Integrating Observational and Microscopic Simulation Models for Traffic Safety Analysis

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

In safety analysis, two questions typically need to be addressed: 1) how to identify unsafe sites for priority intervention? and 2) how to determine the effectiveness of treatments introduced at these and other sites? Two types of approaches have been considered in the literature to provide answers for these questions: (1) observational models based on historical crash data and (2) observed or simulated higher risk vehicle interactions or traffic conflicts. Observational crash-based models are good at predicting higher severity crashes, but they tend to ignore higher risk vehicle interactions that compromise safety, that have not resulted in crashes (e.g. near misses). Proponents of microscopic simulation argue that ignoring these higher risk interactions can severely understate the safety problem at a given site and lead to a misallocation of scarce treatment funds. Another problem with observational crash prediction models is the need for sufficient crash data reported over an extended period of time to provide reliable estimates of "potential" lack of safety. This requirement can be a challenge for certain types of treatment and different sites or locations. Furthermore, observational approaches are not causal in nature, and as such, they fail to provide a sound "behavioural" rationale for "why" certain treatments affect safety.

On the other hand, traffic conflicts occur more frequently than crashes and can provide a stronger experimental basis for estimating safety effects on a short-term basis. This is especially important given the rare random nature of crashes for certain traffic conditions. Additionally, they provide a more rational basis for lack of safety than is normally available from crash occurrence data. Basically, through the application of calibrated behavioural simulation, traffic conflicts can be linked to specific driver actions and responses at a given site, more so than conventional reported crashes. As such, they permit a causal underpinning for possible treatment effects and this is important to decision-makers because it underscores why certain treatments act to enhance safety, rather than simply providing an estimate of the treatment effect itself.

Notwithstanding the usefulness of conflict-based measures, observed crashes remain the primary verifiable measure for representing failures in the transportation systems. Unfortunately traffic conflicts have not been formally linked to observed crashes, and hence their values as indicators for treatment effect have not been fully explored. This presents a challenge on how best to use both conflicts and observed crashes to better understand where safety is most problematic, where intervention is needed, and how best to resolve specific safety problems?

In this thesis, the position is taken that a complete understanding of safety problems at a given site can only emerge from a more inclusive analysis of both observed crashes and traffic conflicts. This is explored by developing two integrated models: (1) An integrated priority ranking model is presented that combines estimates from observational crash prediction with an analysis of simulated traffic conflicts; (2) An integrated treatment model is presented that uses simulated traffic conflicts that are linked statistically to observed crashes to provide estimates of crash modification factor (CMF). The suitability of these integrated models has been evaluated using data for a sample of signalized intersections from Toronto for the period 1999-2006.

In the absence of a benchmark (or true) priority ranking outcome, a number of evaluation criteria were considered, and the integrated ranking model was found to yield better results than both conventional observational crash-based models (including empirical Bayesian, potential for safety improvement methods) and conflict-based models (including conflict frequency and rate for different risk thresholds). For treatment effects, the results suggest that CMFs can be estimated reliably from conflicts derived from microsimulation, where the simulation platform has been sufficiently calibrated. The link between crashes and conflicts provides additional inferences concerning treatment effects, in those cases where treatments were not previously implemented (i.e., no after history). Since there is an absence of crash history, the treatment effect is based exclusively on simulated conflicts. Moreover, the integrated model has the added advantage of providing site-specific CMFs instead of applying a constant CMF across all sites considered for a potential treatment.

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Dedication

I dedicate my PhD thesis to

My beloved Parents,

My beloved brothers, Samy and Muhammad;

My sisters, Shimaa, Sahar and Farida

My beloved wife, Reem;

My beloved sons Abdullah and Abdelrahman;

My co-supervisors Dr. Saccomanno and Dr. Persaud; and

To those who are sacrificing themselves to maintain justice in the world.

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CHAPTER 1
INTRODUCTION

Traffic crashes make up a significant percentage of death and personal injuries reported in many developed countries. For example, in Canada, more than 2,700 persons were reported killed and about 200,000 people injured from traffic crashes in 2007 (Transport Canada, 2010). In the U.S. for the same year, over 41,100 persons were killed from traffic crashes, or about one death every 15 minutes. For every one of these deaths, 60 injuries were reported in the US in a given year, or one injury every 15 seconds (U.S. Census Bureau, 2010). According to a World Health Organization (WHO, 2004), traffic crashes will become the fifth leading cause for death by 2030 if the death rate due to vehicle crashes continues its current trend. The WHO (2004) reports an average of 1.20 million death annually globally as a result of road crashes. This provides strong justification for the development of efficient, objective guidelines for traffic safety analysis.

1.1 PROBLEM STATEMENT

The majority of crashes tend to occur with some consistency over time and, hence, are predictable. Consistent crashes are assumed to be caused by a specific failure in the transportation system, and hence by addressing this failure we expect to reduce these crashes. However, many crashes are purely random in nature and are therefore difficult to predict with respect to observed crash history. These crashes are not reflective of failures in the transportation system and are difficult to explain or predict. For example, if crashes occur with consistency then we would expect a measure of consistency in the priority ranking of sites over time, such that high crash sites in the past would likely be reflected as high crash sites in the future. However, if crashes occur in a random fashion, consistency of prediction will not provide a good metric for identifying high-risk sites in the future. The problem of consistency in crash occurrence over time becomes critically important in developing sound priority ranking models for safety intervention.

Accurately predicting the likelihood of crashes and hence implementing effective treatments is one of the main concerns for traffic safety engineers (e.g., Lord and Mannering, 2010). Crash prediction models are the primary tools to predict crashes and estimate treatment effects (e.g., El-Basyouny, 2006). These models provide answers to two fundamental safety questions: (1) what sites are unsafe (hazardous location identification), such that intervention is advised? and (2) what form should this intervention take so that crashes are reduced in a cost effective and practical manner?

Two approaches have been proposed to provide answers for these questions: (1) crash prediction models based on reported crash data and (2) observed or simulated vehicle interactions and traffic conflicts. While these approaches have been shown to give good results, there are number of issues related to each of these approaches that need to be investigated. In addition, we need to understand how these approaches compare to each another in providing answers for safety analysis. There is also a need to explore an objective way to combine the strengths of both observational crash-based analysis with conflict-based analysis to better resolve problems of priority ranking of unsafe sites and estimation of treatment effects.

1.1.1 Issues with crash-based analysis

The main advantage of using observed crash data is that they provide measurable indicators of transportation system failures. Crash-based safety studies are based on police-reported crash data. Unfortunately, there are a number of problems associated with the use of these data in safety analysis such as, low reporting rates for low severity crashes, incomplete and misreported information, errors in the data entry and other statistical and methodological issues (Hauer and Hakkert, 1989; Elvik and Myssen, 1999; Blincoe, et al., 2002; Nicholson, 1985; Hauer, 2001; Farmer, 2003; Davis, 2004; Saunier and Sayed, 2007; Lord and Mannering, 2010). For example, in North America, only crashes involving personal injury or property damages over a set amount are reported in the database. In Ontario, only crashes that cause property damage more than $1,000 may be reported to Ontario's collision reporting centres (MTO, 2011).

It is worth noting that the rate of police reported crashes increases with the severity of the crash (Blincoe et al., 2002). Hauer and Hakkert (1989) reported that approximately 60% of property-damage-only (PDO) collisions were not reported in the crash data. In addition, they observed that even for those crashes that resulted in serious injuries without hospitalization, around 20% were unreported. Furthermore, Elvik and Myssen (1999) found that the probability of crashes being reported in the data ranges from 70% for serious injuries to 10% for minimal injuries crashes. Mills et al. (2011) compared precipitation-related motor vehicle collisions and injury using both police records and insurance claim data for Winnipeg, Canada (1999–2001). They reported that the insurance data has 64% more injury collisions and 74% more injuries than police records.

Furthermore, since prediction is based on reported crashes, observational models tend to ignore unreported high-risk vehicle interactions or near misses that could lead to crashes. Hence, they can be viewed as being important in assigning lack of safety to a given site for a given set of traffic conditions. Vehicle interactions are expected to vary over time for different traffic conditions and geometric attributes.

Since crashes are rare events, they do not manifest themselves over short time periods. The use of observational analysis for 5 to 10 years creates problems of too many zeroes in the observational crash data used in prediction models, and this results in errors in parameter estimates (Lord and Mannering, 2010). Zero-inflated models have been used to address the problem of too many zeroes in the data (Lord et al., 2005; Shankar et al., 1997). The excess zero is accounted for, in the zero-inflated models, by having two models (i.e., zero-crash model versus a crash prone model). The probability of a given site to be perfectly safe (i.e., in the zero state) or in the non-zero state can be obtained using binary logit or probit models. These models can create theoretical inconsistencies with crash data (Lord et al., 2005; Lord and Mannering, 2010).

One of the major problems associated with observational crash data is presence of regression to the mean (RTM) bias. RTM reflects a treatment selection bias that takes place when the assumptions of random selection is violated (Park and Saccomanno 2007). If the RTM bias is not resolved properly, then sites that happen to encounter a high number of crashes in a certain year will be ranked in the top list of unsafe sites that need treatment. This will give a misleading (over-estimation) of the treatment effect because extreme crash values (higher and lower than long term average) fluctuate around the true mean or tend to return to the average value for each site (Hauer, 1997; Hauer et al., 2004).

The empirical Bayes (EB) approach can solve some of the statistical issues associated with RTM bias (Hauer, 1997; Hauer et al., 2002; Persaud and Lyon, 2007). It does so by estimating a long term average of crashes at each site by combining observed crash frequency at the site with expected number of crashes from similar sites (Safety Performance Function or SPF). It should be noted that EB models require a large sample of untreated reference sites from which to develop SPFs and this can be both costly and impractical (Lan, 2010).

Recently, the full Bayesian (FB), has been proposed to overcome the shortcomings of the EB method (Li et al., 2013; El-Basyouny and Sayed, 2012; Lan and Persaud, 2010; Miaou and Song, 2005; Miranda-Moreno and Fu, 2007; Huang et al., 2009). The FB method tends to be computationally involved and hence unpopular with many practitioners (Persaud and Lyon, 2007).

Using observational crash-based models to evaluate treatments can only be done after implementing treatment(s), and this can only be achieved if sufficient site-years of treatment data are available to ensure statistically meaningful results. As such, observational crash-based models for evaluating treatment effects are not proactive (e.g. Archer, 2005). In addition, crash-based prediction models can also be subject to lack of specification in the crash data. This results when too few years of crash experience data following treatment are available, or when treatments have not yet been applied. This can severely restrict the ability of observational prediction models to explain the potential for crash reduction resulting from specific treatments. This problem is rendered more complex when we wish to isolate the effect of a specific treatment on a given site, where this treatment is part of a mix of treatments introduced at the same time. The question becomes, how can the specific treatment effect be isolated from the group treatment effect? (Cunto and Saccomanno, 2008).

The basic problem with observational crash-based studies in general is that they fail to account for the complex causal relationships affecting crashes at a given site. Thus, while we can estimate treatment effect for a given treatment, we cannot ascertain logically how this treatment acts to modify driver behavior such that safety is enhanced. As such, the approach becomes somewhat of a black box, where results are obtained, but where we are at odds to explain them. In the absence of some form of behavioral transparency, it, therefore, becomes difficult to justify the treatment. Furthermore, where several correlated treatments are considered at a given site, it is difficult for the crash-based approach to distinguish the effect of one treatment from that of another. For example, we can estimate the effect on crashes of a permissive-protected left turn signal at a given intersection, but we cannot obtain reliable CMF estimates for such a treatment if it is introduced simultaneously with changes in signal timing at the same site.

1.1.2 Potential of simulated conflict-based models

Safety studies using high-risk vehicle interactions were initially proposed by Perkins and Harris (1968), researchers from the General Motors laboratory. These interactions, which are referred to as traffic conflicts when they exceed given thresholds, can provide an alternative metric to conventional crash-based analysis in traffic safety studies.

Amundsen and Hyden (1977) defined traffic conflicts as *"an observational situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged"*. The gist of safety studies using traffic conflicts is that conflicts occur more frequently than crashes (Cunto, 2008), and can provide a stronger experimental basis for estimating safety effects on a short-term basis. This is especially important given the rare random nature of crashes for certain traffic conditions. Additionally, they provide a more rational basis for explaining lack of safety than normally available in crash occurrence data.

Observational conflicts can be achieved, for example, using video capture or tracking of the vehicle trajectories in real time (Saunier et. al, 2010; Guido et. al, 2010; Sayed et.al, 2012).

This approach is very costly and requires certain setup guidelines such as camera angle and elevation for accurate vehicle location. This method, like observational crash-based methods, is not proactive when it comes to estimate treatment effect prior to implementation.

Recently, researchers have used microscopic traffic simulation to obtain high-risk vehicle interactions, or traffic conflicts for changing traffic conditions (Sayed and Zein, 1999; Archer, 2005; Cunto, 2008; Archer, 2000, Gettman and Head, 2003, Barcelo et al., 2003, Huguenin et al., 2005; Cunto and Saccomanno, 2008, Ghods et al., 2012).

Basically, through the application of calibrated behavioural simulation, traffic conflicts can be linked to specific driver actions and responses at a given site, more so than conventional reported crashes. As such, they permit a causal underpinning for possible treatment effects and this is important to decision-makers because it underscores why certain treatments act to enhance safety, rather than simply providing an estimate of the treatment effect itself. As such, they permit a causal underpinning to possible treatment effects.

Hyden (1987) assumed that the shape of the severity hierarchy is a three-sided pyramid as shown in Figure 1.1. This Figure illustrates different levels of vehicle interactions or perturbation from undisturbed (base of Pyramid) to high risk or crashes at the apex. As the risk level increases, the frequency of occurrence is reduced. Presumably, as conditions in the traffic stream progress from the base to the peak, the presence of a safety problem becomes more pronounced, as does the likelihood of crashes.

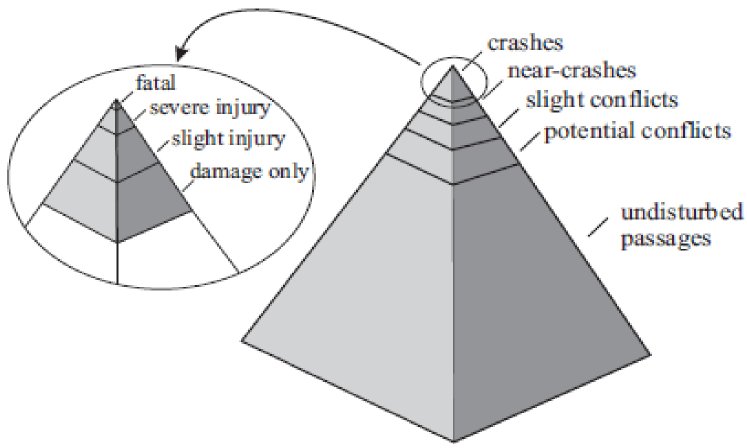

Figure 1.1: Hyden's safety pyramid (Hyden, 1987)

Arguments against using of traffic micro-simulation models in safety studies can be summarized as follows (Tarko and Songchitruksa, 2005; Saunier and Sayed, 2007):

1. Traffic micro-simulation models are based on crash avoidance rules, and cannot fully explain high-risk driver behavior that leads to crashes.
2. Results of a traffic micro-simulation model are only as good as the accuracy and reliability of the input parameters and the model's ability to replicate actual (i.e., real world) driver behaviour and traffic conditions.
3. Surrogate safety indicators are conceptual (i.e., abstract) measures of safety that are not linked to crashes (i.e., they are appropriate only within the context of verifiable crash occurrence).

In addition, to estimate surrogate safety measures from simulation for different weather, road and traffic conditions, the models will need to be calibrated based on real-world observed traffic data for the full spectrum of conditions.

Simulated conflicts are usually targeting conflicts during good weather conditions (i.e., normal weather conditions and dry pavement conditions) because microscopic traffic simulation models are usually calibrated for good weather conditions (Rakha et al. 2010). On the other hand, although observed crash data are representative of a wide range of weather conditions, most observational models do not consider seasonality when predicting the number of crashes at a given location.

The motivation of this thesis research is that a better understanding, and hence better traffic safety analysis, can be obtained if the strengths of both the crash-based and the conflict-based models can be combined, and inference on lack of safety at a given site is drawn from both perspectives.

1.2 RESEARCH OBJECTIVES

Notwithstanding the usefulness of traffic conflicts in safety analysis, observed crashes remain as the primary verifiable measure for representing safety failures in transportation system. The challenge for safety analysis models is how best to integrate both conflicts and accidents to gain a better understanding of where safety is most problematic; what form of intervention should be considered to enhance safety at a given site, and what is the crash-reduction effect of such intervention or treatment.

This study takes the position that a complete understanding of safety problem at a given site can only emerge if both crash potential and traffic conflicts are taken into account. Accordingly, the proposed research has the following specific objectives:

1. Review current observational crash-based models and simulated traffic conflict-based models.
2. Develop integrated approaches that combine observational crash-based and traffic conflict-based measures of safety performance, and apply these approaches to prioritize sites for safety intervention (priority ranking) and evaluating treatments.

3. Apply these integrated models to resolve the two fundamental safety analysis questions: priority ranking of unsafe sites and countermeasure evaluation.
4. Assess the effect of key microsimulation factors (e.g., conflict definition threshold and number of runs) on the number and nature of simulated conflicts and the subsequent estimates of countermeasure effect.

1.3 ORGANIZATION OF THESIS

The reminder of this thesis has been organized into seven chapters. **Chapter 2** presents a review on observational crash-based approach and how it can be used to answer the two fundamental traffic safety questions (i.e., priority ranking of unsafe sites and treatment effectiveness). **Chapter 3** presents a review on surrogate safety measures from microscopic simulation models and how traffic conflicts can be used to answer the traffic safety questions.

Chapter 4 presents the proposed models for priority ranking of unsafe intersections and treatment effect. **Chapter 5** presents the results of the application of the proposed priority ranking models for a sample of signalized intersections from Toronto.

Chapter 6 presents a case study application of the proposed treatment model and compares treatment effects with estimates from empirical Bayes crash-based before-and-after analysis. Finally, **Chapter 7** summarizes the major findings of the research and potential contributions for safety analysis. The Chapter also summarizes the major recommendations for further work to better enhance the integration of traffic conflicts and observed crashes in safety analysis.

CHAPTER 2

REVIEW OF CRASH-BASED APPROACH

This chapter presents the major features of a crash-based approach for crash prediction and safety analysis. Some of the fundamental shortcomings of these models are discussed with respect to their ability to rank sites with respect to priority intervention and to estimate the effects of intervention on potential crash reduction.

2.1 CRASH PREDICTION MODELS

Historically, crash frequency, the number of crashes that expected to occur at a given site during a specific period (Hauer, 1997), and crash rate (frequency divided by exposure), have been widely used to measure lack of safety at different sites.

Expected crash frequency has nonlinear relationship with traffic flow, as shown in Figure 2.1 (based on unpublished report by Ezra Hauer (Kononov and Allery, 2003)). Accordingly, a non-linear relationship between crashes and traffic volume is more appropriate when conducting traffic safety analysis (Hauer, 1997; Persaud et al., 1999; Persaud, 2001).

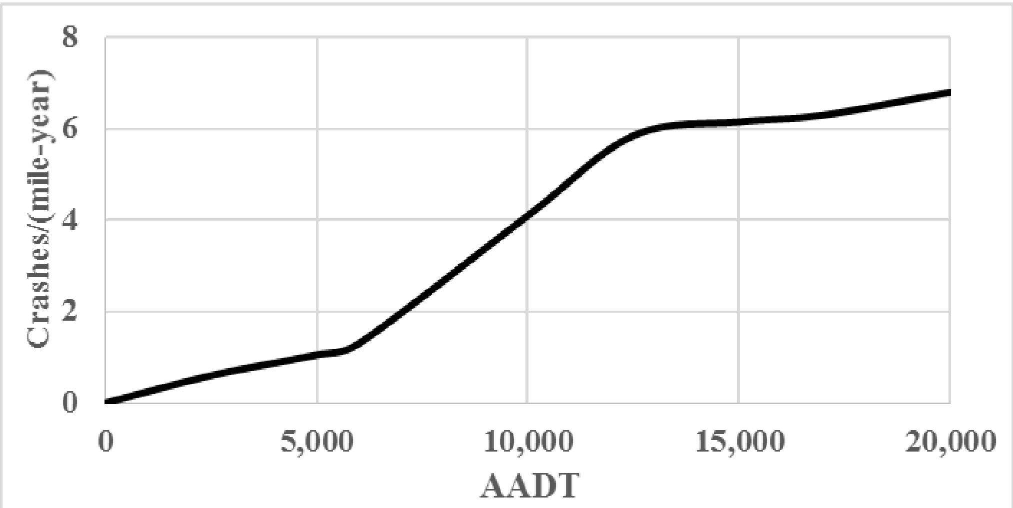

Figure 2.1. Relationship between traffic exposure and crashes [reproduced from Kononov and Allery, 2003]

Crash prediction models, which are statistical multiple- variable models, can be used to fit nonlinear relationships between crash counts as response variable and traffic, geometric and other site characteristics (traffic control type, speed limit, number of lanes, traffic volumes etc.) as independent confounding factors. Equation [2.1] shows a typical linear regression model, where E(y) is the expectation of crashes at a given site:

$$E(y) = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k + \varepsilon \qquad [2.1]$$

and y is the dependent or the response random variable (number of crashes), $x_1,\ x_2, \cdots x_k$ are set of independent variables, $\beta_0,\ \beta_1,\ \beta_2,\ ...,\ \beta_k$ are unkown coefficients and ε is the error term .

An alternative nonlinear form can be used, such that:

$$E(y) = \beta_0 \cdot Exp(\beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \beta_k \cdot x_k) + \varepsilon \qquad [2.2]$$

Linear regression analysis can be used to fit the models in Equations [2.1] and [2.2], and the error term will be assumed to follow the normal distribution. Based on this assumption, the error variance is constant for each value of the independent variables. However, crashes are positive discrete values (i.e., y in the above equations) and as such do not follow a continuous normal distribution. As a result, most crash prediction models use Generalized Linear Model (GLM) structure, where the underlying distribution for crash frequency is a discrete and positive integer variable.

2.1.1 Underlying distribution for crashes

It is generally accepted that crash occurrences follow the Poisson process (Persaud et al., 1999; Kononov and Allery, 2003; etc.), such that:

$$P(X = y_i) = \frac{\mu_i^{y_i} \cdot e^{-\mu_i}}{y_i\,!} \qquad [2.3]$$

Where $P(X=y_i)$ is the probability that the observed crash frequency equals y crashes during time period *i*, and μ_i is the expected number of crashes for the same time period *i*.

For a random variable *X* follows Poisson distribution, its variance is assumed equal to its mean, or

$$X \sim Poisson,\ Var(X)=\mu$$

However, this assumption (i.e., variance = mean) may not hold for all crash data. For rare events like crashes the variance is usually greater than the mean (e.g., the crash data are over-dispersed) (Lord et al. 2005). This is mainly due to the unobserved differences across sites and unmeasured uncertainties associated with the observed and unobservable covariates (Hauer, 1997; Washington et al., 2003; Mitra and Washington, 2007; Lord and Park, 2008, etc.). In such cases crash dataset are better represented by a long tail distribution, indicative of high variation (Boonsiripant, 2009). The negative binomial (NB) distribution can be used instead of the Poisson distribution to solve the problem of over-dispersion in the crash data n that it has the more flexible feature that variance is a non-linear function of the mean, as compared to the Poisson assumption of equality. The Negative Binomial has been the preferred distribution for crash prediction in recent years (Hauer, 1997). It is worth noting that the NB distribution is sometimes referred to as Poisson-Gamma distribution. The NB is of the form:

$$P(Y_{i,t},\mu_{i,t},\phi)=\frac{\gamma(y_{i,t}+\phi^{-1})}{\gamma(\phi^{-1})\cdot y_{i,t}!}\left(\frac{1}{1+\phi\mu_{i,t}}\right)^{\phi^{-1}}\left(\frac{\phi\mu_{i,t}}{1+\phi\mu_{i,t}}\right)^{y_{i,t}} \quad [2.4]$$

Or,

$$Y_{i,t} \sim NB(\mu_{i,t},\ \phi)$$

with,

$$E(Y_{i,t})=\mu,\ \text{and}\ Var(Y_{i,t})=\mu+\phi\mu^2 \quad [2.5]$$

where

$\mu_{i,t}$ = the expected number of crashes at site *i* in year *t*, which can be calculated from one of the SPFs

$y_{i,t}$ = the observed number of crashes at site *i* in year *t*,

$\gamma(.)$= gamma function

ϕ = the dispersion parameter, NB distribution parameter $\phi > 0$.

The NB distribution can also be expressed as:

$$P(Y_i, P(x_i), \varphi) = \frac{(y_i + \varphi - 1)!}{(\varphi - 1)\cdot(y_i)!} P(x_i)^{\varphi} \left[1 - P(x_i)\right]^{y_i} \qquad [2.6]$$

With mean and variance as:

$$E(\mathrm{Y}_i) = \mu_i = \frac{\varphi\left[1 - P(x_i)\right]}{P(x_i)} \quad \text{and} \quad Var(Y_i) = \mu_i + \frac{\mu_i^2}{\varphi} \qquad [2.7]$$

where φ = the inverse of the NB dispersion parameter; and *P(x_i)* is the probability of x crashes at site *i* ($0 \leq P(x_i) \leq 1$). The probability, $P(x_i)$, is assumed to follow the gamma distribution (Hauer, 1997; Lord et al., 2005; Miaou, 1996) with shape parameter φ and scale parameter equals to $\left(\frac{P(x_i)}{1 - P(x_i)}\right)$.

When the dispersion parameter ϕ in Equation [2.5] goes to zero or when the inverse of the dispersion parameter φ in Equation [2.7] goes to infinity, both Equations [2.5] and [2.7] are equal to the Poisson distribution with mean and variance μ.

2.1.2 Generalized linear models (GLM)

Both Poisson and negative binomial distributions are from the exponential family that can be considered in GLM models. Parameter estimation in GLM makes use of the maximum likelihood (ML) techniques . Statistical software such as SAS ® software (SAS, 2014) and R-statistical software (R, 2012) can be used to obtain safety performance function (SPF) for crash prediction.

Generalized Linear Modeling (GLM) consists of three components (Everitt, and Hothorn, 2006; McCullagh and Nelder, 1989):

1. **Random component (the error distribution)**: This component represents the error distribution of the dependent variable (crash count).
2. **Systematic component:** This component consists of the independent variables that will be used to develop the linear model that will serve as the predictor.
3. **Link component:** This component links the random component to the systematic component (i.e., how the linear function of the independent variables is related to the response value). The general form of the link function can be expressed as:

$$g(\mu) = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + + \beta_k \cdot x_k \qquad [2.8]$$

For GLM models, the variance function that represents the relationship between the variance and its mean can be presented as:

$$Var(y) = \phi \cdot V(\mu) \qquad [2.9]$$

Where ϕ is the dispersion parameter (estimated by statistical packages like SAS and R) and $V(\mu)$ is the variance of the model as a function of the mean. When $V(\mu) = 1$ and $\varphi = \phi\ \sigma^2$ the error is normally distributed. When $V(\mu) = \mu$ and $\varphi = \phi = 1$, we assume that the error is Poisson.

2.1.2.1 Tests of goodness of fit

The goodness of fit of a Poisson or NB GLM models to crash data can involve:

1. Statistical significance of model parameters at a given level of significance (usually 5%);
2. Deviance $/(n-p)$ test: it tests the ratio of the deviance of the full model to the degree of freedom $(n-p)$, and its value measures the degree of dispersion in crash data.

For Poisson this deviance can be expressed as:

$$D = 2\sum_{i=1}^{n}\left(y_i \log(y_i/\mu_i) - (y_i - \mu_i)\right) \tag{2.10}$$

The term D in Equation [2.10] follows the chi-squared distribution, with $n-p$ degrees of freedom. n is the number of observations and p is the number of parameters in the model. The value of the Scaled $Deviance/(n-p)$ should be close to 1 for a model based on data that are not over-dispersed (McCullagh and Nelder, 1989).

3. Akaike information criterion (AIC) (Akaike, 1973; Bozdogan, 2000): AIC penalizes extra parameters when the expected log likelihood is estimated by the maximum likelihood techniques, and is expressed as:

$$AIC = -2\log L(\hat{\theta}) + 2k \tag{2.11}$$

where

$L(\hat{\theta})$ = The maximized likelihood function of the parameters in model, at a value θ that maximizes the probability of the data given the model; and

k = The number of free parameters in the model.

A model with a minimum AIC value is chosen as the best-fit model. Other models have a lower $L(\hat{\theta})$ and more parameters.

2.1.3 Empirical Bayes model

The EB approach has been examined and explored by several researchers (Hauer, 1992; Hauer, 1997; Persaud et al., 1999; Hauer et al., 2002) and was found to provide valid results. Hauer et al. (2002) presented a simple systematic procedure on how to implement the EB method in traffic safety studies.

The best estimate of expected crashes at a specific site is obtained by combining:

1. The historical crash record (y) for a specific site (e.g., intersection), and
2. The expected number of crashes (μ) for similar sites, which is usually obtained from a safety performance function (SPF).

By combining the two sources of information regarding crash experience, a long term average (λ) of crashes can be obtained. The EB expected crashes for a specific site can be estimated as:

$$\lambda_i = E(\mu_i \mid \mathrm{y}_i) = \alpha_i \cdot \mu_i + (1 - \alpha_i) \cdot y_i \qquad [2.12]$$

with,

$$E(\lambda_i) = \lambda_i, \quad \text{and} \quad Var(\lambda_i) = (1 - \alpha_i) \cdot E(\lambda_i) \qquad [2.13]$$

where

λ_i = EB Expected number of crashes in *n* years at site *i*,

μ_i = Expected number of crashes in *n* years at similar sites (i.e., from SPFs),

y_i = Observed crash frequency in *n* years at site *i*, and

α_i = The weight factor.

The weight factor (α_i) is usually estimated from the mean and variance of the *SPF* estimate [Equations [2.5] and [2.7]]. In the case of *NB* model, the weight factor can be estimated as follows:

$$\alpha_i = \frac{E(y_i)}{Var(y_i) + E(y_i)} \tag{2.14}$$

or,

$$\alpha_i = \frac{\varphi}{\mu_i + \varphi} \tag{2.15}$$

or,

$$\alpha_i = \frac{1/\phi}{\mu_i + 1/\phi} \tag{2.16}$$

and,

$$1 - \alpha_i = \frac{\mu_i}{\mu_i + 1/\phi} \tag{2.17}$$

Once the weight factor has been estimated, the expected number of crashes (λ_i) at a given site can be estimated using Equation [2.12].

The use of EB method requires the specification of a safety performance functions (SPFs) for crashes at reference sites. The development of the SPFs needs a large sample size of representative site data (Lan, 2010). The negative binomial (or Poisson-Gamma model) distribution, due to its simplicity in computation, is almost the sole distribution that can be used to implement the EB model approach. However, for some datasets the use of the Poisson-Lognormal distribution provides a better fit because lognormal distribution tails is asymptotically heavier than those of the Gamma distribution (Kim et al., 2002).

The EB model will serve as the basis of crash-based prediction results in this research. It is also worth noting that the treatment effects are also compared with sound EB results from other studies applied to the same dataset.

2.2 CRASH-BASED SAFETY ANALYSIS FOR PRIORITY RANKING

Priority ranking of unsafe locations (known also as hazardous locations, black spots, hotspots, sites with promise, etc.) is the first step to improve the safety performance of roadway network. By successively identifying the correct unsafe location, resources can be allocated to treat sites that really need treatment.

Priority ranking of unsafe sites results in a list of sites that are prioritized for detailed engineering evaluations to identify crash patterns, causes, and to select potential treatments that can implemented to reduce crashes (Hauer et al., 2002 and 2004; Montella, 2010).

Crash counts (or accident frequency (AF)) have been used for some time as the main source to identify unsafe sites for further examination and possible treatment. Some European countries still use the crash count alone for ranking purposes such as Austria, Germany, and Norway (Elvik, 2008b).

One of the main problems in identifying certain sites as unsafe locations based on their high crash experience is what is known as the regression to the mean (RTM) treatment bias (Elvik, 2008a; Park and Saccomanno, 2007; Hauer et al., 2004; Persaud et al., 1999; Hauer, 1996). The empirical Bayes (EB) approach can be used to get rid of the RTM problem, as EB design is to estimate a long-term average at each site.

In this research, two commonly applied observational crash-based priority-ranking methods will be discussed, namely:

1. Empirical Bayesian estimate of expected crashes (λ_i), and
2. Potential for safety improvement (PSI).

2.2.1 EB expected number of crashes

The expected number of crashes (λ_i) at each site i is obtained from Equation [2.12]. Sites are prioritized for intervention based on increasing values of (λ_i) or increasing expected number of crashes.

2.2.2 Potential for safety improvement (PSI)

Sites can be similarly ranked based on the potential for safety improvement (PSI) (Persaud et al., 1999), which is the difference between the EB expected crash frequency and the crash frequency predicted from a safety performance functions (SPF), such that:

$$PSI_i = \lambda_i - \mu_i = \alpha_i \cdot \mu_i + (1-\alpha_i)y_i - \mu_i \qquad [2.18]$$

μ_i represents the expected number of crashes on the basis of traffic volume alone from SPFs, and may not be reduced by treatments.

2.3 CRASH-BASED SAFETY ANALYSIS FOR TREATMENT EFFECT

In the EB approach, the effectiveness of a treatment is usually estimated as the difference between expected number of crashes in the after period had the treatment not been applied with the observed crashes post-treatment in the after period at the same site. Before determining the effectiveness of a treatment, two estimates need to be obtained:

1- An estimate of the expected number of crashes for the whole treatment group without treatment in the after period (i.e., λ_A); and

2- An estimate of the expected number of crashes for the whole treatment group with treatment in the after period (i.e., π or $E[Y_A]$).

Crash reduction (usually refer to as δ), Equation [2.19], and the index of treatment effectiveness (i.e., θ), Equation [2.20], are the most common measures that used to estimate treatment effect (Hauer, 1997; Hauer and Harwood, 2002; Persaud and Nguyen, 1998). The estimates of δ and θ can be determined using Equations [2.19] and [2.20].

$$\delta = \lambda_A - \pi \qquad [2.19]$$

$$\theta = \frac{\pi/\lambda_A}{\left(1 + \frac{Var(\lambda_A)}{\lambda_A^2}\right)} \qquad [2.20]$$

where

δ = Crash reduction in terms of number of crashes reduced in the period after implementation,

θ = Index of treatment effectiveness,

λ_A = The expected crashes for the whole treatment group without treatment in the after period, and

$\pi = E(\mathrm{Y}_A)$ = The expected crashes for the whole treatment group with treatment in the after period,

If the value of δ is positive, it implies that treatment is effective in reducing likely crashes. On the other hand if δ is negative, treatment has a harmful effect on safety (i.e., increases in crashes). Likewise, if θ is less than one, it implies that the treatment has been effective in reducing crashes, while if θ is greater than one, treatment is considered to be harmful. θ is also used to estimate the percentage increase or decrease in crashes after the introduction of treatment, such that:

$$\%\ change = (1-\theta)\times 100 \qquad [2.21]$$

For example, if the value of $\theta = 0.80$, this indicates a 20 percent reduction in crashes. The main issue in estimating treatment effect is how to obtain a reliable estimate of expected crashes at a given site in the after period had treatment not been introduced (λ_A). In the EB approach, the expected number of crashes in the before period (λ_B) is estimated at each site using the expression as:

$$\lambda_{Bi} = \alpha_i \cdot \mu_i + (1 - \alpha_i) \cdot \mathrm{y}_i \qquad [2.22]$$

where

λ_{Bi} = expected crash counts in *n* years at site *i* in the before period,

μ_i = expected crashes in *n* years at similar sites (i.e., estimated from SPFs),

y_i = observed crash counts in *n* years at site *i*, and

α_i = the weight given to the estimated expected crashes for similar entities.

The expected number of crashes in the after period without the treatment requires the introduction of an adjustment term that reflects changes between the before and after periods in traffic volumes and other confounding attributes, notwithstanding the treatment itself. This factor is estimated as the ratio of the expected numbers of crashes in the after period to the expected number before as obtained from the SPF.

The variances for δ and θ can be computed as (Hauer, 1997):

$$Var(\delta) = Var(\lambda_A) + Var(\pi) \qquad [2.23]$$

and

$$Var(\theta) = \frac{\theta^2\left[\left(\frac{Var(\lambda_A)}{\lambda_A^2}\right)+\left(\frac{Var(\pi)}{\pi^2}\right)\right]}{\left(1+\frac{Var(\lambda_A)}{\lambda_A^2}\right)^2} \quad [2.24]$$

The variances are usually used to validate the statistical significance of the estimates of δ and θ.

Equations [2.20] and [2.24] are applicable to individual sites for specific treatments. For multiple sites, λ_A is summed over all sites in the treated sample and compared to the sum of observed crashes for all the sites post-treatment. The variance of θ is also summed over all the sites in the treated group and the combined treatment effect is obtained by replacing λ_A and π in Equations [2.20] and [2.24] by their respective summations. A more in depth discussion of the EB before-after method for estimating treatment effects has been provided by Hauer (1997), the Highway Safety Manual (AASHTO, 2010) and by Gross et al, 2010.

The effectiveness of road safety treatments on crash reduction is frequently expressed in terms of a Crash Modification Factor (CMF), which is summed over all treated sites.

"CMF is a multiplicative factor used to compute the expected number of crashes after implementing a given countermeasure at a specific site" (FHWA, 2014). Recommended values of CMF are provided by the FHWA Clearinghouse for different treatments and site attributes. (FHWA, 2014). The values are continually updated as more recent empirical information becomes available and is introduced into the Clearinghouse database. .

2.4 CHAPTER SUMMARY

This chapter presented the key points to develop the safety performance functions, which will be used later on in this research to develop both crash-volume models and crash-conflict models. Crash prediction models can be used to fit nonlinear relationships between crash count as response variable and traffic characteristics as independent variables. Generalized linear models (GLMs) are the most common approaches to fit crash prediction models because they have the ability to use underlying crash frequency distributions (i.e., Poisson and Negative Binomial (NB) distributions). Due to the over-dispersion in most crash datasets, the NB is the most common distribution to be used in GLM models.

One of the major problems associated with observational crash data is presence of regression to the mean (RTM) bias. If the RTM bias is not resolved properly, then sites that happen to encounter a high number of crashes in a certain year will be ranked in the top list of unsafe sites that need treatment. This will give over-estimation of the treatment effect because extreme crash values (higher and lower than long-term average) fluctuate around the true mean or tend to return to the average value for each site.

Due to the RTM treatment bias, the EB approach has been used to obtain a long-term crash frequency at a given site to avoid the RTM problem. The use of EB requires crash-predication models (i.e., SPFs) from similar untreated reference sites.

Furthermore, the Chapter presented he most popular observational methods used in traffic safety analysis for both ranking of unsafe sites and estimating treatment effect. For priority ranking, the most used crash-based models are the EB and the PSI, as both can handle the RTM selection bias. EB is also the state of practice in estimating treatment effect. Observational before and after analysis are not proactive in nature. In other words, to determine treatment effects of a given countermeasure, the countermeasure will need to be implemented prior to the analysis and this may not always be possible.

CHAPTER 3

REVIEW OF TRAFFIC CONFLICT-BASED APPROACH

This chapter introduces the conflict-based approach for safety analysis and the use of microscopic traffic simulation in obtaining conflicts. The results of the traffic simulation are used as inputs into safety performance analysis, which can assist priority ranking of unsafe sites and the estimation of treatment effects.

3.1 TRAFFIC CONFLICTS AND SAFETY

"Crashes represent a complex hierarchical process of inter-related causes and consequences for different driving situations, locations and time intervals. Therefore, a complete picture of lack of safety emerges following a detailed mechanistic analysis of the causes and consequences of crashes at a given location and point in time" (Cunto and Saccomanno, 2005). For complex crashes, different mechanistic structures can be explored to provide insights into how these crashes take place at a given site and how they can best be prevented from occurring in the future. For example, Mehmood et al.(2002) used Systems Dynamics to describe crashes, and Cody (2005) used instrumented vehicles to evaluate drivers behaviours to better understand safety problems from left turns at intersections and hence provide appropriate treatments to prevent left-turn opposing crashes at these intersections.

Although concerns have been raised regarding the use of traffic conflict technique in particular its reliability, validity and data collection costs (Hauer, 1978; Hauer and Garder, 1986), researchers have continued to support its use as a surrogate measure of safety. Migletz et.al. (1985) and Glauz et al. (1985) showed that traffic conflicts provide comparable estimates to expected accident frequencies. In addition, several studies (Risser, 1985; Archer, 2000) have shown that higher rates of traffic conflicts at a given site indicate lower levels of safety. Hyden (1987) concluded that conflicts and crashes shared the same severity distribution based on time-to-accident and speed values.

Sachi et al. (2013) used conflict-based analysis to evaluate a right turn treatment at signalized intersections, and El-Basyouny and Sayed (2013) and Guido (2010) who investigated the relationship between crashes and conflicts. These researchers consistently found that traffic conflicts provide useful insights into the failure mechanism that leads to crashes.

A traffic conflict between two vehicles is assumed to be initiated by one of three possible actions: accepting a gap, changing lanes or braking (Ahmed, 1999; Gettman and Head, 2003). Once a vehicle initiates (i.e., stimulus vehicle) the conflict, the driver of the following vehicle (i.e., response vehicle) that affected by this maneuver should react with an appropriate to avoid a possible crash.

Traffic conflict technique (TCT) was initially used to obtain surrogate safety measures. TCT requires field observers' crews to collect the data and determine the potential number of conflicts along with their severities. This can be done either by collecting the data directly from the study site (e.g., an intersection) or by analysing videotaped data from the study site for a specific time. This process is expensive and subject to unreliable subjective observers (e.g., Archer, 2005; Brown, 1994; Sayed et al., 1994).

This subjectivity issue with TCT can be solved by using tracking data from all vehicles at the study site. For example, image-processing methods can be used to track vehicles and hence to extract traffic conflicts from videotaped data using certain camera-setup guidelines such as camera angle and camera elevation (Saunier et. al, 2010; Guido et. al, 2010; Sayed et.al, 2012). In addition to the cost associated with the data collection, real-time vehicles' tracking is not proactive for estimating treatment effect prior to implementation. Traffic microscopic simulation models can be used as cost-effective tools in determining vehicle trajectories, and as a proactive tool to evaluate effectiveness of treatments.

When properly calibrated, traffic micro-simulation models can provide a less expensive approach and a useful platform from which to measure traffic conflicts and hence provide safety performance measures that can be used in identifying high-risk situations in the traffic stream and guide cost-effective intervention strategies (Gettman and Head, 2003).

3.1.1 Traffic conflicts from microscopic simulation

Surrogate safety measures from microscopic simulation have been used lately to assess safety in transportation systems (Archer, 2000, Gettman and Head, 2003, Barcelo et al., 2003, Huguenin et al., 2005; Cunto and Saccomanno, 2008, Ghods et al., 2012). One of the unique features of microscopic traffic simulation models is that prospective alternatives can be tested before implementation, which is particularly interesting in the transportation scenario where geometric and operational changes are usually expensive and operationally troublesome (Cunto, 2008).

The development of commercially available microscopic simulation platforms has been continuing over the past decade. Original applications focused on multi-model traffic planning and operation analysis. Effort has been spent on developing algorithms to model various traffic environments such as interchanges, roundabouts, transit priority, signalized and un-signalized intersection. Driving behaviour modules have also been added to better reflect traffic pattern and enhance the accuracy of traffic measures output. The movements of vehicles in the traffic network at each time stamp are represented by a pre-set of rules. User-friendly interfaces ease the network setup and model parameters input. The most commonly used simulation packages include PARAMICS (Quadstone, 2014), VISSIM (PTV, 2011), CORSIM (McTrans, 2014), INTEGRATION (Van Aerde and Associates, 2012), and AIMSUN (TSS, 2014).

There are also some free open source microscopic traffic simulation models, such as SUMO (SUMO, 2014) and MITSIMLab (MIT, 2014), and self-developed programs, that were intended to be applied for certain situations. For example, TSS-SIM software (Sayed et al., 1994) was used specifically to simulate traffic conflicts at un-signalized intersections with three and four legs. Ghods and Saccomanno (2014) used an in-house simulation program to investigate unsafe vehicle interactions and passing movements for two-lane highway operations.

According to the FHWA report by Gettman and Head (2003), *"VISSIM microscopic traffic simulation software appears to support most of the modeling features required for obtaining surrogate measures at a reasonable level of fidelity."*

3.1.2 VISSIM micro-simulation platform

VISSIM (PTV, 2011 and 2012) was used in this research to simulate the traffic interaction at intersection locations. The major advantage of VISSIM over other programs is its flexibility in manipulating the built in features such that users can easily remodel the logic to suit their needs. The sophisticated vehicle behaviour modeling captures driver decisions and reactions in different traffic situations. A small time step of 0.1 second provides a high resolution of vehicles trajectories, which provides detailed vehicle interactions. In addition, the VISSIM micro-simulation platform allows the use of different vehicle types and user-defined changes of driving behaviour (e.g. desired speed distribution and car-following behaviour) to better replicate real-world site-specific characteristics (PTV, 2012).

To ensure the validity and reliability of results from simulation programs the model parameters need to be calibrated and validated against real world conditions. Errors in simulated traffic characteristics (speed and volume) contribute to errors in the simulated surrogate safety measures. Most VISSIM calibration studies focused on the measures of effectiveness for the traffic operations, for example delay, speed, and traffic flow. Cunto and Saccomanno (2008) calibrated and validated driving parameters in VISSIM for a signalized intersection based on the surrogate safety measures as the objective function in both the calibration and the validation.

The argument against using surrogate safety measures as the objective function when calibrating simulation models is that models, such as VISSIM, are traffic operation platforms and should be calibrated based on traffic parameters (e.g. speed, volume or density). On the other hand, when using simulation in safety studies, it is quite reasonable to use surrogate safety measures as the basis for calibration, but this should be used in parallel with other traffic parameters. Recently, researchers proposed using a multi-objective criteria approach based on both traffic attributes and traffic safety attributes when calibrating traffic simulation models for safety studies (Duong et al., 2010).

3.1.3 Surrogate safety indicators

The use of micro-simulation in safety studies requires the use of surrogate safety indicators that are a function of 'vehicle-pair' speeds and spacing. Several expressions of safety performance measures have been developed and described in the literature, for example, time-to-collision (TTC) (Hayward, 1972; Hyden, 1987), time exposed time-to-collision Indicator (TET) (Minderhoud and Bovy, 2001), time integrated time-to-collision indicator (TIT) (Minderhoud and Bovy, 2001), time to accident (TTA) (Hyden, 1987); the encroachment time (ET) (Allen et al., 1978), the deceleration rate to avoid the crash (DRAC) (Cooper and Ferguson, 1976), the proportion of stopping distance (PSD) (Allen et al,, 1978; Archer, 2005), the crash potential index (CPI) (Cunto, 2008; Cunto and Saccomanno, 2008), etc. A full description of a wide spectrum of surrogate safety measures, their advantages and shortcomings can be found in Archer (2005) and Cunto (2008).

Gettman and Head (2003) investigated potential surrogate measures of safety from existing traffic simulation models and suggested five safety indicators of relevance in simulation output, as summarized in Table 3.1.

Table 3.1: Surrogate safety indicators from microsimulation (Gettman and Head, 2003)

Surrogate Safety Measure	Description
Time to Collision (TTC)	The time required for two vehicles to collide if they continue at their present speed on the same path
Post-Encroachment Time (*PET*)	The time between the departure of the encroaching vehicle from the conflict point and the arrival of the vehicle with the right-of-way at the conflict point.
Initial deceleration rate (*DR*)	The deceleration rate applied by the driver taking the evasive action.
Maximum Speed (*MaxS*)	The Maximum speed of the two vehicles involved in the conflict event.
Maximum relative speed (*DeltaS*)	Maximum relative speed of the two vehicles involved in the conflict event.

To extract the surrogate safety indicators from traffic micro-simulation models, the vehicle tracking output file needs to be converted to vehicle-pair then vehicle interactions can be classified based on the interaction type (e.g., rear-end, angled) and conflict threshold (e.g., TTC<1.50s). The surrogate safety assessment model (SSAM) (Pu and Joshi, 2008) has been used to extract conflicts with different thresholds. In this thesis, time-to-collision (*TTC*) and deceleration rate (*DR*) are used to reflect the risk associated with rear-end and angled conflicts at intersection sites. These two measures are discussed below in more detail.

3.1.3.1 Time to collision (TTC)

Hayward (1972) and Hyden (1987) were among the first researchers to use the Time to Collision (TTC) as a measure of safety performance. TTC is defined as the time required two vehicles to collide if they continue at their present speed on the same path. During the course of collision between two vehicles, the minimum TTC can be taken as an indicator for the severity. TTC has been widely accepted due to its simple computation procedure and its ability to indicate the severity of a crash.

Archer (2005) suggested that a TTC ≤ 1.50s is the critical value for road safety in urban areas. In addition, Van der Horst (1990) indicated that the likelihood of crashes becomes a concern when TTC≤1.50s

Table 3.2 shows the TTC values associated with the risk of collision (ROC) as suggested by Sayed and Zein (1999). Based on Table 3.2 lower values of TTC indicate higher crash severity. However, it is not necessary that lower TTC indicates higher severity of crashes, and this is because speed is not included in the measure of severity. The argument is that although a lower TTC could indicate a higher probability of crash, it fails to recognize the severity of the crash.

Table 3.2. Time to collision and risk of collision (Sayed and Zein, 1999)

TTC and ROC scores	TTC	Risk of collision (ROC)
1	1.60s to 2.00s	Low risk
2	1.00s to 1.50s	Moderate risk
3	0.00s to 0.90s	High risk

In this thesis, the number of conflicts based on TTC was extracted using the Surrogate Safety Assessment Model (SSAM) (Pu and Joshi, 2008). A space-time diagram identifying TTC, for a conflict point event (e.g., LTOPP or crossing conflicts) is shown in Figure 3.1. The conflict point reflects the potential for angle crashes when the accepted gap, by the encroaching vehicle, is too small. In Figure 3.1, the trajectories of the crossing vehicle and the through vehicle are represented by curve "A" and curve "B", respectively. In such case, the TTC value can be estimated as (Gettman and Head, 2003a,b):

$$TTC = t_4 - t_3 \qquad [3.1]$$

where,

t_3 = the time when either corners of the crossing vehicle leaves the encroachment point (The encroachment end time), and

t_4 = the projected arrival time of the through-vehicle at the conflict point.

SSAM uses a unique algorithm to define conflict events and hence to define different parameters (e.g. times t_1 to t_5, speed and acceleration/deceleration of vehicles in question) related to each conflict event. In this analysis, these parameters were estimated every tenth of a second, as we used a resolution of 10 simulations for each second. More information on how the computational algorithm works and how SSAM estimates different surrogate safety indicators and different conflict types can be found in Gettman and Head (2003b). Further, information on the nature of TTC can be found in Sayed and Zein (1999), Archer (2005) and Cunto (2008).

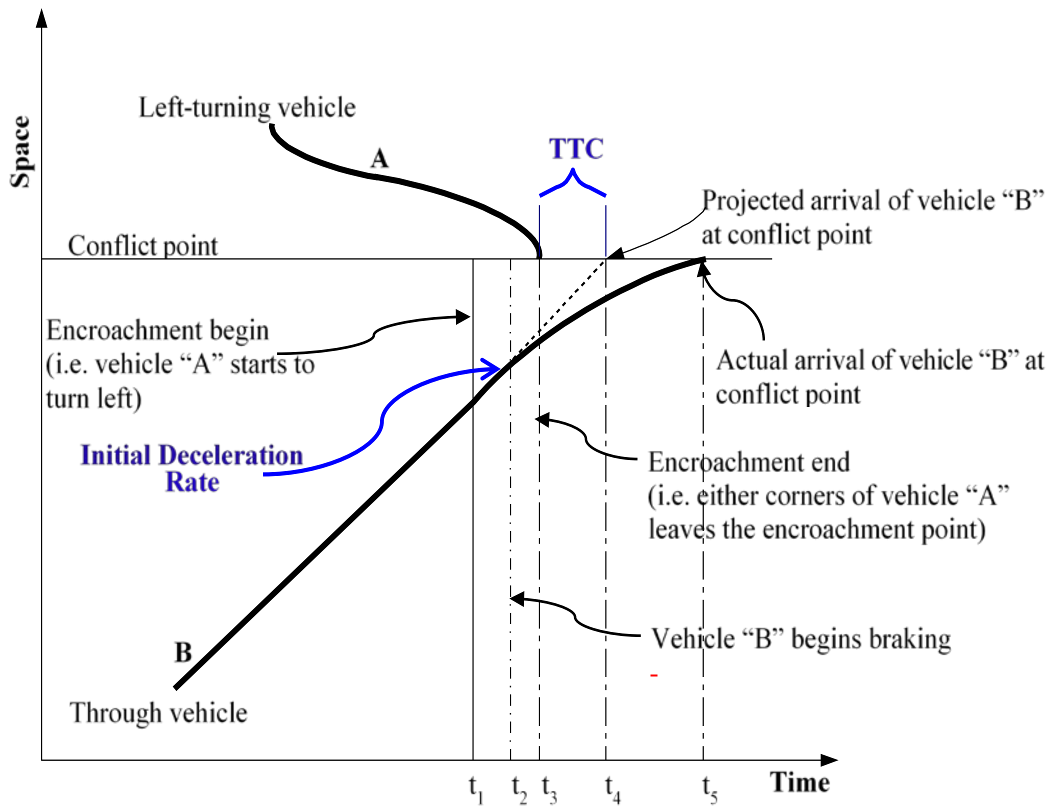

Figure 3.1: Time to Collision (TTC) and Deceleration Rate Identified on Conflict Point Diagram (Modified from Gettman and Head, 2003 a,b)

3.1.3.2 Deceleration rate (DR)

Cooper and Ferguson (1976) were among the first researchers to use the deceleration rate (DR) as a measure of safety. The initial DR can be defined as the deceleration rate applied by the driver taking the evasive action (Gettman and Head, 2003a,b).

McDowell et al. (1983) used five severity levels according to the value of *DR* to classify the severity of a given conflict as shown from Table 3.3. Severity grade 1 is considered the lowest severity conflict while grade 5 is considered the highest severity conflict.

Table 3.3: Severity and deceleration ranges (McDowell et al., 1983)

Severity grade	**Deceleration rate**	**Description**
1	Braking rate > -1.5 m/s^2	Lowest Severe Conflict
2	Braking rate -1.50 to -3.0 m/s^2	
3	Braking rate -3.0 to -4.50 m/s^2	
4	Braking rate -4.50 to -6.0 m/s^2	
5	Braking rate < -6 m/s^2	Highest Severe Conflict

Hyden (1996) suggested another classification for traffic conflicts and severity associated with them based on *DR*, as shown from Table 3.4. Hyden's (1996) classification is based on the expected driver reaction to achieve the required deceleration to avoid possible crash.

Table 3.4: ***DR*** **severity levels suggested by Hyden (Archer, 2005)**

Conflict level	Deceleration-to-safety	Description
No conflict	Braking rate ≤ 0 m/s^2	Evasive action not necessary
No conflict	Braking rate 0 to -1 m/s^2	Adaptation necessary
1	Braking rate -1 to -2 m/s^2	Reaction necessary
2	Braking rate -2 to -4 m/s^2	Considerable reaction necessary
3	Braking rate -4 to -6 m/s^2	Heavy reaction necessary
4	Braking rate < -6 m/s^2	Emergency reaction necessary

3.1.4 Simulated conflict estimation framework

A general framework to estimate simulated traffic conflicts is shown in Figure 3.2. The estimation procedure starts with simulating vehicle movements (e.g., using VISSIM traffic micro-simulation model) at the sites of interest for a given period of time. This time-period can be limited to only the morning or the afternoon peak hours or other periods based on the nature of the countermeasure and the time of day that may be of interest.

The inputs to the simulation platform are the geometry of the site under consideration, number of lanes, number of through and turning vehicles at each approach, signal times, signal plans, etc. In addition, a number of parameters that represent driving behavior need specification, such as, car-following, gap acceptance, lane change behaviors. The value of these inputs is obtained through calibration based on observed vehicle tracking data and simulated output error analysis.

After running the simulation for the pre-specified time and with the traffic and geometric features at the study location, the trajectories that shows locations of all vehicles entered the simulation network for every simulation resolution period (e.g., usually 0.10s) can be obtained.

The next step is to convert individual vehicle trajectories to vehicle-pairs for a given type of interaction (i.e., lead and following vehicles in case of rear-end interactions). It is worth noting that most major micro-simulation models can output vehicles trajectories in formats (e.g., usually trj files) that can be used directly with conflict analysis software such as SSAM (Surrogate Safety Assessment Model). The output files from VISSIM can be then inputted to SSAM model to extract vehicles' interactions. The processed VISSIM outputs in SSAM can be exported to allow further analysis (i.e., remove pedestrian-pedestrian conflicts). Furthermore, by selecting a surrogate safety indicator of interest and conflict threshold, the simulated conflicts can be estimated for the site under study. The simulated conflicts can be also estimated by type (e.g., rear-end conflicts).

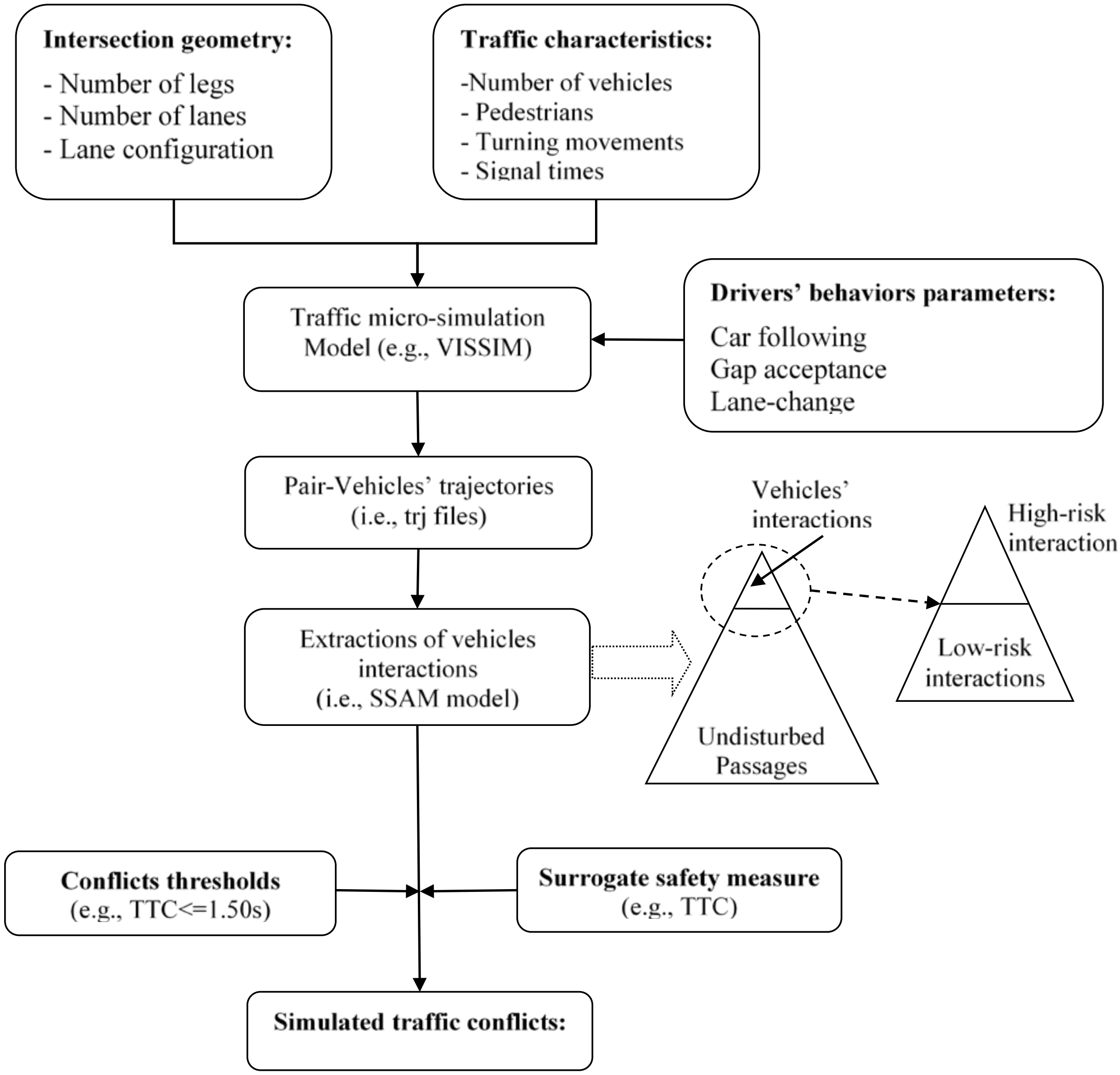

Figure 3.2: Framework for estimating conflicts

3.2 CONFLICT-BASED PRIORITY RANKING OF UNSAFE LOCATIONS

Similar to crash-based methods, conflict frequency (CF) can be used to prioritize unsafe sites for safety intervention. In a FHWA report (Gettman et al., 2008), the rank order of unsafe intersections using simulated conflict frequency was compared to the rank order using crash frequency over three years. The Spearman rank correlation coefficient between the two ranked lists was found to be of 0.463 (i.e., significant agreement).

Another conflict-based ranking method called the average conflict rate (ACR) was introduced by El-Basyouny (2006) as follows:

$$ACR = \frac{\text{Average hourly conflicts}}{\sqrt{\text{hourly volumes from the major and the minor approaches}}} \qquad [3.2]$$

El-Basyouny (2006) compared the ranking estimates using *ACR* based on estimated conflicts from VISSIM and SSAM models with ranking estimates from PSI crash-based method for a sample of intersections. The Spearman rank correlation coefficient was found to be very weak (i.e., 0.132), which indicated minimal agreement in the ranking between the total conflict based-method and the PSI rankings. The same was for the severe ACR conflicts when compared to the PSI (i.e., Spearman rank coefficient = 0.008). In addition, El-Basyouny (2006) conducted the same analysis using conflicts by type (i.e., crossing, rear-end and lane-change conflicts), and there was no significant agreement between ranking orders from conflict-based method and crash-based methods. Spearman rank coefficients were found to be less than 0.06 for the 3 conflict/crash rankings.

3.3 CONFLICT-BASED TREATMENT EFFECT

The change in the number of conflicts in the before and after treatment(s) has been used as an indication of treatment effect at given sites (e.g., Zhou et al., 2010; Sayed et al., 2012; Autey et al., 2012, etc.). To evaluate the safety effects of a treatment using simulation, the site is simulated twice, once without the treatment (i.e., the before period) and the second time with the treatment (i.e., the after period). To account for the treatment only, both the traffic volume and the calibration parameters should be remained unchanged.

Similar to the crash-based methods, the conflict reduction (ΔCF), the index of treatment effectiveness (ρ) and the percentage of change (% change) can be used to estimate the treatment effectiveness based on simulated conflicts as shown in Equations [3.3] - [3.5]:

$$\Delta CF = CF_A - CF_B \quad [3.3]$$

$$\rho = \frac{CF_A}{CF_B} \quad [3.4]$$

$$\%\,Change = (1 - \rho) \times 100 \quad [3.5]$$

where

ΔCF = Conflict reduction in terms of number of conflicts reduced in the period after implementation of the countermeasure,

ρ = Index of treatment effectiveness,

CF_B = Number of conflicts without treatment,

CF_A = Number of conflicts with treatment, and

$\%\,Change$ = Percentage of increase or decrease in simulated conflicts after the implementation of the countermeasure.

3.4 CHAPTER SUMMARY

This Chapter presented the traffic conflict approach, which will be used later on in this thesis in developing the integrated crash-conflict models. Traffic conflicts can be observed in the field at a given site or they can simulated through the use of traffic microsimulation models (e.g., VISSIM).

There are different indicators that can be used as measures of safety. In this thesis research, the TTC and DR will be used to obtain simulated conflicts.

This Chapter also presented how conflict-based methods can be used in ranking unsafe sites and in estimating treatment effects at a given site. The simulated conflict-based approach is proactive in nature in that treatment effects can be estimated prior to implementation. However, treatment effect is obtained as the percentage of simulated conflict reductions between the after and before can be used as exploratory indication of the treatment effectiveness. This is because the reduction in crashes for a given countermeasure is not known.

CHAPTER 4

PROPOSED CRASH-CONFLICT INTEGRATED MODELS

Chapter 4 presents integrated priority-ranking and treatment effect models that combine the expected crash frequency from observational models with simulated traffic conflicts. The models are used to provide insights into two fundamental safety questions: Which sites should receive priority treatment? And what is the crash-reduction benefit of the treatment being considered at a specific site?

4.1 INTEGRATED PRIORITY RANKING MODEL

The high cost of intersection crashes provides strong justification for the development of efficient, objective guidelines for safety intervention (NHTSA, 2012). These guidelines must be based on reliable priority ranking models.

Observational models based on reported crash history are commonly used to identify unsafe sites for priority intervention. Recently, microscopic traffic simulation has been used to yield surrogate measures of safety performance to predict high-risk vehicle interactions for different traffic conditions. This can also be used as a basis for priority ranking. Proponents of latter models argue that taking into account these higher risk interactions can help in gaining a better understanding of the safety problem. Reported crashes tend to underreport less severe crashes, and ignore near misses (Nicholson, 1985; Farmer, 2003; Davis, 2004; Saunier and Sayed, 2007; Hauer and Hakkert, 1989). These low severity crashes and near misses may contain essential information concerning lack of safety that is important from the point of view of effective intervention.

Combining the expected crash frequency with high-risk vehicles' interaction (or traffic conflict) from microscopic traffic simulation models may help in obtain better priority rankings for unsafe sites.

4.2 INTEGRATED PRIORITY RANKING MODEL FORMULATION

An integrated priority ranking measure is proposed based on the weighted sum of EB expected number of crashes and the number of simulated traffic conflicts. This weighted sum is referred to as a priority ranking safety score (SS), which is expressed, as:

$$Safety\ Score_i = CF_i + W \times EB_i \qquad [4.1]$$

where

CF_i = Number of simulated conflicts at site *i*,

EB_i = Expected number of crashes at site *i* estimated by EB method, and

W = Weight factor that represents the importance of EB.

The weight factor in the above expression needs to be determined since we do not know how much importance should be placed on crashes as compared to conflicts. In this thesis, the weight factor value is determined iteratively by using a total score criterion introduced by Montella (2010).

Montella's total score measure combines the results of three evaluation criteria:

1. **Site consistency (C_1):** sum of observed crashes in succeeding time-periods (Cheng and Washington, 2008)
2. **Method consistency (C_2):** number of matching sites in both ranking periods (Cheng and Washington, 2008).
3. **Total rank difference (C_3):** sum of absolute rank differences between rankings in both ranking periods (Cheng and Washington, 2008).

The total score measure (C_4) assumes that the three tests (C_1, C_2 and C_3) have equal weights, such that:

$$C_{4j} = \frac{100}{3} \times \left[\left(\frac{C_{1j}}{\max_j C_1} \right) + \left(\frac{C_{2j}}{\max_j C_2} \right) + \left(1 - \frac{C_{3j} - \min_j C_3}{\max_j C_3} \right) \right] \quad [4.2]$$

where,

$max_j C_1$ = Maximum value of C_1 among the compared methods,

$max_j C_2$ =Maximum value of C_2 among the compared methods,

$max_j C_3$ = Maximum value of C_3 among the compared methods, and

$min_j C_3$ = Minimum value of C_3 among the compared methods.

If the performance of method *j* performed best for all evaluation criteria, the total score value (C_4) is assigned 100%. The goal here is to find the weight *W* that maximizes the total score corresponding to the integrated safety score (*SS*) method.

Figure 4.1 shows a suggested framework to estimate an appropriate weight factor as given in Equation [4.1]. First, different values of the weight factor (e.g., 10, 20, 30, 40, etc.) can be assumed and the total score value (C_4) that corresponds to each assumed weight can be estimated. This process can be repeated until a satisfactory value of the total score test is achieved (e.g., larger than C_4 associated with *EB* method). Alternatively, the results of different weight factors and the total score test values can be plotted, then *W* associated with the highest C_{4j} can be used in the *SS* formula.

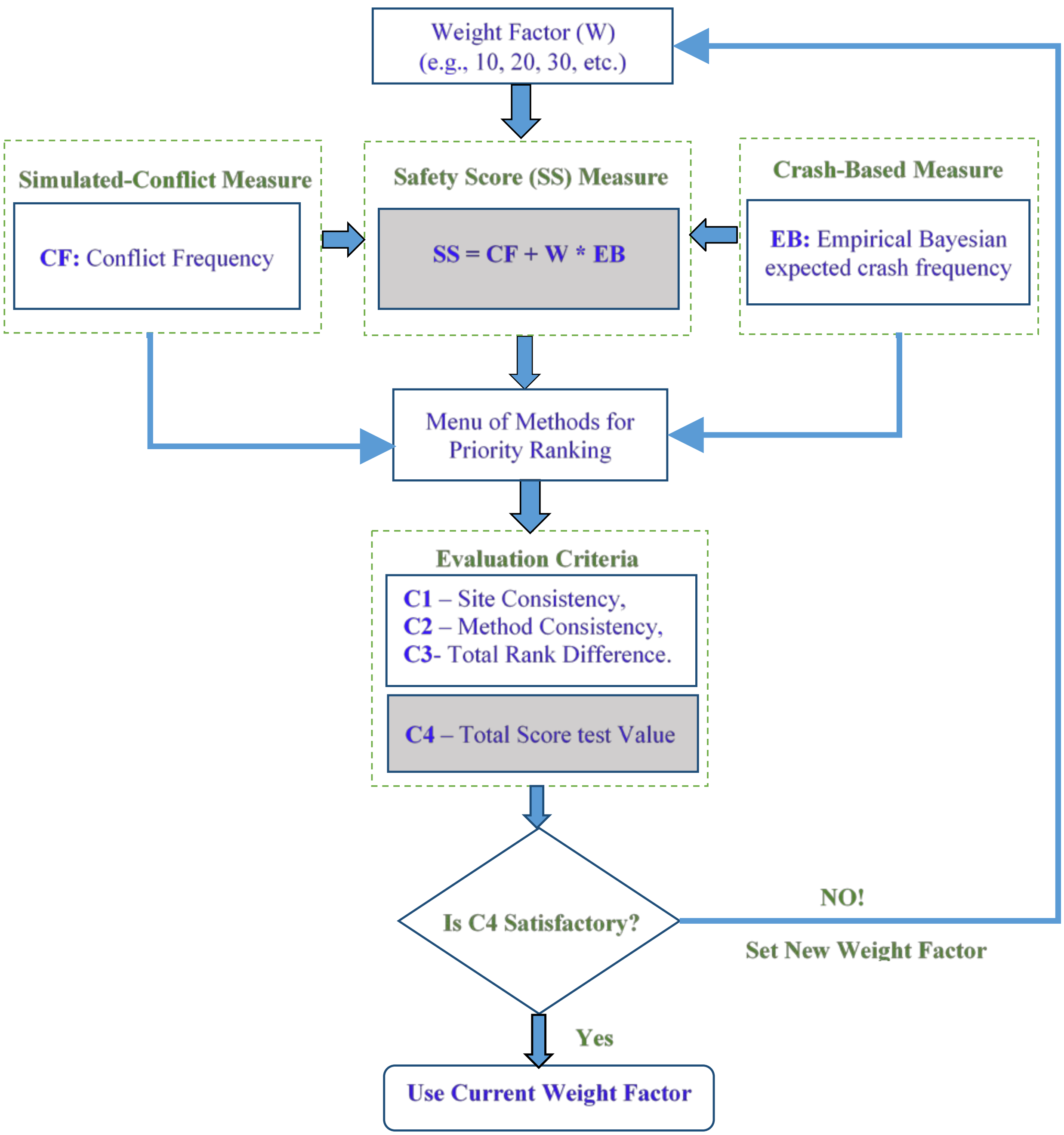

Figure 4.1: Framework to estimate weight factor

4.3 INTEGRATED TREATMENT EFFECT MODEL

This section presents an integrated model for estimating treatment effectiveness at a given site. The method is based mainly on comparing the number of simulated conflicts with and without the countermeasure and then converting the conflict ratio to an equivalent crash modification factor (CMF).

As noted in Chapter 1, observational before-and-after crash-based studies are the most common methods to estimate CMFs for assessing the implication of road safety treatments (Hauer, 1997). Using observational crash-based models to evaluate treatments can only be determined after implementing treatment(s) and this can only be achieved if sufficient site-years of treatment data are available to ensure statistically meaningful results. As such, observational crash-based models for treatment effect are not proactive. In addition, the rationale underlying why certain treatments result in crash reduction remains unexplained because observational crash prediction models do not specify causes and consequences of the crashes and how these are affected by driver behavioural factors.

Simulated traffic conflicts, as noted earlier, can be used to address these drawbacks in the crash-based models, but they have not been formally linked to crashes. As such, traffic conflicts are viewed as abstract representations of lack of safety. The following sections presents a framework for addressing this limitation by integrating observed crash-based and simulated conflict-based indicators to obtain crash modification factors.

4.3 PROPOSED CRASH –CONFLICT CMF FORMULATION

A general framework to estimate a CMF from simulated traffic conflicts is illustrated in Figure 4.2. Estimates of simulated traffic conflicts are obtained for a representative sample of sites for relevant road geometry and traffic inputs. The simulation is carried out with and without a specific treatment, and the corresponding conflict modification factor is obtained. The conflicts are used as inputs in a crash-conflict relationship based on observed crash and simulated conflict data. This relationship is then used to estimate the CMF with its corresponding mean and variance.

From simulation, the estimates of conflicts with and without treatment can be summarized by their mean and variance, such that:

C_b = Summation of the mean number of conflicts without treatment (i.e., before) at all treated sites,

$Var(C_b)$ = Summation of the variance of conflicts in the before period at all treated sites,

C_a = Summation of the mean number of conflicts with treatment (i.e., after) at all treated sites

$Var(C_a)$ = Summation of the variance of conflicts in the after period at all treated sites.

It is worth noting that the mean value of conflicts in the before and after periods can be obtain by dividing the total number of conflicts for all simulation runs divided by the number of simulation runs.

The expected conflict ratio (ρ) is estimated as:

$$\rho = \frac{C_a}{C_b} \quad [4.3]$$

With a variance of:

$$Var(\rho) = (C_a / C_b)^2 \times \left[\left(Var(C_a) / C_a^2 \right) + \left(Var(C_b) / C_b^2 \right) \right] \quad [4.4]$$

Using a separate sample of data for which both conflicts and observed crashes are available, we can establish an empirical relationship between expected crashes and simulated conflicts, such that:

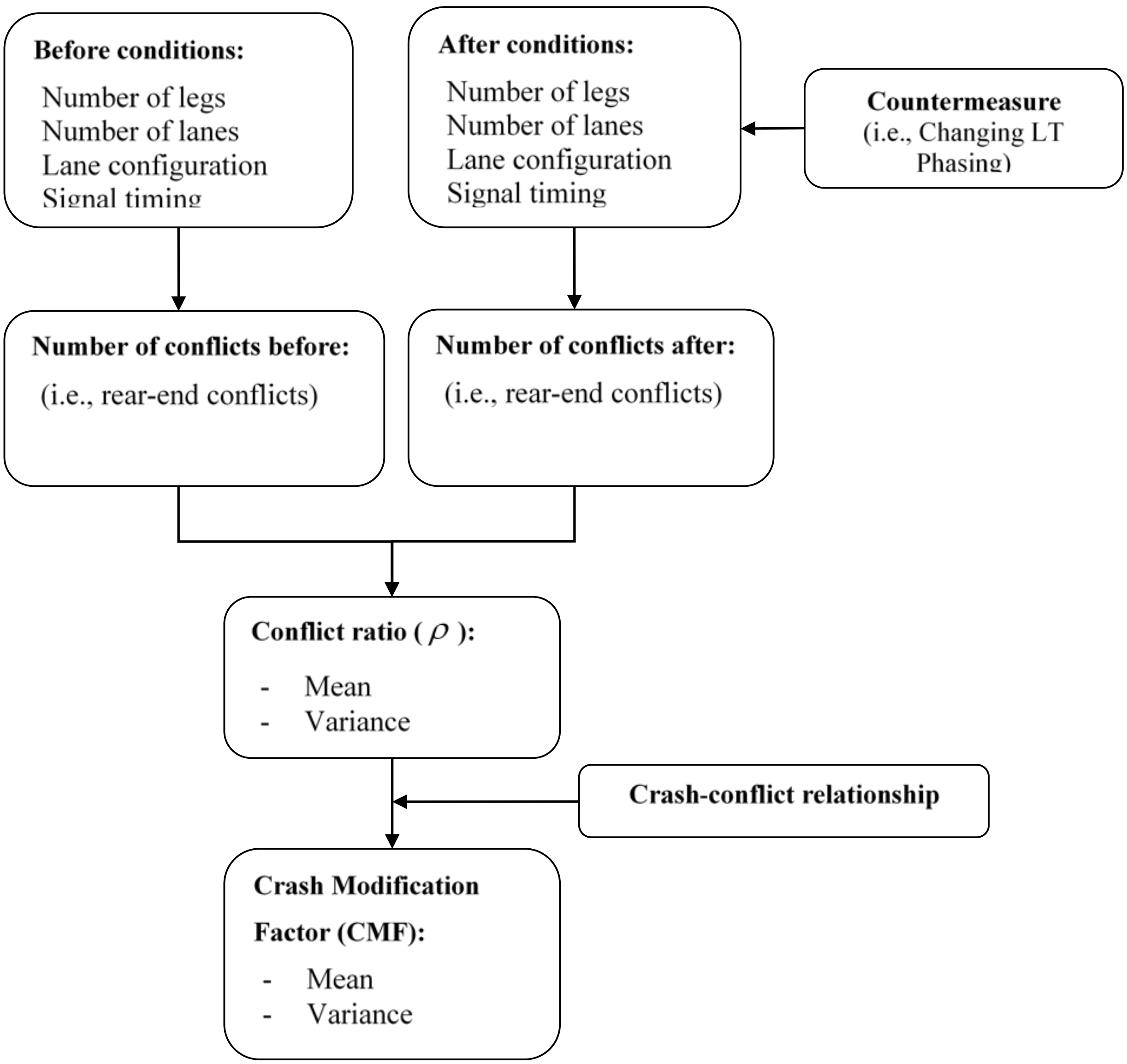

Figure 4.2: Integrated CMF estimation framework

$$Crashes = \alpha \cdot (Conflicts)^{\beta} \quad [4.5]$$

The parameters in Equation [4.5] will need to be obtained empirically using generalized linear models (GLM). As given in Equation [4.6], θ is expressed as the ratio of the expected number of crashes (after over before), such that:

$$\theta = \frac{\alpha \cdot (C_a)^{\beta}}{\alpha \cdot (C_b)^{\beta}} \quad [4.6]$$

$$\theta = \left(\frac{C_a}{C_b}\right)^{\beta} = (\rho)^{\beta} \quad [4.7]$$

The variance associated with θ can be estimated assuming that ρ is normally distributed. θ is a function of ρ such that, $\theta(\rho) = \rho^{\beta}$, which can be represented by the Taylor series:

$$\theta(\rho) = m^{\beta} + \frac{m^{\beta}\beta(\rho - m)}{m} + \frac{(m^{\beta}\beta^{2} - m^{\beta}\beta)(\rho - m)^{2}}{2m^{2}} + \cdots \quad [4.8]$$

where m is the expected value of ρ. Since m and β are assumed constant, new parameters a_1 and a_2 can be introduced, such that:

$$a_1 = \frac{m^{\beta} \cdot \beta}{m} \quad [4.9]$$

$$a_2 = \frac{m^{\beta} \cdot \beta^{2} - m^{\beta} \cdot \beta}{2m^{2}} \quad [4.10]$$

and $\theta(\rho)$ becomes:

$$\theta(\rho) = m^{\beta} + a_1(\rho - m) + a_2(\rho - \mathrm{m})^{2} + \cdots \quad [4.11]$$

The expected value of θ can be estimated using the first term in the Taylor series, such that:

$$E(\theta) = E[\theta(\rho)] = \mathrm{m}^{\beta} \qquad [4.12]$$

and the variance of θ can be estimated as:

$$Var\left[\theta\right] = \int_{-\infty}^{\infty} \left[g(\rho) - E[\theta]\right]^2 f_\rho(\rho) d\rho \qquad [4.13]$$

By substituting $\theta(\rho)$ and $E(\theta)$ from Equation [4.11] and Equation [4.12] in Equation [4.13] , the variance of θ can be expressed as:

$$Var\left[\theta\right] = \int_{-\infty}^{\infty} \left[a_1(\rho - m) + a_2(\rho - m)^2\right]^2 f_\rho(\rho) d\rho \qquad [4.14]$$

and Equation [4.14] becomes more simply as:

$$Var\left[\theta\right] = a_1^2 \cdot Var(\rho) + a_2^2 \cdot \left(3 \times (Var(\rho))^2\right) \qquad [4.15]$$

The parameters a_1 and a_2 can be estimated as:

$$a_1 = \rho^{\beta - 1} \times \beta \qquad [4.16]$$

$$a_2 = \frac{1}{2} \times \rho^{\beta - 2} \times \beta \times (\beta - 1) \qquad [4.17]$$

The above procedure produces estimates of site specific CMF and its variance that are a function solely of the ratios of simulated conflicts (with and without treatment) and the parameter β whose value is established empirically from the fitted crash-conflict expression.

4.4 CHAPTER SUMMARY

This Chapter presented a new priority ranking method that combined the expected crash frequency from observational models and simulated conflict frequency. In addition, it has presented a model for integrating observed crash-based and simulated conflict-based indicators to obtain treatment Crash Modification Factors (CMFs). Once the link between simulated conflicts and crashes is established, the integrated treatment effect model will mainly depend on the simulated conflict ratio. The main advantage of a simulation approach is that it is proactive in nature, meaning that estimates of treatment effects can be determined before implementing the treatments. In addition, the integrated approach ensures that the value of the CMF applied is site specific. This is because CMF varies from site to site depending on the site and/or treatment characteristics. This is a big advantage since most conventional crash-based CMFs available are constant.

This can help transportation engineers in estimating the countermeasure effectiveness of proposed treatments before implementation. In addition, the model has the added advantage of providing a causal underpinning for how vehicle movements and driver responses in the traffic stream act to alter safety at a specific site subject to treatment under an assumed set of geometric and traffic conditions.

CHAPTER 5

CASE STUDY ONE: PRIORITY RANKING OF INTERSECTIONS

Chapter 5 presents the results of two priority ranking case study applications: (1) comparing crash-based priority ranking with conflict-based priority ranking for the same sample of intersections; and (2) applying the priority ranking from an integrated crash-conflict model to the same sample of intersections and comparing the results.

For the first application, six different ranking procedures are used: 1) crash frequency (AF), 2) empirical Bayes expected crash frequency (EB), 3) potential for safety improvement (PSI), 4) conflict frequency (CF) and 5) conflict rate (CR) (sum and cross product of traffic volume). To assess the merits of the resultant rankings, six different evaluation metrics are employed: site consistency, method consistency, total rank difference, total score, sensitivity and specificity (Cheng and Washington, 2008; Montella, 2010; Elvik, 2008a).

For the second application, the integrated model is used to obtain rankings for the same intersection sample. The performance of the integrated model is then compared with crash-based and conflict-based ranking procedures. In this, traffic conflicts were obtained for the intersection sample as simulated from VISSIM 5.30 (*PTV, 2011*). The inputs into the simulation exercise are intersection approach volumes and turning movements. Furthermore, selected input parameter values in VISSIM were obtained from an intersection traffic study using VISSIM by Cunto and Saccomanno (*2008*). The selected parameters are desired deceleration, standstill distance (CC0) and headway time (CC1).

5.1 CASE-STUDY DATA

A sample of 58-signalized intersections from Toronto was used in this analysis. All intersections are four legged and have no exclusive turning lanes. The sample intersections were observed to experience 2,331 crashes (all severities combined) over an eight-year period from 1999 to 2006 or 40 crashes per intersection.

A different set of 35 four-leg signalized intersections, for which turning traffic volume movements were available, were simulated using VISSIM to estimate the expected number of traffic conflicts. The reason for using other intersections is that the turning movements are not available for the 58 sites. The 35-intersections are comparable in that they did consist of two lanes in each approach with no exclusive left-turn or right-turn lanes.

Three of the six ranking procedures used in this analysis (EB, PSI and SS) required the specification of a safety performance function (SPF). The data were separated into two time-periods for the purpose of comparison: the first and the second ranking periods.

The first ranking period used in this analysis was 3-years from 2002 to 2004 and the second ranking-period (i.e., evaluation period) was 2-years from 2005 to 2006, as shown in Figure 5.1. The time period 1999-2001 was used to calibrate the SPF and to estimate the EB expected number of crashes (i.e., prior) for the first analysis period (2002-2004). In addition, the period from 2002 to 2004 was used to estimate the EB expected number of crashes (e.g., prior) in the second analysis period (2005-2006), as shown from Figure 5.1.

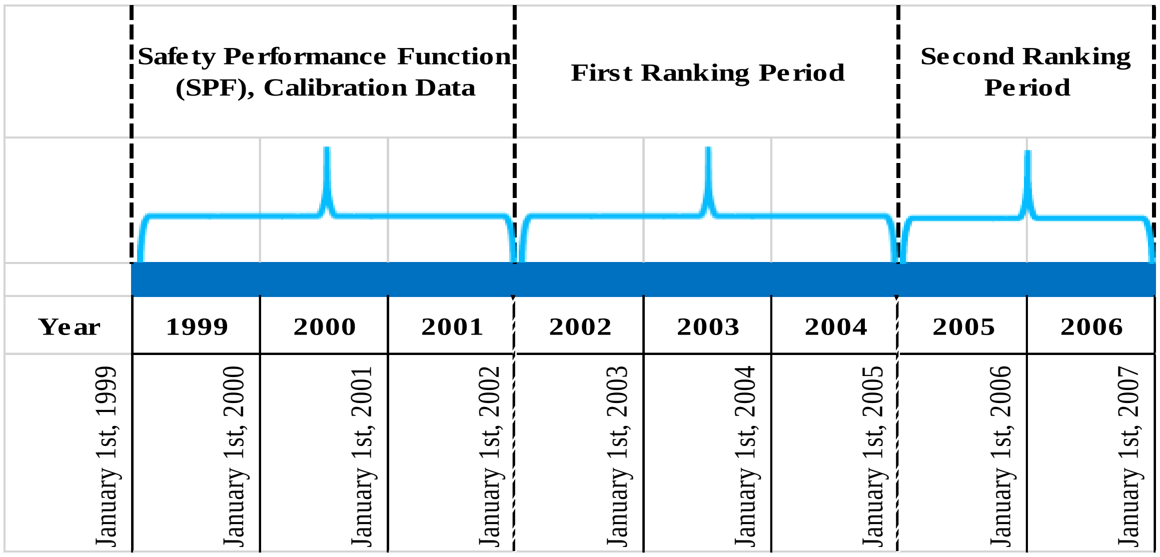

Figure 5.1: Data split diagram between SPFs, first and second ranking periods

5.1.1 Safety performance functions for crashes

Generalized linear modeling (GLM) techniques were used to fit the crash prediction expressions, with a negative binomial (NB) error structure. The model parameters and the dispersion parameter of the NB distribution were estimated by the maximum likelihood method using the PSSL library in R-statistical software (R, 2011). The selected SPF model forms are as follows (Hauer and Bamfo, 1997):

Form (1): $$LN(E(y_i)) = LN\beta 1 + \beta 2 \times LN(AADT_{maj}) + \beta 3 \times LN(AADT_{\min}) \quad [5.1]$$

Form (2): $$LN(E(y_i)) = LN\beta 1 + \beta 2 \times LN(AADT_{maj} + AADT_{\min}) \quad [5.2]$$

Form (3): $$LN(E(y_i)) = LN\beta 1 + \beta 2 \times LN(AADT_{maj} + AADT_{\min}) + \beta 3 \times LN\left(\frac{AADT_{\min}}{AADT_{maj} + AADT_{\min}}\right) \quad [5.3]$$

Form (4): $$LN(E(y_i)) = LN\beta 1 + \beta 2 \times LN(AADT_{maj} \times AADT_{\min}) \quad [5.4]$$

Where,

$E(y_i)$ = Expected number of crashes at site *i*,

$AADT_{maj}^{i}$ = Average annual daily traffic in the major approach at site *i*,

$AADT_{\min}^{i}$ = Average annual daily traffic in the minor approach at site i,

LN = Natural logarithm, and

β1, *β2* and *β3* = Calibration coefficients.

The Akaike information criterion (AIC) was chosen to be the sole measure of goodness of fit, given that the values of "Residual Deviance/Degrees of Freedom" is close to 1 for a model to be considered adequate (McCullagh and Nelder, 1989). The model with a minimum AIC value was chosen to be the best-fitted model.

The best fit models for 1999-2001 and 1999-2004 were found to have the form as in Equation [5.3]. With a larger database, other forms could have been investigated, but finessing the SPF was not necessary for achieving the aims of this analysis. The GLM model estimate and goodness of fit for data between 1999 and 2001 are as follows, with the standard error (SE) indicated in brackets []:

$$\begin{aligned} LN(E(y_i)) &= -6.4641[3.49] + 1.0644[0.35] \times LN(AADT_{maj} + AADT_{\min}) \\ &\quad + 1.0094[0.15] \times LN\left(\frac{AADT_{\min}}{AADT_{\mathrm{maj}} + AADT_{\min}}\right) \end{aligned} \qquad [5.5]$$

Dispersion parameter $= 0.443$, Residual deviance $= 63.157$ *with* 55 degrees of freedoms, $AIC = 415.94$ *and* $2 \times Loglikelihood = -407.938$

The GLM model estimate and goodness of fit for data between 2002 and 2004 is as follows:

$$LN(E(y_i)) = -4.7668[3.18] + 0.9596[0.31] \times LN(AADT_{maj} + AADT_{\min})$$
$$+ 0.9811[0.13] \times LN\left(\frac{AADT_{\min}}{AADT_{\text{maj}} + AADT_{\min}}\right) \quad [5.6]$$

Dispersion parameter = 0.388, Residual deviance = 63.05 *with* 55 degrees of freedoms, $AIC = 484.89$ *and* $2 \times Loglikelihood = -476.890$

It is worth noting that the dispersion parameter reported in this thesis is the inverse of the term usually obtained by "R" statistical software. In this case, the variance of the NB distribution has the form of Equation [2.5].

5.2 ESTIMATION OF CONFLICTS

The thirty-five intersection sample with turning movement counts was simulated using the VISSIM microscopic traffic simulation model (PTV, 2011). In this study, the parameters calibration results from Cunto (2008) for a signalized intersection were used. Among all available driving parameters, Cunto (2008) revealed three parameters that were most sensitive, and the best, to represent traffic operation at a signalized intersection. Those factors are:

1. Desired deceleration: used in achieving predefined desired speed or under Stop-and-Go condition (the calibrated value =-2.6 m/s^2);
2. CC0 (Standstill Distance): the desire distance between stopped cars (the calibrated value = 3 m);
3. CC1 (Headway Time): the time that the following vehicle wants to keep with the lead vehicle (the calibrated value = 1.50s).

In this study only the AM peak hour (surrogate of the daily traffic volume) was considered for the VISSIM micro-simulation to estimate the number of conflicts. It is worth noting that the AM peak hour volumes were obtained for the years 2002 and 2003. For each intersection, 10-simulation runs with 10- random seeds were used to capture the randomness in traffic operation. For each run, the trajectories of simulated vehicles at different times were saved.

The resulting trajectories from VISSIM were then processed using the Surrogate Safety Assessment Model (SSAM) (Pu and Joshi, 2008) to estimate the total number of conflicts (rear-end, crossing and lane change) for different deceleration rate (*DR*) thresholds as suggested by Hyden (1996) [shown in Table 3.4]:

$DR \leq$ - 1.5 m/s^2 (i.e., Low-risk conflict threshold),

$DR \leq$ - 4 m/s^2, and

$DR \leq$ - 6 m/s^2 (i.e., High-risk conflict threshold).

The results of the simulation of the 35-sites were used to develop a model linking conflicts to selected traffic inputs such as volumes. This model provides information for potential traffic conflicts, which replaces the need for simulation at sites with known volumes and other traffic attributes.

Generalized linear modeling (GLM) techniques were used to fit a number of models, and a NB distribution error structure was assumed. The model parameters are estimated in the same fashion as for observational models. The selected SPF forms are the same as in Equations [5.1] to [5.4], with the exception that a) the hourly traffic volumes V_{maj} and $V_{\min}$ in the AM peak hour are used instead of $AADT_{maj}$ and $AADT_{\min}$, for major and the minor approaches, respectively, and b) conflict frequency (CF) is used as the dependent variable instead of the expected number of crashes $(E(y_i))$. Equations [5.7]-[5.9] were found to be the best models.

$$\begin{aligned}&LN(CF1_i) = -19.5855[0.84] + 3.1169[0.11] \times LN(V_{maj} + V_{\min})\\&Dispersion\ \ parameter = 0.036,\ \ \mathrm{Re}\,sidual\ \ Deviance = 32.425\ \ with\ 33\\&\deg rees\ of\ \ freedoms,\ \ AIC = 337.29\ \ \ and\ \ 2 \times Loglikelihood = -331.289\end{aligned} \qquad [5.7]$$

$$\begin{aligned}&LN(CF2_i) = -16.53[0.76] + 2.626[0.10] \times LN(V_{maj} + V_{\min})\\&Dispersion\ \ parameter = 0.0186,\ \ \text{Residual}\ \ \text{Deviance} = 28.82\ with\ 33\\&\text{degrees}\ of\ \ freedoms,\ \ AIC = 271.48\ \ \ and\ \ 2 \times Loglikelihood = -265.476\end{aligned} \qquad [5.8]$$

$$LN(CF3_i) = -14.525[0.92] + 2.303[0.11] \times LN(V_{maj} + V_{\min})$$
$$+ 0.143[0.0.06] \times LN\left(\frac{V_{\min}}{V_{maj} + V_{\min}}\right) \qquad [5.9]$$
$$Dispersion\ \ parameter = 0.00954,\ \ \text{Re}\,sidual\ \ Deviance = 28.939\ \ with\ 32$$
$$\deg rees\ of\ \ freedoms,\ \ AIC = 227.52\ \ and\ \ 2 \times Loglikelihood = -219.516$$

Where,

$CF(1)_i$ = Simulated number of conflicts for $DR \leq$ - 1.5 m/s^2 at site i,

$CF(2)_i$ = Simulated number of conflicts for $DR \leq$ -4.0 m/s^2 at site i,

$CF(3)_i$ = Simulated number of conflicts for $DR \leq$ -6 m/s^2 at site i,

V_{maj} = Hourly traffic volume in the major approach at site i, and

V_{min} = Hourly traffic volume in the minor approach at site i.

Equations [5.7]-[5.9] were then used to estimate the average number of conflicts at each of the 58-intersections. Before estimating the conflicts, the *AADT* had to be converted to hourly volume. This was because the traffic volumes for the 58-intersections were available in the form of daily traffic volumes (*AADT*), while the traffic variables in Equations [5.7]-[5.9] pertain to hourly volume in the AM peak. For this study, a factor of 0.09 was assumed in converting daily traffic volumes to hourly volumes. The average number of conflicts at the 53 sites was calculated, with the summary statistics of the estimated conflicts as given in Table 5.1.

Table 5.1. Summary statistics of the estimated number of hourly-simulated conflicts

Period	$DR \leq -1.5$ m/s^2			
	Average	SD	Maximum	Minimum
2002-2004	222.50	231.50	1246.44	29.37
2005-2006	215.96	225.50	1225.75	26.36
Period	**$DR \leq -4$ m/s^2**			
	Average	SD	Maximum	Minimum
2002-2004	87.70	73.54	393.77	16.74
2005-2006	85.57	71.66	388.26	15.29
Period	**$DR \leq -6$ m/s^2**			
	Average	SD	Maximum	Minimum
2002-2004	35.93	24.67	142.24	8.47
2005-2006	35.20	24.08	140.50	7.82

5.2.1 Traffic conflicts priority-ranking

To facilitate the comparison between observational priority ranking methods and simulated conflicts, two different conflict-based methods were used: first, conflict-based priority ranking methods based on simulated conflict frequency; and second, conflict-based rankings using simulated conflict rate based on the sum and the cross product of traffic volumes as shown in Equations [5.10]-[5.12].

For the conflict frequency methods, three different deceleration rate (DR) thresholds were used:

$DR \leq -1.5$ m/s^2,
$DR \leq -4$ m/s^2, and
$DR \leq -6$ m/s^2.

Similarly, three conflict rates were suggested:

$$CR(1)_i = \frac{CF(1)_i}{AADT^i_{maj} + AADT^i_{\min}} \qquad [5.10]$$

$$CR(2)_i = \frac{CF(1)_i}{AADT^i_{maj} \times AADT^i_{\min}} \qquad [5.11]$$

$$CR(3)_i = \frac{CF(3)_i}{AADT^i_{maj} \times AADT^i_{\min}} \qquad [5.12]$$

Where,

$CF(1)_i$ = Simulated number of conflicts for $DR \leq$ - 1.5 m/s^2 at site i,

$CF(2)_i$= Simulated number of conflicts for $DR \leq$ -4.0 m/s^2 at site i,

$CF(3)_i$= Simulated number of conflicts for $DR \leq$ -6 m/s^2 at site i,

$AADT^i_{maj}$ = Average annual daily traffic in the major approach at site i, and

$AADT^i_{\min}$ = Average annual daily traffic in the minor approach at site i.

5.2.2 Evaluation criteria

To evaluate and compare the performance of the ranking from the simulated conflict-based ranking methods with that obtained from the observational crash-based models, six evaluation criteria were used. These criteria relate to performance attributes, such as, how effective and efficient is the method in identifying sites that show consistently unsafe performance in both the ranking (i.e., 1st period) and the evaluation (i.e., 2nd period) time periods (Montella, 2010). These criteria are:

1. **Site consistency (C_1):** sum of observed crashes in succeeding time-periods.
2. **Method consistency (C_2):** number of matching sites in both ranking periods.

3. **Total rank difference (C_3):** sum of absolute rank differences between rankings in both ranking periods.

4. **Total score: (C_4):** combines the results of the three previous tests assuming that they have the same weight.

5. **Sensitivity ($C_{5\text{-}1}$):** proportion of sites that continue to belong to the worst ranked list in the second period.

6. **Specificity ($C_{5\text{-}2}$):** proportion of sites that continue not to belong to the worst ranked list in the second period.

The nature of these evaluation criteria are now discussed in more depth.

5.2.2.1 Site consistency test (Cheng and Washington, 2008)

The basis of this test is that an untreated site identified as unsafe (i.e., high-risk) during the ranking period (i.e., time period *i*) should also reveal poor safety performance in the evaluation period (i.e., time period *i+1*). The method that identifies high-risk sites in the evaluation period with the highest number of crash frequency is the most consistent one. The test statistic is given as:

$$C_{1j} = Y_j^{i+1} = \sum_{k=n-n\alpha+1}^{n} Y_{j,K}^{i+1} \qquad [5.13]$$

where,

C_{1j} = Site consistency test for method j,

n = Total number of ranked sites,

α = Percentage of worst ranked high-risk sites (e.g., 1%, 2%, 5%, etc.),

Y_j^{i+1} = Sum of observed crashes in the second time period (*i+1*) for ranking method *j*, and

$Y_{j,k}^{i+1}$ = Observed crash counts at worst ranked $n\alpha$ sites by method *j* for the second period *i*+1.

5.2.2.2 Method consistency test (Cheng and Washington, 2008)

This test evaluates a method's performance by computing the number of the same sites identified as high risk in both the ranking and the evaluation time periods. The greater the number of sites identified in both periods the more consistent is the ranking method. The test statistic is given as:

$$C_{2j} = \{\mathrm{k}_{n-n\alpha+1}^{i}, \mathrm{k}_{n-n\alpha+2}^{i}, ..., \mathrm{k}_{n}^{i}\}_j \bigcap \{\mathrm{k}_{n-n\alpha+1}^{i+1}, \mathrm{k}_{n-n\alpha+2}^{i+1}, ..., \mathrm{k}_{n}^{i+1}\}_j \qquad [5.14]$$

where,

C_{2j} = Method consistency test for method j,

$\{\mathrm{k}_{n-n\alpha+1}^{i}, \mathrm{k}_{n-n\alpha+2}^{i}, ..., \mathrm{k}_{n}^{i}\}_j$ = Worst ranked $n\alpha$ high-risk sites by method *j* during the first time period *i*,

$\{\mathrm{k}_{n-n\alpha+1}^{i+1}, \mathrm{k}_{n-n\alpha+2}^{i+1}, ..., \mathrm{k}_{n}^{i+1}\}_j$ = Worst ranked $n\alpha$ high-risk sites by method *j* during the second time period *i+1*.

5.2.2.3 Total rank differences test (Cheng and Washington, 2008)

The absolute sum of total rank differences between the ranks of the high-risk sites identified in the first period *i* and ranks identified in the second period *i+1* for the same group of sites is used to reflect the performance in terms of consistent rankings of sites across periods. A ranking method is considered more consistent when the total rank difference is smaller and vise-versa. The test statistic is given as:

$$C_{3j} = \sum_{k=n-n\alpha+1}^{n} |\, Rank(k_j^i) - Rank(k_j^{i+1}) \,| \qquad [5.15]$$

where,

C_{3j} = Total rank differences test for method j,

$n =$ Total number of sites

$\alpha =$ Percentage of worst ranked high-risk sites,

$Rank(k_j^i) =$ Rank order for site k by method j during period i, and

$Rank(k_j^{i+1}) =$ Rank order for site k for method j for period $i+1$.

5.2.2.4 Total score test (Montella, 2010)

This test combines the results of the three previous tests to give a more comprehensive index of fit (Montella, 2010). The test assumes that the three tests have the same weight. If the performance of method j is the best in all of the previous three tests, the C4 value is equal to 100. The test statistic is given as:

$$C_{4j} = \frac{100}{3} \times \left[\left(\frac{C_{1j}}{\max_j C_1} \right) + \left(\frac{C_{2j}}{\max_j C_2} \right) + \left(1 - \frac{C_{3j} - \min_j C_3}{\max_j C_3} \right) \right] \quad [5.16]$$

where,

$max_j\, C_1$ = Maximum value of C_1 among the compared methods,

$max_j\, C_2$ =Maximum value of C_2 among the compared methods,

$max_j\, C_3$ = Maximum value of C_3 among the compared methods, and

$min_j\, C_3$ = Minimum value of C_3 among the compared methods.

5.2.2.5 Sensitivity and specificity tests (Elvik, 2008a)

This test employs a number of correct positives and correct negatives to assess the performance of various ranking criteria. The idea behind this criterion is that true positives will persist in having a bad safety record, whereas false positives will regress toward a more normal safety record in the second period and not be flagged. There are also false negatives (e.g., sites not detected in the first time period, but which are detected in the second time period). Sensitivity refers to the sites with a safety problem identified in the first period and which have been identified in the second period as well. Specificity refers to sites with no safety problem in the first and the second time periods. The larger the sensitivity and the specificity evaluation measures, the more consistent the method is. Sensitivity and specificity can be calculated as follows:

$$C_{5-1} = {}^{Number\ of\ correct\ positives}\!\big/_{total\ number\ of\ positives} \tag{5.17}$$

$$C_{5-2} = {}^{Number\ of\ correct\ negatives}\!\big/_{total\ number\ of\ negatives} \tag{5.18}$$

where,

C_{5-1} = Sensitivity,

C_{5-2} = Specificity,

Number of correct positives = Number of sites that continue to belong to the worst ranked $n\alpha$ in the second period $i+1$,

Total number of positives = Number of correct (true) positives plus the number of false negatives (Number of new sites that enter the list $n\alpha$ in the time period $i+1$),

Number of correct negatives = Number of sites that do not belong to the worst ranked list $n\alpha$ in both the time periods i and $i+1$,

Total number of negatives = Number of correct negatives plus the number of false positives (Number of sites that drop out of the worst ranked list $n\alpha$ in the second period $i+1$)

5.3 COMPARISON OF PRIORITY RANKING PROCEDURES (1^{ST} APPLICATION)

The priority ranking methods from observational methods (*EB*, *PSI* and *AF*) and simulated traffic conflict methods (*CF(1)*, *CF(2)*, *CF(3)*, *CR(1)*, *CR(2)* and *CR(3)*) , as shown in Table 5.2, were calculated for the two time periods (2002-2004 and 2005-2006) for the 58-signalized intersections samples.

Table 5.2: Conflict-based and crash-based priority ranking methods

Method label	**Description**
EB	empirical Bayesian expected number of crashes
PSI	potential of safety improvement
AF	crash frequency
CF(1)	simulated number of conflicts with *DR* ≤ - 1.5 m/s2
CF(2)	simulated number of conflicts for *DR* ≤ -4.0 m/s2
CF(3)	simulated number of conflicts for *DR* ≤ -6 m/s^2
CR(1)	simulated conflict rate based on *CF(1)* and the sum of traffic volumes (Equation [5.10])
CR(2)	simulated conflict rate based on *CF(1)* and the cross product of traffic volumes (Equation [5.11])
CR(3)	simulated conflict rate based on *CF(3)* and the cross product of traffic volumes (Equation [5.12]

The six evaluation criteria were applied to evaluate and compare the performance of these methods. The comparison results are shown in Table 5.3.

For site-consistency, the *AF* and *EB* methods are the best for ranking the worst 5 and 10 sites. The conflict methods performance is very poor compared with observational models. The CR(3) method is the worst among all other methods with a difference of 142 crashes when compared to either AF or EB methods. PSI method is better than conflict methods in this test, but it is worse than AF and EB in ranking the worst sites.

For method consistency and **rank difference**, the conflict methods are the best ones to identify the worst 5, 10 and 15 sites compared to observational methods. CR(3) method was the best to identify the worst 5, 10 and 15 sites. The PSI method was the worst to identify the worst 5, 10 and 15 sites.

For the total score, the *EB* method was the best to identify the worst 5 sites. *AF* was the second best to identify the worst 5 sites. For the worst 10 sites, the *CF(3)* method was the best, followed by the *AF* method, then by *EB* method. The difference between EB and *CR(3)* was only 1.75%. The *AF* method was the best to identify the worst 15 sites. The *PSI* method again was the worst to identify the worst 5, 10 and 15 sites.

For sensitivity and specificity, the conflict methods were better than observational methods to identify the worst 5, 10 and 15 sites. *CR(3)* is the ideal method in terms of sensitivity and specificity tests. *PSI* method again was the worst to identify the worst 5, 10 and 15 sites in terms of the sensitivity test.

As shown in Table 5.3 observational models (except for *PSI*) are superior to conflict methods in identifying the worst sites in terms of the site consistency test. On the other hand, conflict methods are much better than observational methods in terms of method consistency, rank difference and sensitivity and specificity tests.

For the total score, the observational methods (except for *PSI*) are better than conflict methods in identifying the worst 5 and 15 sites. On the other hand, conflict methods perform well with respect to observational methods in identifying the worst 10 sites with *CF(3)*.

Table 5.3. Evaluation results between crash-based and conflict-based ranking methods

Ranking method	(1) Site consistency test			(2) Method consistency test		
	Worst 5	Worst 10	Worst 15	Worst 5	Worst 10	Worst 15
AF	158	226	287	3	7	12
EB	158	226	283	3	7	12
PSI	122	178	221	2	5	7
CF(1)	35	96	123	5	9	15
CF(2)	35	96	123	5	9	15
CF(3)	64	101	133	4	10	12
CR(1)	35	96	123	5	9	15
CR(2)	20	45	73	5	10	14
CR(3)	16	41	63	5	10	15
Ranking method	**(3) Total rank differences test**			**(4) Total score test**		
	Worst 5	**Worst 10**	**Worst 15**	**Worst 5**	**Worst 10**	**Worst 15**
AF	11	56	69	82.93	78.11	82.48
EB	10	53	79	83.27	78.75	80.45
PSI	98	157	212	39.07	42.92	41.22
CF(1)	0	7	12	74.05	76.01	79.07
CF(2)	0	7	12	74.05	76.01	79.07
CF(3)	1	8	21	73.16	79.86	72.15
CR(1)	0	7	12	74.05	76.01	79.07
CR(2)	2	4	5	70.21	72.45	72.14
CR(3)	0	0	0	70.04	72.71	73.98
Ranking method	**(5-1) Sensitivity**			**(5-2) Specificity**		
	Worst 5	**Worst 10**	**Worst 15**	**Worst 5**	**Worst 10**	**Worst 15**
AF	0.60	0.70	0.80	0.96	0.94	0.88
EB	0.60	0.70	0.80	0.96	0.94	0.93
PSI	0.40	0.50	0.47	0.96	0.94	0.93
CF(1)	1	0.90	1	1	0.98	1
CF(2)	1	0.90	1	1	0.98	1
CF(3)	0.80	1	0.80	0.98	1	0.93
CR(1)	1	0.90	1	1	0.98	1
CR(2)	1	1	0.93	1	1	0.98
CR(3)	1	1	1	1	1	1

*Shaded cells represent the best method for a certain criterion

5.4 PRIORITY RANKING USING INTEGRATED MODEL (2^{ND} APPLICATION)

The same sample of 58 four-leg signalized intersections was used to compare the proposed integrated model rankings with those obtained using observational crash-based and conflict-based methods.

The priority ranking for unsafe sites based on the safety score (*SS*), given in Equation [4.1] with different weight factor (*W*), and observational methods (*EB*, *PSI* and *AF*) along with conflict methods (*CF*, *CR(1)* and *CR(2)*) was done for the two time periods (2002-2004 and 2005-2006) for the 58 signalized intersections. The total score evaluation criterion (*C4*) was applied to evaluate and compare the SS method with weight factor (*W*=1, 10, 100 and 1000) for the observational and conflict methods. The weight (*W*=1) means that every expected crash has a safety score equivalent to one conflict, while the weight (*W*=1000) means that every expected crash has a safety score equivalent to 1000 conflicts. It is worth noting that as the weight increases, the safety score (*SS*) will regress towards the estimate from the *EB* method.

5.4.1 Assessing the ranking criteria

The comparison results are shown in Table 5.4. **For the site consistency (C_1)**, the AF method is the best method for ranking the worst 5, 10, 15 and 20 sites, while the EB method and the SS method with weights of 100 and 1000 perform the same as AF for the worst 5, 10 and 20 sites. The conflict methods (CF and CR(1)) and the SS with W=1 are the worst for ranking the worst 5, 10 and 15 sites.

For consistency (C_2), all conflict-based methods performed best in identifying the worst 5, 10, 15 and 20 sites. The *SS* with *W*=1 is the second best to identify the worst 5 and 10 sites The *SS* with *W*=1 along with conflict methods (*CF* and *CR(1)*) are the best to identify the worst 15 sites. All of the observational methods and SS with W= 1000 performed worst in identifying the worst 5, 10 and 15 sites. *PSI* performed the worst in identifying the worst 5, 10 and 15 sites.

Table 5.4. Evaluation results for the worst 5, 10, 15 and 20 sites

Ranking method	(1) Site consistency test				(2) Method consistency Test			
	Worst 5	Worst 10	Worst 15	Worst 20	Worst 5	Worst 10	Worst 15	Worst 20
EB	158	226	283	335	3	7	12	17
PSI	122	178	221	230	2	5	7	9
AF	158	226	287	335	3	7	12	18
CR(1)	35	96	123	186	5	9	15	20
CR(2)	20	45	73	102	5	10	14	20
CF(3)	35	96	123	186	5	9	15	20
SS(W=1)	35	96	123	232	4	9	15	18
SS(W=10)	149	200	255	296	4	7	12	17
SS(W=100)	158	226	280	331	4	8	12	15
SS(W=1000)	158	226	283	335	3	7	12	17
Ranking method	**(3) Total rank differences test**				**(4) Total score test**			
	Worst 5	**Worst 10**	**Worst 15**	**Worst 20**	**Worst 5**	**Worst 10**	**Worst 15**	**Worst 20**
EB	10	53	79	101	83.27	79.60	81.23	83.06
PSI	98	157	212	282	39.07	43.77	42.01	37.89
AF	11	56	69	108	82.93	78.96	83.27	83.90
CR(1)	0	7	12	22	74.05	76.86	79.85	82.57
CR(2)	2	4	5	6	70.21	73.30	72.92	76.11
CF(3)	0	7	12	36	74.05	76.86	79.85	80.92
SS(w=1)	1	7	10	23	67.04	76.86	80.17	83.70
SS(w=10)	3	20	47	81	90.41	82.77	83.01	81.54
SS(w=100)	7	48	78	105	90.95	83.99	81.04	78.86
SS(w=1000)	9	53	79	99	83.61	79.60	81.23	83.30
Ranking method	**(5-1) Sensitivity**				**(5-2) Specificity**			
	Worst 5	**Worst 10**	**Worst 15**	**Worst 20**	**Worst 5**	**Worst 10**	**Worst 15**	**Worst 20**
EB	0.60	0.70	0.80	0.85	0.96	0.94	0.93	0.92
PSI	0.40	0.50	0.47	0.45	0.96	0.94	0.93	0.92
AF	0.60	0.70	0.80	0.90	0.96	0.94	0.88	0.84
CR(1)	1	0.90	1	1	1	0.98	1	1
CR(2)	1	1	0.93	1	1	1	0.98	1
CF(3)	1	0.90	1	1	1	0.98	1	1
SS(w=1)	0.80	0.90	1	0.90	0.98	0.98	1	0.95
SS(w=10)	0.80	0.70	0.80	0.85	0.98	0.94	0.93	0.92
SS(w=100)	0.80	0.80	0.80	0.75	0.98	0.96	0.93	0.87
SS(w=1000)	0.60	0.70	0.80	0.85	0.96	0.94	0.93	0.92

*Shaded cells represent the best method for a certain criterion

For total rank difference (C_3) the *SS* with *W*=1 is the second best method to identify the worst 5 and 10 and, along with conflict methods (*CF* and *CR(1)*), is the best to identify the worst 15 sites. Conflict methods are the best to identify the worst 5, sites while the *PSI* method is the worst to identify the worst 5, 10 and 15 sites.

For total score (C_4) the *SS* with *W*=100 is the best method to identify the worst 5 and 10 sites, while *AF* is the best to identify the worst 15 sites. The *PSI* method is the worst to identify the worst 5, 10 and 15 sites.

For sensitivity ($C_{5\text{-}1}$) and specificity ($C_{5\text{-}2}$), *SS* for (*W*=1) is the second best after conflict methods to identify the worst 5 and 10 sites. With the conflict methods, *CF* and *CR(1)* are the best at identifying the worst 15 sites. All of the observational methods and *SS* for *W*=1000 are the worst at identifying the worst 5, 10 and 15 sites.

From Table 5.4 the conflict-based methods perform the best in terms of the consistency criterion, total rank difference and sensitivity and specificity tests, while they perform the worst for site consistency. On the other hand, the observational methods (*AF* and *EB*) perform the best only for the site consistency test. Depending on the weight value, the *SS* method performance performed well for site consistency (*W*=100 and 1000). For method consistency, total rank difference and sensitivity and specificity tests it also performed well for *W* =1.

The *SS* method stands out as the best method in terms of the total score test. As a result, it may be concluded that using *SS* with an appropriate value for the weight factor can reveal good results compared to other ranking methods based on either observational crash data or conflicts.

5.4.2 Examining the weight factors

In an attempt to determine an appropriate value of the weight factor for the worst 5 (8.62%), 10 (17.24%),15 (25.86%) and 20 (34.48%) sites, the relationship between the weight factor and the total score test value (C_4) was established as shown in Figure 5.2. From Figure 5.2 for weight factors $W \geq 3$, the SS method performs better than observational and conflict methods for identifying the worst 10 sites. For weight factors with $W \geq 7$ the *SS* method yields better results over other methods for identifying the worst 5 and 10 sites. The highest values of the total score test for identifying the worst 5 sites occur at $12 \leq W \leq 33$, as shown in Figure 5.2 and Figure 5.3.

Table 5.5 shows the range of weights that gives better results than observational crash-based methods and the weight ranges that results in the highest values for the total score test. The weight factor values change based on the number of sites. For the worst 5 and 10 sites, any weight factor larger than seven and three, respectively will yield better results than both crash-based and conflict-based methods. The weight factor range that yields the highest total score values moves from $12 \leq W \leq 33$ for the worst 5 sites to $37 \leq W \leq 73$ for the worst 10 sites.

Table 5.5: Weight factor range for worst 5, 10, 15 and 20 sites

Worst sites	**Weight range**	**Best weight range**
Worst 5 (8.62%)	≥ 7	12 to 33
Worst 10 (17.24%)	≥ 3	37 to 73
Worst 15 (25.86%)	2 to 13; 23 to 38; 52 to 54;and ≥ 104	3 to 8
Worst 20 (34.48%)	1 to 8	1 to 8

For the worst 15 sites, there are four weight ranges (not a continuous range) that yield total score values greater than crash-based and conflict-based methods. For the worst 20 sites, the weight range that produces better results is between one and eight. **Table 5.5** suggests that if it desired to identify a large number of sites (i.e., greater than 17% of sites in this case) the advantages of using the integrated crash-conflict model become less pronounced.

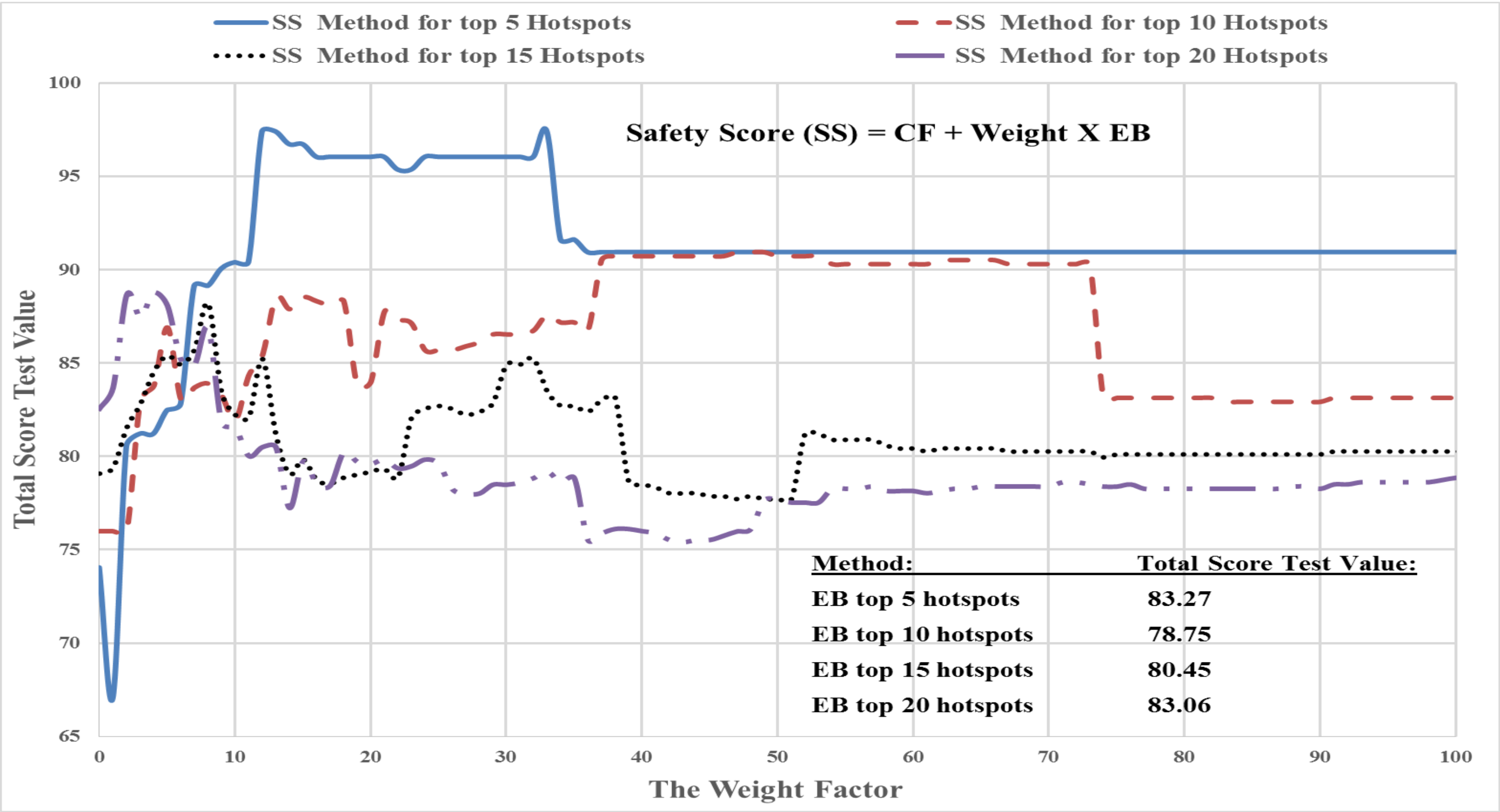

Figure 5.2. Relationship between the weight factor value and the total score test value

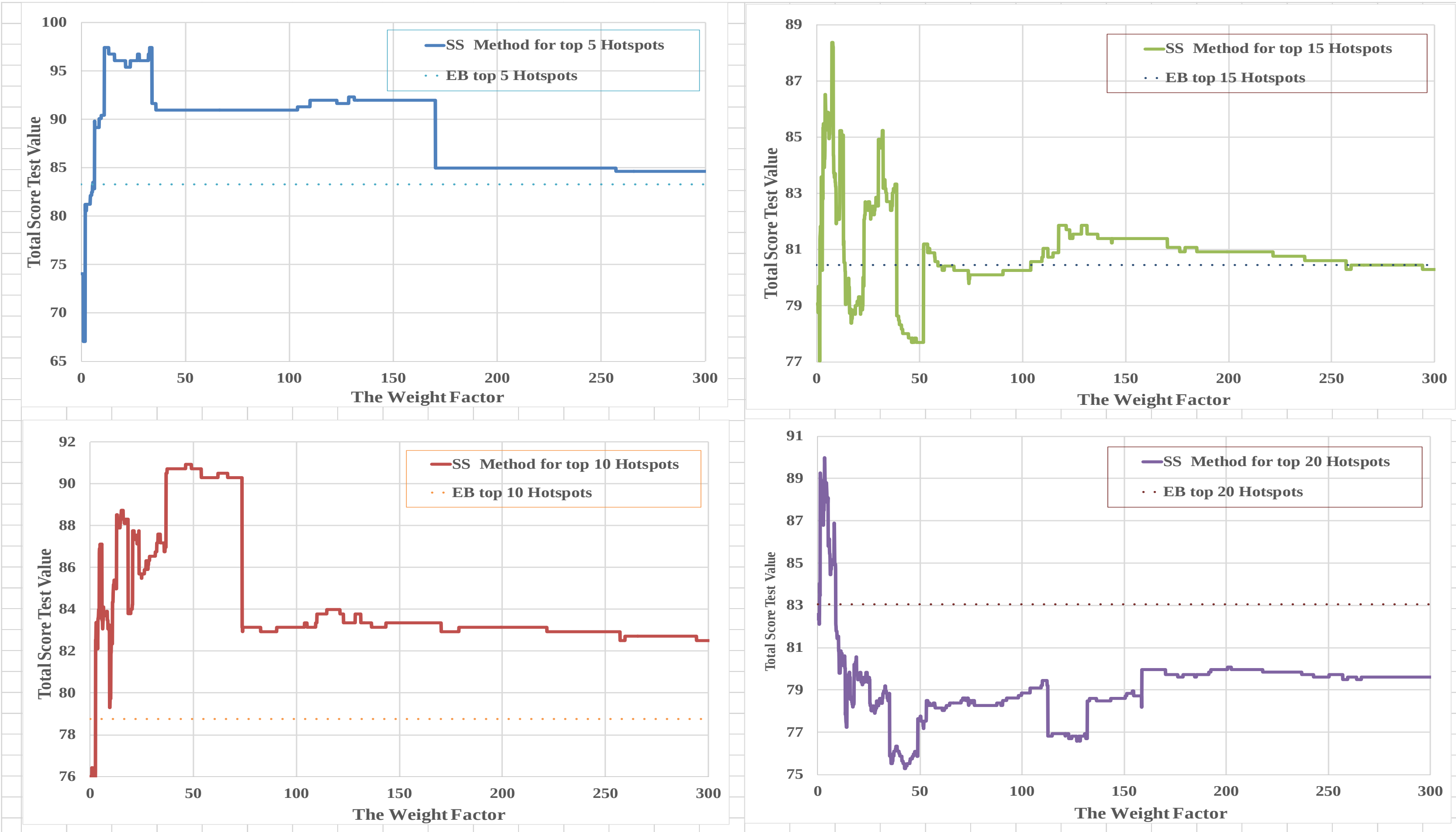

Figure 5.3: SS Method with different weight factors compared to EB method for ranking the worst 5, 10, 15 and 20 sites

5.5 EVALUATION OF SS METHOD WITH AN APPROPRIATE WEIGHT

To assess the SS ranking method, with an appropriate weight factor, compared to the crash-based and conflict-based ranking methods, a weight factor *W*=30 was chosen for the worst 5 sites (for illustration purposes). The evaluation criteria for the SS method with weight factor W=30 is shown in Table 5.6.

For site consistency, the SS method with W=30 is the second best method after EB and AF for identifying the worst 5 sites, with a difference of only 9 crashes in the evaluation period. It was also found to be the best method for identifying the worst 10 sites for the same test. For method consistency, the SS (W=30) and conflict methods were found to perform best for identifying the worst 5 sites. In method consistency, it was found that this method was second best after conflict methods, with a difference of two sites in the worst 10 list. For the total rank difference method, SS (W=30) is the second best after conflict methods. SS (W=30) is found to be the best method to identify the worst 5, 10 and 15 sites based on the total score test. Furthermore, for sensitivity and specificity tests SS (W=30) and conflict methods are the best at identifying the worst 5 sites and the second best after conflict methods in identifying the worst 10 sites.

Overall, it may be concluded that the SS (W=30) is the best method for identifying the worst 5 sites, since it performed well for all evaluation criteria. However, an appropriate weight factor should be used when ranking a different number of sites as summarized in Table 5.7 For example, a weight factor of 30 produced better results for the worst 5 and 15 sites, but not for the worst 10 sites. Similarly, a weight factor of 50 yielded better rankings for the worst 10 sites, but was not as good for ranking the worst 15 sites compared to EB method.

Table 5.6. Evaluation results for worst 5, 10 and 15 sites at weight = 30

Ranking method	(1) Site consistency test			(2) Method consistency test		
	Worst 5	Worst 10	Worst 15	Worst 5	Worst 10	Worst 15
EB	158	226	283	3	7	12
PSI	122	178	221	2	5	7
AF	158	226	287	3	7	12
CF	35	96	123	5	9	15
CR(1)	35	96	123	5	9	15
CR(2)	20	45	73	5	10	14
SS(W=30)	149	228	274	5	8	13
Ranking method	**(3) Total rank differences test**			**(4) Total score test**		
	Worst 5	**Worst 10**	**Worst 15**	**Worst 5**	**Worst 10**	**Worst 15**
EB	10	53	79	83.27	78.45	80.45
PSI	98	157	212	39.07	42.69	41.22
AF	11	56	69	82.93	77.82	82.48
CF	0	7	12	74.05	76.73	79.85
CR(1)	0	7	12	74.05	76.73	79.85
CR(2)	2	4	5	70.21	73.25	72.92
SS(W=30)	6	32	58	96.06	86.54	84.93
Ranking method	**(5-1) Sensitivity**			**(5-2) Specificity**		
	Worst 5	**Worst 10**	**Worst 15**	**Worst 5**	**Worst 10**	**Worst 15**
EB	0.60	0.70	0.80	0.96	0.94	0.93
PSI	0.40	0.50	0.47	0.96	0.94	0.93
AF	0.60	0.70	0.80	0.96	0.94	0.88
CF	1	0.90	1	1	0.98	1
CR(1)	1	0.90	1	1	0.98	1
CR(2)	1	1	0.93	1	1	0.98
SS(W=30)	1	0.80	0.87	1	0.96	0.95

Table 5.7: Total score test value for weights of 30 and 50

Ranking method	Total score test value			Notes
	Worst 5	Worst 10	Worst 15	
EB	83.27	78.45	80.45	
SS(W=30)	96.06	86.54	84.93	Better weight for worst 5 and 15 sites
SS(W=50)	90.95	90.72	77.69	Better weight for worst 10 sites

Table 5.8 shows the rank orders for SS method for W = 30 and W=50, as well as EB, PSI, AF and CF(3) methods. The SS with W= 30 performed best among other ranking methods in identifying the worst 5 sites (i.e., the same sites identified in the 1^{st} period are the same identified in the evaluation period). The *SS* with *W*= 50 performed best in terms of identifying the worst 10 sites. It is worth noting that all the methods were correctly identified the worst site in the list of unsafe sites. Moreover, for other methods (rather than *SS*), at least two sites in the worst unsafe sites (i.e., for *W*=30) were found to be in the worst list of unsafe sites for both analysis periods.

Table 5.8: Comparison between rankings from SS with weights of 30 and 50 with other ranking methods

Intersection number	SS (W=30) 1st Period	SS (W=30) 2nd Period	SS (W=50) 1st Period	SS (W=50) 2nd Period	EB 1st Period	EB 2nd Period	PSI 1st Period	PSI 2nd Period	AF 1st Period	AF 2nd Period	CF(3) 1st Period	CF(3) 2nd Period
1747	1	2	1	1	1	1	1	1	1	1	26	26
82	2	1	3	4	5	12	7	49	5	13	1	1
203	3	5	2	3	2	2	2	2	2	2	23	21
201	4	3	4	2	3	3	52	5	3	3	4	4
130	5	4	8	5	31	29	22	15	27	25	2	2
610	6	9	5	8	4	7	4	43	4	7	15	19
819	7	6	6	6	6	4	39	37	7	4	17	12
186	8	7	7	7	7	5	49	51	8	5	16	13
1331	9	29	9	26	8	21	3	45	6	19	36	36
292	10	11	10	9	9	6	15	21	9	6	34	31
994	11	28	11	30	10	33	11	52	10	33	22	22
715	12	10	12	10	11	9	27	12	11	7	21	23
118	13	8	18	13	38	36	41	36	37	33	3	3
176	14	15	13	12	12	10	56	55	12	11	24	25
516	15	14	15	18	22	24	38	44	23	25	6	7
661	16	33	14	36	15	34	57	58	16	39	25	24
120	17	21	22	24	29	44	28	46	27	44	5	6
500	18	20	16	15	13	11	9	4	13	10	32	35
664	19	23	17	20	17	13	54	56	16	14	28	28
504	20	12	28	16	41	27	25	6	37	19	7	9

5.6 PRACTICAL IMPLEMENTATION

To implement the integrated model for a city like Toronto, representative sample intersections will need to be selected (i.e., not just intersections 4-leg intersection with 2-lanes per approach without exclusive left or right turn lanes, as used in this thesis). Then obtain simulated traffic conflicts by simulating the intersection samples (e.g., using VISSIM). A relationship between simulated conflicts and traffic volumes (i.e., with turning movements) will need to be established for different conflict thresholds (i.e., TTC≤1.50s, TTC≤0.50s, etc.). Similarly SPF functions between crashes (i.e., by type and severity) and traffic volumes and other confounding factors (e.g., number of lanes, number of legs, etc.) will need to be established. These models can be used to obtain EB expected number of crashes at all the sample intersections.

The next step is to obtain the weight factor (i.e., W). This can be accomplished by plotting the total score test value (i.e., C_4) for different weights (i.e., 1, 2, 3, 10, 20, etc.). Then choose the weight factor associated with the highest C_4. This step should be repeated for different required rakings (e.g., top worst 1%, 2%, 5%, etc.). It is important to compare the value of C_4 for the integrated model with C_4 for the EB method, to determine whether to proceed with the integrated model or no. If the difference is large enough, so the integrated model will yield a better ranking results and vise-versa.

The next step is to use the conflict-volume models to obtain the expected number of conflicts (i.e., by type for different thresholds) at all of Toronto intersections. The worst intersections can then be ranked for further investigation (i.e., or treatment).

5.7 CHAPTER SUMMARY

Chapter 5 presented a comparison between observational and traffic conflict methods in identifying unsafe sites using 58-signalized intersections from Toronto. The performance of the methods was evaluated and compared using several evaluation criteria: site consistency, method consistency, rank difference, total score, and sensitivity and specificity tests. Based on the evaluation criteria used, observational and conflict ranking methods suggest different sets of the worst ranked unsafe sites. Low severity crashes and near misses are not usually included in the reported crashes that observational models relay on in estimating the expected number of crashes to identify the worst unsafe sites. These low severity crashes and near misses may contain essential information concerning lack of safety that is important from the point of view of effective intervention.

After comparing both methods, Chapter 5 discussed the results of a case study ranking using an integrated crash-conflict model. This combines the results of a simulation of traffic conflicts with Empirical Bayes crash prediction. The integrated model was found to yield better results than conventional observational crash-based models or traffic conflicts alone. This confirms that higher risk interactions and near misses are important for a better understanding of the safety problem at a given site and hence, should be considered in priority ranking. This should result in a more efficient allocation of scarce intervention funds to those sites most in need of treatment.

The proposed safety score method is conceptually appealing in that it incorporates two partly independent clues about an intersection's safety. Thus, it seems reasonable that future research could develop a theoretical, or at least a logical, basis for the weight used in much the same way that theoretically based weights are used for the empirical Bayes crash predictions. This will facilitate the transferability of methodology for application contexts without having to undertake a cumbersome, iterative, optimization of the weights, as was done for this research.

CHAPTER 6

CASE STUDY TWO: ESTIMATING TREATMENT EFFECTS

This chapter presents a case study application for evaluating the integrated treatment effect model presented in Chapter 4. A before and after analysis is carried out for a sample of treated Toronto intersections, for which left turn signal priority was changed from permissive to protected/permissive.

During the "protected" mode, left-turning vehicles are given exclusive precedence and do not experience conflict with on-coming vehicles in the opposing traffic stream. During the "permissive" mode, left-turning vehicles are permitted to turn on green if a suitable gap with on-coming vehicles takes place. Depending on driver behaviour, accepted gaps for left turn movements will vary.

In this chapter, crash modification factors obtained from the integrated model are compared with values obtained from a conventional EB crash-based before-and-after evaluation for the same sample of intersections.

6.1 CASE STUDY DATA

A set of 47 treated signalized intersections from Toronto, Canada was analyzed to determine CMFs for a change in left turn signal priority from permissive to protected-permissive. The treated dataset consists of traffic volumes, observed crash history and geometric attributes for the period 1999 - 2007. Traffic volumes (total, left turn and right turn) were reported for the major and minor approaches for the AM peak hour. In addition, pedestrian counts and signal timing information are given for all periods with and without LT signal priority treatment. The major, minor and turning volume data in the treated sample are summarized in Table 6.1**.**

Crashes reported for the period 1999-2007 for the 47 intersections were classified into rear-end (RE) and left-turn opposing (LTOPP). These crash types are most likely to be affected by a change in left turn priority. LTOPP crashes refer to potential collisions between left-turn vehicles and on-coming vehicles proceeding through the intersection. Table 6.2 provides a summary of the crash data used in this analysis.

Table 6.1: Traffic volume at treated sites

Summary statistic	Volume in major	Volume in minor	%RT major	%RT minor	%LT major	%LT minor
Mean	2549.43	1349.06	10.28	22.25	10.91	19.95
SD	934.08	761.98	7.15	16.37	5.01	13.01
Minimum	847	157	2	5	1	0
Maximum	4742	3340	40	81	26	66

Table 6.2: Summary statistics for observed crashes before and after treatment

Summary statistic	Rear-end		LTOPP	
	Before	**After**	**Before**	**After**
Sum	1837	1383	558	314
Mean	39.09	29.43	11.87	6.68
SD	35.10	22.98	9.94	6.13
Minimum	0	0	0	0
Maximum	125	88	36	32

6.2 SIMULATION OF CONFLICTS

The signalized intersections were simulated to extract trajectories of vehicles using the VISSIM microscopic simulation platform (version 5.40) (PTV, 2012). The VISSIM parameters were selected to reflect more realistic driving behavior and to ensure that the observed vehicles during the peak-hours can enter the network within a specified simulation period, and these input parameters are summarized in Table 6.3. It is worth noting that the VISSIM simulation parameters were used in this analysis regardless of the number of conflicts generated, as the study focus was on the ratio of conflicts between the after and the before periods.

In this analysis, LTOPP signal priority for the sample intersections was introduced at the 47 treated sites for either AM or PM peak hours. On the other hand only the AM peak hour was used for the untreated 53 sites. This will be discussed in more detail later in this Chapter.

Traffic volume data for AM or PM period serve as inputs into the estimation of traffic conflicts in this study. For each intersection, 50-simulation runs with 50 random seeds were used to capture randomness in traffic. The simulation was carried out with a five-minute warm-up period. Although only one hour of traffic counts was used in this analysis (typically the AM/PM peak hours), a 2-hour simulation time was used to ensure that all vehicles have entered the simulation network. The assumption is that the ratio of peak-hour traffic to average daily traffic is approximately constant across sites and that peak hour volumes and conflicts can reasonably be used as "surrogates" for average daily traffic volumes and daily conflicts.

For each simulation run, the number of conflicts was obtained from the individual vehicle simulated trajectories over time. The Surrogate Safety Assessment Model (SSAM) (Pu and Joshi, 2008) was used to extract the total number of conflicts using two TTC thresholds: $\leq$ 1.50s and $\leq$ 0.50s. The 1.50s threshold reflects a lower level of risk that assumes vehicles are in potential conflicts if drivers have less than 1.50 seconds to perceive a danger and react accordingly. On the other hand, 0.50s threshold reflects a much higher risk wherein a driver only has 0.50 seconds or less in which to take appropriate action to avoid a crash. A time interval of 1.50s may be sufficient for an extreme driver perception and reaction response; however, an interval of 0.50s is too small to allow a driver to respond to a conflict in order to avoid a crash. The average number of conflicts at each site was estimated from the 50 simulation runs.

Table 6.3: VISSIM parameters

Behavioural Parameter	Value
Driving Behaviour	Urban (Motorized)
Car-Following	Wiedemann 74 ax = 2.00 m* bx_add = 2.00** bx_mult = 3.00***
	Smooth close-up
Lane Change	Advanced merging
	Cooperative lane change
Lateral Parameters	Keep lateral distance to vehicles in on next lane(s)
	Consider next turning decision
Signal Control	Decision model: one decision
Conflict Areas (left turn only)	Front gap = 0.00s
	Rear gap = 0.00s
	Avoid Blocking = 0 for all cases and =1 in case of 2 left-turn lanes

*the average standstill distance with standard deviation of 0.30 m;
**the additive part of safety distance;
***the multiplicity part of safety distance.

6.3 SIMULATED TRAFFIC CONFLICT RESULTS

Table 6.4 summarizes the means and standard deviation of conflicts for different TTC types by threshold, as obtained from the simulation of the 47 treated intersection sample. The simulation was carried out for appropriate traffic conditions separately for the before and after treatment periods.

Table 6.4: Simulated conflict results

TTC threshold	Treatment period	Rear-end	LTOPP
≤ 1.50s	Before [SD]	1371.78 [34.85]	164.00 [11.77]
	After [SD]*	1296.42 [34.77]	118.70 [10.13]
	ρ ** [SD]	0.95 [0.04]	0.72 [0.11]
≤ 0.50s	Before [SD]	12.28 [3.59]	19.18 [4.49]
	After [SD]	11.72 [3.68]	16.28 [4.19]
	ρ [SD]	0.95 [0.41]	0.85 [0.33]

*SD: Standard deviation;
** ρ : Conflict ratio between the after and the before.

Table 6.4 indicates that changes in conflicts (before and after treatment) are somewhat sensitive to TTC thresholds. As expected, the lower the threshold, the fewer the number of conflicts. This is true for all conflict types. For LTOPP, ρ equals 0.72 and 0.85, respectively for both TTC thresholds.

The use of traffic conflicts alone to evaluate treatment effects can be influenced by both the measure of conflict (i.e., TTC) and by its corresponding thresholds. It is worth noting that by increasing the conflict threshold, the level of uncertainty with the estimation of the conflict ratio increases correspondingly. For example, for rear-end conflicts, the standard deviation for the conflict ratio increases from 0.035 for TTC≤1.50s to 0.41 for TTC≤0.50s. The higher uncertainty for the latter case may be indicative of a higher number of required simulation runs.

6.4 CALIBRATION OF CRASH-CONFLICT MODELS

6.4.1 Data

As noted earlier the sample of 53 untreated intersections was used to develop the empirical relationship between observed crashes and simulated conflicts. For this untreated sample, traffic volume inputs for simulation are summarized in Table 6.5, and the corresponding crash data for these intersections are summarized in Table 6.6.

Table 6.5: Traffic volume and turning movements at untreated sites

Summary statistic	Volume in major	Volume in minor	%RT major	%RT minor	%LT major	%LT minor
Mean	1301.62	764.91	10.63	16.07	6.36	12.04
SD	417.22	270.57	6.24	8.31	5.87	9.700
Minimum	663	48	0	0	0	0
Maximum	2246	1367	34	54	33	46

Table 6.6: Crash data at untreated sites (2001-2004)

Summary statistic	Rear-end	LTOPP
Sum	915	309
Mean	17.26	5.83
SD	11.34	5.56
Minimum	2	0
Maximum	48	20

Table 6.7 and Table 6.8 summarize simulation results for TTC<=1.50s and TTC≤0.50s, respectively. In this analysis only vehicle-to-vehicle conflicts (i.e., no vehicle-to-pedestrian or vehicle-to-fixed object conflicts) were considered. This is because no calibrated VISSIM parameters for pedestrian were available and because the focus of our analysis was LTOPP vehicle interactions.

Table 6.7: Simulated conflicts for the untreated sites for TTC≤1.50s

Summary Statistic	Rear-End	LTOPP
Sum	348.00	29.78
Mean	6.57	0.56
SD	5.58	0.44
Minimum	0.36	0.00
Maximum	23.98	1.82

Table 6.8: Simulated conflicts for the untreated sites for TTC≤0.50s

Summary statistic	Rear-end	LTOPP
Sum	17.16	8.62
Mean	0.32	0.16
SD	0.37	0.17
Minimum	0.00	0.00
Maximum	1.98	0.90

Crashes were filtered for normal weather (i.e., dry surface conditions and good visibility) conditions to match simulation assumptions in the input VISSIM parameters. This assumption is not expected to significantly affect the results because dry surface conditions and good visibility are the prevalent weather condition found in the input data used in this analysis (i.e., crashes that took place subject to good weather accounted for about 78% of all crashes at these sites).

In finalizing the crash-conflict models used for estimating CMF, it was necessary to explore how the decision to use normal weather crashes as well as key assumptions on TTC thresholds and simulation runs affected the model results. This investigation is discussed in the next section in presenting the models for LTOPP crashes.

6.4.2 Crash-conflict model for LTOPP crashes

6.4.2.1 Effect of excluding crashes during adverse weather conditions

To explore the effect of weather, generalized linear (GLM) Negative Binomial (NB) LTOPP crash-conflict models were fitted separately for all weather conditions and good weather. The model form of the crash-conflict SPF is given in Equation [4.5].

Table 6.9 summarizes the calibration results. For both models at TTC < 1.50s and 0.50s, the AIC difference is greater than 30, which is large enough to indicate that models during good weather conditions produce a better fit. In addition, the dispersion parameters for good weather models (for both thresholds) were found to be lower than for all weather conditions, suggesting reduced variability in the empirical crash prediction. These results support the decision of using crashes for good weather conditions.

Table 6.9: Parameters for LTOPP crash-conflict model (all weather and good weather)

Parameter estimates	TTC≤1.50s		TTC≤0.50s	
	All weather conditions	Good weather conditions	All weather conditions	Good weather conditions
LN α **[SE]**	2.42 [0.15]	2.14 [0.14]	3.09 [0.31]	2.80 [0.30]
β **[SE]**	0.56 [0.12]	0.58 [0.13]	0.55 [0.14]	0.56 [0.14]
Dispersion parameter	0.49	0.42	0.58	0.53
Residual deviance	59.93	59.51	59.45	58.76
Degrees of freedom	51	51	51	51
AIC	316.54	285.55	323.12	293.16
2 log likelihood	-310.54	-279.55	-317.12	-287.16

* SE: standard error

6.4.2.2 Effect of TTC Threshold and number of runs

A sensitivity analysis was carried out to assess the effect of simulation runs on the LTOPP crash-conflict model. Two simulations of 30 and 50 runs were carried out. Table 6.10 summarizes the simulation results for LTOPP conflicts for the two TTC thresholds (≤ 1.5 and ≤ 0.5 seconds).

The results in Table 6.10 indicate that for the lower risk threshold of ≤1.50s, the number of runs (30 versus 50) has little or no effect on the number of conflicts. On the other hand, for the higher risk threshold (TTC ≤ 0.50s), the number of runs was found to have a significant effect on the resultant conflicts. This is reasonable since for the higher risk threshold fewer conflicts are expected and more runs would be needed to obtain stable long-term results.

Table 6.10: Simulated LTOPP conflicts for the 53 untreated sites for 30 and 50 runs

Summary statistic	TTC≤1.50s		TTC≤0.50s	
	30 runs	50 runs	30 runs	50 runs
Average (per run) over all sites	30.37	29.78	3.20	8.62
Mean per site (per run)	0.57	0.56	0.06	0.16
SD	0.46	0.44	0.07	0.17
Minimum	0.00	0.00	0.00	0.00
Maximum	1.73	1.82	0.30	0.90

Table 6.11 summarizes the results of the LTOPP crash-conflict model calibration for TTC ≤1.50s and ≤0.50s. For both thresholds, the AIC difference was found to be less than 10, which is small enough to indicate that there is no significant difference between the two models.

Table 6.11: Parameter estimates for crash-conflict models for 30 and 50 Runs

Parameter Estimates	TTC≤1.50s		TTC≤0.50s	
	30 runs	50 runs	30 runs	50 runs
LN α	2.09	2.14	2.69	2.80
[SE]	[0.14]	[0.14]	[0.41]	[0.30]
β	0.50	0.58	0.34	0.56
[SE]	[0.12]	[0.13]	[0.14]	[0.14]
Dispersion parameter	0.46	0.42	0.63	0.53
Residual deviance	59.46	59.51	59.34	58.76
Degrees of freedom	51	51	51	51
AIC	289.04	285.55	300.01	293.16
2 log likelihood	-283.04	-279.55	-294.01	-287.16

* SE: standard error

The value of the β parameter in Table 6.11 for the crash-conflict model differs significantly depending on whether 30 or 50 simulation runs were carried out. This is important, since it suggests that the number of runs has an effect on the crash-conflict model parameters. This suggests that care should be taken in choosing the appropriate number of simulation runs prior to linking conflicts to crashes. For the higher risk threshold (TTC≤ 0.50s) the results are similar to the lower risk threshold (TTC≤ 1.50s) in that, the value of β in the crash-conflict expressions are also similar.

6.4.3 Crash-conflict model for rear-end crashes

Other GLM (NB) models were fitted to the rear-end crash-conflict data (i.e., non-target interactions) for the 53 untreated intersections for good weather. Table 6.12 summarizes the calibration results for rear-end crashes for TTC ≤ 1.50s and ≤ 0.50s. TTC ≤ 1.50s yields a better model fit, in that AIC was found to be much lower as compared to its value for TTC ≤ 0.50s.

Table 6.12: Parameter estimates for rear-end crash-conflict models (50 runs)

Parameter estimates	TTC threshold	
	≤1.50s	≤0.50s
LN α	2.07	3.27
[SE]*	[0.15]	[0.21]
β	0.46	0.22
[SE]	[0.08]	[0.10]
Dispersion parameter	0.20	0.31
Residual deviance	53.85	55.16
Degrees of freedom	51	51
AIC	370.52	391.58
2 log likelihood	-364.52	-385.58

* SE: standard error

6.5 CMF ESTIMATES FOR LTOPP AND REAR-END CRASHES

In this section, the estimation of CMFs for the treatment introduced for the 47 treated intersection sample is discussed. As noted previously, the treatment considered in this case study is a change in left turn signal priority from permissive to protected-permissive. The CMF was estimated as per Equation [4.7] in Chapter 4. The parameter β in this equation is indicated in Table 6.11 and Table 6.12 **.**

The estimated CMFs are shown in Table 6.13. These results indicate that CMFs for LTOPP conflicts are statistically similar (P-value=0.85 for the difference in CMF estimates) to values in Table 6.14 obtained from EB before-and-after analysis for TTC≤0.50 seconds. The EB results were reported by Srinivasan et al. (2011 and 2012) for the same intersection data and treatment. Both EB and integrated model findings are reasonable in that LTOPP crashes are a key target of left turn priority treatment. For rear-end crashes, both sets of results suggest that there is no statistical effect on safety at 5% significance level.

Table 6.13: CMFs for LTOPP conflicts at treated intersections

TTC Threshold	Parameter	LTOPP	Rear-end
≤ 1.50s	ρ [SD]	0.72 [0.11]	0.95 [0.04]
	β	0.58	0.46
	a_1	0.67	0.48
	a_2	-0.19	-0.14
	CMF [SE]	**0.83*** **[0.01]**	**0.974*** **[**0.002**]**
≤ 0.50s	ρ [SD]	0.85 [0.33]	0.95 [0.41]
	β	0.56	0.22
	a_1	0.60	0.22
	a_2	-0.16	-0.09
	CMF [SE]	**0.91**** **[0.03]**	**0.99*** **[**0.01**]**

*Statistically significantly different from EB estimate at 5% confidence level
**Not statistically significantly different from EB estimate at 5% confidence level

Table 6.14: EB before-and-after study of 47 treated intersections (reproduced from Srinivasan et al. (2011 and 2012))

Crash type	Expected crashes after	Observed crashes after	CMF	SE
LTOPP	341	314	**0.919**	0.069
Rear-end	1266	1383	**1.091**	0.046

6.6 SENSITIVITY OF CMF ESTIMATES TO THE NUMBER OF RUNS AND TTC THRESHOLDS

The research provided an opportunity to investigate the sensitivity of the CMF estimates to the number of simulation runs and TTC thresholds. This section presents the results of that sensitivity analysis which complements the investigation in Section 6.4.2.2 of the effect of these parameters on the crash-conflict models used to generate the SMF estimates.

Table 6.15 summarizes the CMF estimates for the two levels of simulation runs and two TTC thresholds. It is noted that increasing the TTC threshold from high to low risk reduces the effectiveness of treatment. This is expected since the higher threshold (TTC<1.50s) generates a higher number of conflicts.

Table 6.15: Crash modification factors from LTOPP conflicts at treated sites

TTC threshold	**Parameter**	**Number of simulation runs**	
		30 runs	**50 runs**
≤ 1.50s	ρ [SD]	0.72 [0.11]	0.72 [0.11]
	β	0.50	0.58
	a_1	0.59	0.67
	a_2	-0.20	-0.19
	CMF [SE]	**0.85*** **[**0.01**]**	**0.83*** **[**0.01**]**
≤ 0.50s	ρ [SD]	0.85 [0.33]	0.85 [0.33]
	B	0.34	0.56
	a_1	0.38	0.60
	a_2	-0.15	-0.16
	CMF [SE]	**0.95**** **[**0.02**]**	**0.91**** **[**0.03**]**

*Statistically significantly different from EB estimate at 5% confidence level
**Not statistically significantly different from EB estimate at 5% confidence level

The CMF estimates for TTC≤0.50 seconds are closer to those obtained from the EB before-and-after analysis as compared to results for TTC ≤1.50s. CMFs for TTC<0.50s with 30 and 50 runs were not found to be statistically different at the 5% level from the CMFs from the EB before-and-after analysis. It should be noted that CMFs for the 50 simulation runs were found to be closer to the values obtained from the EB analysis.

As the conflict threshold is increased, (e.g. lower TTC), so too is the level of consistency in the results between conflict-based and crash-based models. This is expected since increasing the TTC thresholds reflects increased risk, and these are presumably the kind of conflicts that are most likely to result in crashes.

Based on the results shown in Table 6.15, it can concluded that using higher severity thresholds (e.g., TTC≤0.50s) and higher number of simulation runs yield closer CMF estimates to those obtained from the EB crash-based before and after estimates. This is consistent with the results in Section 6.4.2.2 of the examination of the effect of these parameters on the crash-conflict models used to generate the CMF estimates.

6.7 SENSITIVITY ANALYSIS OF CMFS TO VISSIM INPUT PARAMETERS

The following section presents further analysis for using microscopic simulation models for estimating CMFs. Specifically this section investigates the effect of the simulation input parameters on CMF-estimates.

To examine the sensitivity of CMF estimates to the simulation input parameters, two sets of VISSIM (version 5.40) parameters were used Input1 and Input2. Input1 was obtained from calibrated values reported by Cunto and Saccomanno (2008) based on VISSIM application to NGSIM trajectory data for intersections (NGSIM, 2014). Cunto and Saccomanno (2008) used two safety performance measures in the simulation calibration/validation procedure: crash potential index (CPI), and number of vehicles in conflict. Among all available driving parameters, they suggested three parameters needed to be specified for VISSIM simulation, namely: desired deceleration (DD), standstill distance (CC0) and headway time (CC1). The desired deceleration is considered the most sensitive and the best representation of traffic operations at signalized intersections. It can be used to achieve a predefined desired speed or under Stop-and-Go condition. The standstill distance is the desired distance between stopped cars and the headway time is the time the following vehicle wants to keep behind the lead vehicle (PTV, 2012).

In addition to the above three parameters from Cunto and Saccomanno (2008), other inputs were used to ensure more realistic driving behavior, as given in **Table 6.16**. Cunto and Saccomanno (2008) used the Wiedemann 99 model for car following driving behavior in VISSIM because it gives more flexibility in the calibration process as Wiedemann 99 model has 10 car following parameters.

The VISSIM manual suggested that the Wiedemann 99 model is suitable mainly for interurban motorways except for those having merging/weaving areas (PTV, 2012). In addition, it suggests that the Wiedemann 74 Model is mainly suitable for urban traffic areas. For this another set of parameters (Input 2 as in Table 6.16) was used to show to what extent the Wiedemann 99 and Wiedemann 74 car following models can affect the results. VISSIM default parameters (3 parameters) for Wiedemann 74 car following model were used.

Table 6.16: VISSIM parameters for Inputs 1 and 2

Behavioral parameter	Input 1	Input 2
Driving behavior	Urban (motorized)	Urban (motorized)
Car following	Wiedemann 99 DD = -2.60 m/Sec^2 CC0 = 3.00 meters CC1 = 1.50s	Wiedemann 74 ax = 2.00 m[1] bx_add = 2.00[2] bx_mult = 3.00[3]
	Smooth close-up	
Lane change	Advanced merging	
	Cooperative lane change	
Lateral parameters	Keep lateral distance to vehicles in on next lane(s)	
	Consider next turning decision	
Signal control	Decision model: one decision	
Conflict areas (left turn only)	Front gap = 0.00s	
	Rear gap = 0.00s	
	Avoid Blocking = 0 for all cases and =1 for 2 LT lanes	

[1]the average standstill distance with standard deviation of 0.30 m;
[2]the additive part of safety distance;
[3]the multiplicity part of safety distance.

In this exercise, only 10-simulation runs with 10 random seeds were used to capture the randomness in traffic with 5-minutes warming-up period. Although only one hour (typically the AM peak hour) was used in this analysis, a 2-hour simulation time was used to ensure that all vehicles have entered the simulation network. For each run, the number of conflicts for TTC was calculated from the trajectories of simulated vehicles at different times. The Surrogate Safety Assessment Model (SSAM) (Pu and Joshi, 2008) is used here to estimate the total number of conflicts with different conflict severity levels, typically for TTC $\leq$ 1.50s, TTC $\leq$ 1.00s, and TTC $\leq$ 0.50s. The average number of conflicts at each site is then calculated.

Table 6.17 shows the simulated conflict results for the 47 Toronto treated intersections. The table shows the simulated conflicts in the before period without the treatment, the simulated conflicts in the after period with the treatment, and ρ, the ratio between the number of conflicts in the after period with the treatment divided by the number of conflicts in the before period without the treatment. Three levels of conflict severity based on TTC are used: TTC$\leq$ 1.50s, TTC$\leq$1.00s, and TTC$\leq$ 0.50s. Only simulated conflicts similar to target crashes were presented in Table 6.17, i.e., rear-end conflicts for rear-end crashes, left turn opposing conflicts for LTOPP crashes, and total conflicts for total crashes.

Table 6.17: Simulated conflicts for parameter Inputs 1 and 2

TTC threshold	Parameter	Rear-end conflicts		LTOPP conflicts		Total conflicts	
		Input 1	Input 2	Input 1	Input 2	Input 1	Input 2
≤ 1.50s	Before	277.80	1383.0	152.60	177.80	509.20	1857.60
	After	268.80	1328.00	110.80	130.50	461.00	1746.30
	ρ	0.97	0.96	0.73	0.73	0.91	0.96
≤ 1.00s	Before	44.60	45.20	105.30	116.90	174.80	189.60
	After	42.60	43.70	74.40	83.70	140.60	150.50
	ρ	0.96	0.97	0.72	0.72	0.80	0.79
≤ 0.50s	Before	20.30	12.30	17.80	21.90	48.90	43.20
	After	20.20	14.20	15.20	19.40	46.60	43.40
	ρ	1.00	1.15	0.85	0.89	0.95	1.00

The results for both used VISSIM parameters (Inputs 1 and 2) indicate safety benefits (i.e., Conflict ratio <1) for LTOPP conflicts. Both models show a reduction in conflicts by 73% and 72% for TTC≤1.50s and TTC≤1.00s, respectively. For TTC≤0.50s, Input 1 shows a reduction of 15% while Input 2 shows a reduction of 11%.

The change in simulated LTOPP conflicts for different VISSIM parameters (different car-following driving behaviors) show a reduction in the simulated conflicts, which is in the same direction as the EB before-and-after results from Srinivasan et al (2011, 2012) as shown in **Table 6.14**, which indicates CMF of 0.919. For the LTOPP conflicts, Input 2 shows higher conflict numbers than for Input 1. The difference between conflict estimates ranges is around 25 conflicts for TTC≤ 1.50s and around 4 conflicts for TTC≤0.50s. For rear-end conflicts, the difference between both inputs is very large (more than 1000 conflicts) for TTC≤1.50s, while it is less than 1 for TTC≤1.00s and around 8 conflicts for TTC≤0.50s.

The conflict ratio (ρ) for rear end conflicts is similar in value to CMF of 1.091 obtained in the EB before-after analysis, although for the two larger thresholds ρ shows a modest increase. For the total conflicts, both Input 1 and Input 2 results show change (e.g., decrease) in the total conflicts ranged between 79% to 96% for all ranges of TTC except for TTC ≤0.50s in Input 2 which shows no change in the total conflicts.

Table 6.18: Crash modification factors from LTOPP conflicts

TTC threshold	Parameter	LTOPP		Rear-end	
		Input 1	Input 2	Input 1	Input 2
≤ 1.50s	ρ	0.73	0.73	0.97	0.960
	β	0.58	0.58	0.46	0.462
	CMF	0.83	0.83	0.99	0.98
≤ 0.50s	ρ	0.85	0.89	1.00	1.15
	β	0.56	0.56	0.22	0.22
	CMF	0.91	0.94	1.00	1.03

As shown from Table 6.18, the CMF –estimates at TTC<1.50s are very similar for both LTOPP and rear-end conflicts for the two sets of parameters (Inputs 1 and 2). At TTC<0.50s, there is slight difference between CMF-estimates between the two models (0.023 for LTOPP compared to 0.031 for rear-end conflicts). This difference is expected to be smaller when more simulation runs are used (more than the 10-runs in this exercise).

6.8 PRACTICAL IMPLEMENTATION

To obtain CMFs using the integrated model for a city like Toronto, e.g., for different intersection treatments, representative untreated sample intersections will need to be selected (i.e., not just intersections 4-leg intersection with 2-lanes per approach without exclusive left or right turn lanes, as used in this thesis). Then obtain simulated traffic conflicts by simulating the intersection samples (e.g., using VISSIM). A relationship between crashes (i.e., by type and severity) and simulated conflicts (i.e., by type) will need to be established for different conflict thresholds (i.e., TTC≤1.50s, TTC≤0.50s, etc.). These models will serve as the link function required (i.e., calibrated conflict coefficients) to obtain the integrated CMF.

To obtain CMF values at a given site, the site will need to be simulated (i.e., using VISSIM) with (i.e., after) and without treatment (before). Then the simulated conflicts by type and threshold can be obtained using SSAM for the before and the after. Then the conflict ratio between the after and the before can be obtained. Finally CMF values and their associated variance can be obtained by applying Equations [4.7] and [4.15].

An important step to yield the best estimates of the CMF is to use an appropriate number of runs for the specified analysis period. This can be obtained simply using standard statistical inference expressions, where for a given error tolerance the minimum required number of runs is (Johnson, 2000):

$$N = \left(\frac{t_{(1-\frac{\alpha}{2}),\, N-1} \times \sigma}{E} \right)^2 \tag{6.1}$$

where,

N = minimum required number of simulation runs,

$\sigma =$ the sample standard deviation of the number of simulated conflicts,

t = student's t-statistic for two-sided error of $\alpha/2$ (totals α percent) with N-1 degrees of freedom (for 10 runs, t=2.3), and

E= allowed error range.

The allowed error range can be taken as a percenatge of the mean value such that:

$$E = \varepsilon \times \mu \tag{6.2}$$

where:

μ = the mean of the number of simulated conflicts from initial simulations runs;

ε = the allowable error as a percentage from the mean value.

6.9 CHAPTER SUMMARY

This Chapter has presented a case study application to estimate crash modification factors (CMFs) using the integrated model developed in Chapter 5. A before and after conflict analysis was carried out for a sample of treated Toronto intersections, where left turn signal priority has been changed from permissive to protected-permissive. The CMFs estimates from the integrated model were compared with CMF estimates obtained from an earlier conventional, crash-based empirical Bayes (EB) before-and-after study for the same sample of intersections and treatment.

The conflict-based analysis (the integrated model) presented in this analysis provides a good alternative to EB before-and-after analysis. It can be used to evaluate the safety of entity signalized intersections and the corresponding crash modification factor (CMF) can be reported in a similar way to the crash-based EB before-and-after analysis. The simulation method has a good advantage over the conventional observational methods in that it can be used to estimate countermeasure effectiveness before it is introduced or after a relatively short after period during which traffic volume changes can be observed.

In addition, the results support the view that countermeasure effects can be estimated more dependably from conflicts derived from microsimulation, and more so when an appropriate number of simulation runs and conflict thresholds are used in the calibration of the crash-conflict relationship. Furthermore, as the threshold for conflict definition is increased (e.g. lower time-to-collision), so too is the consistency of the results between conflict-based and crash-based evaluations. This is expected since increased thresholds reflect higher risk conflicts, and these presumably are the events that are more likely to result in crashes.

The number of simulation runs and TTC thresholds were found to have a significant effect on CMF estimates as obtained from the integrated crash-conflict model. Moreover, although the 53 sites, used for to calibrate the crash-conflict model, seem to give reasonable results, more work is needed to investigate the appropriate sample size of reference sites when calibrating the crash-conflict relationship.

CHAPTER 7
CONTRIBUTIONS AND FUTURE WORK

The application of observational models based on reported crash history is the most common approach to identify unsafe sites for priority intervention and assessing treatment effects. Recently, however, microscopic traffic simulation has been used to model high-risk vehicle interactions or traffic conflicts for input into safety performance analysis. Taking into account higher risk interactions can help in gaining a better understanding of safety problems at a given site.

Historically crash observations are considered to be the key verifiable metric for representing failures in the transportation system. One of the major challenges of safety analysis is how to use both conflicts and observational crash history to better understand where safety is most problematic; where intervention is needed; and how best to resolve specific safety problems. In addressing this challenge, this study takes the position that a complete understanding of safety at a given site only emerges if both crash potential and traffic conflicts are taken into account.

The primary objective of this thesis is to develop integrated safety models based on both observed crashes and simulated traffic conflicts, and to use these model to rank sites for priority intervention and to assess treatments at these sites.

7.1 MAJOR CONTRIBUTIONS

The two main contributions in this research are the development of integrated crash-conflict models for safety analysis, namely: (1) an integrated model for priority ranking of unsafe intersections, (2) an integrated model to estimate site-specific crash modification factors (CMFs) for evaluation.

7.1.1 Findings related to priority ranking

An integrated priority ranking measure was established based on the weighted sum of the expected crashes from an Empirical Bayesian formulation and expected traffic conflicts from calibrated microscopic traffic simulation. A weight factor linking crashes and conflicts was determined using six established comparison criteria, such as, site consistency, method consistency, rank difference, total score, and sensitivity and specificity tests.

Fifty-eight signalized intersections from Toronto were ranked using the integrated model. The ranking was compared to that obtained from other crash-based and simulated conflict-based methods. The integrated model was found to yield better priority ranking results than conventional observational crash-based models or conflict-based models alone. These results confirm that higher risk vehicle interactions (i.e., traffic conflicts) are important to gain a better understanding of the safety problems at a given site, that need to be considered in ranking these sites for safety intervention. This should result in a more efficient allocation of scarce safety budgets, i.e., targeting those sites most in need of treatment.

Since the integrated model has a conflict-based component, it is able to rank sites where the observation period could be insufficient to provide a reliable record for crash occurrence. Furthermore, the use of simulated conflicts is able to consider safety problems that have not been reflected in observed crashes, such as near misses. This means that the integrated model developed in this research provides a more comprehensive view of potential safety problems used to guide intervention strategies.

7.1.2 Finding related to treatment effects

To improve safety at a certain location, a suitable treatment should be used. Before introducing such treatment, its net safety gain needs to be estimated for different geometric and traffic conditions, and this gain compared to associated implementation costs. The effectiveness of road safety treatments on crash reduction is frequently expressed in terms of a crash modification factor (CMF), which is normally obtained through the application of observational before and after analysis.

One of the main problems with the use of observational before and after analysis is the non-proactive nature of the procedure, i.e., to determine the effects of treatment, the treatment will need to be implemented prior to the analysis. Of course, this is not always possible. The integrated model presented in this research provides an objective link between simulated traffic conflicts and observed crashes. In the absence of an established crash-history at a given site, treatment effects can only be inferred from changes in simulated traffic conflicts. This permits the estimation of potential treatment effects for those sites where the treatment has not been implemented. Moreover, the integrated model has the added advantage of providing site-specific CMFs, avoiding the need to apply a constant CMF across all sites considered for a potential treatment, as is typical in conventional before and after safety analysis.

Where several correlated treatments are considered at a given site, the integrated treatment model, as it is based mainly on simulation, has the ability to obtain treatment estimates for each treatment separately from the others in addition of course to the combined effect of all treatments.

The integrated model was applied to a sample of treated signalized intersections from Toronto, where left turn signal priority has been changed from permissive to protected-permissive. This dataset was useful, in that we were able to compare the results with those obtained from a conventional crash-based EB before and after analysis for the same treatment and sites.

The results of this comparison were found to be promising in that the crash-conflict integrated model yielded CMF estimates that were found to be consistent with those from conventional EB crash-based estimates. This demonstrated for the sample used, that crashes at the sample sites took place with a fair degree of consistency as compared with traffic conflicts. Had crashes been purely random, it is unlikely the integrated model results would have yielded similar results to those obtained from the conventional EB analysis. The integrated model results would have been influenced more significantly by the pattern of resultant traffic conflicts than by historical crashes themselves.

Since conflicts result from behavioral vehicle interactions, they reflect a more casual structure for explaining why certain treatments would improve safety at a given site. This is important to a safety analyst because it not only provides estimates of the treatment effect, but it is also explains why these effects may vary from site to site. This is accomplished in the integrated models by examining vehicle interactions and driver behaviours associated with each treatment.

7.2 FUTURE WORK

The integrated models for priority ranking and treatment effect evaluation presented in this research can provide the basis for better traffic and safety analysis. However, a number of areas will need to be considered before these models can be systematically applied:

1- The integrated priority ranking model is conceptually appealing in that it is essentially a framework that incorporates two partly independent clues about the lack of safety at a given site. However, the formal link between simulated traffic conflicts and predicted crashes requires the specification of a weight factor. In this research, rather subjective weights were assumed to establish the link between crash potential and simulated traffic conflicts. A more formal and scientific procedure for establishing these weights will need to be developed, such that information gains from various inputs (crashes and conflicts) is maximized.

2- The integrated priority-ranking model was evaluated based on the total crashes and conflicts with all severities combined. It is recommended to evaluate the integrated model with crashes and conflicts by severity;

3- For treatment effect evaluation, a key aspect is the link between simulated conflicts and crashes. In this thesis, the relationship was developed based on a small sample of untreated signalized intersections without exclusive lanes. It is recommended that a larger sample of sites be used to obtain an improved crash-conflict relationship, and hence, the conflict coefficient, and the corresponding treatment effects;

4- For treatment effects evaluation, only crashes by type and simulated conflicts by type were investigated. It is recommended to consider the estimation of CMFs from the integrated model for different crash severities;

5- Only vehicle-vehicle conflicts during normal weather conditions were considered.. It is recommended that other weather conditions also be considered, such as, wet pavement, restricted visibility, etc.. This will require the use of microscopic simulation parameters corresponding to each interaction and different weather conditions. Filling this void will require a calibration process to identify parameters that are sensitive to the change in weather and road surface conditions;

6- In this research, the integrated models were applied to isolated signalized intersections. It is recommended to investigate the models to intersections (signalized and un-signalized) that are a part of a larger related network.

7- In using the integrated treatment model along with conflict-volume prediction models, it is recommended to develop traffic models (or integrate it with current models, such as SYNCHRO (Trafficware, 2014)) to assess safety benefits of changing the geometry, signal timing and/or the control type along with mobility benefits of such change.

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APPENDICES

Appendix A: Priority Ranking Data

A.1- Total crashes per year at the 53 sites

Intersection number	Total crashes							
	1999	2000	2001	2002	2003	2004	2005	2006
53	2	0	0	0	0	0	2	1
82	7	12	18	12	8	16	5	7
84	3	3	3	3	1	5	6	1
118	3	1	3	3	3	1	2	3
120	2	1	1	4	3	3	1	2
122	3	4	0	1	0	1	2	5
130	2	4	4	2	3	5	4	3
176	10	10	12	11	6	4	10	3
186	15	9	20	9	10	11	6	12
201	5	8	19	15	12	16	22	15
203	32	31	24	26	18	16	18	23
292	10	14	16	12	8	9	7	10
307	4	3	1	1	3	6	5	4
313	5	2	2	1	1	1	0	8
368	5	10	17	4	7	6	8	8
370	3	9	1	6	10	1	5	3
371	1	4	4	4	3	3	4	6
376	0	0	2	5	1	3	1	1
500	8	14	8	5	11	4	11	3
504	5	4	4	2	5	0	4	4
516	2	3	1	5	4	5	5	2
610	10	13	15	15	14	10	8	8
657	6	4	1	5	3	3	1	5

Intersection number	Total crashes							
	1999	2000	2001	2002	2003	2004	2005	2006
661	5	4	3	7	6	5	2	2
664	5	7	8	5	7	6	4	6
688	1	2	1	1	2	2	1	2
715	7	5	14	5	10	8	7	9
818	4	5	9	4	7	5	5	8
819	12	3	13	17	9	5	11	9
914	1	1	2	1	2	3	0	0
976	0	2	1	2	0	0	1	1
994	2	3	7	5	12	7	2	3
1063	0	3	2	0	6	1	2	1
1077	3	2	2	4	2	1	3	2
1078	1	6	2	11	4	1	0	5
1098	4	2	1	2	1	1	3	2
1153	5	5	6	10	3	5	6	4
1225	8	7	5	7	8	5	9	1
1252	6	3	3	1	2	1	1	2
1290	0	2	3	3	0	1	1	2
1291	1	5	1	4	0	0	4	2
1308	8	3	3	3	3	4	3	1
1315	3	0	1	0	7	0	3	1
1317	5	1	9	5	2	3	3	1
1319	4	3	0	2	3	3	5	3
1320	10	10	15	4	5	10	3	5
1328	0	0	0	1	1	3	2	2
1331	13	11	9	10	12	10	4	4

Intersection number	Total crashes							
	1999	2000	2001	2002	2003	2004	2005	2006
1359	3	5	7	2	7	5	3	4
1376	0	1	2	4	1	2	1	2
1497	1	0	1	0	2	0	0	1
1500	0	0	2	4	2	0	1	0
1544	0	3	7	2	5	6	3	4
1617	0	0	0	0	0	0	2	1
1747	25	28	22	21	35	25	18	34
1792	2	2	4	1	2	0	0	2
1845	7	7	2	4	1	5	2	0
1849	3	1	0	0	1	2	2	3
SUM	292	305	343	303	304	264	254	266
Mean	5.03	5.26	5.91	5.22	5.24	4.55	4.38	4.59
Stdev	5.76	5.95	6.44	5.38	5.71	4.85	4.48	5.62
MAX	32	31	24	26	35	25	22	34
MIN	0	0	0	0	0	0	0	0

A.2- Average Annual Daily traffic at major approach at the 53 sites

Intersection Number	Average Annual Daily Traffic (AADT) in the major approach							
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
53	36818	36818	36818	36818	36818	36818	36818	36818
82	48623	48799	48799	48559	48333	47927	47923	48109
84	22882	23121	23278	23321	23369	23329	23483	23733
118	44641	44285	43765	43030	42311	41438	40916	40552
120	39574	39292	38866	38248	37644	36903	36474	36186
122	37492	37654	37681	37522	37374	37086	37110	37281
130	53902	53902	53902	53902	53902	53902	53902	53902
176	18206	18097	17921	17657	17400	17079	16902	16790
186	20303	20468	20560	20551	20548	20467	20557	20730
201	21894	21918	21862	21699	21542	21306	21249	21275
203	22478	22478	22478	22478	22478	22478	22478	22478
292	18233	18500	18702	18811	18925	18966	19166	19443
307	31312	31576	31728	31724	31728	31612	31761	32037
313	36264	36021	35645	35094	34555	33891	33512	33264
368	15883	15998	16055	16033	16016	15939	15994	16114
370	13184	13137	13041	12881	12725	12523	12426	12378
371	13598	13740	13833	13858	13887	13862	13954	14102
376	17758	17855	17887	17830	17780	17662	17692	17793
500	25781	25584	25292	24876	24470	23974	23681	23480
504	41581	41316	40899	40281	39677	38929	38509	38239
516	36087	35884	35549	35039	34542	33918	33581	33374
610	24847	24672	24405	24018	23640	23176	22908	22729
657	14923	14989	15001	14940	14883	14770	14781	14851
661	17924	17903	17816	17642	17473	17240	17152	17132

Intersection Number	Average Annual Daily Traffic (AADT) in the major approach							
	1999	2000	2001	2002	2003	2004	2005	2006
664	16453	16532	16551	16489	16431	16312	16330	16413
688	19593	19463	19262	18965	18675	18318	18115	17982
715	25014	24965	24826	24565	24312	23969	23828	23780
818	23700	23524	23261	22884	22516	22065	21801	21622
819	21302	21659	21939	22111	22289	22380	22658	23028
914	35700	35804	35780	35580	35390	35068	35040	35152
976	23327	23505	23599	23577	23561	23457	23549	23735
994	26408	26448	26392	26206	26029	25754	25696	25740
1063	18410	18600	18724	18756	18792	18758	18880	19078
1077	24988	24988	24988	24988	24988	24988	24988	24988
1078	28118	28118	28118	28118	28118	28118	28118	28118
1098	24479	24688	24808	24806	24810	24721	24839	25056
1153	13352	13296	13191	13022	12856	12644	12538	12482
1225	12768	12768	12768	12768	12768	12768	12768	12768
1252	28338	28103	27765	27290	26825	26262	25922	25682
1290	27970	27970	27970	27970	27970	27970	27970	27970
1291	28602	28602	28602	28602	28602	28602	28602	28602
1308	30880	30921	30850	30627	30413	30086	30012	30057
1315	29412	29679	29840	29853	29875	29783	29941	30219
1317	23491	23687	23799	23793	23793	23704	23813	24017
1319	36861	36827	36658	36310	35973	35503	35332	35300
1320	12872	12872	12872	12872	12872	12872	12872	12872
1328	16189	16073	15897	15643	15395	15090	14913	14794
1331	19619	19897	20106	20216	20330	20367	20573	20863
1359	22610	22610	22610	22610	22610	22610	22610	22610

Intersection Number	Average Annual Daily Traffic (AADT) in the major approach							
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
1376	16373	16479	16525	16490	16460	16368	16413	16523
1497	29012	29392	29669	29799	29936	29959	30232	30628
1500	24338	24338	24338	24338	24338	24338	24338	24338
1544	26979	27200	27324	27314	27310	27204	27325	27556
1617	18612	18620	18561	18410	18265	18052	17991	18001
1747	25278	25278	25278	25278	25278	25278	25278	25278
1792	38319	38205	37951	37511	37082	36518	36261	36147
1845	20366	20382	20324	20166	20014	19788	19729	19747
1849	13604	13765	13876	13919	13966	13959	14069	14236
SUM	1477525	1479262	1476804	1468655	1460861	1448829	1446275	1448173
Mean	25474.57	25504.52	25462.14	25321.64	25187.26	24979.81	24935.78	24968.49
Stdev	9422.08	9380.27	9318.28	9229.48	9146.60	9047.12	8997.94	8972.95
MAX	53902	53902	53902	53902	53902	53902	53902	53902
MIN	12768	12768	12768	12768	12724.95	12522.61	12425.81	12377.6

A.3- Average Annual Daily Traffic (AADT) in the minor approach at the 53 sites

Intersection Number	Average Annual Daily Traffic (AADT) in the minor approach							
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
53	2038	2038	2038	2038	2038	2038	2038	2038
82	9752	9787	9787	9739	9693	9612	9611	9648
84	13523	13665	13758	13783	13811	13787	13879	14026
118	4250	4216	4167	4097	4028	3945	3896	3861
120	4122	4093	4048	3984	3921	3844	3799	3769
122	2588	2599	2601	2590	2580	2560	2562	2573
130	3372	3372	3372	3372	3372	3372	3372	3372
176	14248	14163	14025	13819	13617	13366	13228	13141
186	12752	12856	12914	12909	12907	12856	12912	13021
201	18347	18367	18320	18183	18052	17854	17806	17828
203	9364	9364	9364	9364	9364	9364	9364	9364
292	8442	8565	8659	8710	8762	8781	8874	9002
307	3924	3957	3976	3975	3976	3961	3980	4015
313	2954	2934	2904	2859	2815	2761	2730	2710
368	8941	9006	9038	9026	9016	8973	9004	9072
370	8054	8025	7966	7868	7773	7650	7591	7561
371	3701	3739	3765	3772	3779	3773	3798	3838
376	1857	1867	1871	1865	1860	1847	1850	1861
500	5121	5082	5024	4942	4861	4762	4704	4664
504	2768	2750	2722	2681	2641	2591	2563	2545
516	6020	5986	5930	5845	5762	5658	5602	5567
610	10914	10836	10719	10549	10383	10180	10062	9983
657	4577	4598	4601	4583	4565	4530	4534	4555

Intersection Number	Average Annual Daily Traffic (AADT) in the minor approach							
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
661	13865	13848	13781	13646	13516	13336	13268	13252
664	12396	12455	12470	12423	12380	12290	12304	12366
688	2807	2788	2759	2717	2675	2624	2595	2576
715	8254	8238	8192	8106	8022	7909	7862	7847
818	3171	3147	3112	3062	3013	2952	2917	2893
819	10862	11043	11186	11274	11365	11411	11553	11742
914	1757	1762	1761	1751	1741	1726	1724	1730
976	2699	2720	2731	2728	2727	2714	2725	2747
994	6700	6710	6696	6649	6604	6534	6520	6531
1063	3292	3326	3348	3354	3360	3354	3376	3411
1077	2366	2366	2366	2366	2366	2366	2366	2366
1078	2714	2714	2714	2714	2714	2714	2714	2714
1098	2273	2292	2303	2303	2304	2295	2306	2327
1153	5043	5022	4983	4918	4856	4776	4736	4715
1225	4930	4930	4930	4930	4930	4930	4930	4930
1252	8410	8340	8239	8098	7960	7794	7693	7622
1290	2378	2378	2378	2378	2378	2378	2378	2378
1291	5682	5682	5682	5682	5682	5682	5682	5682
1308	1615	1617	1614	1602	1591	1574	1570	1572
1315	2691	2715	2730	2731	2733	2725	2739	2765
1317	3020	3045	3059	3059	3059	3047	3061	3087
1319	4540	4536	4515	4472	4431	4373	4352	4348
1320	7154	7154	7154	7154	7154	7154	7154	7154
1328	2141	2125	2102	2068	2035	1995	1972	1956
1331	5812	5895	5956	5989	6023	6033	6095	6180

Intersection Number	Average Annual Daily Traffic (AADT) in the minor approach							
	1999	2000	2001	2002	2003	2004	2005	2006
1359	3562	3562	3562	3562	3562	3562	3562	3562
1376	7782	7833	7855	7838	7824	7780	7801	7854
1497	1706	1728	1744	1752	1760	1761	1777	1801
1500	1514	1514	1514	1514	1514	1514	1514	1514
1544	2559	2580	2592	2591	2590	2580	2592	2614
1617	2871	2872	2863	2839	2817	2784	2775	2776
1747	5942	5942	5942	5942	5942	5942	5942	5942
1792	1994	1988	1974	1951	1929	1900	1887	1881
1845	2459	2461	2454	2435	2417	2390	2382	2385
1849	4126	4174	4208	4221	4235	4233	4267	4317
SUM	322714	323370	323041	321373	319787	317200	316848	317549
Mean	5564.04	5575.34	5569.67	5540.91	5513.57	5468.96	5462.89	5474.98
Stdev	3916.64	3927.36	3924.37	3902.52	3882.43	3848.43	3847.31	3861.99
MAX	18346.56	18366.55	18319.98	18183.23	18052.15	17854.02	17805.96	17828.24
MIN	1514	1514	1514	1514	1514	1514	1514	1514

A.4- AM peak hour traffic volume at the 35 sites

Intersection number	year	AM peak hour traffic volume per approach											
		NB			EB			SB			WB		
		LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
1007	2003	24	641	22	53	23	46	28	734	50	37	17	48
1009	2003	61	968	63	72	63	71	26	1262	84	102	83	89
1012	2002	11	740	126	10	15	19	148	1283	0	159	0	108
1017	2002	4	689	16	60	54	30	26	448	60	63	144	58
1028	2002	1	1063	92	33	14	11	63	948	12	358	5	269
1030	2003	5	1131	14	140	98	72	16	1299	14	82	33	90
1050	2002	6	730	31	28	5	26	61	1284	20	95	17	60
1051	2002	14	610	4	13	0	4	7	391	59	13	2	21
1052	2002	21	500	58	87	267	79	101	646	101	155	231	111
1060	2002	47	846	43	40	6	63	49	1188	49	155	1	98
1065	2002	51	331	84	123	296	20	266	216	142	60	399	351
1071	2003	11	707	14	6	15	29	41	1301	8	95	25	31
1072	2003	150	983	62	122	279	93	163	1252	306	93	685	188
1073	2003	22	248	18	32	43	46	52	628	34	27	19	58
1077	2003	18	773	22	31	13	42	12	1091	40	37	36	37

Intersection number	year	AM peak hour traffic volume per approach											
		NB			EB			SB			WB		
		LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
1083	2002	21	1676	5	279	32	14	2	2133	294	8	15	213
1085	2003	10	1325	210	38	40	41	64	1107	10	293	19	179
1098	2003	19	829	46	85	11	27	56	926	42	88	10	55
1100	2003	90	1272	133	70	91	60	67	1250	74	220	97	84
1102	2003	24	17	14	42	1272	14	66	29	101	6	648	19
1109	2003	168	695	64	81	527	70	106	1044	109	205	1264	118
1111	2002	43	830	93	48	335	118	63	1471	46	194	537	54
1112	2002	114	867	10	84	95	82	132	839	119	5	265	258
1113	2002	46	596	22	199	38	54	11	744	28	38	35	31
1124	2002	18	760	13	11	6	7	55	452	36	42	16	155
1127	2002	22	609	22	8	24	37	32	722	13	64	21	49
1129	2003	27	996	5	29	23	32	20	1402	36	25	12	40
1131	2003	0	618	15	286	52	5	5	451	322	1	5	6
1132	2002	166	442	37	33	90	186	47	827	50	66	94	47
1140	2003	11	748	21	2	5	26	17	937	8	128	4	44
1151	2003	107	1300	116	146	134	123	138	1671	191	126	136	455

Intersection number	year	AM peak hour traffic volume per approach											
		NB			EB			SB			WB		
		LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
1159	2002	78	533	29	79	47	51	66	1471	98	20	33	8
1160	2002	154	1138	414	60	265	57	208	1065	167	243	258	63
1161	2002	82	959	98	157	767	136	177	1389	74	160	488	128
1164	2003	95	444	79	125	701	232	174	1033	163	213	470	131
SUM		1741	27614	2115	2712	5746	2023	2565	34934	2960	3676	6124	3754
Mean		49.74	788.97	60.43	77.49	164.17	57.80	73.29	998.11	84.57	105.03	174.97	107.26
Stdev		50.80	330.34	76.93	70.39	272.50	50.69	64.76	436.17	84.75	88.65	275.70	100.34
MAX		168	1676	414	286	1272	232	266	2133	322	358	1264	455
MIN		0	17	4	2	0	4	2	29	0	1	0	6

A.5- Total hourly volume and total number of conflicts at the 35-sites

Intersection number	**year**	**Hourly Volume**		**Extracted conflicts from SSAM for different thresholds of deceleration rate (DR)**		
		V_{Maj}	**V_{Min}**	**DR≤-1.5 m/s^2**	**DR≤-4.0 m/s^2**	**DR≤-6.0 m/s^2**
1007	2003	1375	40	40	22	12
1009	2003	2230	146	187	87	41
1012	2002	2023	15	119	56	21
1017	2002	1137	198	26	16	9
1028	2002	2011	19	167	77	35
1030	2003	2430	131	124	63	28
1050	2002	2014	22	91	45	16
1051	2002	1001	2	14	9	5
1052	2002	1146	498	89	34	18
1060	2002	2034	7	123	60	29
1065	2002	547	695	81	36	21
1071	2003	2008	40	89	44	16
1072	2003	2235	964	950	301	120
1073	2003	876	62	18	10	5
1077	2003	1864	49	76	38	15
1083	2002	3809	47	523	193	77
1085	2003	2432	59	276	117	52
1098	2003	1755	21	89	43	20
1100	2003	2522	188	341	128	62
1102	2003	46	1920	85	41	18

Intersection number	**year**	**Hourly Volume**		**Extracted conflicts from SSAM for different thresholds of deceleration rate (DR)**		
		V_{Maj}	V_{Min}	DR≤-1.5 m/s^2	DR≤-4.0 m/s^2	DR≤-6.0 m/s^2
1109	2003	1739	1791	838	282	110
1111	2002	2301	872	520	206	94
1112	2002	1706	360	157	75	43
1113	2002	1340	73	42	22	12
1124	2002	1212	22	35	21	11
1127	2002	1331	45	36	20	11
1129	2003	2398	35	133	67	28
1131	2003	1069	57	32	16	8
1132	2002	1269	184	81	40	23
1140	2003	1685	9	65	33	16
1151	2003	2971	270	787	265	116
1159	2002	2004	80	158	67	30
1160	2002	2203	523	645	196	76
1161	2002	2348	1255	807	264	104
1164	2003	1477	1171	714	231	99
Mean		1787.09	339.14	244.51	92.14	40.03
Stdev		714.57	511.45	281.30	89.08	35.90
MAX		3809	1920	950	301	120
MIN		46	2	14	9	5

Appendix B: Treatment Effect Data

B.1- Treated sites crash/conflict data

Intersection number	Treated Approach	change year	Number of years		LTOPP crashes		Rear-end crashes		number of LTOPP conflicts (TTC<=1.50s, 50 runs)		number of RE conflicts (TTC<=1.50s, 50 runs)		number of LTOPP conflicts (TTC<=0.50s, 50 runs)		number of RE conflicts (TTC<=0.50 s, 50 runs)	
			before	after	before	after	before	after	before	after	before	after	before	after	before	after
59	wb	2002	3	5	1	5	11	27	1.06	0.76	17.20	21.28	0.18	0.10	0.12	0.08
70	nb	2005	6	2	6	1	56	10	0.52	0.78	22.38	22.26	0.12	0.08	0.08	0.08
129	sb	2004	5	3	20	8	34	27	2.06	1.82	26.56	26.16	0.18	0.18	0.24	0.22
181	sb	2002	3	5	3	3	11	21	0.66	0.64	6.98	7.16	0.08	0.14	0.26	0.24
190	sb	2002	3	5	3	5	11	33	0.40	0.40	6.82	6.82	0.06	0.06	0.20	0.20
251	nb	2001	2	6	3	3	10	37	1.52	1.38	47.74	48.48	0.62	0.42	0.24	0.26
320	wb	2006	7	1	22	4	125	13	2.04	2.04	67.86	67.86	0.34	0.34	0.62	0.62
347	eb	2000	1	7	2	4	2	40	3.48	0.98	16.90	11.98	0.18	0.06	0.20	0.16
355	eb	2001	2	6	5	14	21	59	1.30	1.04	21.34	17.70	0.22	0.30	0.38	0.26
379	eb	2003	4	4	17	10	34	33	5.24	3.50	47.72	48.32	1.06	0.68	1.30	0.84

Intersection number	Treated Approach	change year	Number of years		LTOPP crashes		Rear-end crashes		number of LTOPP conflicts (TTC<=1.50s, 50 runs)		number of RE conflicts (TTC<=1.50s, 50 runs)		number of LTOPP conflicts (TTC<=0.5 0s, 50 runs)		number of RE conflicts (TTC<=0.50 s, 50 runs)	
			before	after	before	after	before	after	before	after	before	after	before	after	before	after
412	nb	2004	5	3	36	16	123	49	7.30	5.72	28.92	28.82	0.66	0.58	0.22	0.30
452	sb	2001	2	6	12	32	27	88	5.42	6.62	25.64	22.82	0.92	1.14	0.24	0.30
458	nb	2006	7	1	29	5	102	13	2.26	1.80	29.48	27.74	0.30	0.26	0.24	0.32
461	sb	2006	7	1	28	4	116	15	2.62	2.52	39.16	38.40	0.40	0.40	0.40	0.34
462	sb	2003	4	4	28	17	47	51	10.80	10.50	44.10	41.62	1.72	1.92	0.40	0.60
474	eb	2002	3	5	15	6	23	35	0.92	1.06	41.82	33.08	0.20	0.16	0.22	0.24
517	nb	2006	7	1	17	4	107	20	6.52	3.84	19.16	18.68	0.58	0.30	0.14	0.08
534	wb	2003	4	4	34	12	89	81	9.16	6.92	18.38	16.44	0.72	0.66	0.02	0.04
539	eb	2002	3	5	2	8	22	31	0.56	0.50	7.46	7.34	0.08	0.06	0.34	0.32
564	nb	2001	2	6	4	10	30	87	1.22	1.04	50.64	52.16	0.26	0.16	0.56	0.64
605	sb	2002	3	5	5	7	18	24	0.32	0.34	4.34	4.72	0.08	0.02	0.18	0.22
619	sb	2004	5	3	34	13	106	59	2.66	0.90	51.26	51.82	0.34	0.16	0.56	0.60
621	sb	2004	5	3	6	4	22	1	1.38	0.98	4.10	4.96	0.28	0.24	0.10	0.20

Intersection number	Treated Approach	change year	Number of years		LTOPP crashes		Rear-end crashes		number of LTOPP conflicts (TTC<=1.50s, 50 runs)		number of RE conflicts (TTC<=1.50s, 50 runs)		number of LTOPP conflicts (TTC<=0.5 0s, 50 runs)		number of RE conflicts (TTC<=0.50 s, 50 runs)	
			before	after	before	after	before	after	before	after	before	after	before	after	before	after
631	nb	2006	7	1	2	1	31	3	4.92	3.78	64.22	60.26	0.54	0.26	0.80	0.84
672	sb	2004	5	3	20	10	72	49	2.82	1.68	59.04	53.14	0.32	0.34	0.40	0.46
698	sb	2002	3	5	15	17	37	65	3.18	3.16	47.14	44.88	0.52	0.48	0.68	0.44
750	sb	2003	4	4	16	18	37	50	7.06	4.86	30.10	23.98	0.46	0.42	0.00	0.02
781	eb	2005	6	2	15	3	62	16	2.84	2.20	22.76	21.34	0.20	0.34	0.14	0.12
789	eb	2006	7	1	8	1	35	5	1.78	1.52	24.90	20.64	0.40	0.38	0.22	0.06
829	sb	2004	5	3	8	2	34	13	0.60	0.80	18.66	18.50	0.04	0.08	0.20	0.18
862	sb	2005	6	2	22	6	86	27	5.74	3.96	16.30	15.18	0.38	0.26	0.20	0.32
926	nb	2002	3	5	11	2	25	67	12.74	2.54	128.38	122.06	1.12	0.66	0.56	0.50
967	sb	2005	6	2	11	0	30	8	4.24	2.70	24.94	19.16	0.44	0.20	0.02	0.00
1082	wb	2004	5	3	8	2	13	9	0.66	0.42	5.20	5.66	0.08	0.02	0.20	0.12
1110	wb	2006	7	1	4	3	29	2	0.38	0.38	13.30	12.04	0.00	0.02	0.02	0.06
1183	sb	2004	5	3	21	7	49	24	3.70	3.74	42.64	43.24	0.44	0.42	0.38	0.38

Intersection number	Treated Approach	change year	Number of years		LTOPP crashes		Rear-end crashes		number of LTOPP conflicts (TTC<=1.50s, 50 runs)		number of RE conflicts (TTC<=1.50s, 50 runs)		number of LTOPP conflicts (TTC<=0.50s, 50 runs)		number of RE conflicts (TTC<=0.50 s, 50 runs)	
			before	after	before	after	before	after	before	after	before	after	before	after	before	after
1186	eb	2003	4	4	2	0	2	6	2.44	1.70	11.58	11.30	0.30	0.26	0.04	0.10
1222	wb	2004	5	3	16	9	41	36	6.00	4.88	10.54	8.76	0.66	0.60	0.10	0.02
1243	wb	2001	2	6	7	3	14	39	5.26	5.32	49.90	49.52	0.56	0.74	0.12	0.24
1264	wb	2003	4	4	2	7	18	19	4.12	2.40	21.30	18.86	0.52	0.34	0.12	0.08
1300	eb	2006	7	1	11	3	27	7	1.06	0.50	24.68	23.22	0.20	0.08	0.12	0.10
1486	eb	2003	4	4	11	9	24	20	3.38	2.52	7.56	7.68	0.20	0.32	0.06	0.04
1619	eb	2001	2	6	8	9	5	20	7.60	6.34	14.74	10.12	0.70	0.80	0.10	0.22
1641	eb	2000	1	7	2	3	3	19	2.08	0.60	55.24	52.74	0.10	0.02	0.42	0.10
1710	eb	2000	1	7	0	3	0	10	11.24	5.96	8.50	6.42	1.20	0.72	0.04	0.04
94	wb	2003	4	4	6	1	16	15	0.68	0.58	18.30	14.88	0.22	0.10	0.02	0.10
1995	sb	2006	7	1	0	0	0	0	0.06	0.08	5.90	6.22	0.00	0.00	0.06	0.02
Sum			203	173	558	314	1837	1383	164.00	118.70	1371.78	1296.42	19.18	16.28	12.28	11.72

Intersection number	Treated Approach	change year	Number of years		LTOPP crashes		Rear-end crashes		number of LTOPP conflicts (TTC<=1.50s, 50 runs)		number of RE conflicts (TTC<=1.50s, 50 runs)		number of LTOPP conflicts (TTC<=0.50s, 50 runs)		number of RE conflicts (TTC<=0.50 s, 50 runs)	
			before	after	before	after	before	after	before	after	before	after	before	after	before	after
Mean			4.32	3.68	11.87	6.68	39.09	29.43	3.49	2.53	29.19	27.58	0.41	0.35	0.26	0.25
stdev			1.87	1.87	9.94	6.13	35.10	22.98	3.13	2.26	22.95	22.30	0.35	0.34	0.25	0.21
Max			7	7	36	32	125	88	12.74	10.5	128.38	122.06	1.72	1.92	1.3	0.84
Min			1	1	0	0	0	0	0.06	0.08	4.1	4.72	0	0	0	0

B.2- Treated sites traffic volume data

Intersection number	NB			EB			SB			WB		
	LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
59	57	425	92	99	818	95	211	419	60	130	299	6
70	82	732	37	55	610	118	78	337	75	98	511	102
129	100	1381	219	87	257	79	46	2507	57	103	232	28
181	88	385	21	2	529	81	75	392	8	0	284	72
190	13	313	55	61	703	41	61	241	20	6	302	68
251	187	375	31	256	68	124	21	499	481	12	100	27
320	230	920	72	186	677	415	233	1275	129	108	893	168
347	0	0	0	232	443	0	100	0	194	0	1223	101
355	108	347	178	157	770	107	63	463	158	135	538	68
379	0	719	168	168	651	0	106	785	257	423	2417	92
412	85	671	265	175	1223	72	243	867	143	167	893	254
452	80	695	72	275	1868	43	144	423	100	151	1174	130
458	70	794	111	123	2366	64	127	655	108	108	733	115
461	209	523	29	186	889	114	61	441	322	32	1987	103
462	150	530	46	322	1694	96	154	640	202	129	696	186
474	186	422	57	109	669	147	99	334	158	61	2286	221

Intersection number	NB			EB			SB			WB		
	LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
517	100	1459	262	48	943	71	192	1194	24	179	427	154
534	255	602	137	117	1224	164	195	765	115	106	969	84
539	27	59	43	87	617	52	97	172	58	37	211	48
564	86	180	352	115	880	220	112	390	141	277	483	35
605	37	310	84	23	340	57	65	281	70	4	269	29
619	97	1449	97	195	1638	53	97	1360	240	277	1354	209
621	4	1472	39	2	0	0	39	1789	17	83	4	114
631	371	558	391	95	667	334	63	551	105	312	972	125
672	169	1148	267	328	995	172	173	1247	111	216	974	41
698	144	1094	135	199	1359	206	90	942	158	116	549	158
750	224	1494	115	146	1346	210	143	1162	48	327	1023	229
781	72	575	88	61	1298	100	68	669	90	137	1393	56
789	143	789	91	179	452	109	92	690	122	154	494	147
829	5	504	74	0	413	52	114	576	108	0	766	116
862	215	676	75	58	543	137	108	891	163	152	1128	88
926	103	277	62	1154	946	900	84	580	349	74	656	1012
967	42	539	178	54	135	51	357	803	21	96	53	33

Intersection number	NB			EB			SB			WB		
	LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
1082	81	163	44	0	574	110	136	193	9	16	144	88
1110	47	510	52	23	184	83	52	787	95	119	419	34
1183	116	237	24	218	877	173	261	358	414	44	1252	135
1186	90	151	43	126	822	48	75	139	118	31	1002	89
1222	217	911	78	62	205	103	58	928	32	20	872	72
1243	201	998	403	86	270	92	39	1245	150	477	493	12
1264	164	208	95	90	1416	110	155	149	71	105	1064	173
1300	70	83	86	84	814	14	183	203	301	76	1425	48
1486	85	171	80	52	1060	107	131	522	141	131	832	82
1619	0	0	0	231	1102	0	138	0	70	0	1556	301
1641	8	176	92	412	1140	16	10	94	424	7	1627	105
1710	0	0	0	212	1226	0	30	0	127	0	2095	111
94	122	199	119	141	820	121	72	162	60	140	848	96
1995	0	1424	54	0	0	0	83	1641	0	22	0	15
Sum	4940	27648	5113	7091	38541	5461	5334	30761	6424	5398	39922	5780
Mean	105.11	588.26	108.79	150.87	820.02	116.19	113.49	654.49	136.68	114.85	849.40	122.98
stdev	82.70	439.23	97.62	176.95	505.40	142.84	69.65	514.17	113.72	110.23	595.23	148.29

Intersection number	NB			EB			SB			WB		
	LT	TH	RT	LT	TH	RT	LT	TH	RT	LT	TH	RT
Max	371	1494	403	1154	2366	900	357	2507	481	477	2417	1012
Min	0	0	0	0	0	0	10	0	0	0	0	6

B.3- Untreated sites crash/conflict data

Intersection number	LTOPP veh-veh crashes (2001-2004)	RE veh-veh crashes (2001-2004)	LTOPP conflicts (50 runs)		RE conflicts (50 runs)	
			TTC≤1.5s	TTC≤0.5s	TTC≤1.5s	TTC≤0.5s
3	0	8	0.12	0.12	6.50	0.18
6	3	12	0.02	0.02	5.44	0.08
7	19	18	1.06	0.10	12.94	0.20
8	4	40	0.28	0.06	7.78	0.12
9	19	34	0.30	0.10	5.40	0.14
10	10	35	0.32	0.08	11.54	0.08
16	1	5	0.14	0.02	1.08	0.06
19	2	13	0.28	0.06	2.10	0.16
23	4	20	0.54	0.24	6.08	0.30
34	1	6	0.00	0.00	0.68	0.00
168	3	9	0.18	0.08	2.66	0.04
180	5	17	1.14	0.32	8.70	0.64
181	3	16	0.72	0.10	4.20	0.06
182	1	9	0.18	0.12	1.16	0.20
188	15	33	0.42	0.10	23.14	0.40
190	6	20	0.46	0.10	3.94	0.26
237	7	14	0.88	0.36	7.98	0.68
245	0	4	0.36	0.08	2.12	0.12
246	2	11	0.40	0.08	2.44	0.14
248	3	17	0.36	0.12	1.94	0.18
249	5	26	0.64	0.24	7.00	0.52
265	1	3	0.24	0.06	1.64	0.22
283	3	7	0.50	0.06	10.46	0.06

Intersection number	LTOPP veh-veh crashes (2001-2004)	RE veh-veh crashes (2001-2004)	LTOPP conflicts (50 runs)		RE conflicts (50 runs)	
			TTC≤1.5s	TTC≤0.5s	TTC≤1.5s	TTC≤0.5s
285	3	9	0.16	0.02	2.32	0.12
289	4	5	0.30	0.02	4.90	0.14
292	6	18	0.22	0.02	2.24	0.02
303	19	34	1.48	0.32	14.48	0.42
321	4	44	0.02	0.04	4.14	0.04
324	2	17	0.16	0.02	5.02	0.08
341	12	19	1.02	0.36	18.40	0.46
365	4	17	1.20	0.32	12.60	0.58
369	0	10	0.72	0.10	4.10	0.06
372	6	16	0.78	0.16	9.70	0.40
442	10	13	1.08	0.90	8.74	1.98
483	1	11	0.82	0.30	5.98	0.44
492	15	48	0.80	0.38	23.98	1.12
539	7	25	0.66	0.18	4.16	0.32
543	3	10	0.28	0.08	0.96	0.20
545	3	2	0.44	0.08	1.92	0.32
556	5	11	0.52	0.04	1.82	0.00
605	8	19	0.32	0.10	2.12	0.34
610	15	40	1.62	0.30	10.88	0.62
666	3	12	0.64	0.12	3.46	0.18
669	2	18	0.52	0.10	3.64	0.24
819	10	13	1.52	0.54	16.12	1.30
829	4	25	0.14	0.06	3.28	0.16
833	0	5	0.40	0.16	1.84	0.26

Intersection number	LTOPP veh-veh crashes (2001-2004)	RE veh-veh crashes (2001-2004)	LTOPP conflicts (50 runs)		RE conflicts (50 runs)	
			TTC≤1.5s	TTC≤0.5s	TTC≤1.5s	TTC≤0.5s
842	14	14	1.22	0.18	10.08	0.14
843	7	12	0.38	0.10	3.78	0.36
844	20	39	1.82	0.32	14.70	0.52
845	4	16	0.82	0.58	11.52	1.28
913	1	12	0.18	0.10	3.84	0.22
1273	0	4	0.00	0.00	0.36	0.00
Sum	309	915	29.78	8.62	348.00	17.16
Mean	5.83	17.26	0.56	0.16	6.57	0.32
Stdev	5.56	11.34	0.44	0.17	5.58	0.37
Max	20	48	1.82	0.90	23.98	1.98
Min	0	2	0.00	0.00	0.36	0.00

B.4- Untreated sites traffic volume

Intersection number	V_{Major}	V_{Minor}	Ped+bike	$\%RT_{Major}$	$\%RT_{Minor}$	$\%LT_{Major}$	$\%LT_{Minor}$	%RT	%LT	%Turning
3	1483	681	1359	15.31	22.91	2.02	4.11	17.70	2.68	20.38
6	1694	735	198	8.09	12.79	0.06	0.27	9.51	0.12	9.63
7	2041	797	250	5.14	10.54	5.24	12.42	6.66	7.26	13.92
8	1977	942	562	6.37	13.06	2.12	7.96	8.53	4.01	12.54
9	2172	865	548	9.35	9.25	2.72	0.35	9.32	2.04	11.36
10	2246	1037	700	6.86	10.13	0.18	8.10	7.89	2.68	10.57
16	844	607	276	5.57	6.43	2.37	4.61	5.93	3.31	9.24
19	927	660	937	16.61	15.91	5.61	3.79	16.32	4.85	21.17
23	1058	1053	621	8.98	18.99	6.24	6.36	13.97	6.30	20.27
34	1114	715	2212	0.00	0.00	0.00	0.28	0.00	0.11	0.11
168	857	628	249	8.28	14.01	4.55	10.19	10.71	6.94	17.64
180	1156	1051	494	12.28	11.89	11.07	11.51	12.10	11.28	23.38
181	969	968	397	2.99	15.81	9.08	0.21	9.40	4.65	14.04
182	846	480	362	7.45	18.54	4.26	10.21	11.46	6.41	17.87

Intersection number	V_{Major}	V_{Minor}	Ped+bike	$\%RT_{Major}$	$\%RT_{Minor}$	$\%LT_{Major}$	$\%LT_{Minor}$	%RT	%LT	%Turning
188	1817	1249	236	2.97	10.09	0.06	6.73	5.87	2.77	8.64
190	1181	703	403	9.23	10.67	5.67	2.70	9.77	4.56	14.33
237	1412	385	326	16.15	29.61	14.16	20.78	19.03	15.58	34.61
245	732	581	233	14.34	11.36	10.79	6.71	13.02	8.99	22.01
246	817	736	499	18.36	13.86	7.34	2.04	16.23	4.83	21.06
248	837	610	258	13.86	13.28	5.97	11.48	13.61	8.29	21.91
249	1305	891	407	15.33	16.27	6.97	11.45	15.71	8.79	24.50
265	927	422	806	11.22	22.27	4.96	14.93	14.68	8.08	22.76
283	1194	999	93	22.28	5.71	9.88	11.91	14.73	10.81	25.54
285	1006	597	299	5.77	19.60	5.77	3.18	10.92	4.80	15.72
289	1129	887	168	5.49	17.70	8.86	12.97	10.86	10.66	21.53
292	1533	464	418	2.28	17.67	1.89	5.82	5.86	2.80	8.66
303	1654	1056	387	5.93	12.12	8.40	14.39	8.34	10.74	19.08
321	1628	1107	730	21.81	9.94	0.06	0.18	17.00	0.11	17.11
324	1364	796	601	9.02	13.82	0.07	5.15	10.79	1.94	12.73
341	1713	1367	1262	10.68	10.24	0.41	7.46	10.49	3.54	14.03

Intersection number	V_{Major}	V_{Minor}	Ped+bike	$\%RT_{Major}$	$\%RT_{Minor}$	$\%LT_{Major}$	$\%LT_{Minor}$	%RT	%LT	%Turning
365	1416	1169	210	10.17	13.17	33.05	35.93	11.53	34.35	45.88
369	895	746	440	10.06	18.77	13.41	11.39	14.02	12.49	26.51
372	1111	1107	426	18.00	10.48	7.56	10.12	14.25	8.84	23.08
442	1231	858	122	34.44	5.36	12.84	34.27	22.50	21.64	44.14
483	1303	322	830	11.90	35.09	12.74	46.27	16.49	19.38	35.88
492	1670	1001	342	20.00	25.07	6.59	16.28	21.90	10.22	32.12
539	1052	456	528	9.51	22.15	11.79	14.04	13.33	12.47	25.80
543	811	482	355	15.29	16.80	3.33	18.46	15.85	8.97	24.83
545	663	589	323	11.61	24.45	21.87	19.19	17.65	20.61	38.26
556	1084	380	169	8.03	24.47	4.52	17.11	12.30	7.79	20.08
605	847	722	334	18.18	11.91	4.84	3.74	15.30	4.33	19.63
610	1696	850	296	5.84	22.00	8.20	18.94	11.23	11.78	23.02
666	1213	783	100	7.83	16.60	8.33	8.94	11.27	8.57	19.84
669	1164	574	1000	8.25	17.42	4.21	17.77	11.28	8.69	19.97
819	1957	1026	145	8.74	21.54	9.20	23.29	13.14	14.05	27.19
829	1074	1001	371	9.59	10.59	0.28	1.20	10.07	0.72	10.80

Intersection number	V_{Major}	V_{Minor}	Ped+bike	$\%RT_{Major}$	$\%RT_{Minor}$	$\%LT_{Major}$	$\%LT_{Minor}$	%RT	%LT	%Turning
833	735	541	371	18.91	13.68	9.25	22.74	16.69	14.97	31.66
842	1738	1036	93	6.96	6.18	3.91	11.58	6.67	6.78	13.45
843	1465	541	180	5.12	13.49	3.89	9.43	7.38	5.38	12.76
844	1846	1112	122	8.67	14.84	5.90	11.42	10.99	7.98	18.97
845	1986	729	250	8.81	19.48	3.63	11.52	11.68	5.75	17.42
913	1452	398	1397	9.44	19.60	1.17	28.89	11.62	7.14	18.76
1273	944	48	349	0.00	54.17	0.00	27.08	2.62	1.31	3.93
Sum	68986	40540	25044	563.33	851.78	337.30	637.86	636.15	424.14	1060.29
Mean	1301.62	764.91	472.53	10.63	16.07	6.36	12.04	12.00	8.00	20.01
Stdev	417.22	270.57	391.50	6.24	8.31	5.87	9.70	4.40	6.23	9.16
Max	2246	1367	2212	34.44	54.17	33.05	46.27	22.50	34.35	45.88
Min	663	48	93	0.00	0.00	0.00	0.18	0.00	0.11	0.11