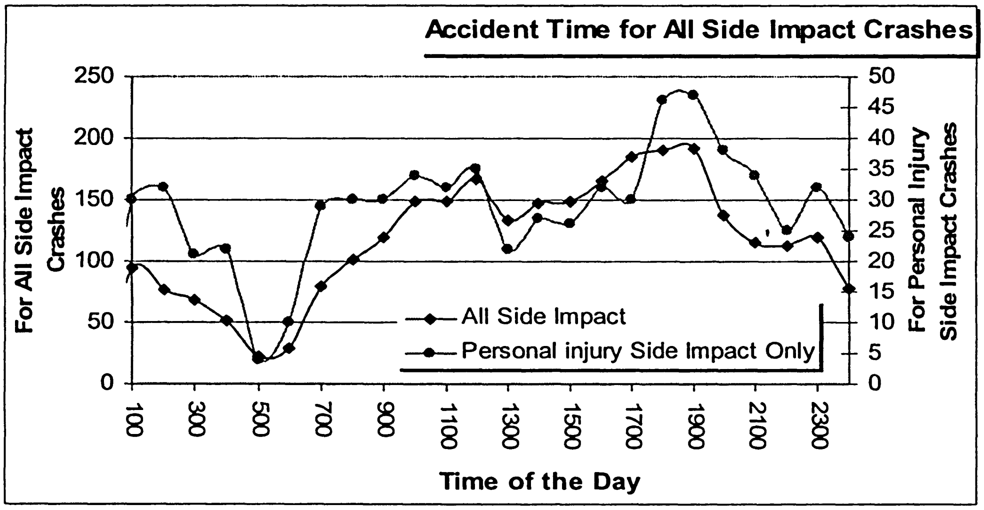


Figure 3-13: Side Impact Crash Variation in Different Time of the Day

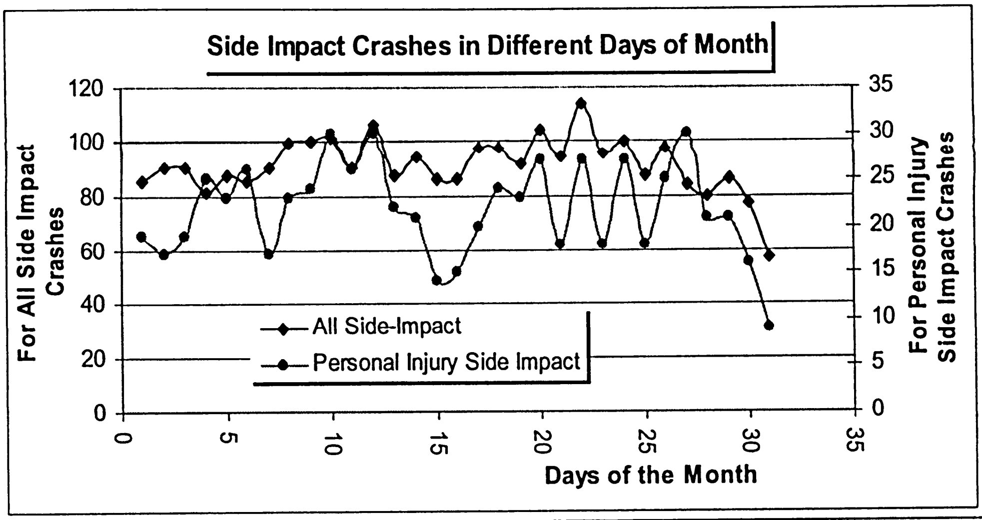


Figure 3-14: Side Impact Crash Variation in Different Days of Month

As well as reviewing crash trends during the course of several years, it is often helpful to view data seasonally or monthly. Figure 3-12 shows side impact crash frequency for all side impact crashes and for personal injury cashes by month of year. There is a peak in crash frequency in December, Canada's longest vacation season. The summer months also show an increased frequency of personal injury side-impact crashes due to the high traffic volumes associated with summer vacationers.

Figure 3-13 provides an analysis by time-of-day. All side impact crashes peak between 4:00 and 7:00 pm. Injury side impact crashes peak from 6:00 to 7:00 pm. This finding strengthens the general hypothesis that school and commercial trip generation explain abnormalities in the signalized intersection's temporal crash data distributions.

Temporal distribution data can also be used to decide on the most appropriate times of the day/week/month to conduct field reviews. Figure 3-14, however, does not suggest any clear pattern or distinguishable peak in the side impact accident frequency for any particular day of the month.

3.4.6 Effects of Weather

Weather conditions have a significant impact on accident counts, although the direction of the impact may sometimes seem counterintuitive. Fridstrom et al. (1995) found that rain is likely to increase the accident toll, but that snow seems to have the opposite effect. It is also necessary to consider the number of days with fine and poor weather. There are more fine days than days with bad weather.

Figure 3-16 shows that most crashes occurred in fine weather, but a significant percentage occurred in bad weather. The category most seriously affected by bad weather is the urban unsignalized intersection which accounted for 13.5% of the accidents.

Figure 3-15: Effects of Weather on Side Impact Crashes

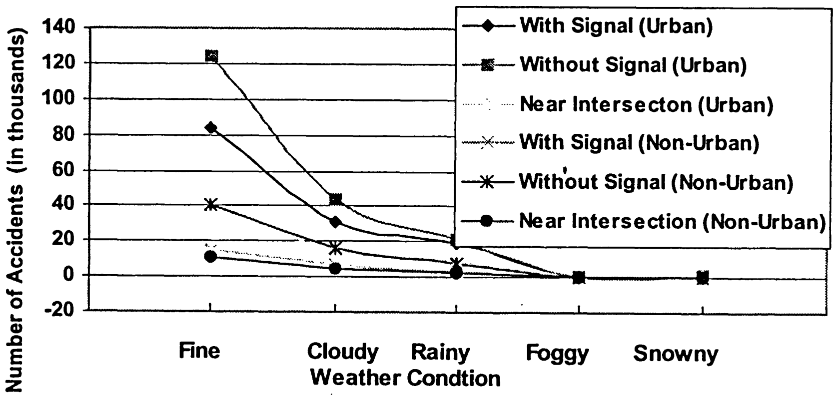
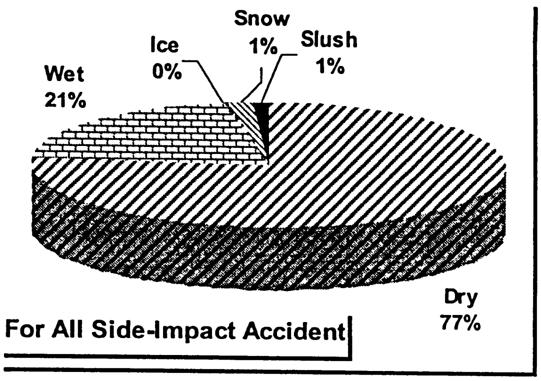
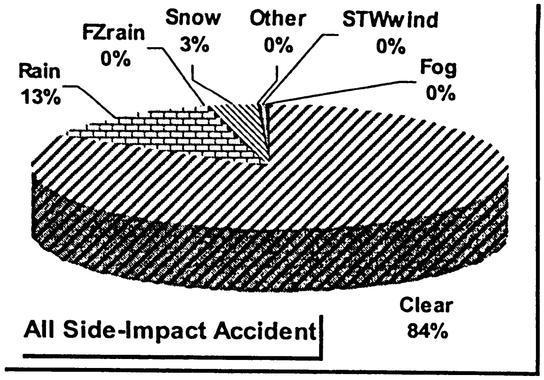


Figure 3-15 shows that 77% of all side impact crashes and 84% of the injury crashes included in the study's database occurred during dry and clear weather.

Figure 3-16: Effects of Road Surface Conditions and Weather on Side Impact Crashes at 70 Selected Signalized Intersections in the City of Toronto, 1999 to 2004





3.4.7 Intersection Accident by Day and Night

Table 3-6 shows that there are some marked differences in the occurrence of intersection accidents during the day vs. during the night. Most accidents occur during the day, but in the case of urban intersections with a signal, most accidents occur at night. All the urban data shown in table 3-6 suggest that night time accidents are a problem, especially when it is considered that the night is relatively short and traffic volumes decrease. It is possible that a night time increase in heavy vehicle movements contributes to accidents, and drivers may tend to disregard the possibility of other traffic during the night.

Table 3-6: Effects of Day and Night on Accidents at Intersections with and without a Signal and on Accidents near an Intersection, 1999 (source: Transport Canada Statistics, 1999)

	With Signal		Without Signal		Near intersection	
	Day	Night	Day	Night	Day	Night
Urban	0.39	12.72	35.25	10.71	9.77	5.31
Non-urban	3.79	2.14	12.58	2.92	3.13	1.29

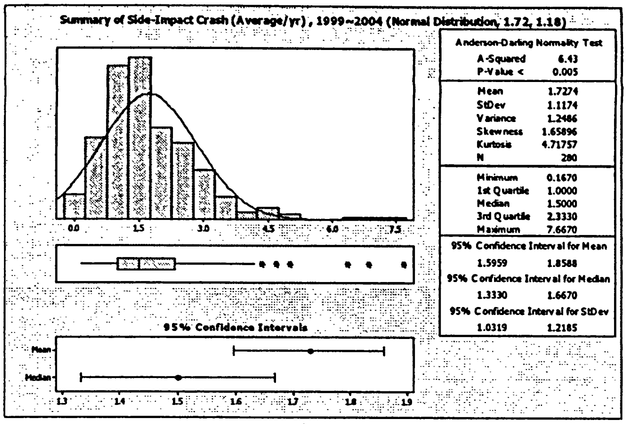
3.6 CRASH DISTRIBUTIONS FOR INTERSECTION ACCIDENTS

Most regression theory is based on the assumption that the error structure is normal with a mean equal to zero and a constant variance. This hypothesis is not, however, valid in road safety analysis because residuals tend to increase with larger fitted values. A number of intersection related studies (Belanger, 1995, Bonneson 1994, Carson 2001, Fridstrom 1995, Hauer 1988, Mannering 1995, Pernia 2002) have concluded that a negative binomial type of error is more appropriate to describe the variations in the number of accidents at selected sites. The choice is based on the assumption that the variation in the number of accidents at any particular location can be described by a Poisson process and that variations in the levels of safety in a group of similar intersections can be fitted by a Gamma distribution.

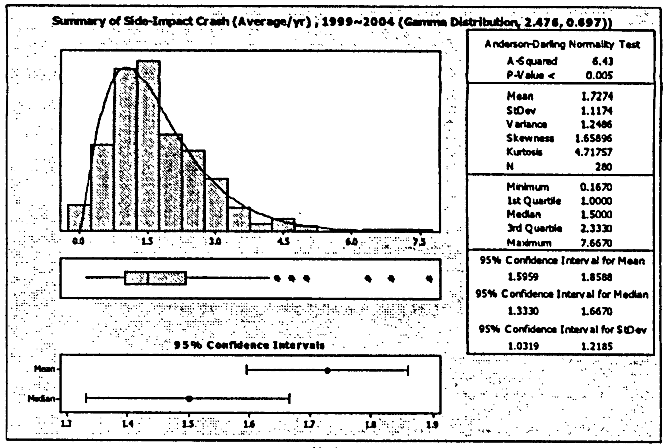
3.6.1 Distribution Fittings for Number of Crashes

This section provides a numerical example of distribution fittings for the types of side impact crash considered in this study. Figure 3-17 is a good example of data visualization. The Figure shows the nature of intersection accident count and the fitting of both a Normal (Figure 3-17 a) and a Gamma (Figure 3-17 b) distribution. It is clear that Figure 3-17 b shows the appropriateness of the Gamma distribution for intersection crash frequency.

Figure 3-17: Comparison of Fitting of Normal and Gamma Distributions to Side Impact Crash Count (selected Database)



(a)



(b)

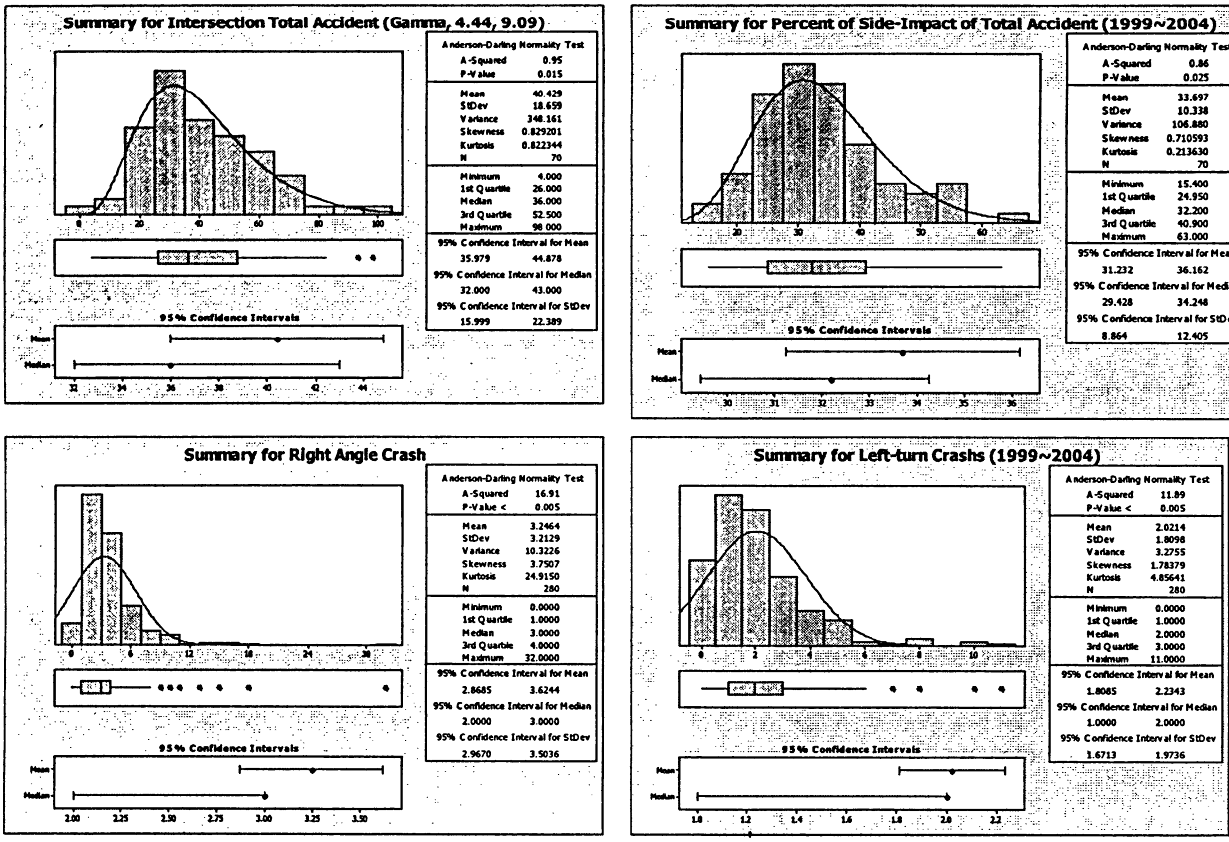
Crash distribution modeling was performed separately for the total number of side-impact crashes, right-angle crashes and left-turn crashes. The distributions in Figure 3-18 show how the crash distributions varied and the type of distribution they followed. As examples, Figures 3-16 presents the crash distributions for the total number of crashes per year. Based on the frequency distributions and the cumulative probability for the total number of crashes, the mean and variance were calculated for the distribution fitting. The mean or expected value of the discrete random variable X, denoted as E(x), and the variance of x, denoted as V(x), are calculated as

$$E(X) = \sum_{x} x * f(x) \qquad (3\text{-}1)$$

$$V(X) = \sum_{x} (x - E(x))^2 * f(x) \qquad (3\text{-}2)$$

Where f(x) = the probability of each random variable x.

Figure 3-18: Summary of Fitted Distributions for Major Side Impact Crashes



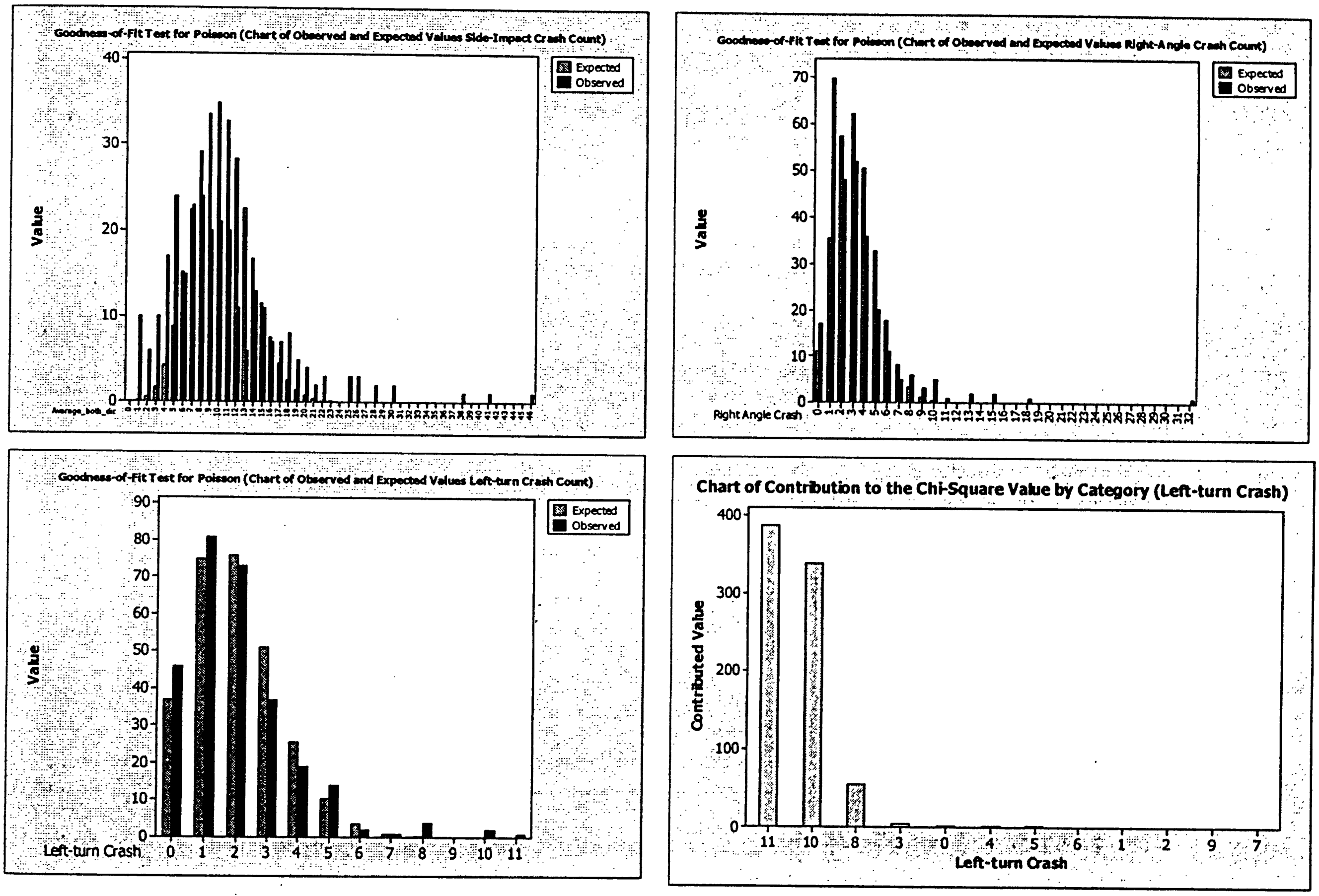
3.6.2 Goodness-of-fit Tests for Poisson Distribution

Using the observed mean and variance, the Poisson and Negative Binomial distributions were fitted to the crash data distribution for different crash types and severities. The Chi-square goodness-of-fit test was used to test whether the average number of major side impact crashes at the signalized intersections follows a particular distribution. The test procedure required a set of randomly selected samples of size n from X, whose probability density function is unknown. The n observations were then plotted into a frequency histogram of k class interviews. Table 3-7 shows that the Chi-Square test for the Poisson distribution fitted for the total number of crashes for the 1999 to 2004 period.

The Chi-Square calculation value obtained from the Poisson distribution fitted for the observed total number of crashes was calculated with:

$$\chi_0^2 = \sum_{i=0}^{k} (f(i) - f(x))^2 / f(x) \quad (3\text{-}3)$$

Figure 3-19: Goodness-of-fit Test for Poisson Distribution for Major Side-Impacts Crashes



It can be shown that, if the population follows the hypothesized distribution, χ^2 has approximately a Chi-square distribution with k-p-1 degrees of freedom, where p represents the number of parameters and p represents the hypothesized distribution estimated by sample statistics. This approximation improves as n increases. If the calculated value of the test statistic $\chi^2 > \chi_{a,k-p-1}^2$, the hypothesis that the distribution of the population is the hypothesized distribution would be rejected at α=0.05.

Table 3-7: Example Distribution Fittings for Side-Impacts Crashes

Descriptive Statistics

N	N*	Mean	StDev	Median	Minimum	Maximum	Skewness	Kurtosis
280	0	1.72737	1.11739	1.5	0.167	7.667	1.65896	4.71757

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	6.434	<0.005	
Lognormal	3.263	<0.005	
3-Parameter Lognormal	0.699	*	0.000
Exponential	20.265	<0.003	
2-Parameter Exponential	13.586	<0.010	0.000
Weibull	1.589	<0.010	
3-Parameter Weibull	1.623	<0.005	0.021
Smallest Extreme Value	23.388	<0.010	
Largest Extreme Value	0.804	0.038	
Gamma	1.028	0.013	
3-Parameter Gamma	0.956	*	0.742
Logistic	3.488	<0.005	
Loglogistic	1.624	<0.005	
3-Parameter Loglogistic	0.732	*	0.002

ML Estimates of Distribution Parameters (* Scale: Adjusted ML estimate)

Distribution	Location	Shape	Scale	Threshold
Normal*	1.72738		1.11739	
Lognormal*	0.33137		0.71187	
3-Parameter Lognormal	0.72079		0.45939	-0.55786
Exponential			1.72738	
2-Parameter Exponential			1.56205	0.16533
Weibull		1.64149	1.93680	
3-Parameter Weibull		1.49725	1.79057	0.10941
Smallest Extreme Value	2.35637		1.62156	
Largest Extreme Value	1.24976		0.79458	
Gamma		2.47699	0.69737	
3-Parameter Gamma		2.59973	0.67538	-0.02843
Logistic	1.60218		0.57720	
Loglogistic	0.38016		0.38445	
3-Parameter Loglogistic	0.65027		0.28118	-0.42099

The Chi square results (Figure 3-18) indicate that the hypothesis which states that the distribution of the total number of crashes in the six year period is the hypothesized Poisson distribution is rejected. Table 3-7 includes Anderson-Darling statistics and the corresponding p-value for a distribution. For a critical value α, a p-value greater than α suggests that the data follow that distribution. A p-value for the Likelihood ratio test (LRT P), which tests whether a 2-parameter distribution wouid fit the data equally well compared to its 3-parameter counterpart. The p-value indicates that gamma distributions fit the data well. The LRT P value of 0.742 suggests that the 3-parameter gamma distribution might improve the fit compared to the 2-parameter gamma distribution.

3.6 DESIGN OF THE DATABASE

The database design followed those adopted by Hauer (1988) and by Wang et al. (1998). The different kinds of analysis performed in this study require different data. For example, if we analyze the effects of land use patterns, we need to rearrange our accident data according to land use patterns. It is difficult to create a single database that meets the needs of various kinds of analysis. . The strategy for solving this problem is to have basic databases and to generate a derivative database for each analysis if necessary. The basic specialized databases are traffic flow by year, database of accident by year, and database of road environment related factors. By setting links to the basic specialized databases, we can generate derivative databases for various objectives. The advantages of stratifying spatially are as follows:

(1) It is easy to maintain consistency across all the databases. For example, when an input error is detected, we need to correct the error only in the basic specialized database. The derivative database will then be corrected automatically; and

(2) Databases for various analyses can be kept to a suitable and reasonable size which can help to increase the speed of the analysis.

3.7 CHAPTER SUMMARY

Data analysis and data processing are most important factors when developing accident models. The collection of the geometric and regulation related variables was the most difficult task in this study. Without proper data processing and appropriate conversion, accident models cannot be developed efficiently. Effective data analysis makes it possible. The study's analyses are described in Chapters 4 and 5.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

The objective of this study is to develop microscopic accident occurrence models of the annual accident frequency on individual intersection approaches. Approaches at four-legged intersections refer to all four directions – Northbound, Southbound, Eastbound and Westbound. To derive the microscopic model, an overview of the available statistical tools is described in Section 4.1.1. and 4.1.2. This Chapter section describes the evolution and emergence of Non-linear accident modeling giving special emphasis to the use of the Negative Binomial model in traffic accident analyses. Four major types of side impact accident model are then described, giving special emphasis to the detailed mechanism of accident occurrence at signalized intersections. The four different models are 1) the total side-impact model; 2) the right-angle accident model; 3) the left-turn accident model; and the 4) right-turn accident model.

4.1.1 Negative Binomial: Testing for Over-dispersion in Poisson Regression

Deviance and Pearson Chi-Square divided by the degrees of freedom are used to detect over-dispersion or under-dispersion in the Poisson regression. Values greater than 1 indicate over-dispersion (the true variance is bigger than the mean). Values smaller than 1 indicate under-dispersion (the true variance is smaller than the mean). Evidence of under-dispersion or over-dispersion indicates an inadequate fit of the Poisson model. The test for over-dispersion can be performed with a likelihood ratio test based on Poisson and negative binomial distributions. This test tests the equality of the mean and the variance imposed by the Poisson distribution against the alternative that the variance exceeds the mean. For the negative binomial distribution,

the variance = mean + k mean^2 ($k>= 0$, the negative binomial distribution reduces to Poisson when $k=0$). The null hypothesis is: $H0 : k=0$

and the alternative hypothesis is: $Ha : k>0$.

To carry out the test, the steps are as follows:

(i) Run the regression model using negative binomial distribution, record LL (log likelihood) value,

(ii) Record LL for the Poisson model,

(iii) Use the LR (likelihood ratio) test, that is, compute the LR statistic, -2(LL (Poisson) – LL (negative binomial)).

The asymptotic distribution of the LR statistic has probability mass of one half at zero and one half – Chi-sq distribution with 1 degrees of freedom (Cameron and Trivedi, 1998). To test the null hypothesis at the significance level α, use the critical value of Chi-square distribution corresponding to significance level 2α, that is reject H0 if LR statistic > $\chi2$ ($1-2\alpha$, 1 df).

4.1.2 Multivariate Statistical Analysis

To identify sites that have potential for improvement, knowledge of the sites' long-term mean number of accidents, defined as the 'safety', is required. To reduce regression to mean bias and to alleviate reference population homogeneity, a multivariate statistical analysis was proposed (Hauer 1992) to enhance the benefits of Empirical Bayesian (EB) methods. A regression model was first developed to estimate the moments E(m) and VAR(m) that describe the distribution of m's in an imaginary group of intersections having the same characteristics as the site under analysis. Once E(m) and VAR(m) become available, they are combined with the accident frequency (x) at the intersection of interest to obtain the updated estimate of safety, E(m/x) and its variance VAR(m/x)

$$E(m|x)=aE(m)\ (1-a)x$$
$$VAR(m|x)=a(1-a)E(m)+(1-a)^2 x \tag{4-1}$$
$$with\, a=\frac{E(m)}{E(m)+VAR(m)}$$

4.1.3 Negative Binomial Regression

During their investigation of the empirical relationship between truck accidents and highway geometry, Miaou et al. (1992) uncovered a limitation of the Poisson model. In most accident data, the variance of accident frequency exceeds the mean and the data are considered dispersed. When over dispersion existed in the data and Poisson model was used, the variance of the estimated model coefficients tended to be underestimated. This makes the application of the Poisson model less appropriate (Shankar et al., 1995). The assumed equality of the conditional mean and the variable functions is usually considered a major shortcoming of the Poisson Regression Model. To overcome this deficiency of the Poisson model, we must release the requirement (of the mean equal to the variance). Many alternatives have been suggested. There are several ways of releasing the requirement, one of which is to assume that the Poisson parameter itself is a Gamma distributed variable. This leads to the Poisson distribution model becoming a negative binomial distribution model due to a natural formulation of cross-section heterogeneity as shown below. (For a detailed discussion, see Thomas et al., 1989.)

By introducing an individual, unobserved effect into the conditional mean, the Poisson model can be generalized as

$$\log \mu_i = \beta' x_i + \varepsilon_i \\ = \log \lambda_i + \log u_i, \tag{4-2}$$

where ε_i = the disturbance - reflects either a specification error as in the classical regression model or the kind of cross-sectional heterogeneity that normally characterizes accident data,

y_i = the distribution of y_i conditioned on x_i,

u_i = (i.e. ε_i) remains Poisson with conditional mean and variance u_i;

$$f(y_i|u_i) = \frac{e^{-\lambda_i u_i}(\lambda_i u_i)}{y_i!} \tag{4-3}$$

The unconditional distribution $f(y_i/x_i)$ is the expected value (over u_i) of $f(y_i/x_i,u_i)$,

$$f(y_i|x_i) = \int_0^{\infty} \frac{e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i}}{y_i!} g(u_i)\,du_i \tag{4-4}$$

The choice of a density for u_i defines the unconditional distribution. For mathematical convenience, a gamma distribution is usually assumed for u_i $=\exp(\varepsilon_i)$. As the Poisson distribution parameter u_i is assumed to obey the Gamma (θ,λ_i) distribution, u_i has the density function given in Equation 4-4. As in the other models of heterogeneity, the mean of the distribution is unidentified if the model contains a constant term (because the disturbance enters multiplicatively) so $E[\exp(\varepsilon_i)]$ is assumed to be 1.0. With this normalization,

$$g(u_i) = \frac{\theta^\theta}{\Gamma(\theta)} e^{-\theta u_i} u_i^{\theta-1} \tag{4-5}$$

The mixed Poisson distribution for density for y_i can then be written as

$$
\begin{aligned}
f(y_i|x_i) &= \int_0^{\infty} \frac{e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i}}{y_i!} \frac{\theta^{\theta} u_i^{\theta-1} e^{-\theta u_i}}{\Gamma(\theta)} du_i \\
&= \int_0^{\infty} \frac{\theta^{\theta}\lambda_i^{y_i}}{y_i!\Gamma(\theta)} e^{-(\lambda_i+\theta)u_i} u_i^{\theta+y_i-1} du_i \\
&= \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)\Gamma(y_i+1)} \int_0^{\infty} e^{-(\lambda_i+\theta)u_i} u_i^{\theta+y_i-1} du_i \quad [y_i! = \Gamma(y_i+1)] \\
&= \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)\Gamma(y_i+1)} \int_0^{\infty} e^{-au_i} u_i^{n-1} du_i \quad [where a = (\lambda_i+\theta) and n = \theta + y_i] \\
&= \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)\Gamma(y_i+1)} \frac{a^{-n+1}}{a} \int_0^{\infty} e^{-au_i} (au_i)^{n-1} d(au_i) \\
&= \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)\Gamma(y_i+1)} \frac{\Gamma(n)}{a^n} \\
&= \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)\Gamma(y_i+1)\,(\lambda_i+\theta)^{\theta+y_i}} \\
&= \frac{\Gamma(\theta+y_i)}{\Gamma(\theta)\Gamma(y_i+1)} \frac{\theta^{\theta}\lambda_i^{y_i}}{(\lambda_i+\theta)^{\theta+y_i}} \\
&= \frac{\Gamma(\theta+y_i)}{\Gamma(\theta)\Gamma(y_i+1)} \frac{\theta^{\theta}}{(\lambda_i+\theta)^{\theta}} \frac{\lambda_i^{y_i}}{(\lambda_i+\theta)^{y_i}} \\
&= \frac{\Gamma(\theta+y_i)}{\Gamma(\theta)\Gamma(y_i+1)} \left(\frac{\theta}{\lambda_i+\theta}\right)^{\theta} \left(\frac{\lambda_i}{\lambda_i+\theta}\right)^{y_i}
\end{aligned} \tag{4-6}
$$

Integrating Formula 4-4, it becomes

$$P(y_i = n_{rt}) = \frac{\Gamma(6+n_{rt})}{\Gamma(\theta)\Gamma(n_{rt}+1)} (\frac{\lambda_i}{1+\lambda_i})^{\theta} (\frac{1}{1+\lambda_i})^{n_{rt}} \tag{4-7}$$

which is the negative binomial distribution with parameters (θ, λ_i). If we specify

$$\frac{6}{\lambda_i} = e^{\sum \beta_j x_{jrt}} \tag{4-8}$$

with λ_i common both across places and across time, the mean and variance of u_i are then

$$E(u_i) = e^{\sum \beta_j x_{jn}} \tag{4-9}$$

$$V(u_i) = \frac{e^{\sum \beta_j x_{jn}}(1+\lambda_i)}{\lambda_i} \tag{4-10}$$

Therefore the variance to mean ratio $\omega = V(u_i)/E(u_i) = (1+\lambda_i)/\lambda_i > 1$. Thus, the negative binomial specification allows for over-dispersion with the original Poisson a limiting case as $\lambda_i \to \infty$. The problems of the negative binomial distribution model are that the estimation of unknown parameters is more difficult than in the Poisson model and the variance to mean ratio, ω, is imposed as a constant value among intersections and over time.

4.2 MODELING METHODOLOGY

This section follows the logic of accident occurrence developed by Karim (2005) and describes the approach to modeling vehicle-to-vehicle accidents at intersections in detail. Several estimation techniques and assumptions were also adopted from Wang (1998) and Poch and Mannering (1995).

The occurrence of correctable vehicle-to-vehicle accidents has some common features. The occurrence of accidents is considered to flow from two essential starting points. One is the emergence of an "subject" vehicle, and the other is the failure of the driver of a "target" vehicle to avoid a collision with the subject vehicle. The frequency of meeting subject vehicles is usually related to "disturbances". A disturbance can be anything that can interrupt smooth traffic flows. If, for example, the emergence of a disturbance has caused the deceleration of the leading vehicle, then the leading vehicle becomes an obstacle for the following vehicle. The following vehicle, also known as the "target vehicle", has to take some measure to avoid a collision. If the following vehicle driver fails to avoid the collision, an accident will occur.

Thus if the probability of meeting an subject vehicle is denoted by P_o, and the probability of the target vehicle driver failing to avoid the collision is denoted by P_f, then the probability of this driver being involved in an accident is the product of P_o and P_f, as they are normally independent. The accident risk can be expressed as

$$P_{risk} = P_o \cdot P_f \tag{4-11}$$

The empirical log link functions are adopted for P_o and P_f as follows

$$\ln(P_o) = \boldsymbol{\beta}_o \mathbf{x}_o \text{ and } \ln(P_f) = \boldsymbol{\beta}_f \mathbf{X}_f \tag{4-12}$$

where $\boldsymbol{x}_o$ and $\boldsymbol{x}_f$ are vectors of explanatory variables for P_o and P_f respectively, and $\boldsymbol{\beta}_o$ and $\boldsymbol{\beta}_f$ are the vectors of the corresponding unknown parameters to be estimated. Then the accident risk can be expressed as

$$\ln(P_{risk}) = \boldsymbol{\beta}_o \mathbf{x}_o + \boldsymbol{\beta}_f \mathbf{x}_f = \boldsymbol{\beta}\mathbf{x} \tag{4-13}$$

where $\boldsymbol{\beta}=(\boldsymbol{\beta}_o, \boldsymbol{\beta}_f)$ and $\boldsymbol{x}=(\boldsymbol{x}_o, \boldsymbol{x}_f)'$.

To simplify the problem, it can be assumed that all the vehicles using an intersection leg in certain time period have the same accident risk. Then, the number of accidents that occurred within this flow complies with the Binomial Distribution

$$P(n) = \binom{f}{n} P_{risk}^{n} (1 - P_{risk})^{f-n} \tag{4-14}$$

where

f: average annual traffic volume;

n: number of rear end accidents that occurred;

P_{risk}: average accident risk.

Which expectation and variation can be written as

$$E(n) = f \cdot P_{risk} \tag{4-15}$$

$$V(n) = f \cdot P_{risk} \cdot (1 - P_{risk}) \tag{4-16}$$

Since we know that an accident is very rare case (so P_{risk} is normally very small) and we know that traffic volume is high (f is very large), the Poisson distribution is a good approximation to the binomial distribution (Pitman, 1993):

$$P(n) = \frac{m^n \cdot \exp(-m)}{n!} \tag{4-17}$$

with Poisson distribution parameter

$$m = E(n) = f \cdot P_{risk} = f \cdot \exp(\boldsymbol{\beta}\mathbf{x}) \tag{4-18}$$

The Poisson distribution has been commonly used in predicting accident numbers (Miaou *et al*, 1992). Due to its non-negative, discrete and random features, the Poisson model is usually the first choice when modeling traffic accidents. The Poisson model, however, has only one parameter, and this requires the expectation and variance to be equal. As most accident data are likely to be overdispersed, the applicability of a Poisson model is therefore limited. An easy way to overcome this difficulty (i.e. that the mean must be equal to the variance), is by adding an error term, ε, to the link function as shown by Formula 4-18. That is:

$$\ln m = \ln(fP_{risk}) + \varepsilon \tag{4-19}$$

Assume $\exp(\varepsilon)$ is a Gamma distributed variable with mean 1 and variance α. Substituting m in Formula 4-17 by Formula 4-19, we have

$$P(n \mid e) = \frac{\exp(-fP_{risk}\exp(e)) \cdot (fP_{risk}\exp(e))^n}{n!} \tag{4-20}$$

According to the integration of e shown in equation 4-6, the negative binomial distribution is derived as:

$$P(n) = \frac{\Gamma(n+\theta)}{\Gamma(n+1)\Gamma(\theta)}\left(\frac{\theta}{f \cdot P_{risk} + \theta}\right)^{\theta}\left(\frac{fP_{risk}}{f \cdot P_{risk} + \theta}\right)^{n} \tag{4-21}$$

where $\theta = 1/\alpha$. The expectation of this negative binomial distribution equals the expectation of the Poisson distribution, as shown in Formula 4-21. Its variance is changed to be

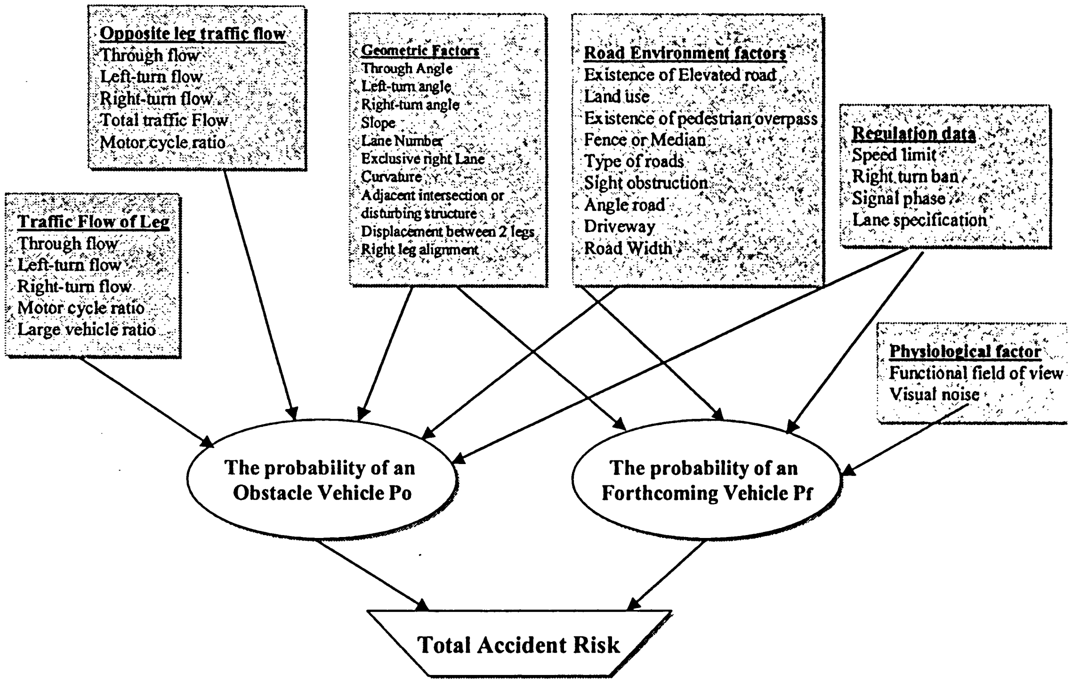
$$V(n) = E(n)[1 + \alpha E(n)] \tag{4-22}$$

The choice between the Negative Binomial model and Poisson model can largely be determined by the statistical significance of the estimated coefficient α. Since α can be larger than zero (as measured by t-statistics), the restraint that the mean must be equal to the variance in the Poisson model is released. If α is significantly different from zero, then the Negative Binomial is the correct approach. Therefore, the negative binomial distribution can deal with overdispersed data. In this study, all the models will be estimated by negative binomial regression.

By using Formula 4-22, total accident risk can be estimated using the number of accidents and the traffic volume of the leg observed. As the occurrence mechanism is not as clear for each specific accident, the canonical link function in generalized log-linear models as shown in Formula 4-13. Factors relating to accident risk are selected and applied in the estimation. The factors are shown in Figure 4-1. The estimation method and corresponding results are discussed in Chapter 5.

It is worth mentioning that if a model has several variables, there is a possibility that some of the explanatory variables would be related causing the property known as multi-collinearity. Although multi-collinearity would not cause the estimators to be biased, inefficient, or inconsistent, and does not affect the forecasting performance of the model (Abdel-Aty, 2000), it might increase the standard errors of the coefficients, thus making the coefficients less significant. Multi-collinearity could be identified by low values for the t-statistics, high values for the correlation coefficients between the variables, and the sensitivity of the estimated coefficients to specification. None of these symptoms were identified in the models described in this study. Pair wise correlations among explanatory variables did not have high values, and the estimated coefficients were not drastically altered when variables were added or dropped. Furthermore, the coefficients in the estimated models were significant and had meaningful signs and magnitudes. Therefore, there is no need to be concerned about multi-collinearity.

Figure 4-1: Explanatory Factors Influencing Vehicle-to-Vehicle Accident Risk at Signalized Intersections



4.3 MODELING RIGHT-ANGLE (AG2) ACCIDENT RISK

4.3.1 Basic concepts of AG2 Accident Occurrence

Figure 4-2 provides a conceptual diagram of the AG2 accident occurrence mechanism at signalized intersections (see conceptual detail in Karim 2005).

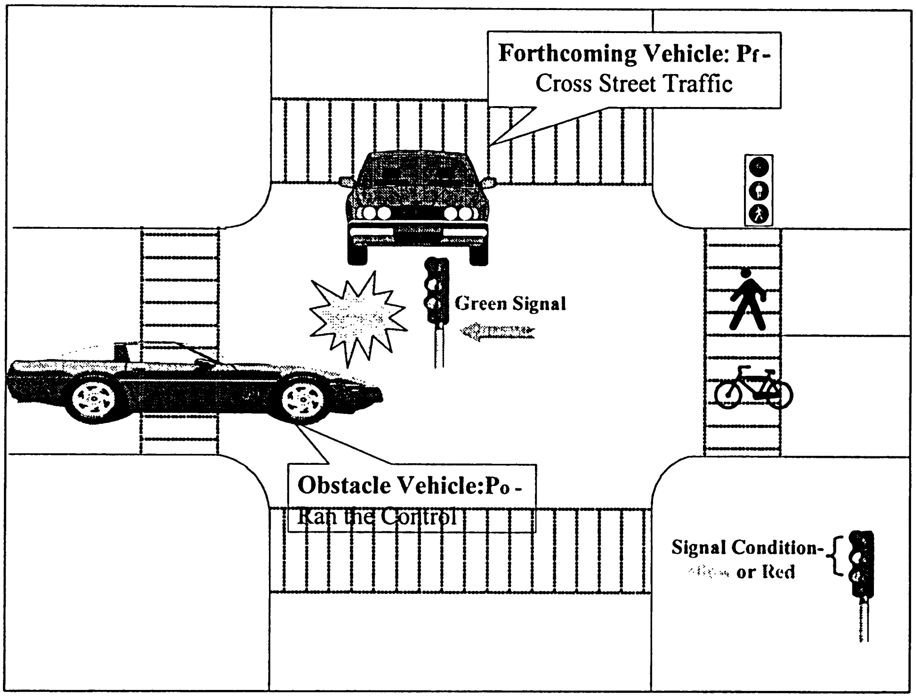
AG2 accidents may occur in some circumstances when the driver must make a decision depending on his current speed and the position of the vehicle on the 'main' street at the onset of the amber light or the beginning of the red light. The 'cross-street' vehicle may have to attempt to decelerate and avoid a red-light runner within a very short time period. Depending on the driver's perception-reaction time (PRT) and decision either to stop or to run-the-red, the main vehicle is transformed into the 'subject vehicle' and emerges as an impediment for the target vehicle.

The concept underlying this model is that each vehicle carries a certain portion of the 'total risk' probability of a right-angle accident. This key consideration was not the focus of past research since, from the police accident investigation to the prosecution of the offence, each system involved in a crash makes an effort to identify the 'main' offender. With the "proportional risk" concept, multiplying the individual probabilities, which are assumed independent of each other, provides the total right-angle accident risk. To simplify the task of modeling, only two vehicle crashes are considered for the analysis.

Depending on the situation, the main vehicle driver could react in three different ways: gradually decelerate before the stop line to be on the safe side; stop the vehicle by sudden braking; or continue with his current speed or even speed-up to 'beat-the-red'. The last action carries the possible risk of a RA accident. The second action (sudden braking) increases the risk of rear-end accidents. Hence, the main vehicle possesses the higher probability of risk for violating the traffic rules and is the principal contributor to AG2 accidents.

In contrast, the target vehicle driver's choice is restricted by the position and speed of the main vehicle. The target vehicle driver can decide to stop his vehicle by sudden braking or he may have to stay on the collision course due to insufficient time. The first action (sudden braking) increases the risk of a rear-end accident with the following vehicle behind the target vehicle. Insufficient time and the intersection geometry may not allow the target vehicle to detect the 'obstacle vehicle', increasing the risk of a right-angle accident. Obviously, the probability that a 'target' vehicle that misses the emergence of an obstacle vehicle from the main street will incur an accident will be much lower than the probability that a main street vehicle that breaks the law (or fail to address the high demanding situation within a short interval) will incur an accident. The results of the microscopic model also support giving different probability 'weights' to the different vehicles involved in an accident.

Figure 4-2: Conceptual Idea for AG2 Conflict between Two Through Vehicles



4.3.2 Formulation of AG2 Accident Risk

From the discussion of the AG2 accident model development, it is clear that although the movement for AG2 accidents is different from the movements for left or right-turn accidents, the logic behind the AG2 accident occurrence is quite similar for all side-impact crash models.

For AG2 accidents that occur during red or yellow signal time, the red signal itself becomes an important disturbance which, along with other disturbances, ultimately leads a vehicle to become a subject vehicle for a right or left-approach through traffic vehicle. The target vehicle has to deal with the emerging subject vehicle within the driver's available PRT to avoid the collision. If the P_f's driver's reaction is fast enough, an AG2 accident is avoided; otherwise, an AG2 accident will happen.

A) Formulation of P_f

The derivation of the probability of crash risk of the main vehicle depends on the frequency of signal changes, the types of signals and phases, and the geometric characteristics that influence a driver's 'stop-or-go' decision. It is reasonable to assume that the occurrence of such 'disturbances' follows a Poisson process. Mannering and Kilareski (1998) suggest that the time intervals between acceleration and deceleration-inducing disturbances are exponentially distributed.

A driver must constantly perceive the changing traffic situation and adjust his own driving to suit the changing situation. This is the main process of driving. To avoid a potential collision, the driver needs time to note, process and respond to the emerging disturbance. The quality of his response is important. Johansson et al (1971) noted that the main factors determining whether or not an accident can be avoided is the driver's PRT (perception and response time).

The value of the PRT changes depending on the complexity of the solution, and the driver's expectancy of the hazard (Bates, 1995). Two types of PRT are considered in this study: available PRT, and necessary PRT. Available PRT refers to the time available for a driver to complete his perception and response. It is normally decided by highway design and specific traffic situation. Necessary PRT refers to the driver's ability to react and orient himself in the minimum possible perception reaction time. PRT is likely to be different from person to person.

A driver can not avoid a collision if his necessary PRT (NPRT) is longer than his available PRT (APRT). If the distributions of the two variables are known, the probability of the target vehicle driver failing to avoid the collision, P_f can be easily calculated.

Researchers have been measuring drivers' NPRT for several decades. Silva (1936) created a brake reaction time test in a laboratory. He tested 2,000 subjects and found that NPRT decreased from 15 to 23 years old and then increased with age. Other researchers also conducted various kinds of experiment to understand how drivers' NPRT changes with age and environmental factors (e.g. Welford, 1977, Olson et al., 1986, and Liebermann et al.1995). The findings showed both consistencies and inconsistencies. For example, Welford (1977) (like Silva) concluded that NPRT increases with age, whereas Olson et al (1986) found that old and young drivers have almost the same NPRT when exposed to a surprising situation that required a response.

Wang (1998) assumed that the age distribution of drivers was the same on all the intersection legs and he did not allow for age related differences in NPRT. He assumed all driver's follows the same Weibull (α,λ) distribution. The density function of the Weibull distribution can be written as

$$f(t) = \alpha\lambda\, t^{\alpha-1}e^{-\lambda t^{\alpha}} \quad \text{for } t>0 \qquad (4\text{-}23)$$

If a driver has APRT of t_{av}, P_f can be calculated by integrating Formula 4-23 from t_{av} to infinite (Formula 4-24). The failure probability is also illustrated in Figure 4-3.

But normally, t_{av} is also a variable larger than 0. If we assume that t_{av} is also a Weibull (v, γ) distributed variable with density function

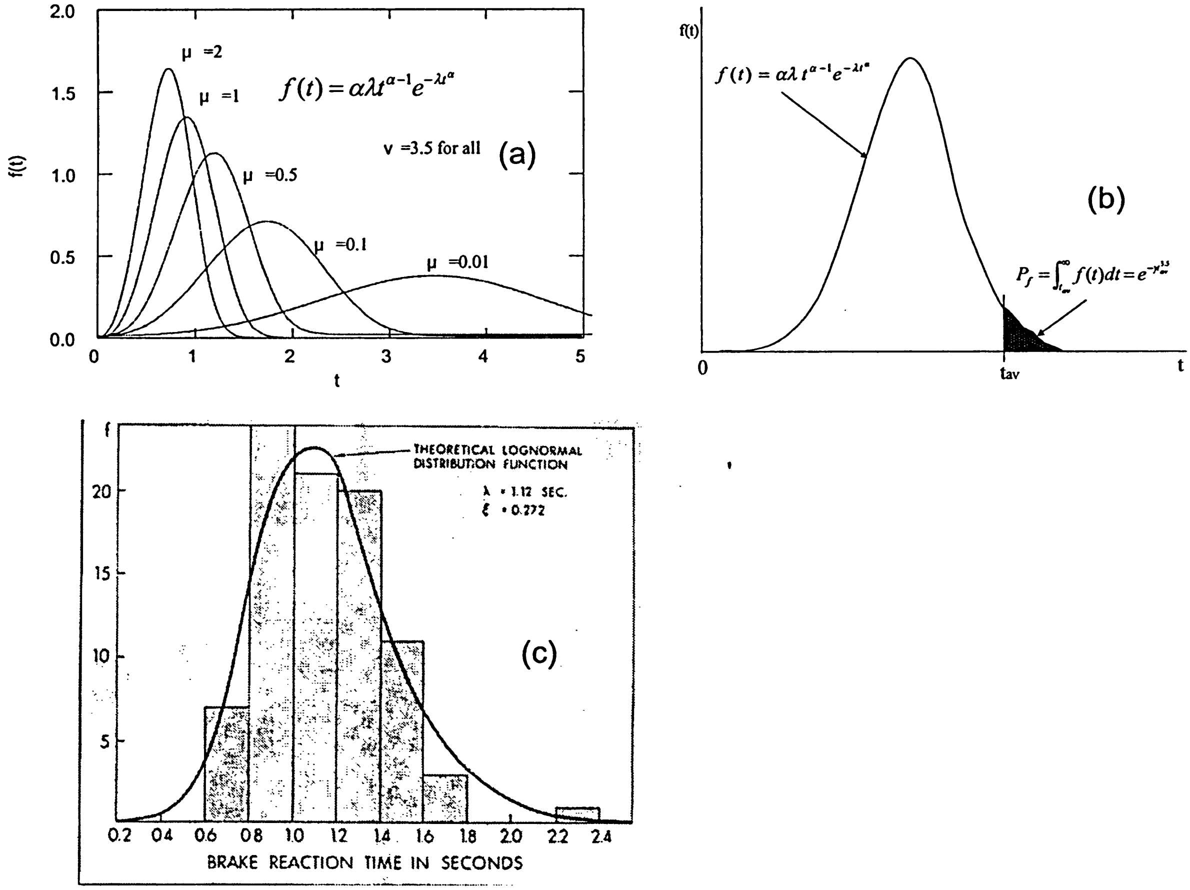
$$f(t_{av}) = \alpha\gamma\, t_{av}^{v-1}e^{-\gamma t_{av}^{\alpha}} \qquad (4\text{-}25)$$

Then P_f can be calculated by

$$P_f = \int_0^{\infty}\int_{t_{av}}^{\infty} f(\lambda,t)f(\gamma,t_{av})dtdt_{av} = \int_0^{\infty} e^{-\lambda t_{av}^{v}}\alpha\gamma t_{av}^{\alpha-1}e^{-\gamma t_{av}^{v}}dt_{av} = \frac{1}{1+\lambda/\gamma} \qquad (4\text{-}26)$$

Formula 4-26 shows that P_f is only decided by μ and γ, and has no relationship with v. If λ is bigger, the expectation will be small. As the expectation of APRT is normally larger than that of NPRT, γ should be smaller than λ which implies that P_f is smaller than 0.5.

Figure 4-3: Weibull distribution density functions and Illustrations of driver's failure probability (Source: a) Kao 1960, b) Plait 1962, and c) Taoka 1989)



$$P_f=\int_{t_{av}}^{\infty}f(t)dt=e^{-\gamma t_{av}^{3.5}} \quad (4\text{-}24)$$

Since parameters λ and γ are nonnegative variables, we can use various functions, which can give nonnegative values. λ/γ can be related to various factors by an exponential link function. The corresponding Pf can be written as

Formula 4-28.

$$\mu / \gamma = \exp(-\boldsymbol{\beta}_h \mathbf{x}_h) \quad (4\text{-}27)$$

$$P_f = \frac{1}{1+\exp(-\boldsymbol{\beta}_h \mathbf{x}_n)} \quad (4\text{-}28)$$

In Formula 4-28, β_h and x_h are vectors of unknown parameters and explanatory variables respectively. The variables that affect drivers' task load and complexity were included in x_h.

B) Formulation of Po

Some police statements (76%) provided information on whether or not the P_o vehicle came to a full stop at the stop sign before proceeding into the intersection. In 53% of the accidents for which this information was available, vehicle P_o did come to a complete stop, but in 47% of the cases, the drivers rolled past the stop sign or ignored the stop sign. The crash reports suggest that only a relatively few drivers did not see the stop sign.

At signalized intersections, P_o drivers who admitted entering an intersection on a yellow or red signal, were 50% more likely to be involved in a crash with a vehicle Pf approaching from the left than with a vehicle Pf approaching from the right.

From the target vehicle (i.e. target vehicle) driver's point of view, the driver's chance of perceiving unexpected obstacles depends on the number of vehicles approaching a red or yellow light on the main-street, the quality of their drivers' response, and the geometric configuration of main-street's approaches. The distribution of gaps in between the traffic is determined by the volume and platooning characteristics of the main-street's approaches.

RA accident frequency is not, however, directly proportional to cross-street volume (Baguley 1988). The available gaps in the traffic flow represent the required perception-reaction time that can be assumed to have a Weibull distribution due to their good approximation to a Normal distribution (Abernethy 1996). The required perception-reaction time varies with driver characteristics, intersection geometry and traffic conditions (Bates 1995), but can again can be assumed to have a Weibull distribution. Integrating the perception-reaction distribution and the related explanatory variables using an exponential distribution generates the probability of cross street vehicles avoiding an RA accident.

As the occurrence of disturbances is discrete, nonnegative and random, it is a Poisson arrival process. In such a process, the times between arrivals are independent and follow the same exponential distribution (Pitman, 1993). The probability of disturbance *j*'s happening within t_d is

$$f(t)=\lambda_{dj}e^{-\lambda_{dj}t} \qquad t>0 \qquad (4\text{-}29)$$

where λ_{dj} is the arrival rate of disturbance j;

and t_d is the time difference between disturbance and leading vehicle.

According to the memory-less property of the exponential distribution, the probability of a disturbance j occurring within t_{dj} is related with the time waited. Hence, the probability of the subject vehicle meeting the disturbance j within t_{dj} seconds can be calculated as

$$P_{dj}=\int_0^{t_d}\lambda_{dj}e^{-\lambda_{dj}t}dt=1-e^{-\lambda_{dj}t_d} \qquad (4\text{-}30)$$

Since any disturbance can cause the deceleration of the leading vehicle, the probability of encountering an subject vehicle is identical to that of at least one disturbance occurring. Therefore the formulation of P_o becomes

$$P_o=1-\sum_{j=1}^{z}(1-P_{dj}) \qquad (4\text{-}31)$$

Substituting P_{dj} the simpler form of Po is

$$P_o = 1 - e^{-\sum_{j=1}^{z} \lambda_{dj} t_{dj}} \tag{4-32}$$

Since $\sum_j^z \lambda_{dj} t_{dj}$ should be a positive variable and should be affected by related explanatory variables, here again we adopt an exponential link function, based on the results of trial and error, to consider the effects of the variables.

$$\sum_j^z \lambda_{dj} t_{dj} = e^{\beta_d x_d} \tag{4-32}$$

Then P_o can be expressed as

$$P_o = 1 - e^{-e^{\beta_d x_d}} \tag{4-34}$$

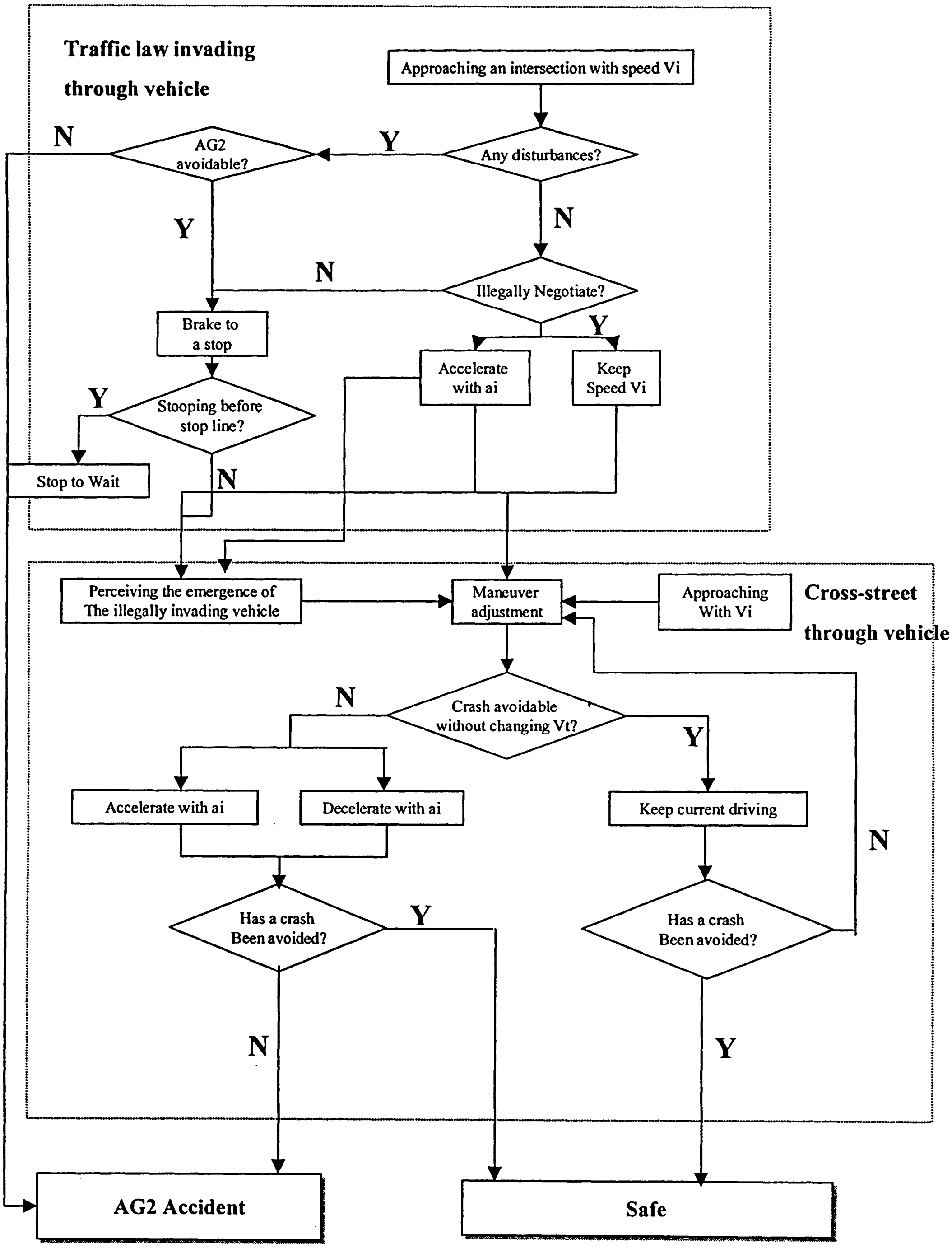
In Formulae 6-32 and 6-33, β_d and x_d are vectors of unknown parameters and explanatory variables of disturbance frequency respectively. β_d does not change with locations, while x_d varies from place to place.

Replacing P_o and P_f in the Formula 4-11, a generalized AG2 accident risk model can be derived which contains road environment and traffic regulation and human related factors.

$$P_{AG2} = P_o * P_f = \frac{1 - e^{-e^{\beta_d x_d}}}{1 + e^{-\beta_h x_h}} \tag{4-35}$$

Finally, the right-angle accident probability can be calculated by multiplying the probability of the cross street vehicle encountering the main-street vehicle (Equation 4-28) and the probability of the cross street vehicles avoiding the accident (Equation 4-35). It can be assumed that both events are independent of each other. The expected number of RA accident can then be estimated by multiplying the right angle accident probability by the through traffic volume of the approaching street.

Figure 4-4: Flow Chart of Right-Angle Accident (AG2)



4.4 MODELING RIGHT-TURN (AG3) ACCIDENT RISK

4.4.1 Basic Concepts of AG3 Accident Occurrence

The key issues affecting AG3 accident occurrence are right-turning maneuvers and the lane changing mechanism used to reach the right lane for a right - turning maneuver. After an extensive literature review of AG3 accidents and detailed field observations, it could be concluded that AG3 accidents are probably due to a right-turning vehicle on the left most lane interrupting the second vehicle's right-turn maneuvering on the right lane.

Based on pre-crash actions, the vehicle that arrives in the right-lane first and decides to go right is defined as the "Subject Vehicle". The vehicle that arrives in the left-lane later, after changing lanes, and finds another vehicle already occupying the left lane in order to make a left-turning movement, is defined as the "Target Vehicle". There are several reasons for defining the first right-turning vehicle as the 'obstacle,' but the most important is possibly inattentive driving or intending to disregard the emergence of disturbances and misjudgment of right-leg identification. Another important point related to AG3 accident is the size of vehicle.

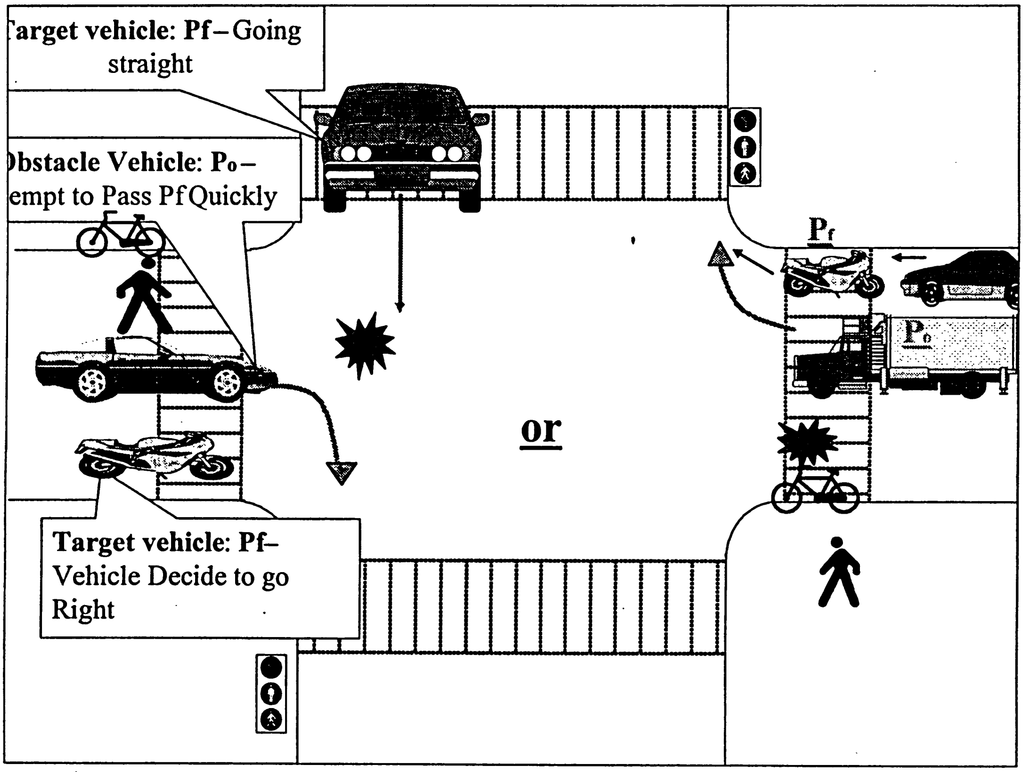
Figure 4-5 shows how an AG3 accident occurs. On the left of the Figure, a vehicle in the right lane decides to go right although it must cut across a target vehicle or a vehicle that is already in the right lane. On the right of the Figure, a vehicle in the right lane decides to go right although it must cut across a vehicle on its right that is difficult to visualize because of its size.

In each case, the subject vehicle is the first turning vehicle and the target vehicle is going straight or second vehicle next to right-turning vehicle.

When a right turning vehicle arrives at an intersection under two phase control, the vehicle tries to get into the right lane, but faces disturbances at the entrance point of the right lane. This vehicle positions itself in the right lane as it intends to go right. It then tries to go right by turning right and going in front of the cross-street through vehicle or another vehicle in the right lane, creating an AG3 accident.

The first i.e. subject vehicle checks the available headway in current leg for right-turning and emergence of disturbance to which it should deal and overcome to go right. The reason why the right turning vehicle driver should also check the existing of disturbance is because the emerging disturbance may prevent him/her from completing his/her intended movement. For example, they may have to decelerate or stop down to wait for the crossing of a pedestrian on right leg, and this will result in an intentionally avoidable conflict.

Figure 4-5: Conceptual Representation of Conflict (AG3) between Vehicles Coming from Same Leg



Once it overcomes the disturbances, the right-turning action will be conducted. If the Pf vehicle is a motorcycle and the Po vehicle is a large vehicle or a car, it is difficult for the driver of the Po vehicle to see the motorcycle. The driver of the Pf vehicle may only discover the Po vehicle when he already trying to go right. In both situations, if the second right-turning vehicle fails to identify the first vehicle, an AG3 accident will occur. The geometry and detailed road environment of the right-leg are critical factors for AG3 crashes. If the judgment of the subject vehicle driver is wrong about the right-leg or the possibility of turning right, an AG3 accident becomes inevitable. A detail explanation of right-turning accidents is provided in Figure 4-6 (in Section 4.3.3). The Figure is a flow chart showing the sequence of decisions that leads either to a safe outcome or to an accident.

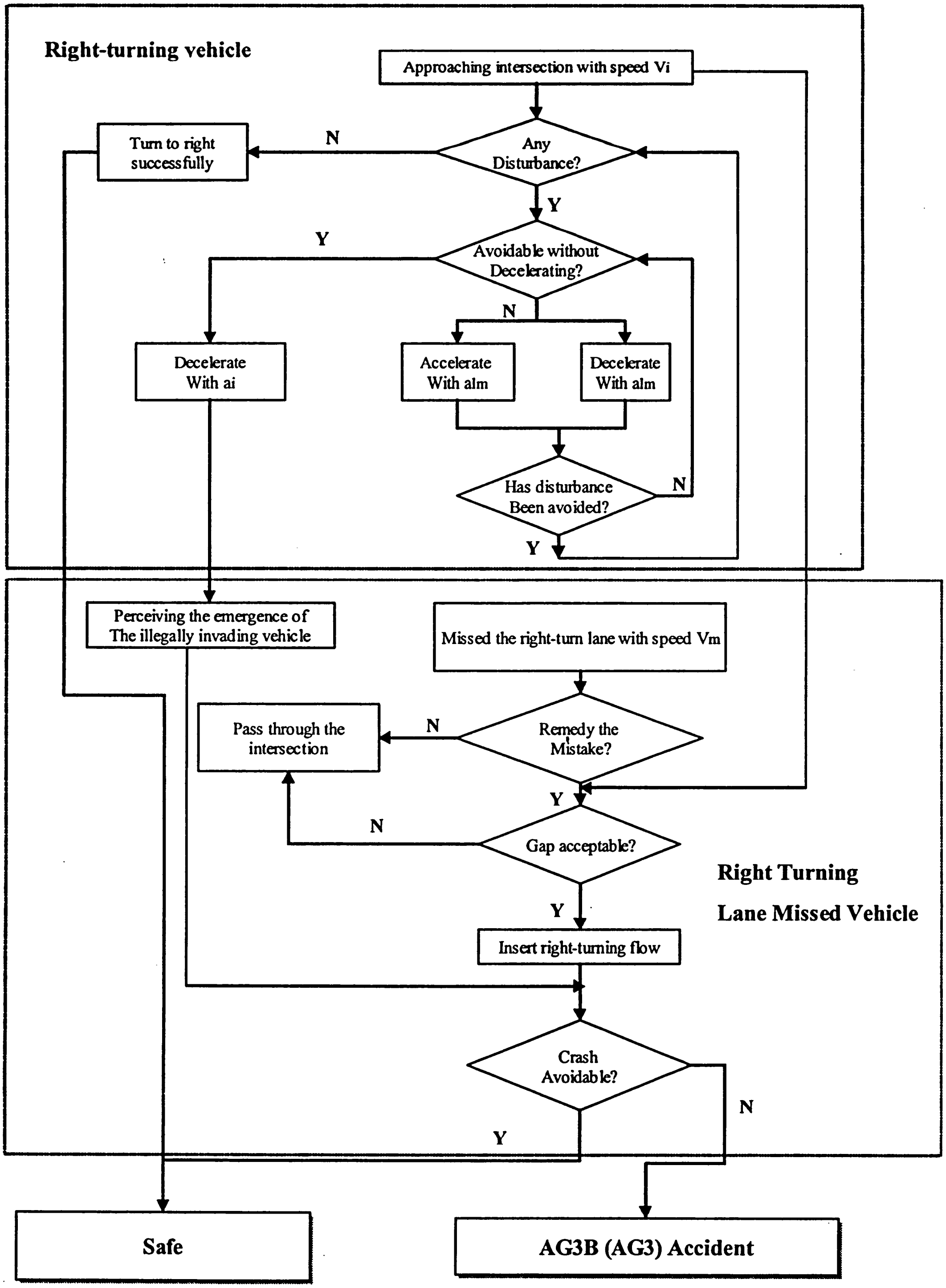
4.4.2 Formulation of AG3 Accident Risk

In AG3 accidents, there is also a disturbance that can lead to a right-turning vehicle becoming an obstacle for another right-turning vehicle coming from different lane. The driver of the second right-turning vehicle has to deal with the emerging subject vehicle within his APRT to avoid the collision. If the P_f's driver reaction is fast enough, an AG3 accident is avoided. If not, an AG3 accident will occur.

A) Formulation for P_f

Nearly one-third of AG3 crashes occurred when the Pf stopped suddenly due to the emergence of the Po vehicle. A possible reason for this type of behaviour may be that when the driver of the subject vehicle disregarded the requirement to stop, continued moving right and is struck by the Pf vehicle on the left side of Po. The situation when the Po vehicle was struck while preparing to turn right is similar to that in which the Pf vehicle was unable to stop in time.

Figure 4-6: Flow Chart of Right-turning Angle Accident (AG3B or AG3)



It can be assumed that the drivers' necessary and available PRT's (NPRT and APRT) are Weibull distributed with parameters (α,μ) and (α, γ) respectively. Here α, λ, and γ are positive constants. Then the probability of the target vehicle driver failing to avoid a collision is

$$P_f = \frac{1}{1+\lambda/\gamma} \tag{4-36}$$

As the value of λ/γ is nonnegative and decided by various related factors, an exponential function is used to consider the effects of those factors as follows

$$\lambda/_{\gamma} = \exp(-\boldsymbol{\beta}_{\mathbf{h}}\mathbf{x}_{\mathbf{h}}) \tag{4-37}$$

$$P_f = \frac{1}{1+\exp(-\boldsymbol{\beta}_{\mathbf{h}}\mathbf{x}_{\mathbf{n}})} \tag{4-38}$$

In Formula 4-38, β_h and x_h are vectors of unknown parameters and explanatory variables respectively. Variables that affect the drivers' task load and complexity were included in x_h. Formula 4-38 is applied to AG3 accident risk evaluation.

b) Formulation for Po

When competing with the cross-street traffic stream to turn right, the driver of the Po vehicle makes an incorrect assumption about the actions of the driver of vehicle Pf, or he fails to identify the Pf vehicle's presence. After finding that the Po vehicle has stopped due to disturbances, the Pf vehicle tries to move right before Po vehicle does.

Whether or not a right turning vehicle becomes an obstacle is determined by the judgment of the right turning vehicle driver. The occurrence of making a mistake in judgment (whether misjudging the cross-street through traffic stream headway or any other disturbance occurrence) is assumed to be a Poisson process. The probability of encountering an subject vehicle is derived following exactly the same procedure as in AG2 accidents. The formula derived for P_o is as follows,

$$P_o = 1 - e^{-e^{\beta_d x_d}} \tag{4-39}$$

where β_d and x_d are vectors of unknown parameters and explanatory variables of disturbance frequency respectively. Formula 4-39 is adopted in the estimation of AG3 accident risk model.

If we use P_{AG3r} to represent the AG3 accident risk, the exact formulation of P_{AG1r} (by combining the formulations of P_o and P_f,) is as follows.

$$P_{AG3r} = P_o * P_f = \frac{1 - e^{-e^{\beta_d x_d}}}{1 + e^{-\beta_h x_h}} \tag{4-40}$$

What should be emphasized here is that although in Formula 4-40, for the purpose of achieving a common expression of models for different types of accidents, we used the same vector symbol as in Formula 4-35 to represent unknown parameters and explanatory variables, the contents of the vectors are different from model to model. This point will be made clear in the model estimations given in Chapter 5.

4.4 FORMULATION OF AG1 ACCIDENT RISK MODELING

From the discussion on AG1 accidents' occurrence procedure and modeling procedure, we can conclude that the movements of the vehicles involved in AG1 accidents and the logic behind this type of accident are quite well understood. In AG1 accidents, there are also disturbances that can lead a left turning vehicle to an obstacle created by an opposite through vehicle. The formulation of the subject vehicle includes the same characteristics as the AG2 obstacle faces. The opposite through vehicle driver has to deal with the emerging subject vehicle within the available perception and response time (APRT). If APRT is greater then the NPRT AG1 accidents happen.

If P_{AG1r} represents the AG1 accident risk of the leg (left-turning lane) under study, to which the left turning vehicle belong at certain time period, the exact formulation of P_{AG1r} (combining the formulations of P_o and P_f,) as follows

$$P_{AG1r} = P_o P_f = \frac{1 - e^{-e^{\beta_d x_d}}}{1 + e^{-\beta_h x_h}} \quad (4\text{-}41)$$

4.5 MAXIMUM LIKELIHOOD ESTIMATION (MLE)

Maximum likelihood estimation (MLE) is probably the most general and straight-forward procedure for finding the estimators. Other estimation methods include QLE (quasi-likelihood estimation), GMM (generalized method of moments), regression based estimation, and WLSE (weighted least square estimation). The MLE is favoured for the following reasons:

- The MLE has been used for many years for fitting the negative binomial distribution to a large sample (Anscombe, 1950);
- The MLE is well understood and its asymptotic properties are readily recognized;
- The MLE may be particularly useful for large samples (Piegorsch, 1990) in contrast to QLE which is more accurate for small sample size (N>20) and α is not very small (Clark and Perry, 1989). ; and
- The MLE is applied in estimating probabilistic models of accidents (Poch et al, 1996, Shankar et al, 1995, Hyodo et al, 1993, Maher 1996 and Wang et al, 1998).

4. 5.1 Maximum Likelihood Estimation for Model Development

For estimation purpose, the Poisson distribution has been commonly used in modeling the temporal variability in accident frequency at a given location (Miaou et al. 1994) due to its nonnegative, discrete and random features. However, the Poisson distribution has only one parameter, and this parameter requires that the expectation and variance be equal. As accident counts over space are likely to be overdispersed, the applicability of a Poisson model is questionable for modeling spatially variability. In any event, the choice between the Negative Binomial model and Poisson model can largely be determined by the statistical significance of the estimated coefficient α or β (Poch and Mannering, 1996). The Negative Binomial distribution was used in this study since the Poisson, even if it were valid, is a special case of the Negative Binomial distribution.

The models used in this study were estimated by standard maximum likelihood methods. To explain the model estimation procedure, the estimation of AG1 accident risk model is reviewed in this section.

Formula 4-35 (Section 4.3.3) is the form of the AG1 accident risk model for a specific leg for certain period. In a more general form, the AG1 accident risk of leg k (k ranges from 1 to 4), intersection m (m=1,2,...115), year i can be expressed as

$$P_{AG1rmki} = P_{AG1omki} P_{AG1fmki} = \frac{1 - e^{-e^{\beta_d x_{dmki}}}}{1 + e^{-\beta_h x_{hmki}}} \tag{4-42}$$

As the traffic flow and environment related variables of the selected intersection's approaches were quite stable between 1999 and 2004, six-year accident data are combined in the estimation in order to reduce the effect of errors in data collection. Thus, all our observations belong to the same time category and the subscription of the time category can be omitted:

$$P_{AG1rmk} = P_{AG1omk} P_{AG1fmk} = \frac{1 - e^{-e^{\beta_d x_{dmk}}}}{1 + e^{-\beta_h x_{hmk}}} \tag{4-43}$$

If a vehicle is randomly selected from through traffic flow, f_{otmk}, of leg k, intersection m, then the probability of having n_{RE1mk} accidents from 1992 to 1994 follows the binomial distribution:

$$P(n_{AG1mk}) = \binom{f_{tmk}}{n_{AG1rmk}} P_{AG1rmk}^{n_{RE1mk}} (1 - P_{AG1rmk})^{f_{tmk} - n_{AG1mk}} \tag{4-44}$$

where f_{otmk} denotes the total three-year opposite leg through traffic volume of leg k, intersection m. As f_{otmk} is very large and P_{AG1rmk} is very small, the Poisson distribution very closely approximates the negative binomial distribution. The Poisson model is subject to the important limitation that the mean and variance are constrained to be equal, but over-dispersion (variance greater than the mean) or under-dispersion (variance less than the mean) in the data violates this constraint and leads to biased coefficient estimates. It is well known, based on the findings of many previous research efforts, that accident frequency data tend to be overdispersed, with the variance being significantly greater than the mean (Shankar *et al*, 1995). To overcome this problem, the negative binomial distribution, which includes a gamma-distributed error term (mean 1 and variance α), is appropriate because it relaxes the Poisson's mean-variance equality constraint. The negative binomial model is derived as follows (Section 4.5.2 provides further detail):

$$P(n_{AG1mk}) = \frac{\Gamma(n_{AG1mk}+\theta)}{\Gamma(n_{AG1mk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{tmk}\cdot P_{AG1rmk}+\theta}\right)^{\theta}\left(\frac{f_{tmk}P_{AG1rmk}}{f_{tmk}\cdot P_{AG1rmk}+\theta}\right)^{n_{AG1mk}} \quad (4\text{-}45)$$

In Formula 4-45, $\theta = 1/\alpha$, the variance of this negative binomial distribution is

$$V(n) = E(n)[1+\alpha E(n)] \quad (4\text{-}46)$$

Since α can be larger than 0, the Poisson model's restraint that the mean must equal the variance is released. Therefore, the negative binomial distribution can deal with the overdispersed data.

Replacing P_{AG1rmk} by Formula 4-35, we have

$$P(n_{AG1mk}) = \frac{\Gamma(n_{AG1mk}+\theta)}{\Gamma(n_{AG1mk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{otmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}+\theta}\right)^{\theta}\left(\frac{f_{otmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}}{f_{otmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}+\theta}\right)^{n_{AG1mk}}$$

(4-47)

where β_d and β_h are vectors of unknown parameters of the probability of encountering subject vehicle (P_o) and the probability of the target driver's failure to avoid the collision (P_f) respectively; x_{dmk} and x_{hmk} are vectors of explanatory variables of P_o and P_f respectively for leg k, intersection m.

4.5.2 Maximum Likelihood Equation

Based on Formula 4-47, the likelihood function and log-likelihood function can be given as follows:

$$L(\boldsymbol{\beta}_h, \boldsymbol{\beta}_d, \theta) = \prod_{m=1}^{115} \prod_{k=1}^{4} P(n_{AG1mk}) \tag{4-47}$$

$$l(\boldsymbol{\beta}_h, \boldsymbol{\beta}_d, \theta) = \ln L(\boldsymbol{\beta}_h, \boldsymbol{\beta}_d, \theta) = \sum_{m=1}^{115} \sum_{k=1}^{4} \ln(P(n_{AG1mk})) \tag{4-48}$$

That is

$$l(\boldsymbol{\beta}_h, \boldsymbol{\beta}_d, \theta) = \sum_{m=1}^{115} \sum_{k=1}^{4} \ln\left(\frac{\Gamma(n_{AG1mk}+\theta)}{\Gamma(n_{AG1mk}+1)\Gamma(\theta)} \left(\frac{\theta}{f_{otmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}} + \theta}\right)^{\theta} \left(\frac{f_{otmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}}}{f_{otmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}} + \theta}\right)^{n_{AG1mk}}\right) \tag{4-49}$$

By maximizing Formula 4-49, we can find the best estimation of vectors β_h and β_d, and variable θ. The log-likelihood functions for AG1, AG2 and AG3 models are shown in Formulae 4-50, 4-51 and 4-52 respectively:

$$l(\boldsymbol{\beta}, \theta) = \sum_{m=1}^{115} \sum_{k=1}^{4} \ln\left(\frac{\Gamma(n_{mk}+\theta)}{\Gamma(n_{mk}+1)\Gamma(\theta)} \left(\frac{\theta}{f_{mk} \cdot e^{\boldsymbol{\beta}\mathbf{x}_{mk}} + \theta}\right)^{\theta} \left(\frac{f_{mk} \cdot e^{\boldsymbol{\beta}\mathbf{x}_{mk}}}{f_{mk} \cdot e^{\boldsymbol{\beta}\mathbf{x}_{mk}} + \theta}\right)^{n_{mk}}\right) \tag{4-50}$$

$$l(\boldsymbol{\beta}_h, \boldsymbol{\beta}_d, \theta) = \sum_{m=1}^{115} \sum_{k=1}^{4} \ln\left(\frac{\Gamma(n_{AG2mk}+\theta)}{\Gamma(n_{AG2mk}+1)\Gamma(\theta)} \left(\frac{\theta}{f_{tmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}} + \theta}\right)^{\theta} \left(\frac{f_{tmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}}}{f_{tmk} \cdot \frac{1-e^{-e^{\boldsymbol{\beta}_d \mathbf{x}_{dmk}}}}{1+e^{-\boldsymbol{\beta}_h \mathbf{x}_{hmk}}} + \theta}\right)^{n_{AG2mk}}\right) \tag{4-51}$$

$$l(\beta_h,\beta_d,\theta)=\sum_{m=1}^{115}\sum_{k=1}^{4}\ln\left(\frac{\Gamma(n_{AG3mk}+\theta)}{\Gamma(n_{AG3mk}+1)\Gamma(\theta)}\left(\frac{\theta}{f_{lmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}+\theta}\right)^{\theta}\left(\frac{f_{lmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}}{f_{lmk}\cdot\frac{1-e^{-e^{\beta_d x_{dmk}}}}{1+e^{-\beta_h x_{hmk}}}+\theta}\right)^{n_{AG3mk}}\right)$$

(4-52)

In Formula 4-50, β denotes the vector of unknown parameters; $\mathbf{x}_{mk}$ represents the vector of explanatory variables of leg k, intersection m; f_{mk} and n_{mk} are, respectively, total traffic volume and the number of accidents observed on leg k, intersection m. In Formula 4-51, f_{tmk} and n_{AG2mk} are, respectively, current leg through traffic volume and the number of AG2 accidents observed on leg k, intersection m. In Formula 4-52, f_{lmk} and n_{AG3mk} are, respectively, current leg left-turn traffic volume and AG3 accident number observed in leg k, intersection m. The models are independent from each other. The same symbols, such as θ, have different values in different models.

Although finding the maximum points of the Formulae 4-5 to 4-52 is laborious work, the Gauss-Newton and some other methods provide an efficient means to solving the problems. In this study, the Gauss-Newton method is applied to find the solution of the log likelihood functions for the models. (Christensen (1997) provides additional details about the Gauss-Newton method.) The cumbersome work of solving the non-linear equations was completed using SYSTAT statistical software (SPSS, 1966).

4.5.3 Basic Tests in the Model Development Process

For the estimation of maximum likelihood estimation, two important statistics are used to make the correct assessments: the asymptotic t-test; and the confidence interval.

A) Asymptotic t-test

The asymptotic t-test is used primarily to test whether a *particular* parameter in the model differs from some known constant, often zero. For non-linear models, this test is valid only asymptotically, i.e. it is valid only for large samples. The critical values for the test statistics are percentiles of a standardized normal distribution which, for two-tailed tests at the frequently used significance levels of 0.10 and 0.05, are 1.65 and 1.96 respectively.

B) Confidence Interval

Although computationally difficult, it is possible to construct confidence intervals for two or more parameters jointly. The vector of estimated coefficients β^*, found by the method of maximum likelihood, is asymptotically normally distributed with β and covariance matrix Σ_β. Therefore, the quadratic form

$$(\beta^* - \beta)' \Sigma_\beta (\beta^* - \beta) \tag{4-53}$$

is asymptotically χ^2 distributed with K degrees of freedom, K being the dimension of β. This is also true for any sub vector of β^* with its corresponding sub matrix of Σ_β. The (1-α) confidence interval for the vector β is of the form

$$\Pr\left[(\beta^* - \beta)' \Sigma_\beta^{-1} (\beta^* - \beta) \le \chi^2_{K,\alpha}\right] = 1 - \alpha \tag{4-54}$$

where $\chi^2_{K,\alpha}$ is the percentile of the χ^2 distribution with K degrees of freedom for the α level of significance.

4.6 GOODNESS-OF-FIT MEASURES

In order to decide which subset of independent variables should be included in an accident estimation model, Akaike's Information Criterion (AIC) was used (Abdel-Aty M.A., 2000). AIC identifies the best approximating model among a class of competing models with different numbers of parameters. AIC is defined as follows:

$$AIC = -2 * ML + 2 * k \qquad (4\text{-}55)$$

where ML is the maximum l(θ) and k is the number of variables in the model.

The smaller the value of AIC, the better the model is. Starting with a full set of independent variables and their interactions, a stepwise procedure has been used to select the best model based on minimizing the AIC value.

4.6.1 Likelihood Ratio Test

To measure the overall goodness-of-fit statistics, the deviance value 2(LL(θ) – LL(0)) which follows a chi-square distribution has been used for testing overall goodness of fit ,as suggested by Agresti (1990).

For measuring overall statistical fit, it is more convenient to compare the value of likelihood ratio index or ρ^2-square (similar to R^2 regression analysis), which indicates an additional variation in accident frequency (explained by the obtained model to the constant term), was also used (Detail is provided by Fridstorm et al., (1995)).

$$\rho^2 = 1 - \frac{\ell(\theta)}{\ell(0)} \text{------}(6) \qquad (4\text{-}56)$$

where $l(\theta)$ = log-likelihood at convergence; and $l(0)$ = log-likelihood with only a constant term(i.e. other coefficients are zero except constant terms).

The value of 0.20 is quite satisfactory considering the variance in the data and also considering that ρ^2 values tend to be generally lower than typical R^2 values (Ben-Akiva and Lerman, 1985).

4.7 CHAPTER SUMMARY

This chapter discussed the methodology related to the development of side-impact crash risk models. Past applications of the Negative Binomial model are discussed to demonstrate the overdispersion issue related to accident data. The Negative Binomial model is used to develop models for various types of angle accident at four-legged signalized intersection. The mechanisms underlying the occurrence of accident type (right-angle, left-turning and right-turning accidents) were developed with the help of an approach-based accident modeling technique.

Explanatory factors such as traffic related variables, and geometric and road environment factors can be incorporated into these models. This subject is described in Chapter 5.

CHAPTER 5

MODEL ESTIMATION RESULTS

5.1 INTRODUCTION

This chapter presents the model estimation results for four types of side impact crash with special emphasis on discussion of the predictor variables and their influence on accident risks at signalized intersection in Toronto. Graphical illustrations of the continuous predictor variables provided a clear insight into how the same variable could have a different impact on the different types of side impact crash. The overdispersion, which occurs when the variance of crash-frequency data is greater than its mean, estimation of all major side impact crashes is explained and the appropriate choice of the statistical distributions used in the modeling is discussed. The chapter includes a discussion of the specification issues involved in addressing any violation of independency that could significantly affect model results. Finally, the goodness-of-fit of the model is assessed using the likelihood ratio index and cumulative residual values plotted against fitted values.

5.2 VARIBALES FOR CRASH RISK MODELS

After a careful examination of the results of the preliminary data analysis, the dependent and predictor variables were selected. For modeling purposes it was determined that the potential explanatory variables (included in the vector x_d in equation 4-40) had to be representative of an approach condition. An approach condition was determined to be a traffic or geometric entity that could reasonably be expected to influence the frequency of accidents. The interpretation of the variables and their influence on side impact crashes is described in Section 5.4.

5.2.1 Dependent Variables

The total number of approach accidents includes all the reported and eligible side impact accident types that occurred at the selected sites in the City of Toronto. The dependent variables adopted in the modeling process were:

1. The average number of all side impact crashes per year;
2. The average number of right-angle crashes per year;
3. The average number of left-turn crashes per year; and
4. The average number of right-turn crashes per year.

It is important to note that the crash types were selected using the accident classification described in Section 2.4. Because one of the side impact accident types could predominate on an intersection approach, separate models of right-angle, left-turn and right-turn crashes should provide additional valuable insights that might reveal in the model for all side-impact crashes.

The determination variables were based on the preliminary crash data frequency fitting distribution (Section 3.6) and dominant accident types at signalized intersections in City Toronto, as presented in Section 3.3.3.

5.2.2 Predictor Variables

Several types of variables were examined in the analysis, including the main-street and cross-street flow, the right and left-turn volume on an entering approach, the total flow on the opposing approach, the lane configuration (crossing approach width, lane restrictions and lane sharing information, exclusivity of right-turn lane), the intersection geometry (approach curvature, angle between the approaches, sight distance, elevation of structures, presence of median or driveway), the traffic control type (e.g., phase types length of red phase), and vehicle driver characteristics (e.g., functional field of view). The selection of variables was based on the data available and on engineering judgment. The task was carried out from the result of the database building process for the modeling.

A correlation matrix for the selected variables is given in Table B-5 and B-6 in Appendix B, to assess how multicollinearty may affect the stability of the parameter estimates calculated in the multiple regression models. Estimated regression coefficients may be far from their true value if such effects are substantial. In addition, standard errors of the coefficients are likely to be large and consequently, an estimated regression coefficient can be insignificant. In the actual model fitting, stability of estimated parameters was achieved by adding independent variables one at a time. A variable was accepted if its estimated coefficient remains essentially the same following the addition of subsequent variables to the model.

After considering the 116 variables that were collected during the site survey, only 48 were found relevant in terms of statistical significance tests, the logic of model development, and knowledge obtained from the literature review. Of these 48 variables, 28 had an impact on the probability of subject vehicles being involved in an accident and 20 affected the same probability for target vehicles. The number of selected variables selected for the crash model development is presented in Table 5-1. The following sections provide a detailed description of the model estimation results, an explanation of predictor variables and an analysis of all the variables selected for the study.

Table 5-1: Number of Selected Explanatory Variables used in the Accident Risk Modeling

Variables Related to	Total Variable	All Side-Impacts Crash Model	Right-Angle Crash Model	Left-Turn Crash Model	Right-Turn Crash Model
Subject Vehicle Probability (P_{sv})	28	19	19	14	12
Target Vehicle Probability (P_{tv})	20	9	11	9	10

5.3 ESTIMATION RESULTS OF CRASH RISK MODELS

Tables 5-2 and 5-3 show the model estimation results. Each intersection was divided into separate approaches. The number of accidents on each approach in one-year intervals was used in the analysis. (In the event that an accident occurred in the intersection proper, the accident was assigned to the approach used by the approach vehicle involved in the accident. This decision was based on the logic used in this study for further classifying side impact crashes. For example, a vehicle invading the red or yellow signal was identified as a 'subject vehicle' if it struck a "target" vehicle that was obeying the traffic signal from a cross-street approach.). Each four-approach intersection provided four observations (one for each approach) for each of the six years from 1999 to 2004: 24 observations in all. A total of 1,680 observations were provided by the 70 intersections studied in this research. The taking of repeated observations from each intersection or approach might create a possible correlation problem. This issue is empirically explored in Section 5.5.

The Negative Binomial model explored the relationship (Tables 5-2 and 5-3) between side impact accidents and the explanatory variables by estimating the goodness of fit, coefficients, predicted values, and t-value (in parenthesis) for each variable. The customized programming module of the SYSTAT statistical software package was used to estimate the model coefficients and other goodness-of-fit tests. The models were estimated by standard maximum likelihood methods. A positive sign indicates an increasing effect on the probability of a side impact accident whereas a negative sign indicates a decreasing effect. All the parameters are statistically significant at the 5% level (the lowest t-statistic is 1.645, p=0.05 with degrees of freedom=number of observation – number of parameter to be estimated).

The average probability of the cross-street (i.e. target) vehicle having a side impact accident is lower than for the subject vehicle. This result was expected (Section 4.2) and provides evidence of the hypothesis and concept of "proportional risk", according to which multiplying the individual driver risk probabilities, which are assumed independent of each other, provides the total side impact accident risk. To simplify the task of modeling, only crashes involving two vehicles are considered in the analysis.

In addition, the estimation results support the concept of "different approach drivers having different crash risk probabilities" where different sets of variables are responsible for the different vehicles involved in side impact accidents.

Overdispersion, which occurs when the variance of accident frequency data is greater than the mean, is a common phenomenon in intersection accident data, and can result in a biased model co-efficient and erroneous standard-errors. A biased co-efficient can result in an over or understatement of accident likelihood. Consideration of the negative binomial error structure overcomes the over dispersion concern. Table 5-5 shows an estimation of the overdispersion of selected accident data. The details of dispersion parameter estimation were adopted from Pham and Ragland (2006).

5.4 GOODNESS-OF-FIT EVALUATION

Several goodness-of-fit measures were considered in the model selection process:

- General residual plot;
- Prediction ratio;
- Comparison between observed and predicted values; and
- Cumulative residual (CURE) plot.

Details are shown in Figures 5-1 to 5-3 and in Appendix D.

Table 5-2: Variables Affecting the Probability of Encountering Subject Vehicle

Parameters in Model	Coefficients (and t-statistics)			
	Side-Impact, SI	**Left-Turn, AG1**	**Right-Angle, AG2**	**Right-Turn, AG3**
Constant	-2.689 (-4.892)	-7.614 (-13.816)	-9.141 (-11.126)	-3.745 (-10.261)
Combined through-left, left turn drop lanes and two or more lanes on the approach[2]	0.114 (2.141)	0.345 (3.980)	0.374 (3.451)	-
Intersection in commercial areas[1]	0.187 (2.211)	-	-	0.086 (2.181)
Left-turn restriction[1]	-0.192 (-1.917)	0.066 (2.258)	0.075 (2.404)	-
Right-turn restriction[1]	-	-	0.396 (2.035)	-
Total no. of lane of current approach	0.418 (4.261)	0.146 (2.681)	0.396 (2.358)	-
Total lane no. of right approach	-0.21105	-0.11 (3.134)	-	-
Exclusive left-turn lane[1,*]	-	-0.372 (-4.263)	-	-
Angle of road in between two adjacent legs[1]	-	0.112 (1.92)	0.197 (4.265)	-
Absolute displacement between two apposite legs[1]	-	0.373 (2.645)	-	-
Curvature on approach leg[1]	-	0.438 (2.648)	0.207 (2.01)	-
Speed limit of entering approach	-0.06* (2.148)	-0.026* (-3.468)	0.191* (1.948)	-
Intersection sheltered by elevated road[1]	0.059* (-5.141)	0.079 (2.451)	0.089 (2.145)	0.118 (2.471)
Existence of fence in median of entering approach[1]	-0.112 (2.456)	-	-	-0.142 (2.462)
Central road median[1]	-0.292 (-4.128)	-	-0.231 (3.313)	-
Signal Progression[1]	-0.254 (2.467)	-	-	0.219 (3.451)
Signal control pattern[4]	-0.043(-1.972)	-0.368 (-4.137)	-	-
Intergreen period on current leg[3]	-	-	-1.352 (3.461)	-
Road width of current leg(m)	-0.038 (-1.997)	-	-0.048 (2.673)	-
Shoulder width (both far and near side in meter)	-0.127 (-2.129)	-	-0.147 (-2.674)	-0.089 (-2.084)
Number of tree (on both near and far side)	-0.245 (-2.071)	-	-0.143 (-2.795)	-0.215 (-2.346)
Transit exit or stop existence on current approach[1]	-0.038 (-2.697)	-	-0.031 (-2.098)	-
Truck Volume (6 years) of the current approach[5]	0.029 (2.972)	-0.029 (1.984)	0.046 (1.957)	-0.025 (2.146)
Total Entering Traffic Volume (6 years) of the current approach[5]	0.046 (1.98)	-	-	-
Left-turn traffic volume (6 years) of the current approach[5]	0.249 (1.95)	0.034 (2.06)	-0.077 (1.90)	-
Through traffic volume (6 yrs) of the cross-street approach[5]	-	-	0.075 (1.94)	0.039 (2.10)
Through traffic volume (6 years) of current approach[5]	-	-	0.076 (1.91)	-
Left-turn traffic volume (6 years) of the opposite approach[5]	-	-	-0.059 (2.08)	0.041 (2.02)
Avg. probability of encountering a subject vehicle (P_{sv})	0.428	0.139	0.407	0.208

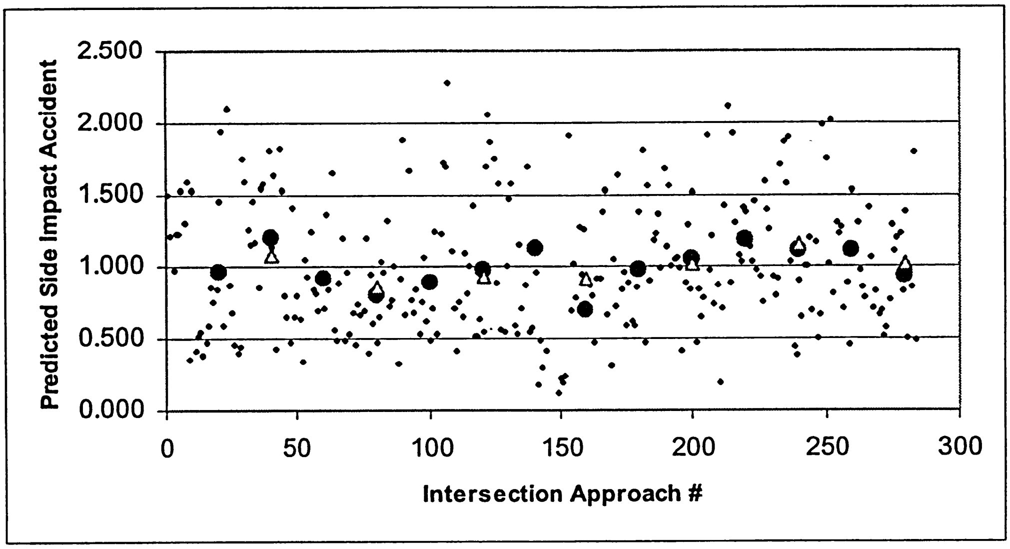
Notes: *: Parameter significant also for target vehicle; 1. If exist 1, 0 otherwise; 2. If there are two or more combined through-right or right-turn drop lanes exist 1, 0 otherwise; 3. If period longer than 3 sec then 1, 0 otherwise; 4. For four phase control 1, 0 otherwise; 5. Traffic volume in thousand.

Table 5-3: Variables Affecting Target Vehicle Failure Probability

Parameters In Model	Coefficients (and t-statistics)			
	Side-Impact, SI	Left-Turn, AG1	Right-Angle, AG2	Right-Turn, AG3
Constant	-4.975 (-13.744)	-2.556 (-2.312)	-4.040 (-11.264)	-5.17 (-2.134)
Existence of driveway[1]	-	-	0.138 (2.094)	0.243* (3.467)
Angle between entering approach and opposing approach[2]	0.1566* (2.192)	0.059* (3.156)	0.391 (2.441)	0.180 (2.192)
Exclusive left-turn lane[1,*]	-1.199 (-4.321)	-	-1.028 (-1.982)	-
Permissive left turn[1]	-	-	-2.115 (3.156)	-
Left-turns not aligned and not single lane approach[1]	-	-	-0.164 (2.941)	-
Existence of more than one right-turn lanes[1]	-	-	-	-0.143 (2.145)
Through lane no. of right approach	-	-	-	0.11 (3.4567)
Total no. of approach lanes	0.441 (4.256)	0.268 (2.456)	-	0.12 (2.146)
Shoulder width (both far and near side in meter)	-	-0.128 (-3.454)	-	-
Existence of transit stop, exit[1]	-	-0.279 (-1.959)	-	-0.142 (-2.058)
Existence of driveways[1]	-	0.104 (3.125)	-	0.144 (2.465)
All Red Period on current leg	-	-	-0.314 (-2.708)	-
Slope of entering approach	0.622 (5.198)	0.30 (2.928)	-	-
Local street approach[3]	-	-	0.0881 (2.646)	-
Large vehicle ratio of current leg	-0.047 (-2.583)	-0.021 (2.499)	0.157 (3.164)	-0.034 (3.373)
Functional field of view[4]	-0.426 (2.156)	-0.812 (2.492)	-0.702 (-5.467)	-0.492 (-2.214)
Visual noise (from level 0 to 4)	0.130 (2.493)	-	-	-
Night-to-day traffic flow ratio	1.588 (3.461)	-	1.382 (2.844)	-
Presence of trees at approach corner	0.091 (1.764)	-	-	0.074 (12.124)
Pedestrian volume (6 years) of current approach[6]	-	-0.046 (-2.196)	-	-0.055 (-3.469)
Right-turn volume (6 years) of current approach[6]	0.072* (2.412)	-	-	0.091 (2.031)
Bicycle ratio of opposite through traffic	-	-0.686 (-3.254)	-	-0.321* (-2.554)
Overall Estimation Results (Sample Number 1680)				
Likelihood Ratio Index	0.42	0.48	0.59	0.39
Overdispersion parameter	1.83	2.41	2.24	3.22
Average probability of the failure of target vehicle driver (P_{tv})	$2.04*10^{-6}$	$1.28*10^{-6}$	$3.22*10^{-6}$	$2.07*10^{-6}$

Notes: *: Parameter also significant for subject vehicle; 1. If exist 1, 0 otherwise; 2. If the angle is less than 15^0 then 1, 0 otherwise; 3. If local street with traffic less than 10,000 approach and long red time 1, 0 otherwise; 4. If angle of clear view is less than 10^0 or any kind of disturbances exist in opposite side of current leg then 1, 0 otherwise; 5. If greater than ±3% then 1, 0 otherwise; 6. Traffic volume in thousand.

Figure 5-1: Prediction Ratio for Total Side Impact Crashes



The prediction ratio results (Figures 5-1, Figure D-1 and Figure D-2) for side-crash models are symmetrically distributed around 1 with upper and lower bounds of 1.7 to 0.40 respectively. These bounds contain 92 percent of the ratios. The block circles and triangles represent the average for 20 and 40 intersections respectively shown together.

Figures 5-2, D-3 and D-4 reveal some important aspects of using the Negative Binomial error structure instead of the Poisson model. It is clear that the variability of the ratios decreases as the estimated crash-frequency value increase. This is a departure from the linear normal distribution error model. On a similar note, Figures E-7 to E-9 show that predicted to observe value line closely depicts a good performance of high-quality prediction models.

The cumulative residual (CURE) plot was proposed by Hauer and Bamfo (1997) and by Hauer (2001). The plot shows the cumulative residuals (the difference between actual and fitted values for each intersection) plotted in increasing order for each covariate separately. The graph shows how well the model fits the data with respect to each individual covariate.

Figure 5-2: Prediction Ratio and Estimated Value for Right-Angle Crashes

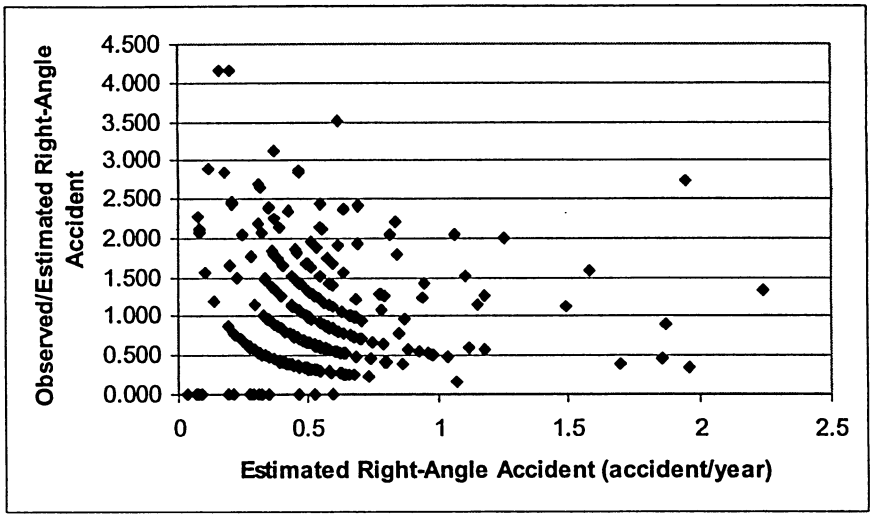
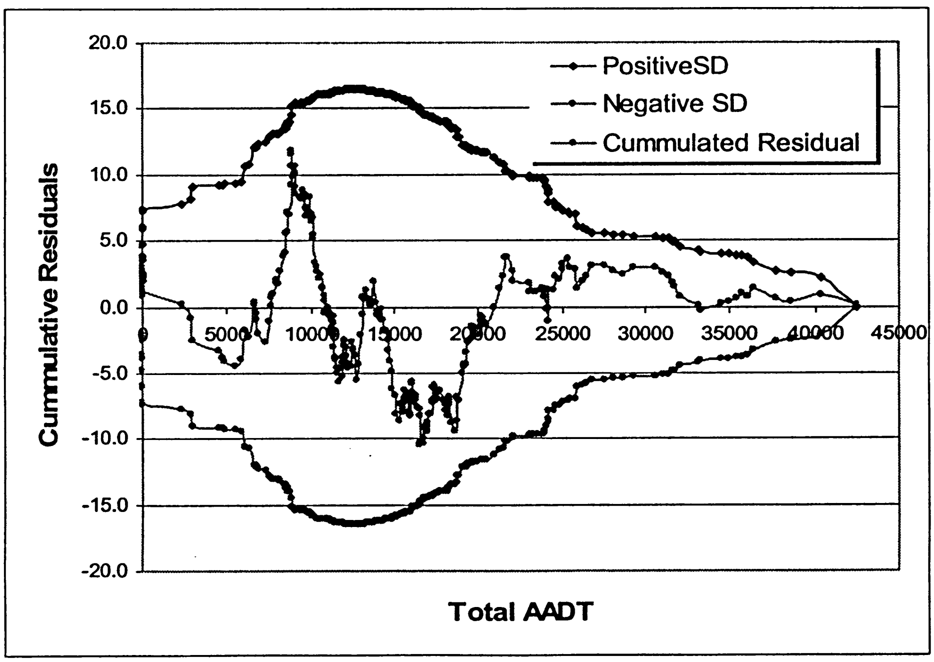


Figure 5-3 clearly shows that all models in this study provide satisfactory predictions. All of the CURE plots (Figures 5-3, D-7 and D-8) show that the cumulative residuals oscillate around the zero value and lie between the two standard deviation boundaries.

Figure 5-3: Cumulative Residual (CURE) Plot for Total Side Impact Crashes (SD represents two standard deviation)



5.5 SPECIFICATION ISSUES AND TESTS

A number of possible problem areas in the modeling should be considered. For example, the set of observations obtained for each intersection and the set of observations used in the model estimation are not exactly the same from year to year due to missing accident data.

There could be correlation problems due to the repeated use of the same road environment data as very few of the road environment related factors changed during the six years. That is, the gamma error term in the negative Binomial model could be correlated from one observation to the next, which is a violation of the error-term independence assumption made to derive the model. This problem was noted by Poch et al. (1996). The consequence of non-independence of error terms is a loss in estimation efficiency (i.e. the standard errors of the estimated coefficients will become larger), and this could lead one to draw erroneous conclusions regarding the coefficient estimates. Details of estimation procedure were adopted from Poch et al. (1996).

The basic idea of the tests applied in this study is to segment the sample into subsets of data that are less likely to be affected by correlation problems. If these smaller data subsets produce model estimation results that are not significantly different from the estimation results produced by the overall data sample, it can be concluded that any independent violations are not significantly affecting model results (see Ben-Akiva and Lerman, 1985 for applications of this approach).

To test for possible correlation problems from one year to the next (which could result, for example, from the use of annual expansion factors to estimate traffic volumes), the AG2 accident dataset (for example) was spit into three subsets: one each for 1999 to 2004 (combined to obtain model convergence). Since 30 parameters were used in the total side impact crash model, the degrees of freedom were 18 according to Formula 4-40. The results are shown in Table 5-4.

Table 5-4: Test for the Effects of Correlated Road Environment Related Factors for Right-Angle Crash Model

Year Group	$L_N(\beta)$ 6-year	$L_N(\beta_1)$ 1999	$L_N(\beta_2)$ 2000	$L_N(\beta_3)$ 2001	$L_N(\beta_2)$ 2002	$L_N(\beta_2)$ 2003	$L_N(\beta_2)$ 2004	X^2	Degrees of freedom	p-value
Log-likelihood	-512	-92	-88	-74	-83	-90	-85	32	18	0.88

The test results in Table 5-4 show that we can have only 12% confidence in saying that the correlation between observed years is significantly affecting the estimation results.

5.6 INTERPRETATION OF MODEL ESTIMATION RESULTS

Table 5-5 and 5-6 depict the influence of all variables in the models. From the estimated parameters of the models in Tables 5-2 and 5-3, Accident Modification Factors (AMFs) can be inferred as shown in the Tables 5-5 and 5-6. These AMFs represent the change in mean predicted accident risk when the value of a variable is increased by one unit. Thus, e.g., an AMF of 0.8 represents a (100(1-0.8)) = 20% reduction in risk.

Table 5-5: Influence of Explanatory Variables on Probability of Encountering Subject Vehicle

Parameters In Model	Effect of Explanatory Variables on Po Risk							
	Side-Impact, SI		Left-Turn, AG1		Right-Angle, AG2		Right-Turn, AG3	
	AMF	% Change	AMF	% Change	AMF	% Change	AMF	% Change
Combined through-left, left turn drop lanes and two or more lanes on the approach[2]	1.12	12.08	1.41	41.20	1.45	45.35	-	-
Intersection in commercial areas[1]	1.21	20.56	-	-	-	-	1.09	8.98
Left-turn restriction[1]	0.83	-17.47	1.07	6.82	1.08	7.79	-	-
Right-turn restriction[1]	-	-	-	-	1.49	48.59	-	-
Total no. of lane of current approach	1.52	51.89	1.16	15.72	1.49	48.59	-	-
Total lane no. of right approach	0.81	-19.02	0.90	-10.42	-	-	-	-
Exclusive left-turn lane[1,*]	-	-	0.69	-31.06	-	-	-	-
Angle of road in between two adjacent legs[1]	-	-	1.12	11.85	1.22	21.77	-	-
Absolute displacement between two apposite legs[1]	-	-	1.45	45.21	-	-	-	-
Curvature on approach leg[1]	-	-	1.55	54.96	1.23	23.00	-	-
Speed limit of entering approach	0.94	-5.82	0.97	-2.57	1.21	21.05	-	-
Intersection sheltered by elevated road[1]	1.06	6.08	1.08	8.22	1.09	9.31	1.13	12.52
Existence of fence in median of entering approach[1]	0.89	-10.60	-	-	-	-	0.87	-13.24
Central road median[1]	1.15	14.80	-	-			-	-
Signal Progression[1]	0.78	-22.43	-	-	-	-	1.24	24.48
Signal control pattern[4]	0.96	-4.21			-	-	-	-
Intergreen period on current leg[3]	-	-	-	-	*0.87*	*-12.65*	-	-
Road width of current leg(m)	0.96	-3.73	-	-	0.95	-4.69	-	-
Shoulder width (both far and near side in meter)	0.88	-11.93	-	-	0.86	-13.67	0.91	-8.52
Number of tree (on both near and far side)	0.78	-21.73	-	-	0.87	-13.32	0.81	-19.35
Transit exit or stop existence on current approach[1]	0.96	-3.73	-	-	0.97	-3.05	-	-
Truck Volume (6 years) of the current approach[5]	1.03	2.94	0.97	-2.86	1.05	4.71	0.98	-2.47
Total Entering Traffic Volume (6 years) of the current approach[5]	1.05	4.71	-	-	-	-	-	-
Left-turn traffic volume (6 years) of the current approach[5]	1.28	28.27	1.03	3.46	0.93	-7.41	-	-
Through traffic volume (6 yrs) of the cross-street approach[5]	-	-	-	-	1.08	7.79	1.04	3.98
Through traffic volume (6 years) of current approach[5]	-	-	-	-	1.08	7.90	-	-
Left-turn traffic volume (6 years) of the opposite approach[5]	-	-	-	-	0.94	-5.73	1.04	4.19

Notes: *: Parameter significant also for target vehicle; 1. If exist 1, 0 otherwise; 2. If there are two or more combined through-right or right-turn drop lanes exist 1, 0 otherwise; 3. If period longer than 3 sec then 1, 0 otherwise; 4. For four phase control 1, 0 otherwise; 5. Traffic volume in thousand.

Table 5-6: Influence of Explanatory Variables on Target Vehicle Failure Probability

Parameters In Model	Effect of Explanatory Variables on Pf Risk							
	Side-Impact, SI		Left-Turn, AG1		Right-Angle, AG2		Right-Turn, AG3	
	AMF	% Change	AMF	% Change	AMF	% Change	AMF	% Change
Existence of driveway[1]	-	-	-	-	1.15	14.80	1.28	27.51
Angle between entering approach and opposing approach[2]	1.17	16.95	1.06	6.08	1.48	47.85	1.20	19.72
Exclusive left-turn lane[1,*]	*0.89*	*-11.30*	-	-	*0.90*	*-9.77*	-	-
Permissive left turn[1]	-	-	-	-	0.81	-19.06	-	-
Left-turns not aligned and not single lane approach[1]	-	-	-	-	0.85	-15.13	-	-
Existence of more than one right-turn lanes[1]	-	-	-	-	-	-	0.87	-13.32
Through lane no. of right approach	-	-	-	-	-	-	1.12	11.63
Total no. of approach lanes	1.55	55.43	1.03	2.72	-	-	1.13	12.75
Shoulder width (both far and near side in meter)	-	-	0.88	-12.01	-	-	-	
Existence of transit stop, exit[1]	-	-	0.76	-24.35	-	-	0.87	-13.24
Existence of driveways[1]	-	-	1.11	-10.96	-	-	1.15	15.49
All Red Period on current leg	-	-	-		0.73	-26.95	-	-
Slope of entering approach	*1.06*	*6.42*	*1.03*	*3.05*	-		-	-
Local street approach[3]	-	-	-	-	1.09	9.21	-	-
Large vehicle ratio of current leg	0.95	-4.59	0.98	-2.08	1.17	17.00	0.97	-3.34
Functional field of view[4]	0.65	-34.69	0.44	-55.60	0.50	-50.44	0.61	-38.36
Visual noise (from level 0 to 4)	1.14	13.88	-	-	-	-	-	-
Night-to-day traffic flow ratio	*1.17*	*17.21*	-	-	*1.15*	*14.82*	-	-
Presence of trees at approach corner	1.10	9.53	-	-	-	-	1.08	7.68
Pedestrian volume (6 years) of current approach[6]	-	-	0.96	-4.50	-	-	0.95	-5.35
Right-turn volume (6 years) of current approach[6]	1.07	7.47	-	-	-	-	1.10	9.53
Bicycle ratio of opposite through traffic	-	-	*0.93*	*-6.63*	-	-	0.97	-3.16

Notes: *: Parameter also significant for subject vehicle; 1. If exist 1, 0 otherwise; 2. If the angle is less than 15^{0} then 1, 0 otherwise; 3. If local street with traffic less than 10,000 approach and long red time 1, 0 otherwise; 4. If angle of clear view is less than 10^{0} or any kind of disturbances exist in opposite side of current leg then 1, 0 otherwise; 5. If greater than ±3% then 1, 0 otherwise; 6. Traffic volume in thousand.

The subsections to follow provide further interpretation of each key predictor variables used in the side impact model development process with special reference to Figures 5-4 to 5-15. It is important to note that the figures are constructed using average accident frequency to compare the effect of same variables estimated by crash risk models.

5.4.1 The Effect of Traffic Flow

Side impact accidents have a unique relationship with traffic flow compared with other types of accident at signalized intersection (Figure 5-4). As noted earlier, Baguley (1988) hypothesized that the rate of red-light running is not a simple function of the major flow. The higher the ADT on the cross-street, and the fewer the number of gaps available, the higher is the chance of a 'subject' vehicle encountering 'target' vehicle. AMF's and percent change presented in Table 5-4 and 5-5 showed that except left- and right-turn volume, other traffic flow does not influence greatly on side-impacts crash at signalized intersection.

Four types of traffic flow and their impact on side impact accident were explored in this study's analysis. The findings do not support Baguley's hypothesis. On the contrary, through traffic volume in this study has little effect on right-angle (increase 7.7%) crash-risk. This finding supports the expectation that right-angle accidents are not heavily dependent on through traffic volume. Figure 5-5 illustrates the point: through traffic volume does not explain right-angle accidents on the minor street. Thus, these models overcome the weakness of traffic volume dependency in accident prediction models.

As expected, left and right-turn crashes are dependent on the corresponding turning traffic volume (Figures 5-6 and 5-7). A high number of left-turns seems to be associated with a reduction in the number of left-turning accidents as a major part of the through flow is diverted to the left-turn flow, decreasing the number of through vehicles which could become an obstacle for the cross-street traffic flow. The increased total flow of the subject approach has a positive effect on the accident risk associated with all major side impact crash types. This effect was also found by the Highway Safety Information System (HSIS, 2000). On the contrary, high cross-street flows (cross-street left and right traffic flows) result in lower headways and hence a higher chance of encountering an obstacle vehicle. Other researchers have reported identical results regarding cross-street flows. Figure 5-8 shows the effect of the cross-street flow on side impact accident risk. It is noted that after a certain cross-street traffic volume ratio, the effect disappears. The reason for the type of association is not clearly understood.

Figure 5.4: The Effect of Total Traffic Volume on Side Impact Crashes

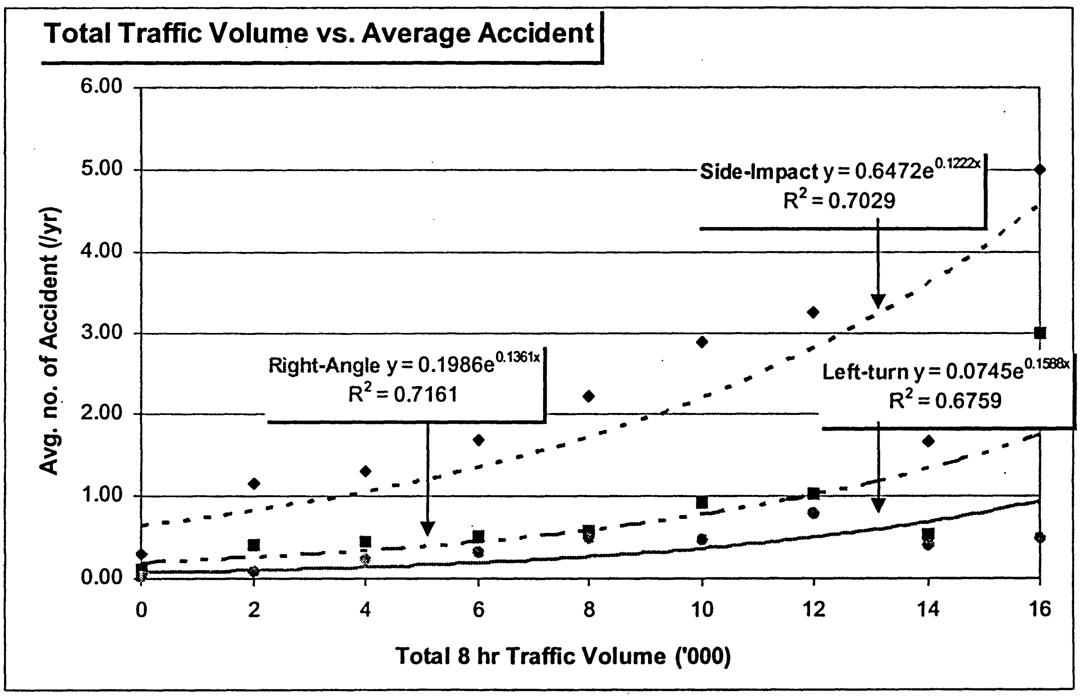


Figure 5-5: The Effect of Through Traffic Volume on Side impact Crashes

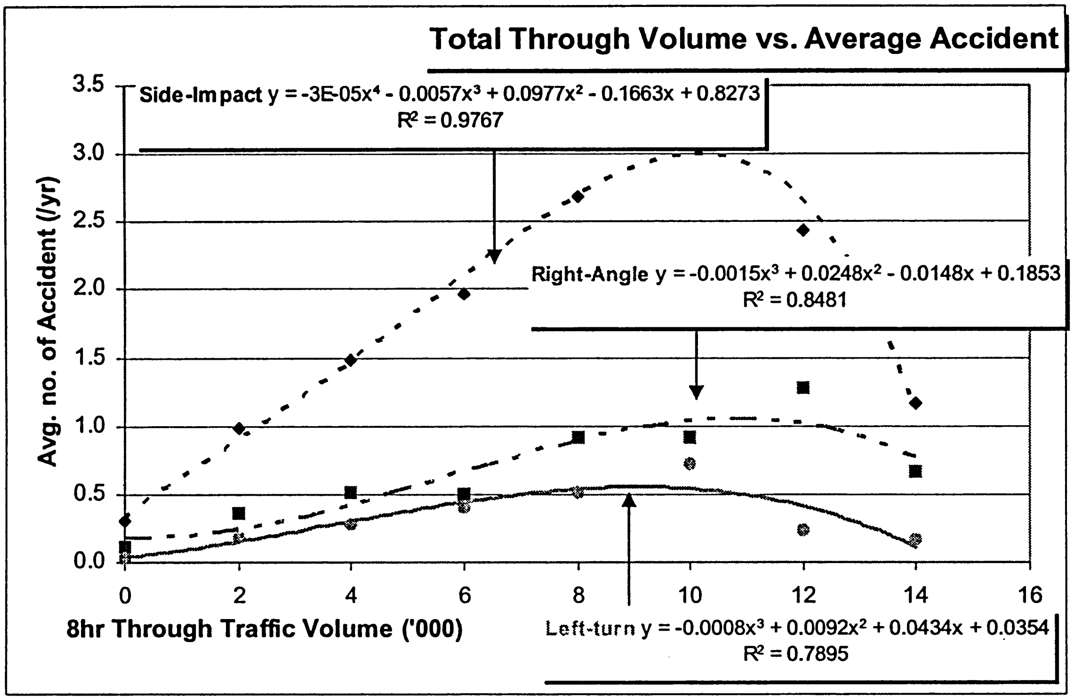


Figure 5-6: The Effect of Left-Turn Traffic Volume on Side impact Crashes

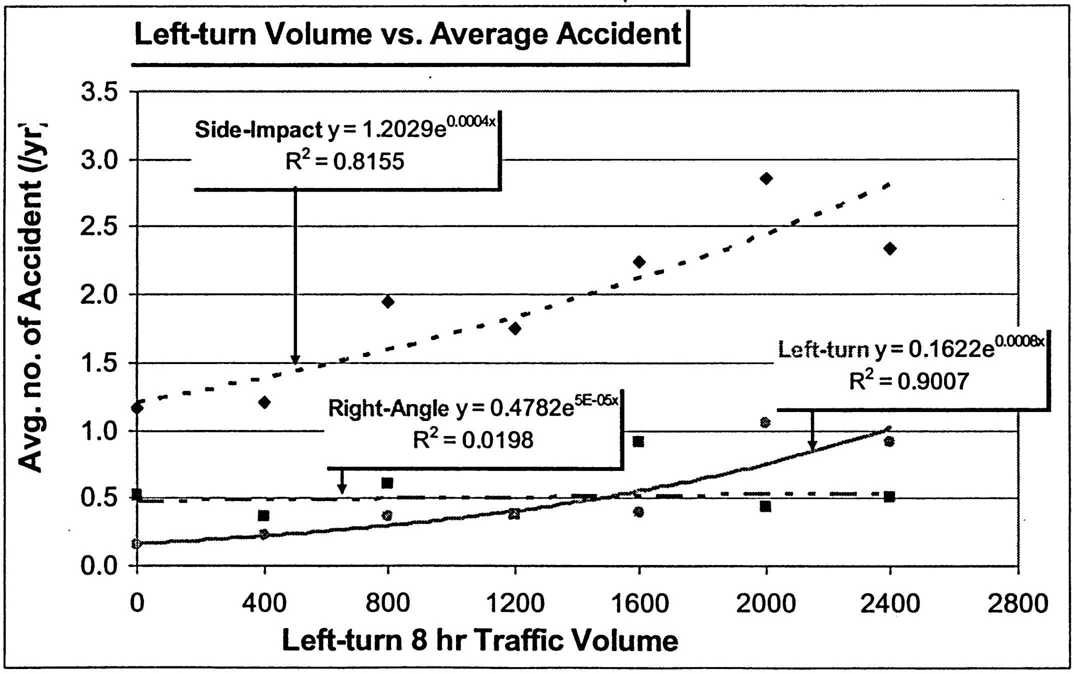


Figure 5-7: The Effect of Right-Turn Traffic Volume on Side impact Crashes

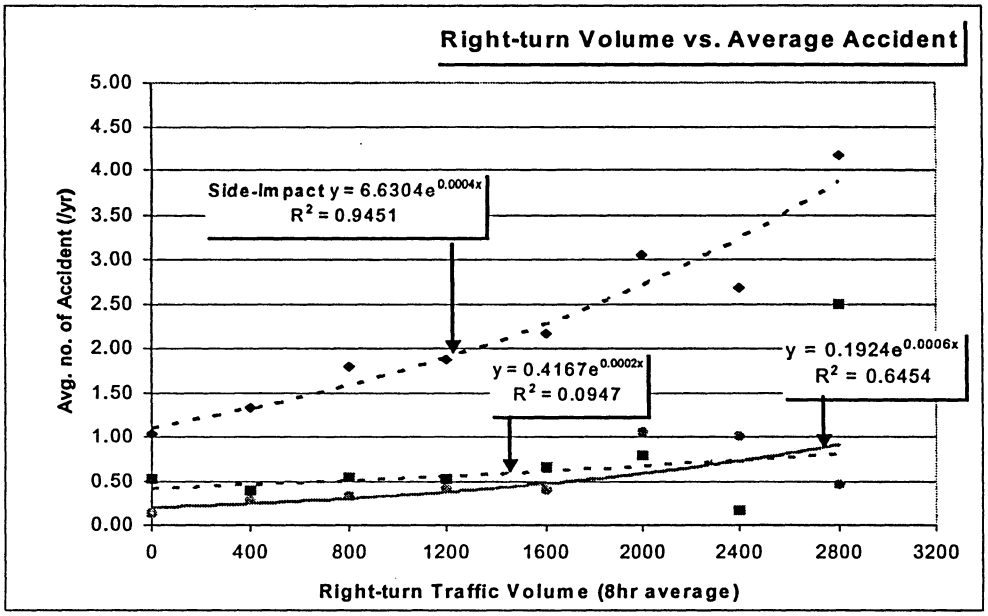
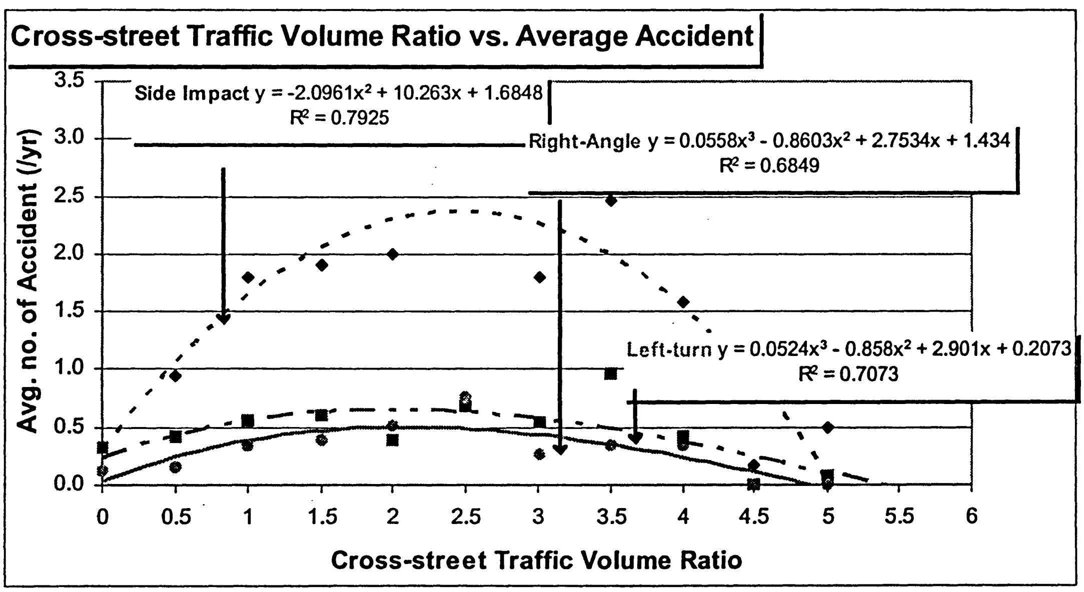


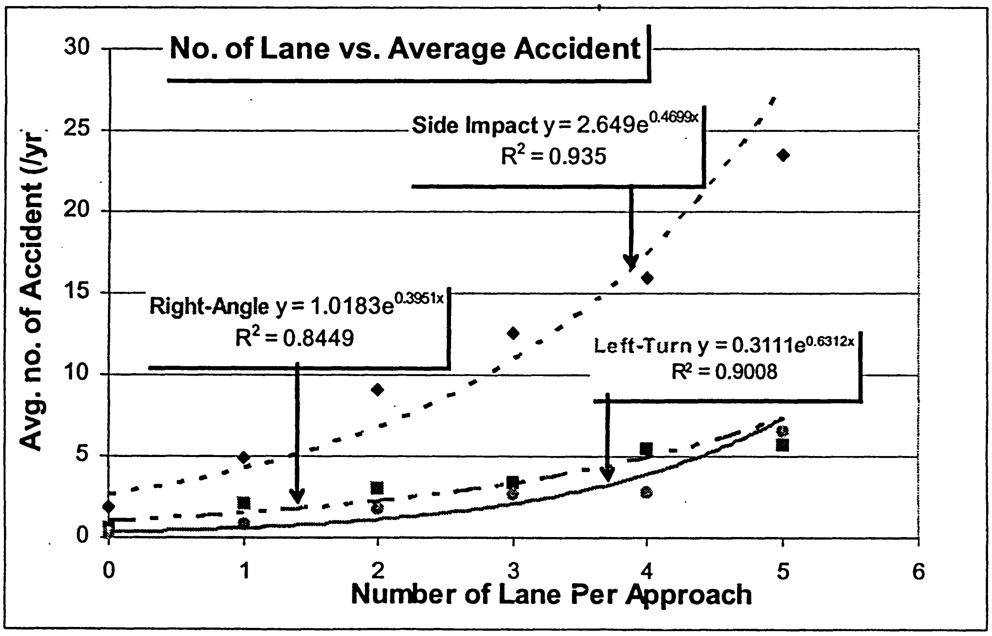
Figure 5-8: The Effect of Cross Street Traffic Volume Ratio on Side Impact Crashes



5.4.2 The Effect of Lane Configuration

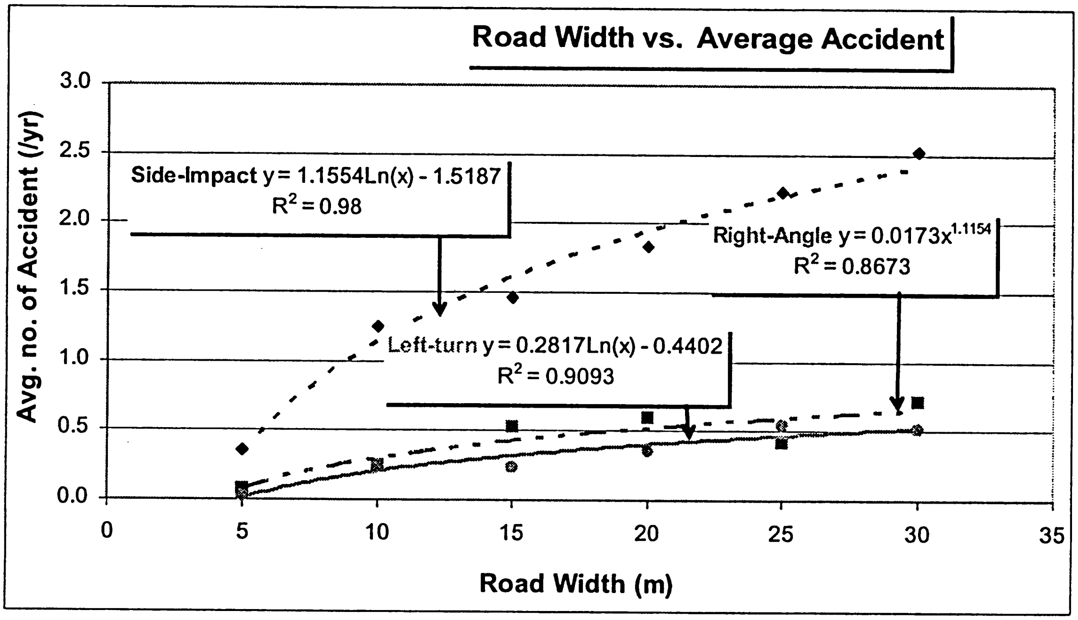
The number of lanes on the major road is one of the most important geometric factors explaining the occurrence of side impact crashes (Figure 5-9) since ir may be hypothesized that more lanes may indicate more lane changing lane near the intersection, leading to an increased risk of side-impact crashes. An increase of one lane is associated with an increased risk of total side impact crashes of 52%, an increases of 16% and 49% in the risk of left-turn crashes and right-angle crashes respectively (see Table 5-4) Although there is a correlation between the number of lanes and the traffic volume (Abdel-Aty et al. 2006), it is not always true that high traffic volume implies more lanes (The correlation is not high, as is seen in the correlation matrix in Table B-5 in Appendix B. (The correlation between total number of lane to total and through traffic volume is 0.424 and 0.418 respectively, but total entering traffic volume is statistically significant only for the total side-impact crash model. Together with traffic volume, however, the number of lanes on the current approach directly influences of the number of all types of side impact crashes. Figure 5-6 indicates that the number of lanes is strongly associated with the number of side impact crashes compared to traffic volume (Figure 5-4) of the current approach.

Figure 5-9: The Effects of the Number of Main Street Lanes on the Number of Side Impact Crashes



The effects of several types of lane configuration were explored. A right turning vehicle approaching at intersection from a combined through and right lane slows down to make the maneuver required to turn right. The following vehicle that intends to proceed straight through the intersection will regard the right turning vehicle as an obstacle and will move to an exclusive through lane if one is available, increasing accident risk. Sharing lane strongly influence right-angle risk (46% increase) compare to other types of side-impact crashes.

Figure 5-10: The Effect of Road Width on Side Impact Crashes



The effect of road width on side-impact accidents is complex and may be contradictory. Figure 5-10 shows (for target vehicle) the effects of road width on the observed side impact accident frequency. For obstacle vehicle road has an opposite influence on crash risk probability (reduces to 5%). Road width greater than 22m does not significantly affect right-angle or left-turn accident risk. The estimation results of this variable should be examined with caution, especially as Toronto is a highly congested city where streets with more than four lanes are rare. HSIS (2000) suggests that the effect of road width is probably a combination of the width of the cross-street and the cross-street volume. On the other hand, the existence of an exclusive right turning lane reduces the likelihood of a right angle accident because it provides an opportunity for smooth maneuvering to the right-turning vehicle. The right turning lane also reduces the probability of conflict at the intersection approach for through traffic vehicles by decreasing through traffic volume in individual through lanes (Datta, 1991).

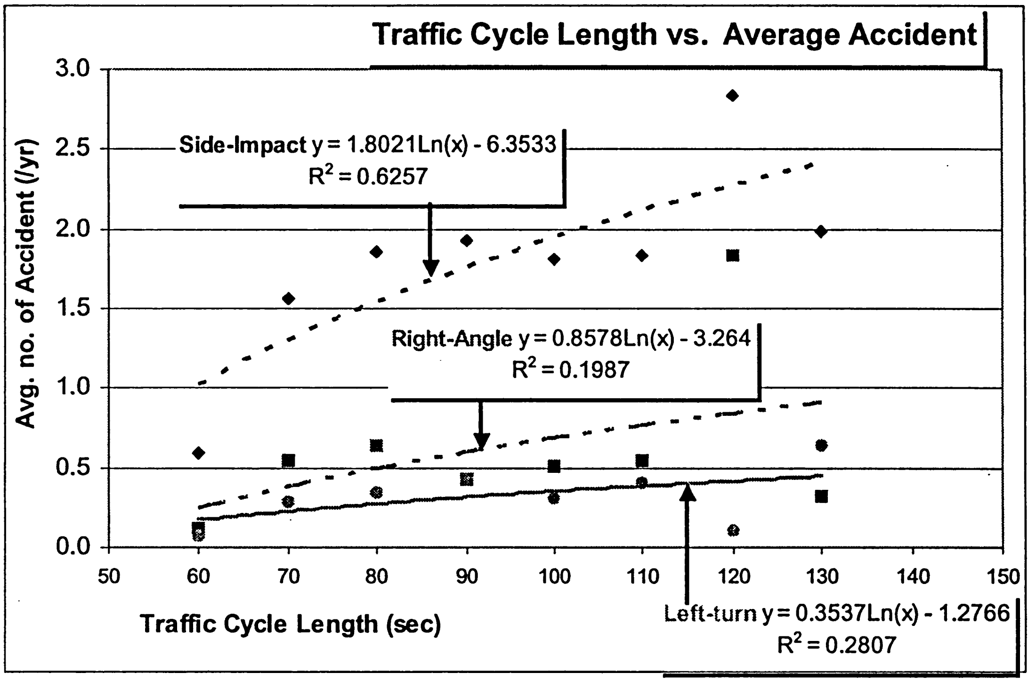
5.4.3 The Effect of Traffic Control

The influence of the length of the change interval (the intergreen period) on red-light running has been extensively studied (Retting and Greene 1997 and Chin 1989). The change interval consists of a 'steady yellow signal warning of an imminent change in right-of-way that may be followed by an all-red phase during which traffic approaching the intersection is required to stop (see estimation results in Table 5-2). A negative sign for the intergreen period variables used in this analysis confirmed the conclusion of previous research which found that longer change intervals can reduce right-angle accident risk.

The variables indicating protective right turn, permissive right-turn or combined left and right restriction have different effects on side-impact accidents for different types of driver. The estimation results show that if the major approach has a protected right turn, the RA accident risk tends to increase due to the high resulting through traffic volume. Poch and Mannering (1996), however, reported a decrease in total accidents at intersection with right-turn restrictions. Where target vehicle drivers are not sure of, the existence of right turn lanes with right-turn permission on the main street, difficulties may arise for opposite through vehicle drivers leading to shortened average APRT and less time to avoid the chance of a crash. The cross-street intergreen period variable is a composite variable representing the combination of the low ratio of minor-to-major traffic flow, longer red times, and low traffic volume. HSIS (2000) hypothesized that the long red phases of the cross-street, coupled with low crossing volume may cause red-light crashes at fixed time signals. The results of this analysis confirm the HSIS hypothesis as the sign for the relevant coefficient is positive.

For the subject vehicle intergreen period acts in the opposite way, reducing the crash risk by 12% (table 5-4).

Figure 5-11: The Effect of Total Traffic Signal Cycle Length on Side Impact Crashes



There is no strong evidence connecting traffic signal cycle length with right-angle or left-turn crash risk at signalized intersections. Figure 5-11 suggests that longer traffic signal cycle length is associated with side impact crashes.

5.4.4 The Effect of Driver and Vehicle Characteristics

The idea of a functional field of view (Miura T., 1992) was adopted in this study and refers to the number of disturbances and the angle of functional view from 30m away from the edge of current approach. Miura suggested that human peripheral vision narrows to 18^0 to 20^0 in a demanding situation like an urban intersection. The coefficient sign and percent decrease due to the functional field variable indicates that functional field of view reduces all side-impact accident risk: an absence of narrowed vision or turmoil enables a driver to detect the subject vehicle easily and consequently reduces the probability of an AG2 accident for the target vehicle driver.

The large vehicle ratio variable represents the greater perception and reaction time required by large vehicle drivers to avoid a right-angle accident collision. The variable represents the insufficient time available and the heavy braking required by a large vehicle trying to avoid a red-light runner. In this study, the variable's positive sign confirms this problem.

Left and right-turn crashes are negatively (decrease by 3% and 2.5% respectively) associated with truck-volume. This suggests that the increased time taken by large vehicles to turn right or left and reduces the number of turning accidents.

After reviewing data for 19 intersections, Polanis (2002) concluded that right-angle crashes are more likely to occur during a period of low traffic volume with a flashing signal in operation. The variable night-to-day traffic flow ratio reflects increased perception time at night and increased driver failure probabilities to avoid right-angle accident risk. Due to time constraints, flashing signal operation data are not included in this study's analysis.

5.4.5 The Effect of Geometric Variables

Seven of eight geometric variables are statistically significant for the probability of encountering a subject vehicle. The angle between the adjacent right or left approach and the main-street is the best predictor of RA accident risk. A large angle on the approach to an intersection creates a situation where the subject vehicle can increase its speed as the greater angle between the approaches causes a visual impediment to determine the existence of target vehicle.

After studying several types of signalized intersection, Hall (1986) concluded that intersection crashes, particularly left-turn and right-angle crashes were likely to increase when the angle between adjacent legs exceeds 105 degrees.

An irregularly configured intersection presents more complexities than does a regularly shaped intersection.

This study's model results indicate that when the angle between adjacent legs is less those 15 degrees, the target vehicle driver is more able to see an intersection disturbance and needs less APRT, reducing the risk of a collision with the subject vehicle.

Instead of using a single variable to represent sight distance restrictions, this study used four geometric variables to represent obstruction of drivers' vision:

- The presence of a commercial sign or unusual structure at the intersection corner;
- The presence of elevated structures;
- The presence of approach curvature; and
- The presence of a central road median.

This study explored the microscopic detail of each element that obstructs driver vision near an intersection. In Toronto, intersections where there are poorly designed or positioned commercial signs or unusual structures (roadside corner obstruction variable) experience a high frequency of turning accidents. Obstructions at the corner restrict driver vision and increase the time required to decide whether to stop or go as the signals change. Sight-distance restriction variable positive sign implies that vision restriction could also occur due to horizontal or vertical curvature across the intersection.

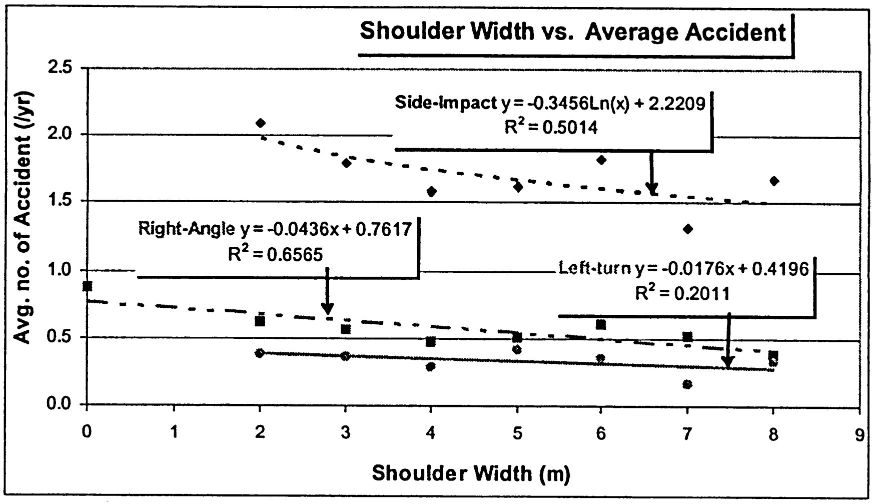
The positive sign obtained in this study for the relevant variable confirms similar results obtained by Poch and Mannering (1996). Poch and Mannering hypothesized that a vision restriction created by an object on the median would be realized when the largest identifiable gap in the main approach traffic is not adequate to provide the right-turning vehicle time to identify the gap and complete the maneuver. Similar principles could be applied to a subject vehicle needing to detect the existence of a target vehicle. Due to land resource constraints in Toronto, most of the elevated expressways are built over urban streets. If an elevated road covers an intersection, the darkness delays the perception of through vehicles in the intersection and hence increases the likelihood of right-angle accident frequency.

The existence of driveways near an intersection approach creates disturbances that affect safety positively for the target vehicle driver. This is because the unexpected emergence of vehicles from driveways near an intersection causes the left lane through traffic vehicle driver to perceive the position of the subject vehicle. Turing crashes, for example left-turn and right-turning crashes, were greatly influenced by the existence of driveways increasing risk by 11% and 15% respectively.

5.4.6 The Effect of Road-Side and Street User Characteristic Variables

The objective of exploring road-side objects and intersection user (e.g. pedestrian, bicycle) characteristics is to provide deeper insight into significant factors that affect side impact crash risk at a signalized intersection. The estimation results demonstrate some surprising disagreements with the usual view that certain road-side objects (i.e. number of trees, speed limit, existence of transit facilities near intersection approach) have a positive influence on single vehicle crash safety.

Figure 5-12: The Effect of Shoulder Width on Side Impact Crashes



Ivan et al. (1999) found that shoulder width was associated with a reduction in single-vehicle, "fixed object" crashes only. They are also associated with a statistically significant increase in total crashes, with an increase in multiple-vehicle crashes offsetting safety gains achieved through a reduction in fixed-object crashes. However, the authors' comment on shoulder width is troubling. Figure 5-12 shows that the total number of side impact and right-angle crashes decrease with an increase in right shoulder width (both near and far side of intersection approach). The decrease is not relevant for left-turn crashes. The negative sign in the model estimation results supports the expectation of that safety would increase with increased shoulder width.

On a similar note, wider shoulders imply more pedestrian volume, which reduces driver speed and decreases the likelihood of side-impact crashes, especially in an urban environment (see Figure 5-13). In this regard, right-angle crashes are not significant because pedestrian activities and the distance of through lane from the shoulder do not seem to affect right- angle crashes.

Figure 5-13: The Effect of Pedestrian Volume on Side Impact Crashes

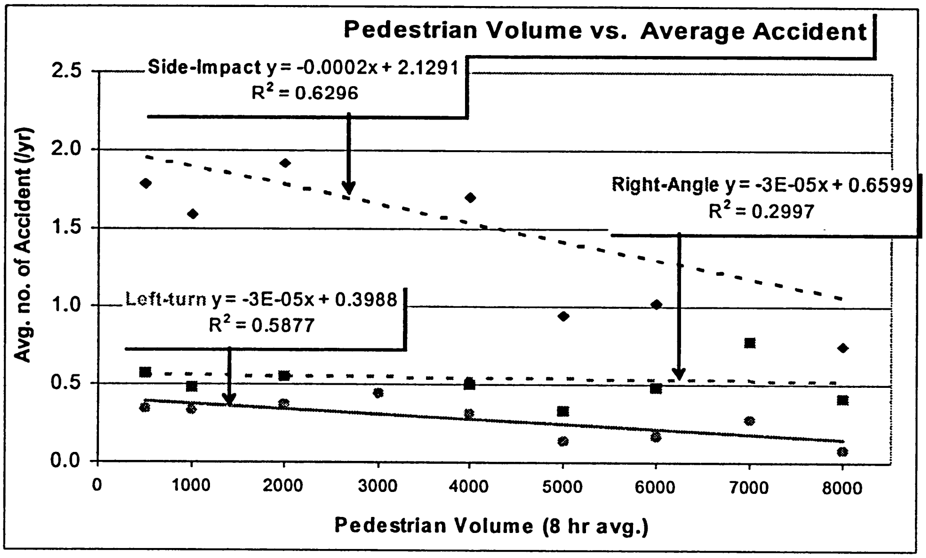


Figure 5-14: The Effect of Total Bicycle Volume on Side Impact Crashes

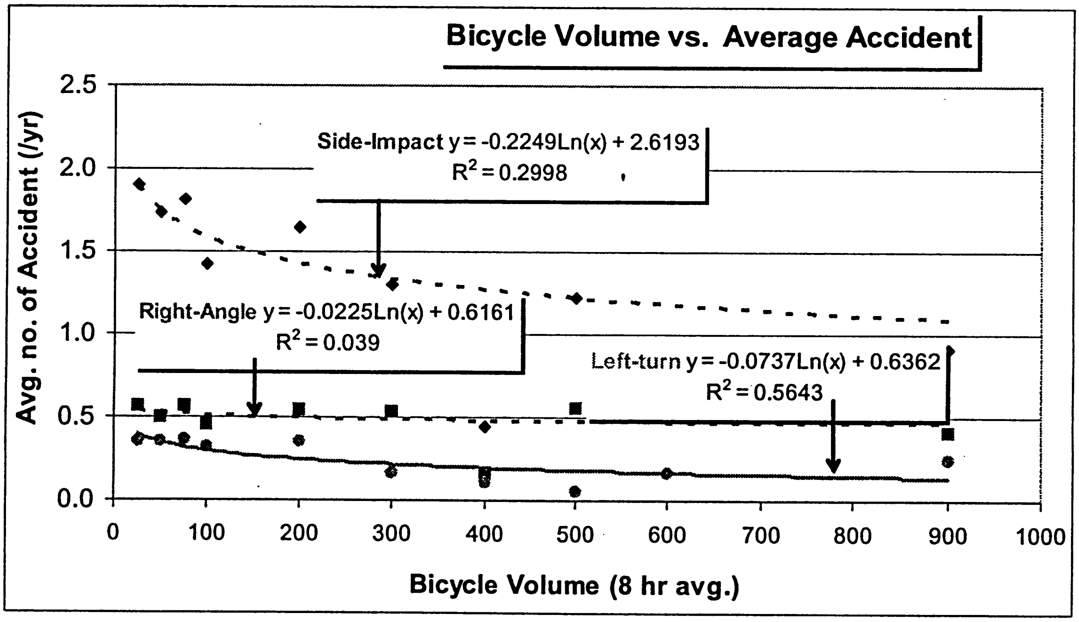
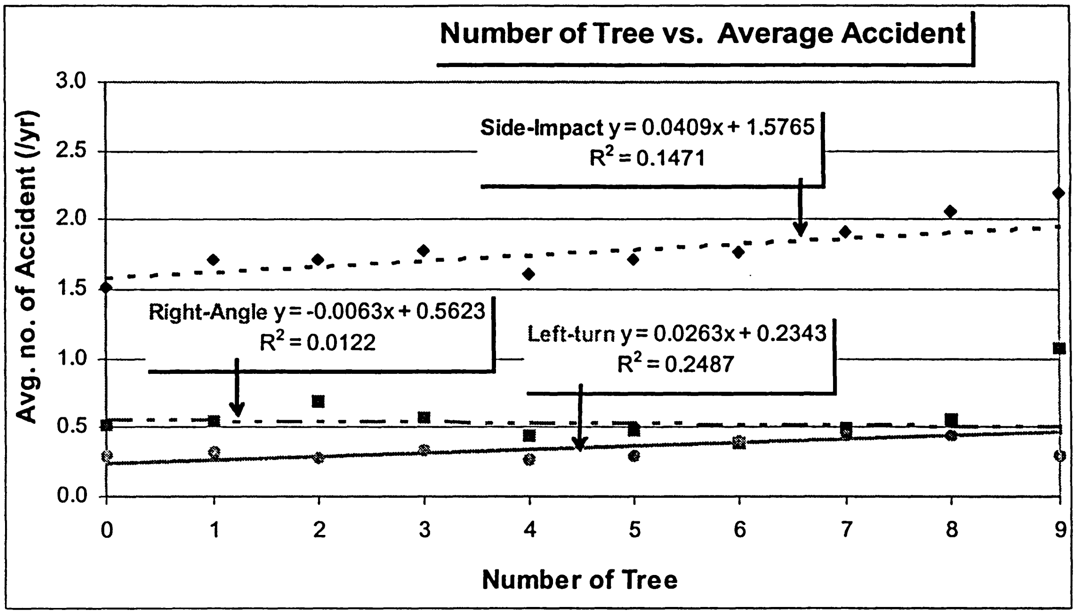


Figure 5-15: The Effect of the Number of Trees (Both Side) on Side Impact Crashes



Similar conclusions can be made regarding the effects of bicycle volume on side impact crashes. The presence of higher bicycle activities to the right or the left lane forces a turning driver to take extra precautions and to give right-of-way to the other intersection users.

The presence of trees (on the near and far side of the intersection approach, but not at the corner) in urban areas is associated with a decrease in the probability of a two-vehicle crash occurring at a signalized intersection. The presence of trees at the corner of an intersection is responsible for an increase in the number of right-turn crashes. Corner tress obstruct the view of right-turning drivers, and increase the perception and reaction time needed to search for gap while checking pedestrian, bicycle and other road-side activities. Lee and Mannering (1999) examined similar factors and found that the presence of trees and other features near an intersection is associated with a statistically significant decrease in number of urban run-off crashes. This study results supports similar phenomena for two-vehicle side-impact intersection crashes.

5.9 CHAPTER SUMMARY

Three types of side impact crash risk models were successfully developed using the new approach described in Chapter 4. The statistical results shown in this chapter refer to the estimation statistics and their corresponding variables. The explanations of the variables largely coincide with the results of past studies. The concepts and hypothesis assumed in Chapter 4 are shown to be satisfactory as all the selected predictor variables are significant in the estimation process. The logic of the results, the residual plot and the goodness-of-fit tests show that the model developed in this study performed well for four types of side impact crash risk at signalized intersection. The model developed in this study offers a new method for estimating side impact crashes at intersections and is consistent with the crash prediction models developed by safety researchers during the last two decades.

CHAPTER 6

SUMMARY AND CONCLUSIONS

6. 1 PURPOSE OF THE STUDY

The objective of the study was to develop a microscopic accident model that would improve our understanding of the detailed mechanism underlying the occurrence of three major types (four models including one for total side impact crashes) of side impact accident at signalized intersections. The study developed a negative binomial model to investigate a "proportionate driver risk" modeling using an approach-based concept. The investigation estimated accident probability as distinct from accident frequency. The study's purpose was to ascertain the critical reasons for side impact accidents to aid in devising countermeasures in safety management.

Accident risk was investigated by developing a set of explanatory factors for each driver involved in a two vehicle side impact accident. The explanatory factors were based on the microscopic elements that explain driver behaviour and actions. The factors were developed to take into account the very different issues affecting the drivers entering an intersection from different approach legs. An understanding at the microscopic level is important to improving our understanding of the cause of side impact accidents, the most frequent and dangerous type of crash at signalized intersections.

The study was conducted using six years of data (1999 to 2004) from a sample of 70 signalized intersections in Toronto.

6.2 SUMMARY OF THE STUDY

Separate sets of explanatory factors for the driver on different approaches driver were incorporated into the model to develop effective measures to improve intersection traffic safety. The identification of the microscopic elements that explain driver behaviour and actions along with their distinctly dissimilar association to major side-impact crashes can be used to further understand the cause of the most dangerous crashes, both in total and of specific types.

This thesis was presented in four major parts

1. Setting up the database to reveal important characteristics of side-impact crashes;
2. Development of the concepts that provide the foundation for estimating crash risk by considering their microscopic details that account for accident occurrence;
3. Selection of the important elements and explanatory factors (based on engineering judgment, an understanding of the logic of the accident occurrence mechanism, and an extensive literature review); and
4. Development of a crash risk model to establish the relationship between explanatory variables and their association with major types of side impact crashes.

The database was built using the SYSTAT and SPSS software packages. Important issues in the data collection included: 1) selecting useful variables for data analysis; 2) using a classification of side-impact accidents to select or exclude crashes from the database;, 3) aggregating the crashes that occurred on a certain approach; 4) obtaining and collecting data from various sources, including on-site surveys; and 5) discarding intersections for which the information available proved inadequate for the needs of the model development.

Building the concepts underlying the development of models was the most difficult part of this research. The development of the fundamental concepts was based on several important considerations: 1) an in-depth search for knowledge on the factors that might affect driver psychology as a driver crosses a signalized intersection, and possible quantitative measures to allow these factors to be included in the crash risk model; 2) detailed consideration of a driver's perception, reaction and response time, talking into account the visual information presented to the driver, and how human processing capacity varies in a demanding situation like an intersection; 3) a detailed investigation of side impact crash data; and 4) an understanding of the microscopic detail underlying the accident occurrence mechanism for side-impact accidents and its relevance to the interpretation of police accident report used in this study.

In-depth data analysis and visualization techniques were explored to capture the true nature in side impact crashes. Side-impacts occur at a signalized intersection when two different vehicles entering from different approaches collide with each other. The two drivers approaching from the two legs of the intersection experience two completely separate sets of 'disturbance and perception-reaction times', resulting in different probabilities of crash risk. The research identified the important factors keeping in mind the basic logic of accident occurrence.

In the modeling phase of the study, crash risk models were developed to estimate the risk of various categories of side impact crash: total side impact crashes; right-angle crashes; and left-turn and right-turn crashes. The regression parameters were estimated using the maximum likelihood method in the SYSTAT programming module. The goodness-of-fit for the models was evaluated using a likelihood ratio test, CURE plots, and a residual analysis technique.

6.3 RESEARCH FINDINGS AND CONCLUSIONS

Several interesting insights were obtained during the course of the data analysis. The intersection crash occurrence mechanism was explored in detail to gain a deeper understanding of the mechanism and of crash risk model development.

The microscopic approach to understanding intersection accidents showed that the vehicles involved in a side impact accident have different risk probabilities that are affected by different sets of variables. The average risk probability of the bullet (or main) vehicle was higher than the average risk probability of the target vehicle. This finding supports the hypothesis that the vehicles entering an intersection from different approaches do not have the same risk of a side impact crash.

The underlying mechanism of side-impact crashes was uncovered using two separate factors that affect the risk of different vehicle driver. The model suggests that the subject vehicle has a higher risk of an accident due to it's failure to assess the amount of "disturbance" while approaching an intersection. The reason for this failure could be that the driver does not have the human capacity to handle so much information in so short a time, or the driver may be deliberately disregarding the traffic rules. When the main vehicle becomes an "obstacle" for the cross-street vehicle, the available perception and reaction time is the only way to avoid an accident. If the perception and reaction time are inadequate, a side impact accident is the inevitable outcome.

A close examination of the effect of the flows entering an intersection showed that side impact accident risk does not seem to depend strongly on the larger of the traffic flows. This finding is contrary to the indication from traffic flow only models that there will be a very small number of collisions when traffic volumes are extremely low and therefore that no special safety features are required. In reality, safety managers should not overlook intersections where traffic volumes are low and collision frequency is low and minimum safety features should always be included in an intersection design phase.

Using the crash frequency history of four side-impact crash models, a negative binomial model was developed to relate a set of 'explanatory' variables which included flow, regulation and design characteristics of the intersections. The statistically significant relationships which emerged from the study's analysis are of an associative character, and the interpretation of individual results must rest on professional judgment as to whether the associations indeed have a causative basis.

The results of the estimation of the four side impact accident models support the conclusions of past literature that the negative binomial formulation is superior to the more restricted Poisson regression. This study attempted to add to the literature on modeling by investigating new dimensions for modeling total, side impact, right-angle angle, left-turn and right-turn accidents including the effects of driver, traffic and geometric related variables in accident involvement.

The study's results suggest that poor signal design coupled with complex geometric design is a principal contributor to side impact accident risk at signalized intersections. More than 15 factors were found to be associated with side impact intersection crashes. The most significant factors were traffic regulation related variables such as presence of an exclusive left-turn lane, a separate left-turn signal phase, a right-turn ban, two phase signals, the existence of two or more left-turn lanes, and the existence two or more sharing lanes. A short green time on the local street was associated with reduced right-angle accident frequency, perhaps because it forced drivers to check conditions on the major street more carefully.

This study also explored issues relating to factors pertaining to human psychology. Statistically significant factors such as roadside variables, vehicle characteristics, and visual information might be useful in identifying environmentally friendly and low-cost treatments that will help to reduce side impact accidents at signalized intersections in urban areas.

6.4 STUDY LIMITATIONS

A number of limitations were noted during the study:

- A proper searching method is needed to better determine the explanatory variables. Although a literature review and preliminary t-tests were conducted during the model's development, it was difficult to establish the most relevant variables for each type of accident;
- Some important data were difficult or impossible to obtain. For example, the data on traffic signal type and signal change history were inadequate, but these data are very important for right-angle accidents. The absence of these variables required the consideration of alternative variables to represent these effects; and
- There was no literature available to verify the reasonableness of the models for estimating the crash risk of different drivers while approaching an intersection.

6.5 RECOMMENDATIONS FOR FUTURE RESEARCH

The study developed four crash risk models to predict the probability of total side impact, right-angle, and left-turn and right-turn crashes. Our understanding of the fundamental concepts and microscopic elements involved in side impact can be expanded in several directions:

- Depending on the availability of data for the explanatory variables, this model, which was developed for Toronto data, may be transferable to other jurisdictions; this transferability needs to be tested;
- A microscopic model is a pre-requisite for the application of intelligent transport systems (ITS). This study could provide an important basis for before and after studies that analyze the effectiveness of these types of

safety improvements. For example,, the approach presented here can be used make a thorough evaluation of the safety impacts of variable-message/speed-limit signs, in-vehicle units, and other ITS technologies. Such evaluation will serve as a basis for justifying future ITS expenditures;

- The knowledge obtained in this study can be used at the project development and construction stages of new intersections and for retro-fitting intersections. The identification and correction of elements that increase the number of crashes at intersections can most easily be accomplished in the plan review stages.

In general, the study's model formulation could also be used for other types of intersection accidents, and for other types of intersections. In addition, the microscopic approach presented in this study could provide an important theoretical foundation for exploring the effects of innovative measures such as intelligent traffic safety warning systems, and safety support systems for improving side impact collision safety at intersections.

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APPENDIX A

IMPORTANCE OF INTERSECTION ACCIDENT IN ONTARIO AND CITY OF TORONTO

APPENDIX A

Figure A-1: Accident Trend at Intersection in Ontario (ORSAR, 1993~2003)

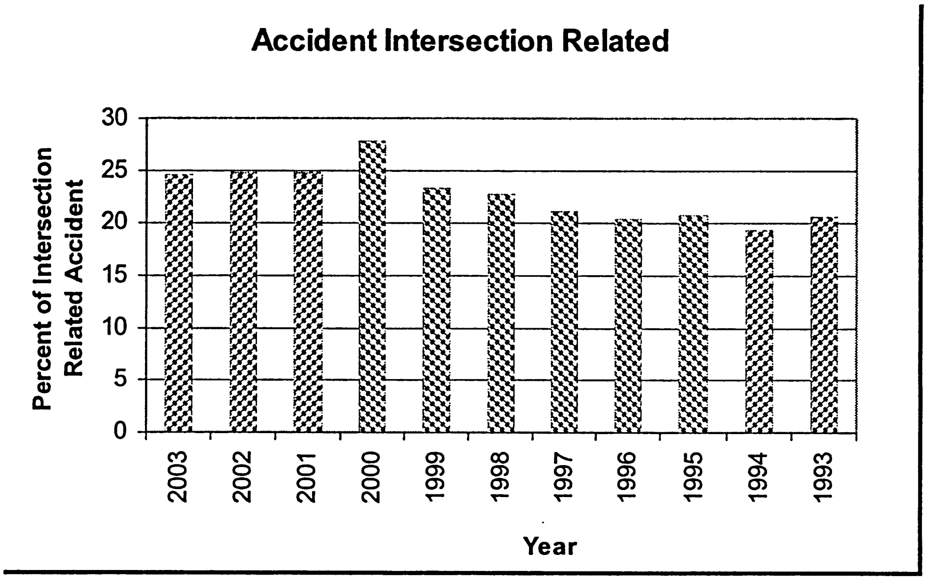


Figure A-2: Intersection Related Accident Trend in Ontario (ORSAR, 1993~2003)

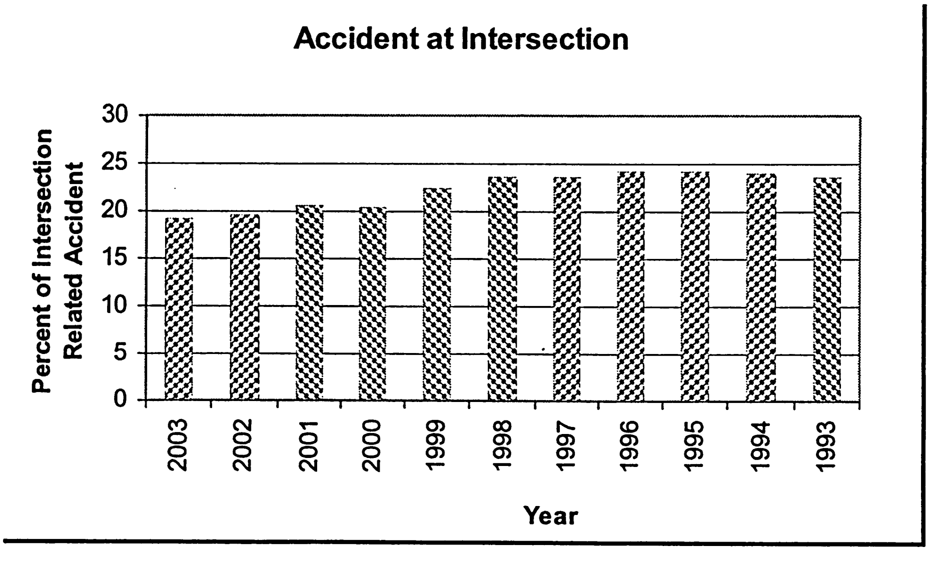


Figure A-3: Intersection Accident in Ontario (ORSAR, 1993~2003)

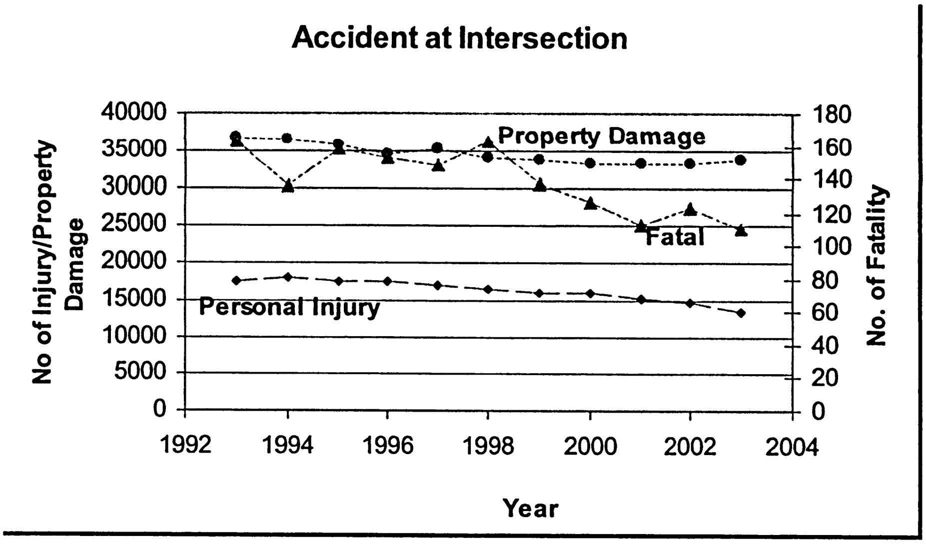


Figure A-4: Intersection Related Accident in Ontario (ORSAR, 1993~2003)

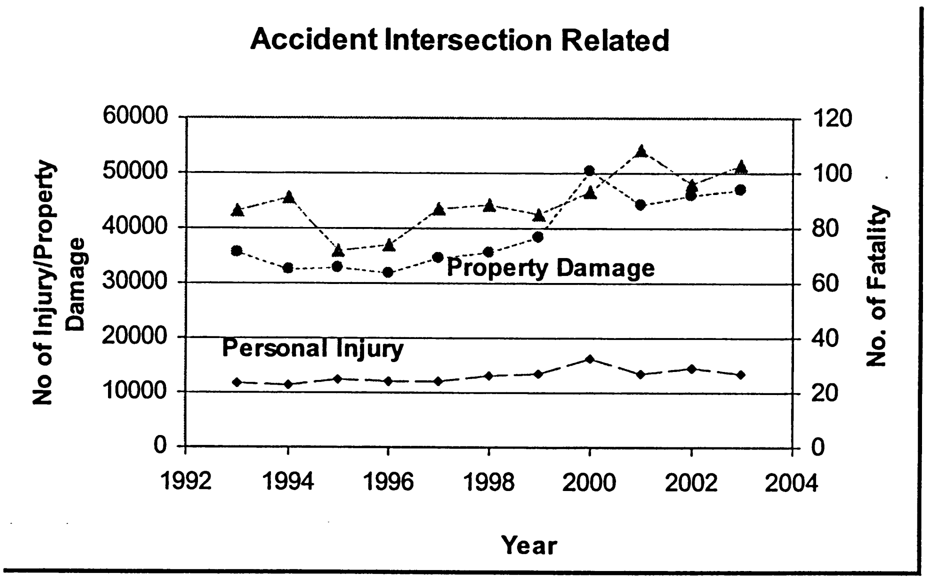


Figure A-5: Major Intersection Accident Trend in Ontario (ORSAR, 1993~2003)

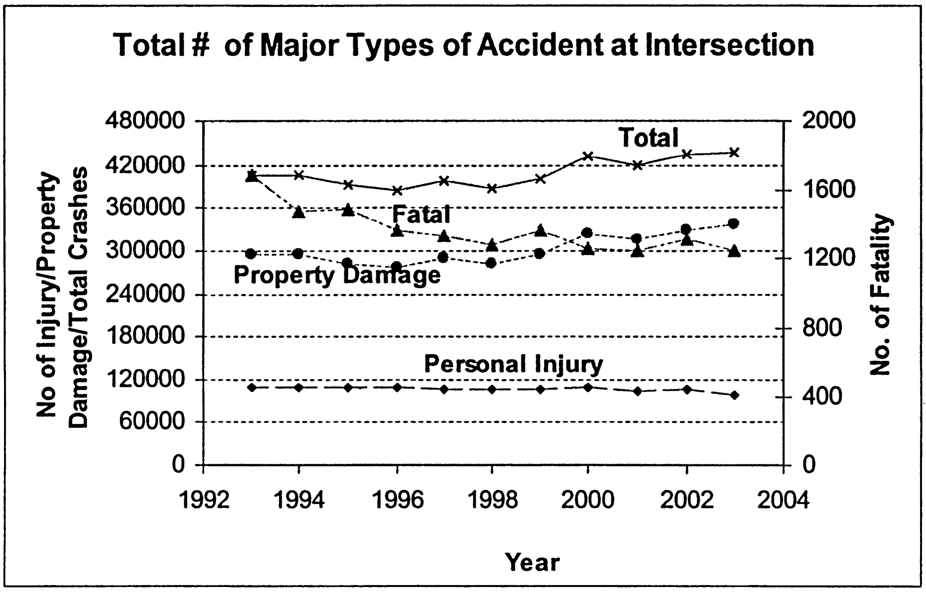


Figure A-6: Fatality Involve in Major Intersection Accident in Ontario (ORSAR, 1993~2003)

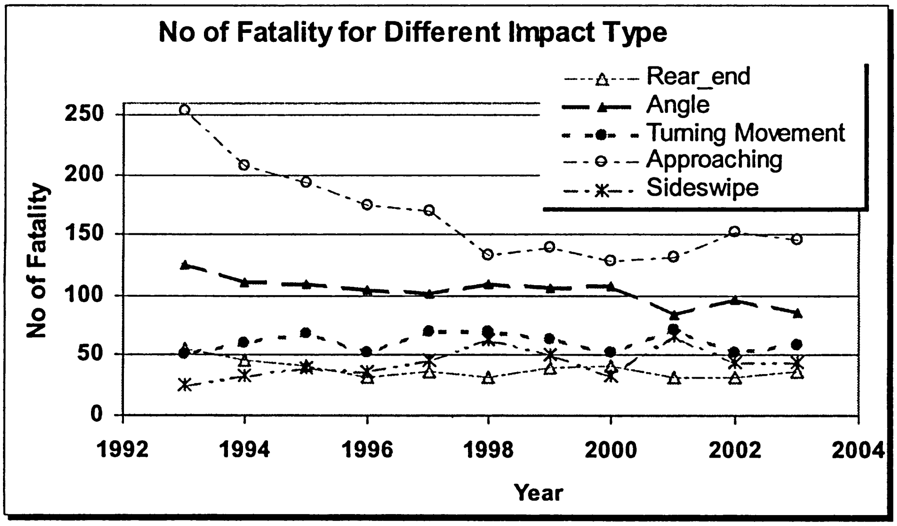


Figure A-7: Personal Injury Involve in Major Intersection Accident in Ontario (ORSAR, 1993~2003)

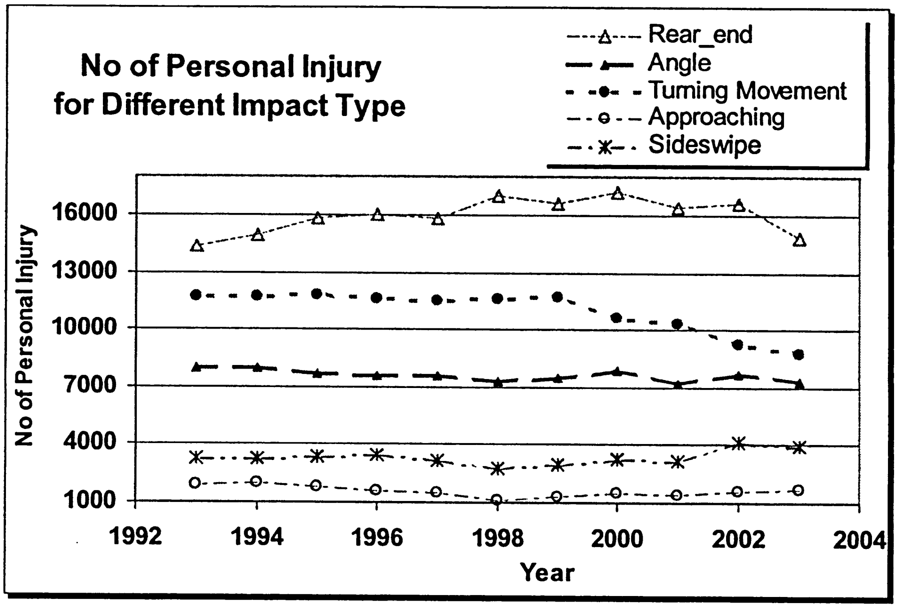


Figure A-8: Property Damage Involve in Major Intersection Accident in Ontario (ORSAR, 1993~2003)

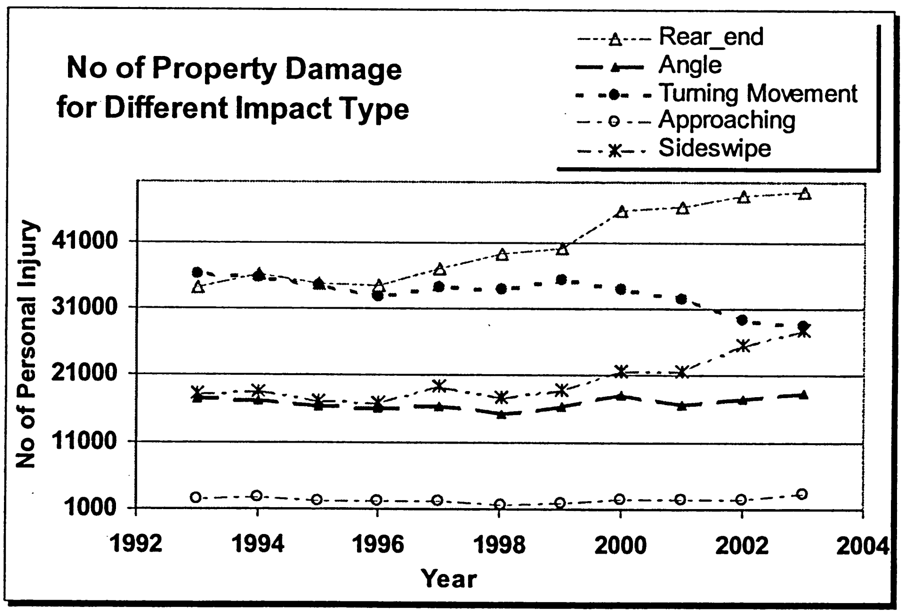


Figure A-9: Fatality, Personal Injury and Property Damage Involve in Major Intersection Angle Accident in Ontario (ORSAR, 1993~2003)

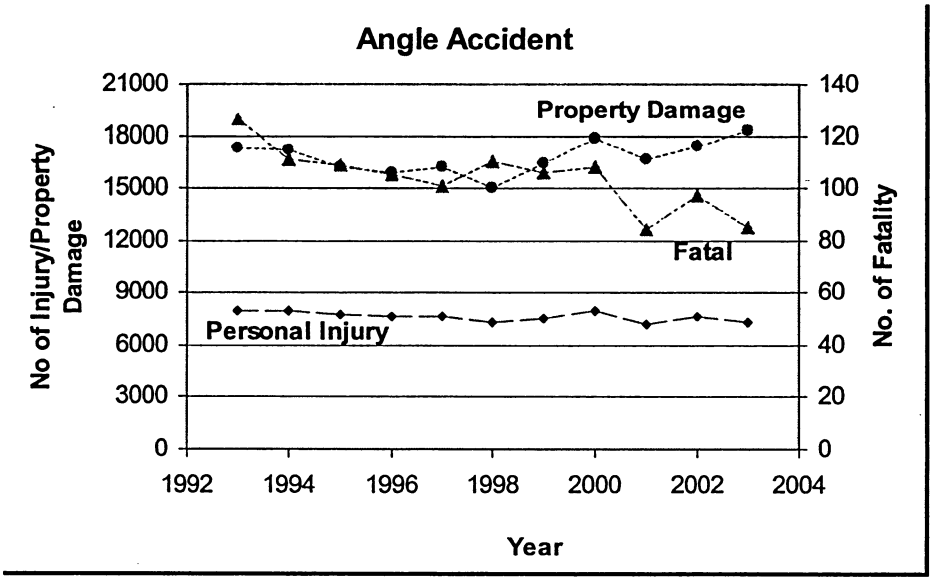


Figure A-10: Fatality, Personal Injury and Property Damage Involve in Major Intersection Turning Accident in Ontario (ORSAR, 1993~2003)

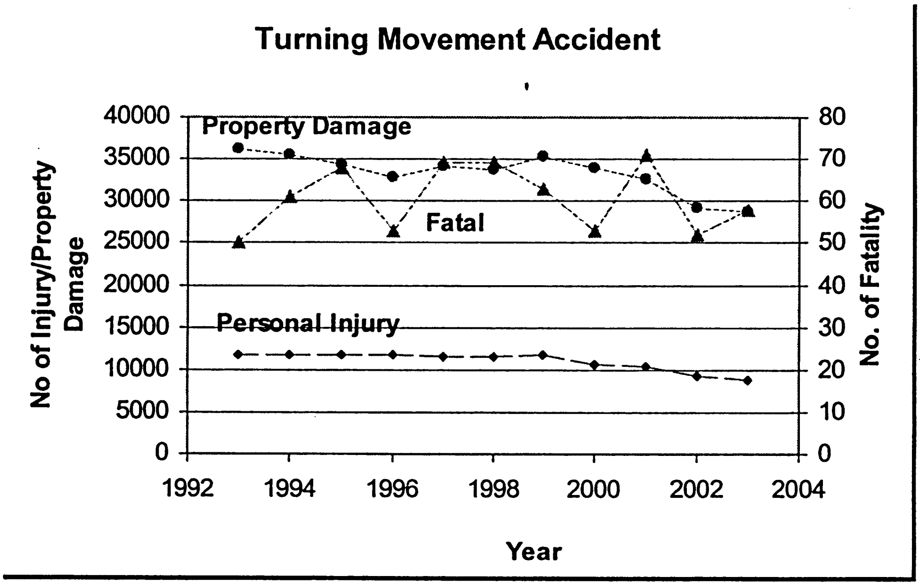


Figure A-11: Fatality Involve in Major Type of Vehicle Maneuver that Lead to Intersection Accident in Ontario (ORSAR, 1993~2003)

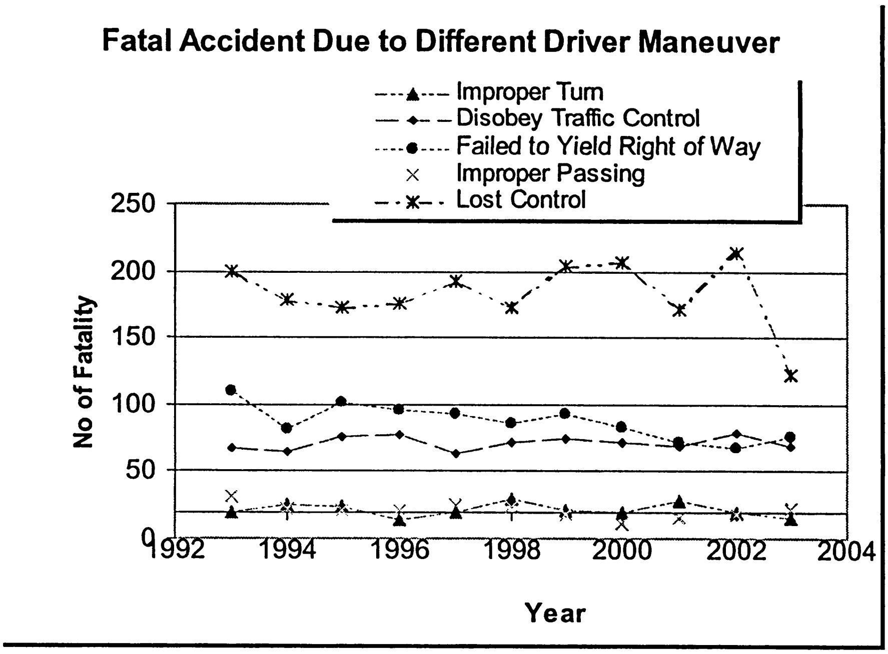
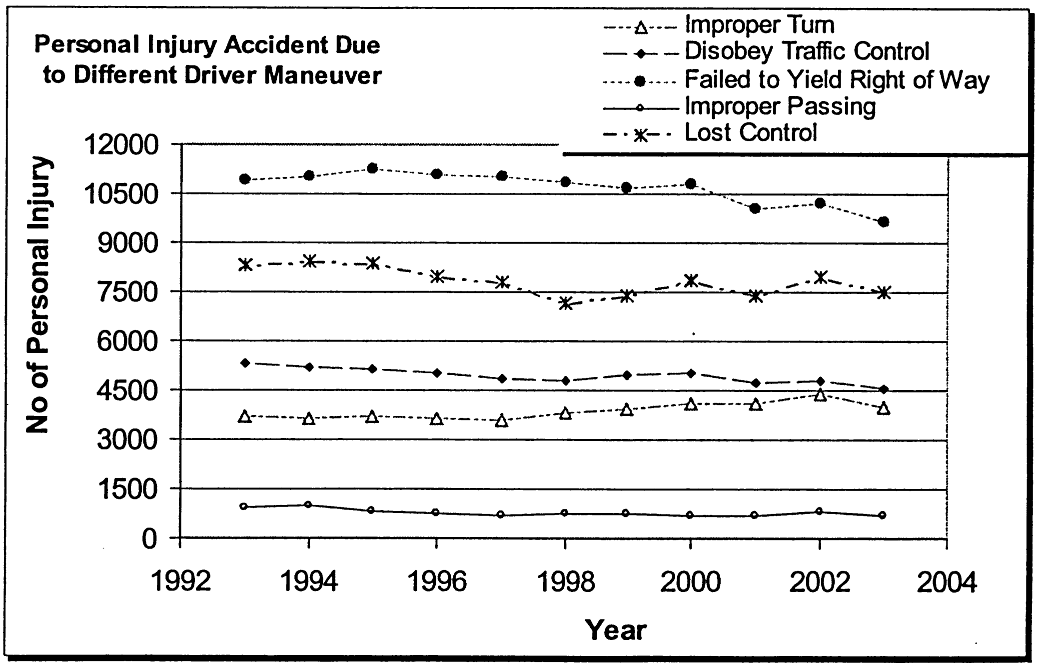


Figure A-12: Personal Injury Involve in Major Type of Vehicle Maneuver that Lead to Intersection Accident in Ontario (ORSAR, 1993~2003)



APPENDIX B

DATA COLLECTION AND ANALYSIS FRAMEWORK

Table B-1: Selected intersection and major types of side-impact accident counts in City of Toronto (from 1999~2004)

							Side-Impact		Right-Angle		Left-turn	
Intersection #	St.1 Name	St.1 Type	St.2 Name	St.2 Type	Direction	Total Accident	Side Impact Total	Percent of Total Accident	Right-Angle Total	Percent of Total Side Impact	Left-turn Total	Percent of Total Side Impact
1	Church	St	Dundas	St	Two-way	104	46	44.2	16	34.8	10	21.7
2	Bathurst	St	Dupont	St	Two-way	159	65	40.9	22	33.8	12	18.5
3	Dundas	St	University	Ave	Two-way	100	24	24.0	12	50.0	3	12.5
4	College	St	University	Ave	Two-way	110	25	22.7	10	40.0	5	20.0
5	Dufferin	St	Glencairn	Ave	Two-way	87	43	49.4	16	37.2	5	11.6
6	Gerrard	St	Jarvis	St	Two-way	163	69	42.3	10	14.5	26	37.7
7	Bathurst	St	Glencairn	Ave	Two-way	71	16	22.5	2	12.5	4	25.0
8	Dundas	St	Jarvis	St	Two-way	141	67	47.5	39	58.2	12	17.9
9	Bathurst	St	St. Clair	Ave	Two-way	249	54	21.7	12	22.2	12	22.2
10	Bathurst	St	Habord	Ave	Two-way	153	56	36.6	19	33.9	14	25.0
11	Richmond	St	University	Ave	Oneway	175	98	56.0	64	65.3	10	10.2
12	Broadview	St	Danforth	Ave	Two-way	154	33	21.4	3	9.1	12	36.4
13	Adelaide	St	Bay	St	Oneway	104	36	34.6	11	30.6	8	22.2
14	Jarvis	St	Wellesley	St	Two-way	100	36	36.0	5	13.9	9	25.0
15	Bloor	St	Islington	Ave	Two-way	168	41	24.4	8	19.5	12	29.3
16	Bloor	St	Keele	St	Two-way	149	50	33.6	7	14.0	11	22.0
17	Adelaide	St	Simcoe	St	Oneway	56	32	57.1	21	65.6	2	6.3
18	Logan	St	Queen	St	Two-way	53	28	52.8	17	60.7	8	28.6
19	Bay	St	King	St	Two-way	50	23	46.0	14	60.9	0	0.0
20	Jarvis	St	The Esplanade	Ave	Two-way	38	14	36.8	5	35.7	5	35.7
21	Don Mills	Rd	Gateway	Blvd	Two-way	166	48	28.9	7	14.6	16	33.3
22	Queen	St	River	St	Two-way	41	20	48.8	11	55.0	2	10.0
23	King	St	Spadina	Ave	Two-way	171	49	28.7	12	24.5	3	6.1
24	Dupont	St	Spadina	Rd	Two-way	96	32	33.3	12	37.5	4	12.5
25	King	St	York	St	Oneway	75	28	37.3	15	53.6	2	7.1
26	Blue Jays	Way	Front	St	Two-way	80	29	36.3	5	17.2	9	31.0
27	Lake Shore	Blvd	Yonge	St	Oneway	192	55	28.6	35	63.6	2	3.6
28	Belmont	St	Yonge	St	Two-way	70	22	31.4	4	18.2	8	36.4
29	Parliament	St	Richmond	St	Oneway	92	58	63.0	28	48.3	3	5.2
30	Richmond	St	Victoria	Ave	Oneway	65	21	32.3	9	42.9	5	23.8
31	Dupont	St	Lansdowne	Ave	Two-way	179	82	45.8	24	29.3	11	13.4
32	Coxwell	Ave	Dundas	St	Two-way	62	26	41.9	12	46.2	4	15.4
33	University	Ave	Wellington	St	Oneway	97	55	56.7	19	34.5	10	18.2
34	Danforth	Ave	Woodbine	Ave	Two-way	136	34	25.0	2	5.9	7	20.6
35	Gerrard	St	Victoria Park	Ave	Two-way	96	32	33.3	7	21.9	11	34.4
36	College	St	Huron	St	Oneway	24	9	37.5	4	44.4	0	0.0
38	Church	St	Gould	St	Two-way	26	4	15.4	0	0.0	0	0.0
39	Coxwell	Ave	Gerrard	St	Two-way	88	36	40.9	8	22.2	10	27.8
40	Don Mills	Rd	Eglinton	Ave	Two-way	297	93	31.3	12	12.9	35	37.6

41	Front	St	Jarvis	St	Two-way	77	24	31.2	11	45.8	3	12.5
							Side-Impact		**Right-Angle**		**Left-turn**	
Intersection #	St.1 Name	St.1 Type	St.2 Name	St.2 Type	Direction	Total Accident	Side Impact Total	Percent of Total Accident	Right-Angle Total	Percent of Total Side Impact	Left-turn Total	Percent of Total Side Impact
42	Adelaide	St	Yonge	St	Oneway	140	63	45.0	21	33.3	13	20.6
43	Dundas	St	Greenwood	Ave	Two-way	59	24	40.7	8	33.3	6	25.0
44	Bay	St	Queen	St	Two-way	95	21	22.1	5	23.8	3	14.3
45	Adelaide	St	Sherbourne	St	Oneway	73	30	41.1	12	40.0	4	13.3
46	College	St	Ossington	Ave	Two-way	115	36	31.3	7	19.4	5	13.9
47	Bathurst	St	Dusdas	St	Two-way	188	45	23.9	15	33.3	12	26.7
48	College	St	Dufferin	St	Two-way	131	48	36.6	19	39.6	10	20.8
49	Dufferin	St	Dundas	St	Two-way	102	28	27.5	5	17.9	7	25.0
50	Bathurst	St	Queen	St	Two-way	165	41	24.8	14	34.1	6	14.6
51	Dundas	St	Ossington	Ave	Two-way	105	26	24.8	7	26.9	5	19.2
52	Bloor	St	Ossington	Ave	Two-way	127	42	33.1	14	33.3	7	16.7
53	Dupont	St	Ossington	Ave	Two-way	155	31	20.0	7	22.6	7	22.6
54	Bloor	St	Dufferin	St	Two-way	234	67	28.6	12	17.9	14	20.9
55	Davenport	Rd	Dufferin	St	Two-way	172	56	32.6	11	19.6	11	19.6
56	Dufferin	St	St.Clair	Ave	Two-way	216	57	26.4	12	21.1	13	22.8
57	Dundas	St	Lansdowne	Ave	Two-way	110	37	33.6	17	45.9	6	16.2
58	Bloor	St	Lansdowne	Ave	Two-way	112	36	32.1	12	33.3	5	13.9
59	Bloor	St	Dundas	Ave	Two-way	219	69	31.5	31	44.9	12	17.4
60	Christie	St	Dupont	St	Two-way	87	24	27.6	4	16.7	3	12.5
61	Bathurst	St	Bloor	St	Two-way	168	39	23.2	8	20.5	5	12.8
62	Avenue	Rd	St.Clair	Ave	Two-way	158	48	30.4	10	20.8	10	20.8
63	St.Clair	Ave	Yonge	St	Two-way	158	50	31.6	10	20.0	10	20.0
64	Avenue	Rd	Eglinton	Ave	Two-way	186	52	28.0	17	32.7	5	9.6
65	Eglinton	Ave	Yonge	St	Two-way	207	32	15.5	12	37.5	10	31.3
66	Bayview	Ave	Eglinton	Ave	Two-way	237	63	26.6	15	23.8	12	19.0
67	Broadview	Ave	Dundas	St	Two-way	88	29	33.0	8	27.6	10	34.5
68	Broadview	Ave	Gerrard	St	Two-way	102	20	19.6	4	20.0	8	40.0
69	Carlaw	Ave	Gerrard	St	Two-way	82	34	41.5	23	67.6	7	20.6
70	Danforth	Ave	Pape	Ave	Two-way	175	43	24.6	7	16.3	11	25.6
71	Danforth	Ave	Greenwood	Ave	Two-way	111	26	23.4	12	46.2	4	15.4

Figure B-1: Data collection area in Toronto Metropolitan City (Maps Created from Yahoo Maps© system)

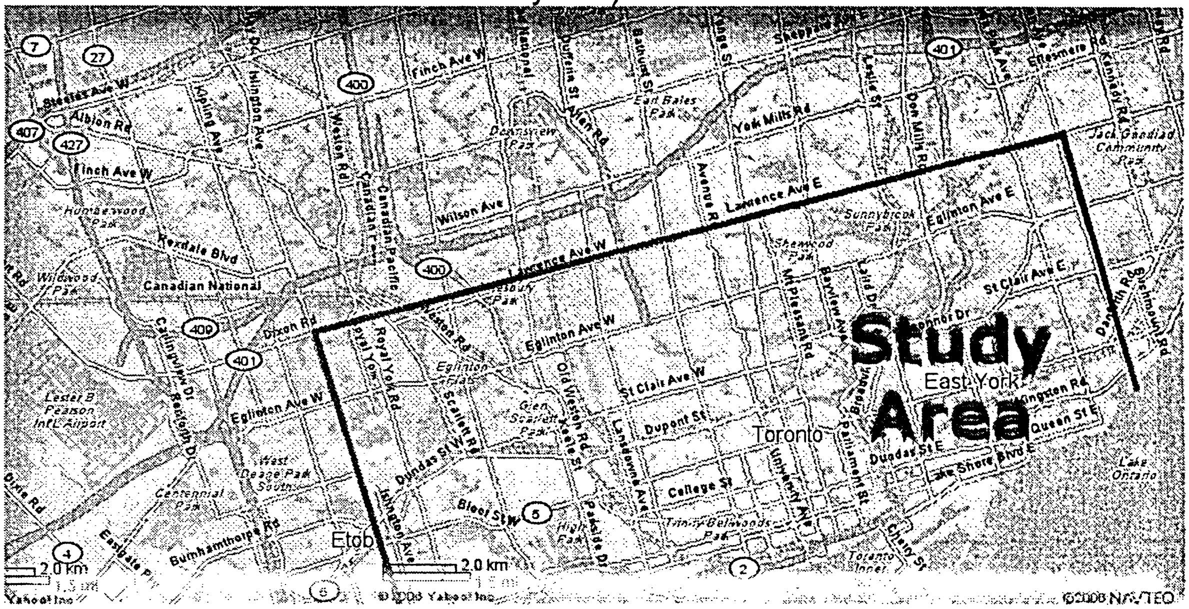


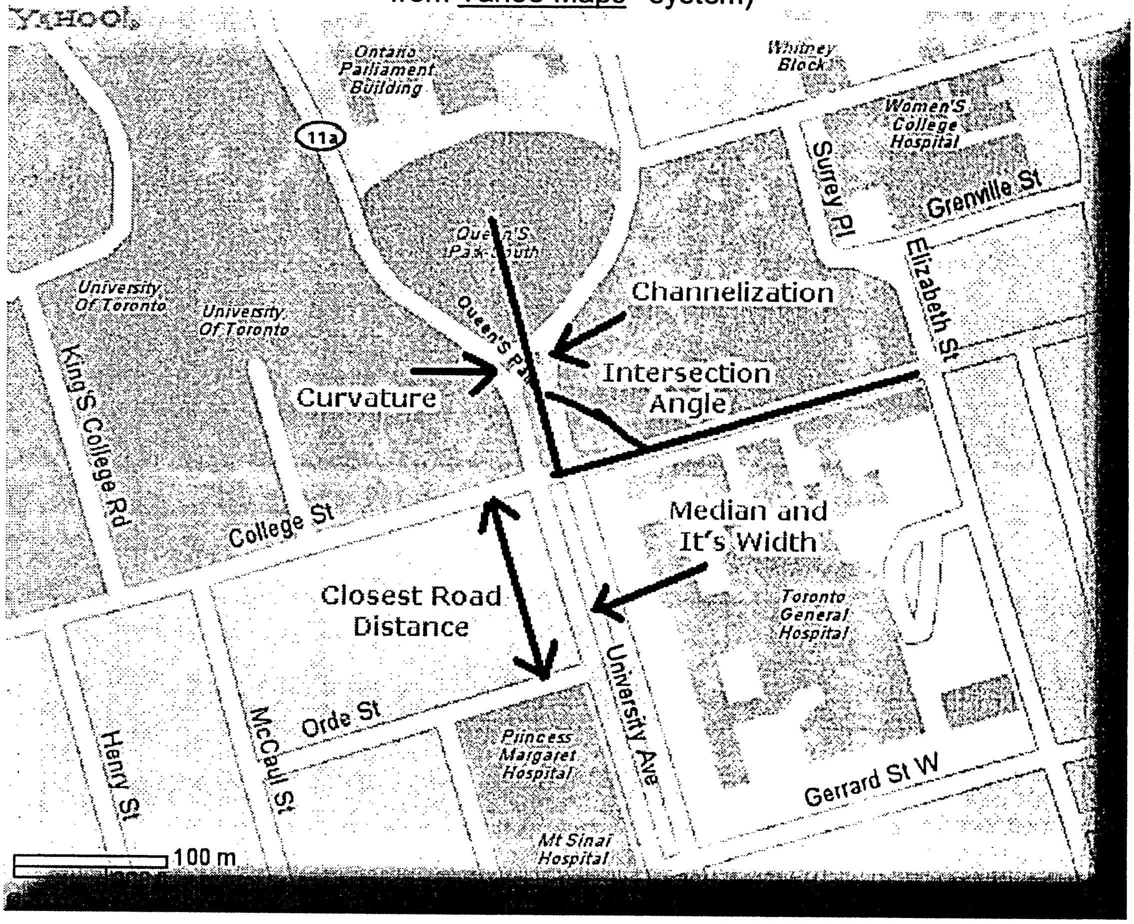
Table B-2: Types of collected data and their sources

Data Types	Source	Colleted Data
Accident Data	City of Toronto, Traffic Safety Bureau	❑ Yearly Accident database from GIS systems ❑ Accident Police reports and descriptions ❑ Broad classification of intersection accident types
Demand Data	City of Toronto, Traffic Volume Database	❑ Entry volumes (traffic entering the study area) ❑ Turning movements at intersections ❑ Bus stop locations, Bicycle lanes/paths, Crosswalks and other pedestrian facilities
Control Data	City of Toronto, Traffic Signal Division And Field Inspection	❑ Location and types of traffic control devices ❑ Field inspection to verify signal-timing ❑ No control, Yield signs, Stop signs ❑ Signals (pretimed, actuated, real-time traffic adaptive) ❑ Pedestrian signal and flashing timing ❑ Signal installation history and signal density
Geometric Data	Field Inspection	❑ Types of road – major, minor, arterial, collector or local ❑ Street name, direction, allowable traveling direction ❑ Number of lanes (right/left-turn exclusive/shared lane, transit lane, HOV lane, through shared/unshared lane, bike lane, lave merging/expansion data)) ❑ Road width, shoulder width, nearest building distance ❑ Existence of driveway/close road/elevated structure, , curvature, angle with adjacent approach, absolute displacement between the approach ❑ Designated turn lanes and their vehicle storage lengths ❑ Approach slope (positive or negative slope, reverse or adverse slope direction)

Continued to Next page

Data Types	Source	Colleted Data
Traffic Operations & Management Data	Field Inspection	❑ Lane restriction (partial or full restriction on U-turn, left and right turn), parking restriction and allowable data ❑ Warning data (incidents, lane drops, exits, etc.) ❑ Regulatory data (speed limits, variable speed limits, HOVs, lane channelizations, lane use) ❑ Information (guidance) data (dynamic message signs and roadside beacons) ❑ Other restriction (No standing, vendor restriction, snow route, two-way zone, school zone)
Road-side data	Field Inspection	❑ Adjacent building information (number of floor, type of building, building corner round or not) ❑ Street ornamentation data (Existence of fence, number of newsstand, post-box, electrical box, trash and telephone booth location, commercial sign board and other miscellaneous features) ❑ Number of tree (location, size of tree) ❑ Transit features (Transit stops, nearby station exit) ❑ Parking spot location and exits
Demand Data	City of Toronto Traffic Volume Database	❑ Entry volumes (traffic entering the study area) ❑ Turning movements at intersections ❑ Bus stop locations, Bicycle lanes/paths, Crosswalks and other pedestrian facilities
Background accident and transport Information	Transport Canada, ORSAR, Road Safety Vision, Statistics Canada	❑ Population and driver license information ❑ Accident trend, classification, intersection accident trend ❑ Fatality, injury and property damage information ❑ Accident causal trend information ❑ Road safety improvement target and future plan
Events/Scenarios Data	Field Inspection	❑ Work zones ❑ Parking activity in curb lane ❑ Blockages and incidents
Driver Behavior Data	Field Inspection and literature review	❑ Driver's aggressiveness (for minimum headway in car-following, gap acceptance for lane changing, response to yellow interval) ❑ Availability of (real-time) information for the driver.
Software and Related Information	Software Manual and literature review	❑ SAS, SPSS, Minitab and Systat code user manual ❑ Selection of independent and dependent variables ❑ Importance of different factors affecting side-impact accident ❑ Goodness-of-fit and analysis procedure ❑ Statistical distribution, tables, merits and demerits of distribution ❑ Other system parameters to run the model.
Vehicle Dimensions and Performance	Vehicle manufacturer, Government Standards and literature review	❑ Vehicle length of various car manufacturers used by Motor and Equipment Manufacturers Association (MEMA), FHWA, and the U.S. (EPA) ❑ Vehicle manufacturing information

Figure B-2: Sample of Data Collection from Intersection Aerial Maps (Maps Created from Yahoo Maps© system)



Sample of Basic Definition of Indicator Variables

Figure B-3: Summary of Collected Total Traffic Flow Data for 70 Signalized Intersections in City of Toronto (Average flows from1999 to 2004)

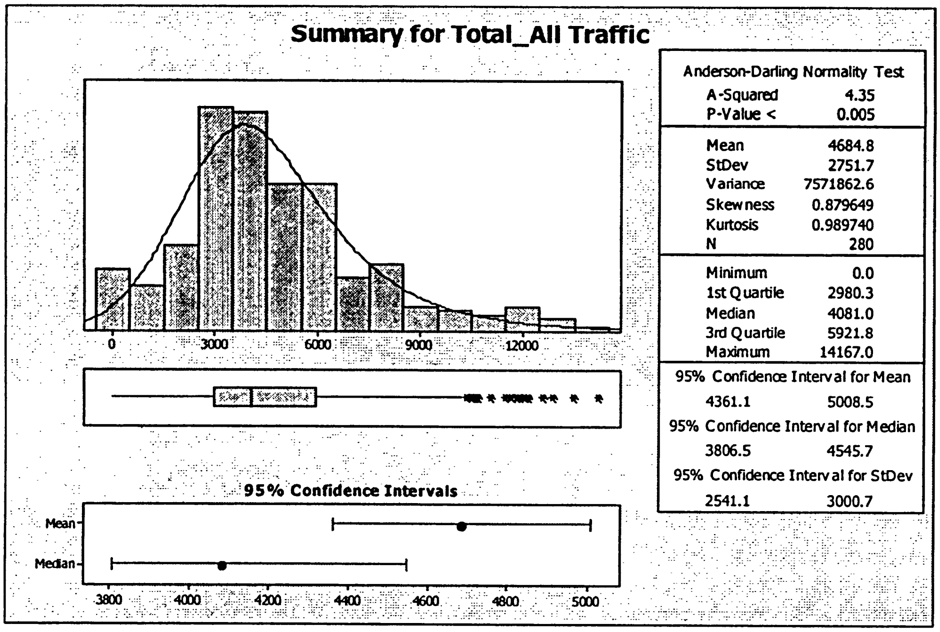


Figure B-4: Summary of Collected Through Traffic Flow Data for 70 Signalized Intersections in City of Toronto (Average flows from1999 to 2004)

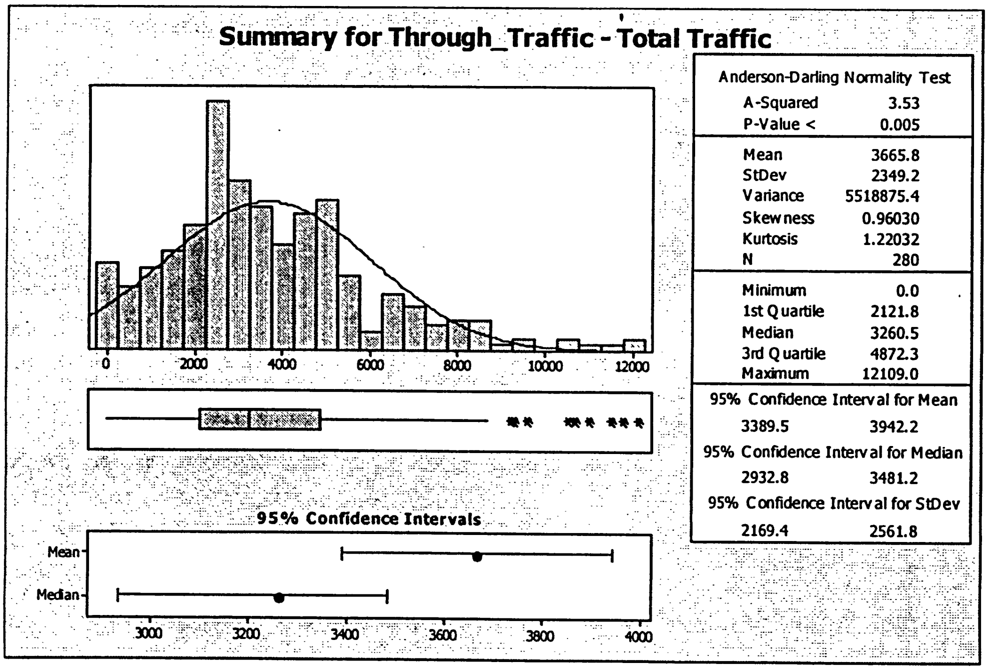


Figure B-5: Summary of Collected Left-turn Traffic Flow Data for 70 Signalized Intersections in City of Toronto (Average flows from1999 to 2004)

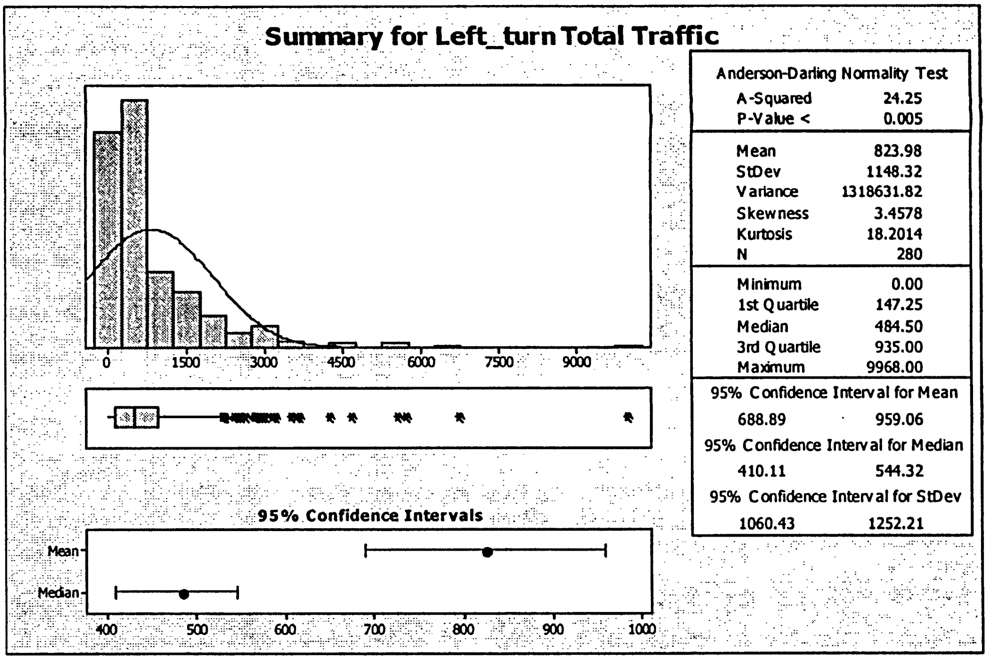


Figure B-6: Summary of Collected Right-turn Traffic Flow Data for 70 Signalized Intersections in City of Toronto (Average flows from1999 to 2004)

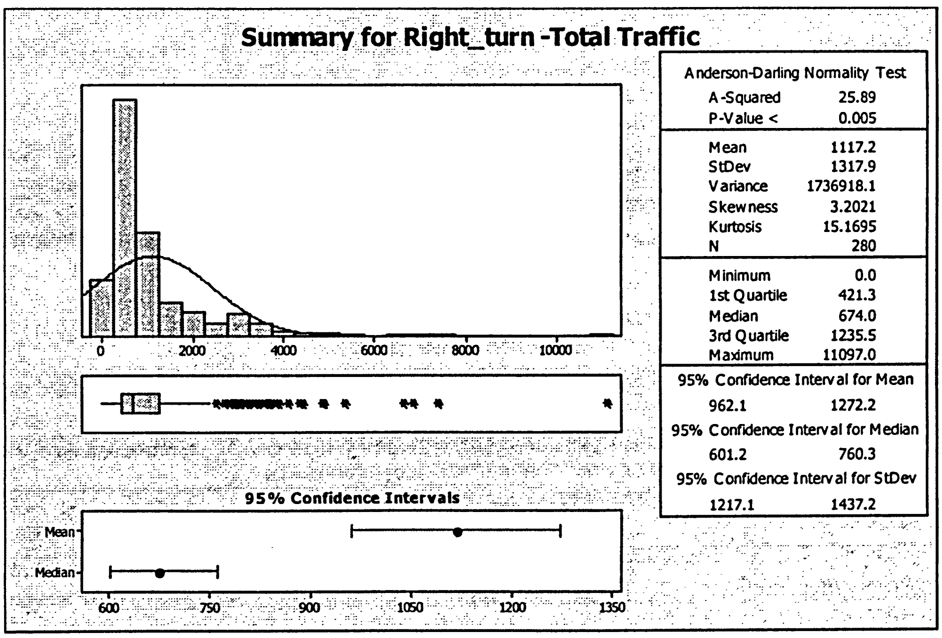


Table B-3: Detail Description of Subject Vehicle Explanatory Variables

Parameters in Side-Impact Model	Definition of Variables	Source of Data
Combined through-left, left turn drop lanes and two or more lanes on the approach	1 if approach contains combined through-left, left turn drop lanes and two or more lanes, 0 otherwise	Intersection field visit
Intersection in commercial areas	1 if there is commercial centre at approach corners (e.g. bank, shopping mall, commercial building etc.) , 0 otherwise	Intersection field visit
Left-turn restriction	1 if all day or working hour left-turn restriction (from 7am to 6am restriction) , 0 otherwise	Intersection field visit
Right-turn restriction	1 if all day or working hour right-turn restriction, 0 otherwise	Intersection field visit
Total no. of lane of current approach	Total number of left-, right-turn, transit and through lanes on current approach	Intersection field visit
Total lane no. of right approach	Total number of left-, right-turn, transit and through lanes on cross street approach	Intersection field visit
Exclusive left-turn lane	1 if exclusive left-turn exist, 0 otherwise	Intersection field visit
Angle of road in between two adjacent legs	1 if the field of view (from the center of approach) angle is greater than 15^0, 0 otherwise	Digital maps
Absolute displacement between two apposite legs	1 if two opposite approach center displaced more than 5m, 0 otherwise	Intersection field visit and digital maps
Curvature on approach leg	1 if curvature exist more than 50 on current approach, 0 otherwise	Intersection field visit
Speed limit of entering approach	Speed limit posted on the right side of approach	Intersection field visit
Intersection sheltered by elevated road	1 if approach sheltered by railway or highway bridge, 0 otherwise	Intersection field visit
Existence of fence in median of entering approach	1 if fence or tree barrier exist on road median, 0 otherwise	Intersection field visit
Central road median	1 if physical barrier or median exist, 0 otherwise	Intersection field visit
Signal Progression	1 if coordination of adjacent traffic signals exist (if traffic can make it through 2 or more traffic signals in a row without having to stop, then there is progression), 0 otherwise	Intersection field visit
Signal control pattern	1 if signal phase consist left or right-turn or flashing green phase, 0 otherwise	City of Toronto Traffic Signal database
Intergreen period on current leg	Current approach yellow or amber time in second	City of Toronto Traffic Signal database
Road width of current leg (m)	Road width from the edge of curve to other side edge of curve	Intersection field visit
Shoulder width (both far and near side in meter)	Shoulder width from edge of curve to edge of pedestrian pavement	Intersection field visit
Number of tree (on both near and far side)	Total number of small and large trees on the both near and far side	Intersection field visit
Transit exit or stop existence on current approach[1]	1 if transit exit or streetcar stop or bus stop exist on both near and far side, 0 otherwise	Intersection field visit
Truck Volume (6 years) of the current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Total Entering Traffic Volume (6 years) of the current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Left-turn traffic volume (6 years) of the current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database

	Table B-3 Continues	
Parameters in Side-Impact Model	**Definition of Variables**	**Source of Data**
Through traffic volume (6 yrs) of the cross-street approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Through traffic volume (6 years) of current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Left-turn traffic volume (6 years) of the opposite approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database

Table B-4: Detail Description of Target Vehicle Explanatory Variables

Parameters In Side-Impact Model	Definition of Variables	Source of Data
Existence of driveway	1 if exist on near side of current approach, 0 otherwise	Intersection field visit
Angle between entering approach and opposing approach	1 if angle between current and adjacent approach in between 75^0 to 105^0, 0 otherwise	Digital maps
Exclusive left-turn lane	1 if exclusive left-turn exist, 0 otherwise	Intersection field visit
Permissive left turn	1 if permissive left-turn exist, 0 otherwise	Intersection field visit
Left-turns not aligned and not single lane approach	1 if left-turns are not aligned and not a single lane approach, 0 otherwise	Intersection field visit
Existence of more than one right-turn lanes	1 if more than one shared or unshared lane exist, 0 otherwise	Intersection field visit
Through lane no. of right approach	Total number of through lanes on right side cross street	Intersection field visit
Total no. of approach lanes	Total number of left-, right-turn, transit and through lanes on current approach	Intersection field visit
Shoulder width (both far and near side in meter)	Shoulder width from edge of curve to edge of pedestrian pavement	Intersection field visit
Existence of transit stop, exit	1 if transit exit or streetcar stop or bus stop exist on both near and far side, 0 otherwise	Intersection field visit
All Red Period on current leg	All red period on current approach in second	City of Toronto Traffic Signal database
Slope of entering approach	1slope exist more than 3^0, 0 otherwise	Intersection field visit
Local street approach	1 if local approach exist (less than 5000 ADT) on current approach	Intersection field visit
Large vehicle ratio of current leg	Ratio of large vehicle (Truck and bus) to total traffic volume of same approach	City of Toronto Traffic Volume database
Functional field of view	1 if the field of view (from the center of approach) angle is greater than 15^0, 0 otherwise	Intersection field visit
Visual noise (from level 0 to 4)	If visual barrier exist like tel. booth, post box, signboard, electrical box, trash, newspaper stand, fence on current approach 1 for 1 visual barrier structure 2 for 2 visual barrier structure 3 for 3 visual barrier structure 4 for 4 visual barrier structure 5 for more than 5 visual barrier structure Visual structure is compared to traffic, pedestrian, bicycle volume	Intersection field visit
Night-to-day traffic flow ratio	Ratio of morning (7.0 am to 8.0 am) and night (4.30 pm to 5.30 pm) of traffic volume	City of Toronto Traffic Volume database
Presence of trees at approach corner	1 if more than two tree exist at right of near side of current approach, 0 otherwise	Intersection field visit
Pedestrian volume (6 years) of current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Right-turn volume (6 years) of current approach	Eight hour volume converted to yearly volume	City of Toronto Traffic Volume database
Bicycle ratio of opposite through traffic	Ratio of bicycle volume to opposite through traffic volume	City of Toronto Traffic Volume database

Table B-5: Correlation Matrix for Subject Vehicle Variables

Parameters in Side-Impact Model	Combined through-left, left turn drop lanes and two or more lanes on the approach[2]	Intersection in commercial areas	Left-turn restriction	Right-turn restriction	Total no. of lane of current approach	Total lane no. of right approach	Exclusive left-turn lane	Angle of road in between two adjacent legs	Absolute displacement between two apposite legs	Curvature on approach leg	Speed limit of entering approach	Intersection sheltered by elevated road	Existence of fence in median of entering approach
Combined through-left, left turn drop lanes and two or more lanes on the approach	1.00												
Intersection in commercial areas	0.168	1.00											
Left-turn restriction	0.007	0.146	1.00										
Right-turn restriction	-0.142	0.124	-0.06	1.00									
Total no. of lane of current approach	-0.015	0.089	-0.02	0.021	1.00								
Total lane no. of right approach	0.049	0.063	0.116	0.243	0.209	1.00							
Exclusive left-turn lane	-0.461	0.246	-0.29	0.009	0.321	0.364	1.00						
Angle of road in between two adjacent legs	-0.028	-0.095	-0.04	0.062	0.050	0.043	0.0570	1.00					
Absolute displacement between two apposite legs	-0.101	-0.046	-0.13	0.085	0.069	0.074	0.163	0.049	1.00				
Curvature on approach leg	-0.057	-0.118	0.051	-0.05	-0.054	-0.038	-0.087	0.130	0.19	1.00			
Speed limit of entering approach	0.064	0.106	0.053	0.156	0.114	0.105	0.082	-0.079	0.110	-0.243	1.00		
Intersection sheltered by elevated road	-0.021	0.143	-0.13	0.025	0.044	0.046	0.119	0.05	0.07	-0.02	0.051	1.00	
Existence of fence in median of entering approach	-0.061	-0.076	0.023	0.078	0.001	0.028	0.03	0.021	-0.010	0.035	0.104	0.136	1.00
Central road median	-0.262	-0.059	0.016	-0.030	0.436	0.217	0.273	0.127	0.061	0.286	0.093	0.219	0.042
Signal Progression	0.079	-0.218	0.019	0.193	0.046	0.164	0.143	0.034	0.058	0.104	0.165	0.183	0.035
Signal control pattern	-0.213	0.049	0.316	0.352	0.267	0.262	0.382	0.034	0.134	0.046	0.114	0.109	0.042
Intergreen period on current leg	0.118	0.097	0.059	-0.05	0.421	0.149	0.174	0.057	0.108	0.14	0.186	0.058	0.058
Road width of current leg(m)	-0.101	-0.146	0.105	-0.01	0.482	0.297	0.320	0.036	-0.040	0.145	0.072	0.026	-0.028

Table B-5: Correlation Matrix for Subject Vehicle Variables

Parameters in Side-Impact Model	Combined through-left, left turn drop lanes and two or more lanes on the approach^2	Intersection in commercial areas	Left-turn restriction	Right-turn restriction	Total no. of lane of current approach	Total lane no. of right approach	Exclusive left-turn lane	Angle of road in between two adjacent legs	Absolute displacement between two apposite legs	Curvature on approach leg	Speed limit of entering approach	Intersection sheltered by elevated road	Existence of fence in median of entering approach
Shoulder width (both far and near side in meter)	0.036	0.220	0.217	0.001	0.084	0.262	-0.101	-0.078	-0.011	0.036	-0.079	-0.181	-0.181
Number of tree (on both near and far side)	-0.210	-0.069	-0.04	-0.04	0.386	0.060	0.253	-0.021	-0.052	0.168	0.110	0.016	0.203
Transit exit or stop existence on current approach	0.169	0.112	0.165	-0.06	0.249	0.164	0.03	0.025	0.082	-0.09	-0.238	-0.009	0.015
Truck Volume (6 years) of the current approach	0.107	-0.046	0.05	-0.02	0.372	0.243	0.168	0.020	-0.068	-0.009	0.13	0.073	-0.004
Total Entering Traffic Volume (6 years) of the current approach	-0.001	-0.146	0.124	-0.06	0.424	0.397	0.301	0.074	-0.091	0.082	0.089	-0.019	-0.010
Left-turn traffic volume (6 years) of the current approach	-0.173	0.108	-0.46	0.021	0.477	0.349	0.531	0.077	0.012	0.10	0.137	0.115	0.031
Through traffic volume (6 yrs) of the cross-street approach	-0.199	0.089	0.166	-0.27	0.172	0.134	0.204	0.033	0.145	0.035	0.167	-0.04	0.009
Through traffic volume (6 years) of current approach	0.049	0.096	0.224	-0.04	0.418	0.413	0.174	0.046	-0.101	0.05	0.219	-0.040	-0.040
Left-turn traffic volume (6 years) of the opposite approach	-0.255	0.111	-0.3	-0.07	0.233	0.280	0.373	0.034	-0.033	0.059	0.118	0.12	0.07

Table B-5: Correlation Matrix for Subject Vehicle Variables

Parameters in Side-Impact Model	Central road median	Signal Progres sion	Signal control pattern	Intergreen period on current leg	Road width of current leg(m)	Shoulder width (both far and near side in meter)	Number of tree (on both near and far side)	Transit exit or stop existence on current approach	Truck Volume (6 years) of the current approach	Total Entering Traffic Volume (6 years) of the current approach	Left-turn traffic volume (6 years) of the current approach	Through traffic volume (6 yrs) of the cross-street approach	Through traffic volume (6 years) of current approach	Left-turn traffic volume (6 years) of the opposite approach
Combined through-left, left turn drop lanes and two or more lanes on the approach														
Intersection in commercial areas														
Left-turn restriction														
Right-turn restriction														
Total no. of lane of current approach														
Total lane no. of right approach														
Exclusive left-turn lane														
Angle of road in between two adjacent legs														
Absolute displacement between two apposite legs														
Curvature on approach leg														
Speed limit of entering approach														
Intersection sheltered by elevated road														
Existence of fence in median of entering approach														
Central road median	1.00													
Signal Progression	0.128	1.00												
Signal control pattern	0.113	0.151	1.00											
Intergreen period on current leg	0.248	0.043	0.175	1.00										
Road width of current leg(m)	0.589	-0.118	-0.351	0.416	1.00									

Table B-5: Correlation Matrix for Subject Vehicle Variables

Parameters in Side-Impact Model	Central road median	Signal Progres sion	Signal control pattern	Intergreen period on current leg	Road width of current leg(m)	Shoulder width (both far and near side in meter)	Number of tree (on both near and far side)	Transit exit or stop existence on current approach	Truck Volume (6 years) of the current approach	Total Entering Traffic Volume (6 years) of the current approach	Left-turn traffic volume (6 years) of the current approach	Through traffic volume (6 yrs) of the cross-street approach	Through traffic volume (6 years) of current approach	Left-turn traffic volume (6 years) of the opposite approach
Shoulder width (both far and near side in meter)	0.002	0.047	0.107	0.058	0.150	1.00								
Number of tree (on both near and far side)	0.355	0.193	0.042	0.263	0.480	0.125	1.00							
Transit exit or stop existence on current approach	-0.003	0.026	0.249	0.201	0.206	-0.037	0.030	1.00						
Truck Volume (6 years) of the current approach	0.22	0.147	0..49	0.315	0.414	0.075	0.144	0.052	1.00					
Total Entering Traffic Volume (6 years) of the current approach	0.358	0.316	0.409	0.347	0.511	0.195	0.337	0.180	0.422	1.00				
Left-turn traffic volume (6 years) of the current approach	0.259	0.189	0.157	0.249	0.265	-0.22	0.255	0.045	0.365	0.343	1.00			
Through traffic volume (6 yrs) of the cross-street approach	0.170	0.384	0.461	0.145	0.177	0.033	0.146	0.099	0.164	0.161	0.218	1.00		
Through traffic volume (6 years) of current approach	0.298	0.168	0.125	0.288	0.440	0.273	0.264	0.237	0.363	0.516	0.127	0.057	1.00	
Left-turn traffic volume (6 years) of the opposite approach	0.191	0.117	0.171	0.124	0.148	-0.249	0.249	0.055	0.170	0.183	0.399	0.233	0.041	1.00

Table B-6: Correlation Matrix for Target Vehicle Variables

Parameters In Model	Existence of driveway	Angle between entering approach and opposing approach	Exclusive left-turn lane	Permissive left-turn	Left-turns not aligned and not single lane approach	Existence of more than one right-turn lanes	Through lane no. of right approach	Total no. of approach lanes	Shoulder width (both far and near side in meter)	Existence of transit stop, exit	All Red Period on current leg	Slope of entering approach
Existence of driveway	1.000											
Angle between entering approach and opposing approach	0.003	1.00										
Exclusive left-turn lane	0.219	0.057	1.00									
Permissive left turn	-0.168	0.460	-0.342	1.00								
Left-turns not aligned and not single lane approach	0.216	0.039	0.199	-0.352	1.00							
Existence of more than one right-turn lanes	0.217	0.068	0.443	-0.545	0.427	1.00						
Through lane no. of right approach	0.137	0.081	0.217	-0.362	0.242	0.264	1.00					
Total no. of approach lanes	0.182	0.050	0.521	-0.405	0.528	0.487	0.233	1.00				
Shoulder width (both far and near side in meter)	-0.181	-0.078	-0.101	0.141	-0.097	-0.136	-0.078	0.084	1.00			
Existence of transit stop, exit	0.090	0.025	0.028	-0.159	0.024	0.150	0.075	0.249	-0.037	1.00		
All Red Period on current leg	0.014	0.094	0.050	-0.275	0.054	0.228	0.174	0.269	-0.101	0.144	1.00	
Slope of entering approach	0.193	0.129	0.256	-0.193	0.253	0.218	0.118	0.186	-0.168	-0.168	0.154	1.00
Local street approach	-0.178	-0.035	-0.150	0.073	-0.151	-0.082	-0.022	-0.511	0.001	-0.425	-0.233	-0.239
Large vehicle ratio of current leg	0.046	-0.037	-0.137	-0.008	-0.149	-0.023	-0.066	0.098	-0.080	0.275	0.151	0.184
Functional field of view	0.029	0.216	0.059	-0.089	0.114	0.058	-0.152	0.245	0.119	0.087	0.046	-0.231
Visual noise (from level 0 to 5)	0.024	-0.041	0.117	-0.183	0.112	0.168	0.111	0.333	0.075	0.238	0.251	0.137
Night-to-day traffic flow ratio	0.114	0.108	0.046	0.043	0.168	0.049	0.125	0.213	0.037	0.067	0.137	0.154
Presence of trees at approach corner	0.014	0.032	0.081	-0.300	0.085	0.289	0.178	0.214	-0.001	0.043	0.173	0.067
Pedestrian volume (6 years) of current approach	-0.199	0.006	-0.214	0.117	-0.214	-0.134	0.045	-0.080	0.441	-0.037	-0.057	-0.218
Right-turn volume (6 years) of current approach	0.073	0.110	0.291	-0.333	0.267	0.375	0.169	0.523	-0.006	0.159	0.199	0.115
Bicycle ratio of opposite through traffic	-0.106	0.056	-0.181	0.131	-0.181	-0.156	-0.052	-0.160	0.085	0.095	0.02	-0.164

Table B-6: Correlation Matrix for Target Vehicle Variables

Parameters In Model	Local street approach	Large vehicle ratio of current leg	Functional field of view	Visual noise (from level 0 to 5)	Night-to-day traffic flow ratio	Presence of trees at approach corner	Pedestrian volume (6 years) of current approach	Right-turn volume (6 years) of current approach	Bicycle ratio of opposite through traffic
Existence of driveway									
Angle between entering approach and opposing approach									
Exclusive left-turn lane									
Permissive left turn									
Left-turns not aligned and not single lane approach									
Existence of more than one right-turn lanes									
Through lane no. of right approach									
Total no. of approach lanes									
Shoulder width (both far and near side in meter)									
Existence of transit stop, exit									
All Red Period on current leg									
Slope of entering approach									
Local street approach	1.00								
Large vehicle ratio of current leg	-0.406	1.00							
Functional field of view	0.143	-0.124	1.00						
Visual noise (from level 0 to 5)	-0.211	0.164	0.341	1.00					
Night-to-day traffic flow ratio	0.125	0.045	0.112		1.00				
Presence of trees at approach corner	-0.046	-0.084	-0.216	0.117	0.026	1.00			
Pedestrian volume (6 years) of current approach	0.136	-0.05	0.113	-0.027	0.016	0.005	1.00		
Right-turn volume (6 years) of current approach	-0.288	0.076	0.067	0.177	0.046	0.228	0.037	1.00	
Bicycle ratio of opposite through traffic	-0.047	0.151	0.055	-0.081	0.018	0.073	0.095	-0.072	1.00

APPENDIX C

GRAPHICAL ILLUSTRATION OF
MICROSCOPIC ACCIDENT OCCURENCE MECHANISM AND RELATED VARIABLES

Figure C-1: Explanatory Variables for Obstacle Vehicle for AG2 Accident

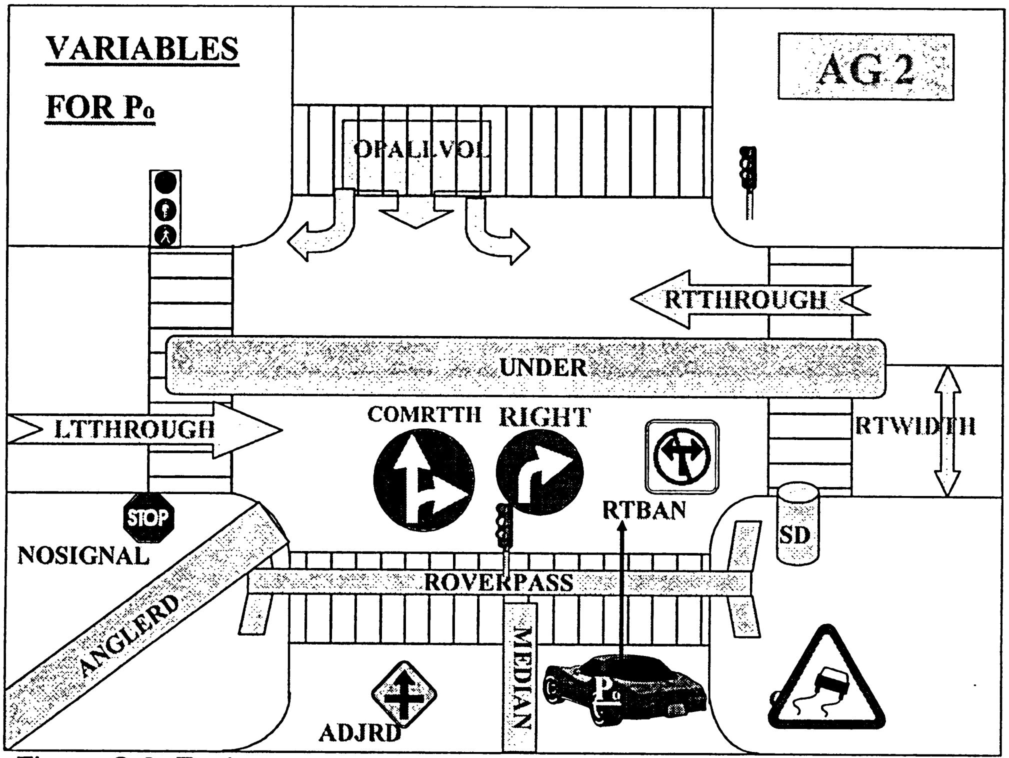


Figure C-2: Explanatory Variables for Following Vehicle for AG2 Accident

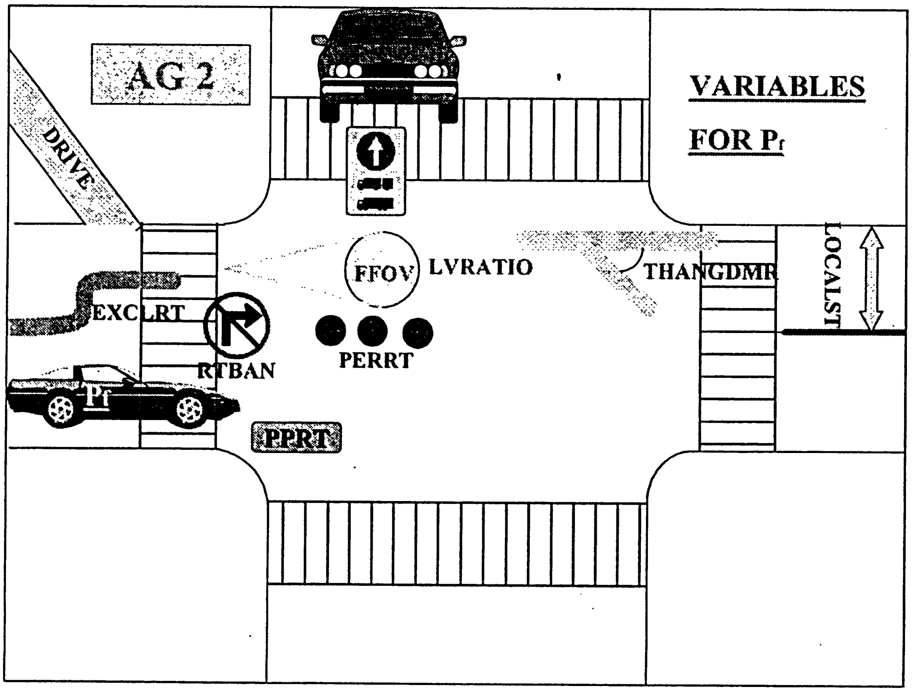


Figure C-3: Explanatory Variables for Obstacle Vehicle for AG3 Accident

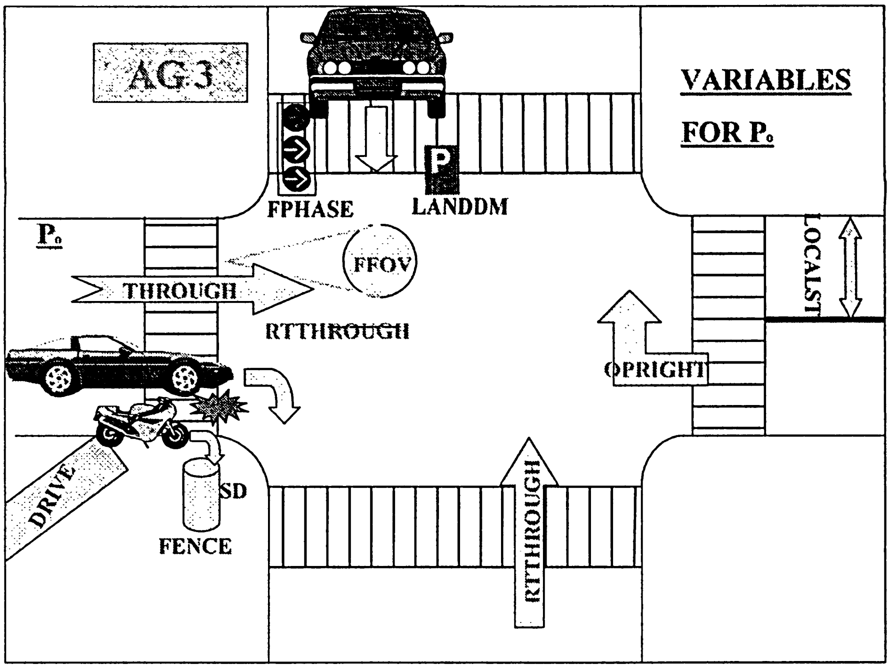
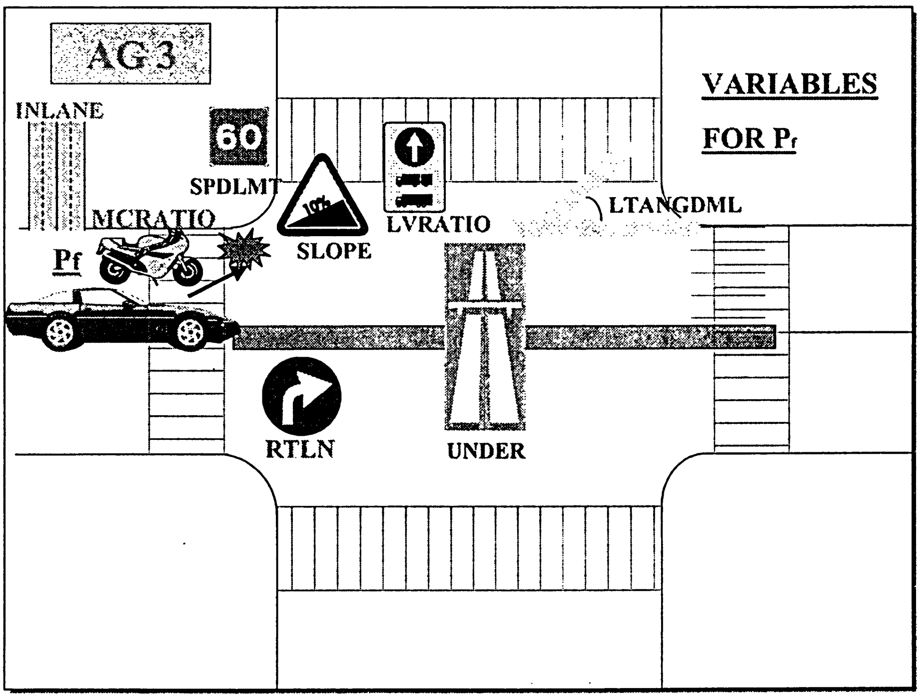


Figure C-4: Explanatory Variables for Following Vehicle for AG3 Accident



APPENDIX D

GOODNESS-OF-FIT RESULTS

Figure D-1: Prediction Ratio for Right-Angle Crashes

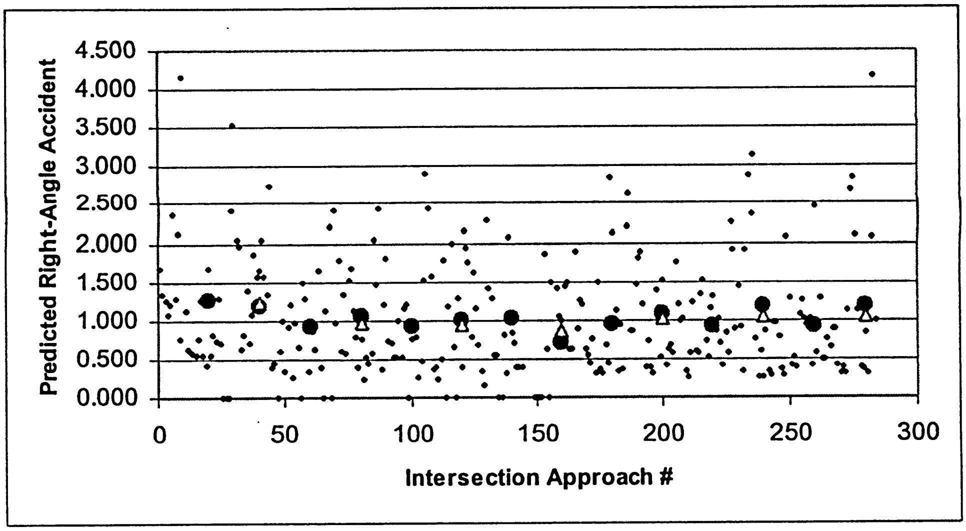


Figure D-2: Prediction Ratio for Left-Turn Crashes

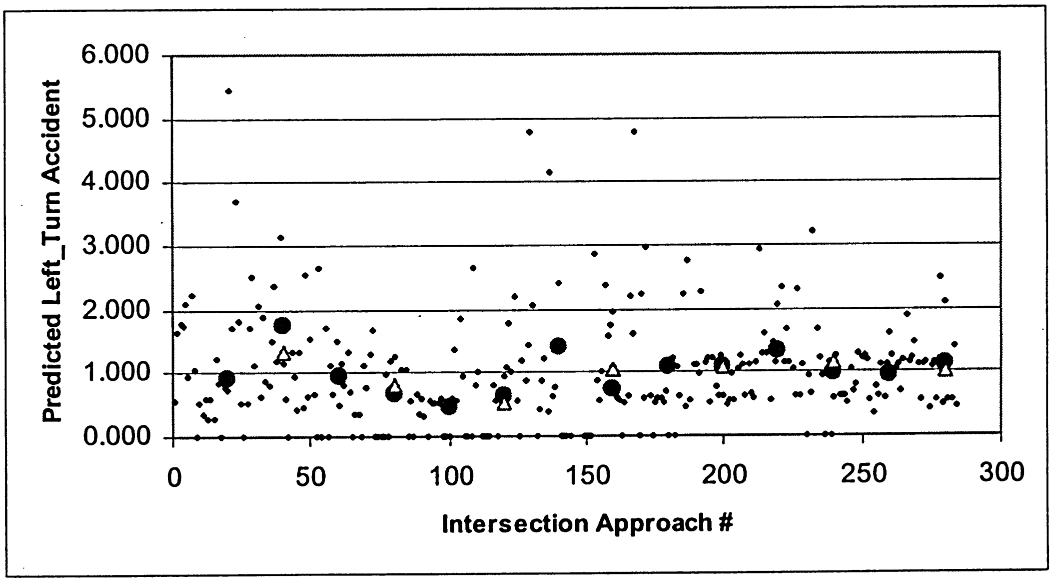


Figure D-3: Prediction Ratio and Estimated Value for Total Side-Impact Crashes

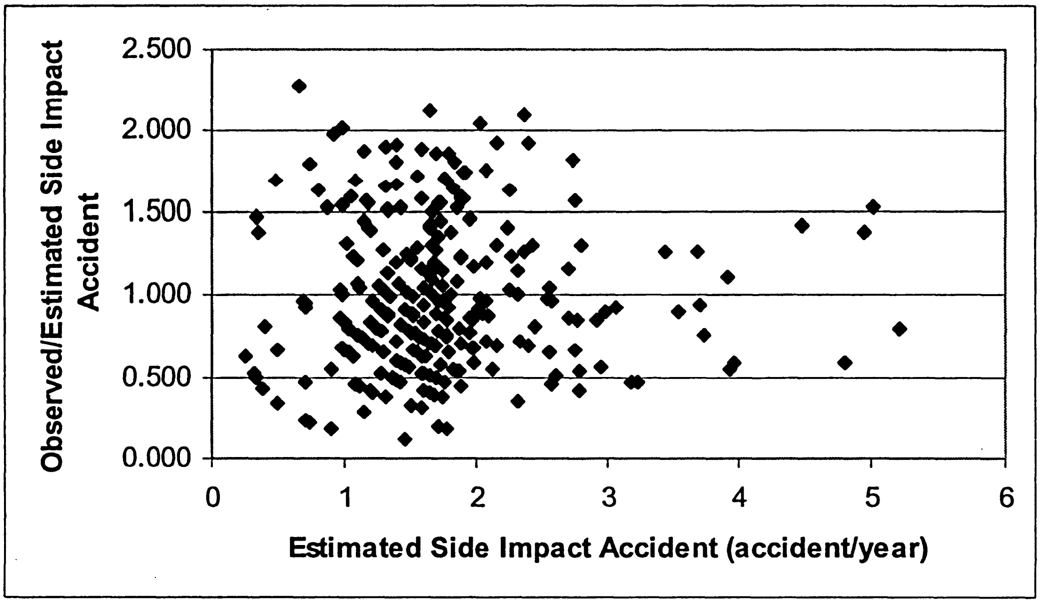


Figure D-4: Prediction Ratio and Estimated Value for Left-Turn Crashes

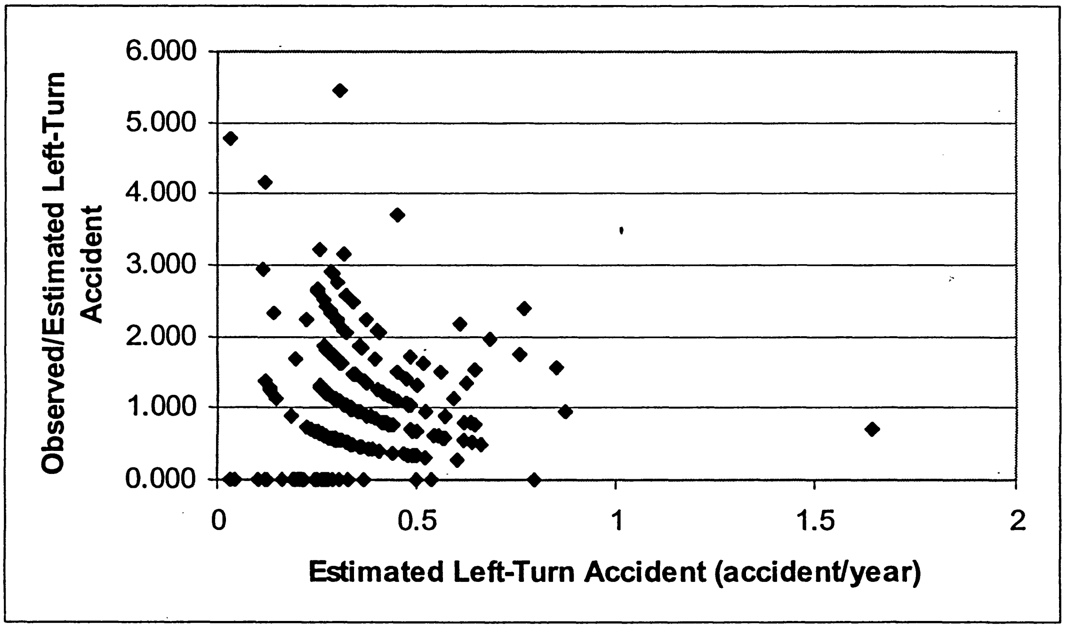


Figure D-5: Predicted and Observed Value for Total Side-Impact Crashes

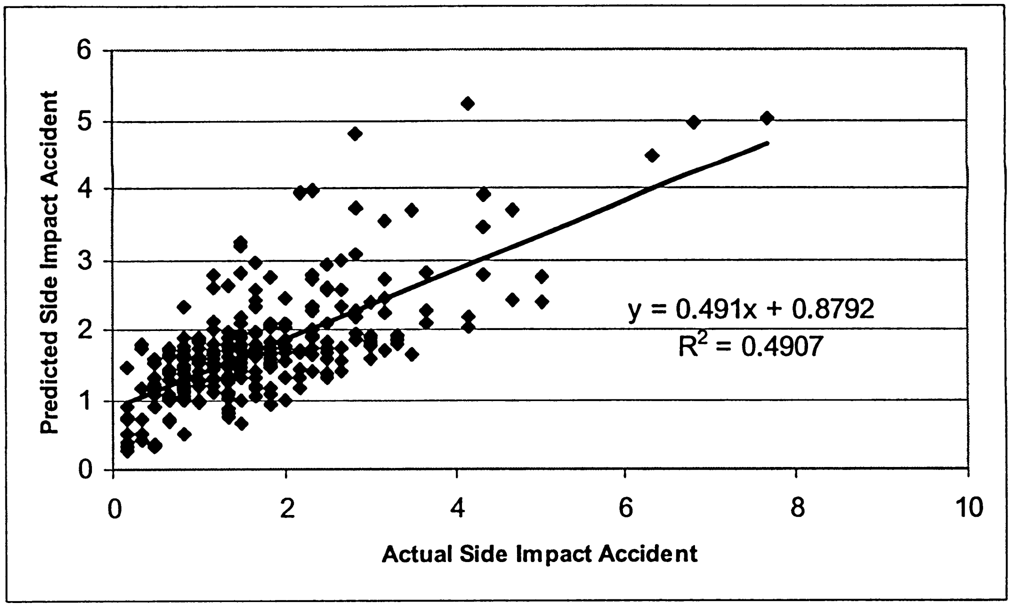


Figure D-6: Predicted and Observed Value for Side-Impact Crashes

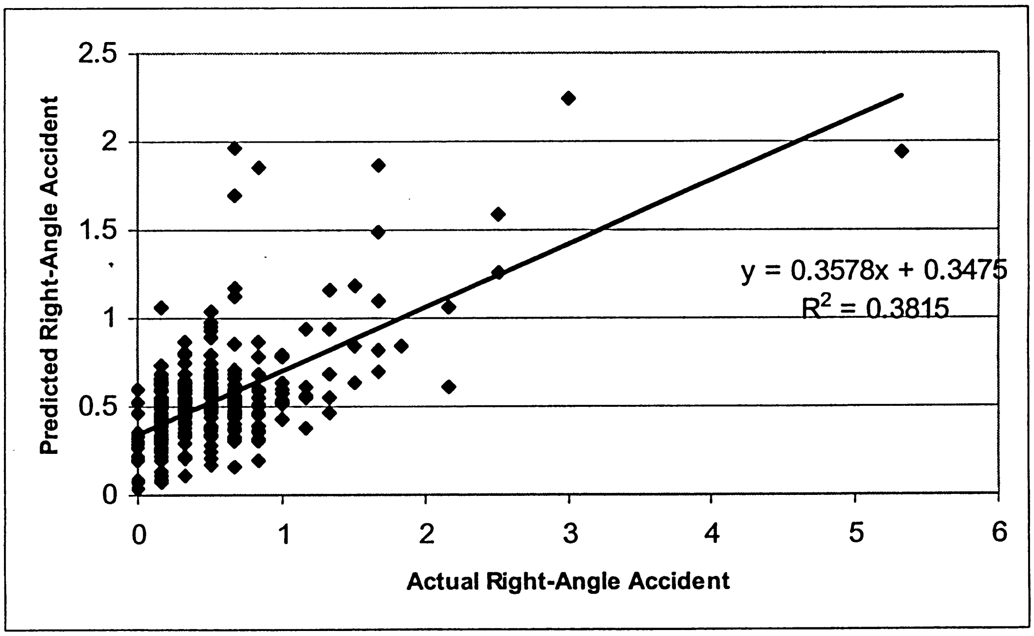


Figure D-7: Predicted and Observed Value for Left-turn Crashes

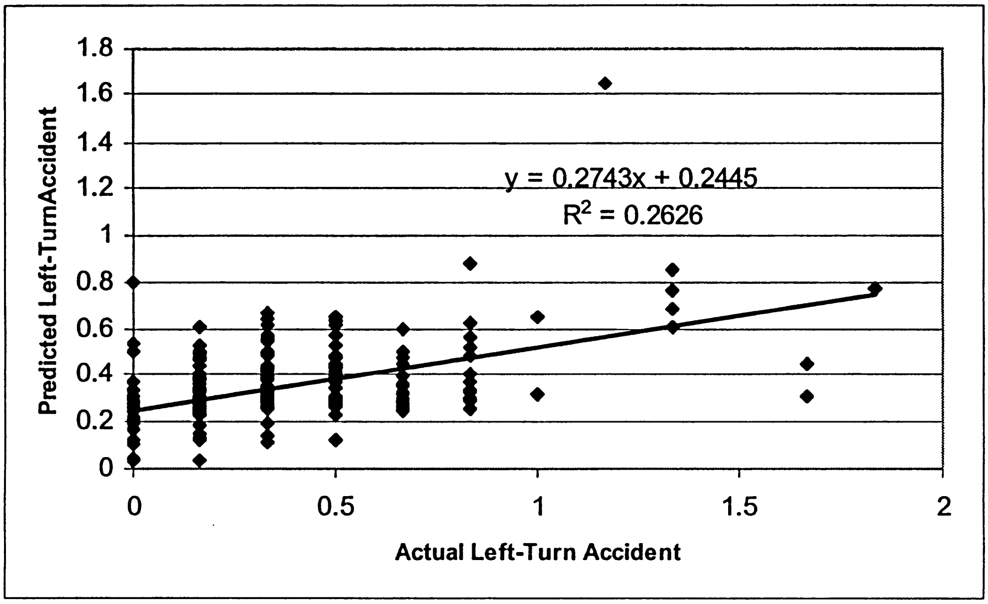


Figure D-8: Cumulative Residual (CURE) Plot for Right-Angle Crashes.

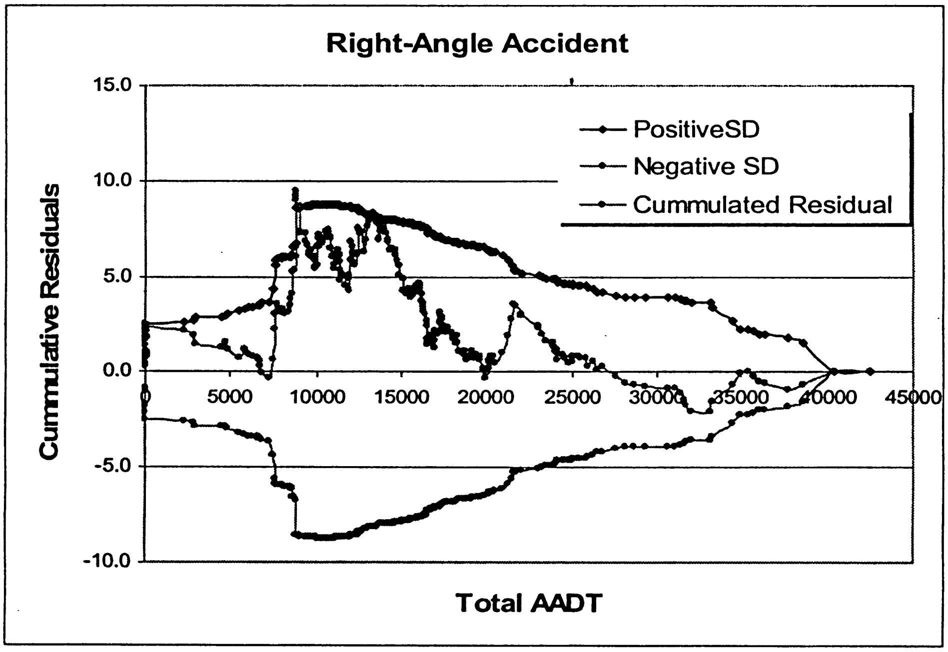


Figure D-9: Cumulative Residual (CURE) Plot for Left-Turn Crashes