SIMULATION-BASED EVALUATION OF TRAFFIC SAFETY PERFORMANCE USING SURROGATE SAFETY MEASURES

by

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A Dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Civil and Environmental Engineering

Written under the direction of

Kaan Ozbay

and approved by

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New Brunswick, New Jersey

[January, 2012]

ABSTRACT OF THE DISSERTATION

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Traffic safety evaluation is one of the most important processes in the analysis of transportation systems performance. The use of traditional crash-data-oriented methodologies to analyze traffic safety problems has been frequently questioned due to shortcomings such as unavailability and low quality of historical crash data. The advancement of traffic conflict techniques and micro-simulation tools motivated this dissertation to develop a simulation-based approach of combining micro-simulation models and traffic conflict technique to investigate the safety issues in traffic systems.

The proposed simulation-based approach consists of two major components: the development of surrogate safety measures; and the integration of the developed surrogate safety measures with micro-simulation models. In this dissertation, a new surrogate safety measure is derived and applied in micro-simulation models to capture the conflict risk of the interactions among vehicles. The conceptual and computational logics of the proposed surrogate safety indicator are described in detail. A calibration procedure that

focuses on safety evaluation using the simulation model with the new surrogate measure has been proposed. The proposed calibration approach has been developed based on the stochastic gradient approximation algorithms to find optimal parameters of the stochastic traffic simulation models. The calibration methodology has been implemented on a selected traffic simulation platform to test its performance. Simulated operational measurements and traffic conflict risk in terms of the surrogate safety measure are quantified and compared with observations derived from high resolution vehicle trajectory data. The calibrated traffic model has also been validated by using independent vehicle trajectory data saved as a hold-out sample. The results show that the fine-tuning of parameters using the proposed calibration approach can significantly improve the performance of the simulation model to describe actual traffic conflict risk as well as operational performance.

The applicability of the proposed new surrogate measure and the simulation-based safety evaluation approach using this surrogate measure has been successfully demonstrated through several cases studies. The overall findings can inform road safety investigators as to how operations-oriented simulation models in conjunction with the surrogate safety measure can complement traffic safety evaluation in cases to which traditional approaches are not applicable.

Acknowledgements

There are so many people I want to thank for their essential and gracious support, help, and encouragement with this dissertation and my graduate career. I realize how fortunate I am to be surrounded by incredible family, many lifetime advisors, and friends. I could not have done it without you.

First and foremost, I would like to express my deepest gratitude and appreciation to my doctoral advisor Dr. Kaan Ozbay for guiding, supporting, encouraging, and caring me through each step of my graduate career. This dissertation would not have been possible without his supervision, guidance, assistance, extreme patience, and grace extended to me. Thanks for providing me such great opportunities to enrich both the personal and the professional levels.

Second, I am honored to have my committee members, Dr. Hani Nassif, Dr. Dilruba Ozmen-Ertekin, Dr. Eric Gonzales, and Dr. Bekir Bartin. They shared their valuable time, insights, wisdom and experience to guide me through hurdles. Their efforts and support are deeply appreciated. A very special thank you to Dr. Bekir Bartin, a very good collaborator, instructor, and friend, for helping me successfully complete my graduate program. To the faculty and staff of Civil and Environmental Engineering Department at Rutgers University for their help and support: Dr. Nenad Gucunski, Dr. Perumalsamy Balaguru, Dr. Ali Maher, Dr. Patrick Szary, Dr. Qizhong Guo, Dr. Trefor Williams, Connie Dellamura, Linda Szary, Gina Cullari, and Azam Kalantari. Thanks for your professional instruction, assistance, and guidance throughout my graduate career.

In addition, I acknowledge the generous funding support from the New Jersey Department of Transportation, the New Jersey Turnpike Authority, and the Rutgers' Center for Advanced Infrastructure & Transportation which supported me throughout my graduate program and made this work possible.

There is a special group of graduate friends here at Rutgers I would like to appreciate. Without their support and help I would not have stayed sane through these difficult years. First, I am grateful to my colleagues Eren Erman Ozguven, Sandeep Mudigonda, and Mustafa Anil Yazici who shared the office with me and helped me bear the pressure of a tough first semester. Moreover, special thanks are extended to my colleagues and collaborators Ozgur Ozturk, Mehmet Yildirimoglu, Shri Iyer, Ender Faruk Morgul, Sami Demiroluk, and Nusrat Jahan. In addition, I would also like to thank my friends Baiyang Liu, Yun Pu, Zhenghong Bao, Dong Dai, Jun Tan, Kaiyuan He, Zhen Hou, and Dan Su for making my life here wonderful. Last but not least, I am especially thankful to Jian Li, my lab mate since we were in Tongji University. Together Jian and I shared the best, worst, exciting, unbelievable, and unforgettable road trips, study, and daily life in North America. All these mentioned friends and those I have left out are indeed precious and valuable gift that I will always treasure in my life.

In the meantime, a group of people in Tongji University will never be forgotten. I am deeply grateful to my advisor Dr. Xiaohong Chen in Tongji for her tremendous encouragement, support and advice no matter when I was in Tongji or in Rutgers. I realize how fortunate I am to be her student. I would also like to express my sincere appreciation to Dr. Hangfei Lin, Dr. Ye Li, Dr. Chao Yang, Dr. Jiaorong Wu, Dr. Xuesong Wang, Dr. Zhaoyi Huang, Dr. Jianhong Ye, Dr. Pengyao Ye, and Pengfei Li who always helped me. Specially, I am deeply thankful to Mr. Shengfeng Han, a generous and best big brother, who has always been there to encourage and help.

I also offer my sincere gratitude to my beloved family. My mother Daofen Guy and father Guofa Yang have expressed unconditional love and support during the long years of my education. My wife, Yifang Ma, is always there cheering me up and standing by me through the good times and difficult moments. Though thousands miles away, I can always feel their endless support, care, and love. Deeply thanks!

In closing, as I come to the end of this mile and the beginning of the next, I would like to once again thank everyone who ever navigated, educated, supported, encouraged, helped, and loved me on my way. Thank you for having made me successfully complete this mile and prepare well for the next journey in life.

Sincerely,

Hong Yang

Dedication

This dissertation is dedicated to my dear mother Daofen Gu, father Guofa Yang, and my lovely wife Yifang Ma. Thank you for your love and support throughout my lifetime.

Preface

The major work performed in this dissertation has been presented and published in several conferences and journals. Below is the list of selected publications derived from this dissertation.

K. Ozbay, **H. Yang**, B. Bartin, and S. Mudigonda (2008). Derivation and Validation of New Simulation-Based Surrogate Safety Measure. In *Transportation Research Record: Journal of Transportation Research Board,* No. 2083, pp. 105-113.

H. Yang and K. Ozbay (2011). Estimation of Traffic Conflict Risk for Merging Vehicles on Highway Merge Section. In *Transportation Research Record: Journal of Transportation Research Board,* No.2236, pp. 58-65.

H. Yang, K. Ozbay, and B. Bartin (2010). Application of Simulation-Based Traffic Conflict Analysis for Highway Safety Evaluation, Paper ID C4-02303. In *Selected Proceedings of 12th World Conference on Transport Research Society*, ISBN 978-989-96986-1-1 (Editors: J. Viegas & R. Macário*)*, Lisbon, Portugal, July 11-15.

H. Yang and K. Ozbay (2011). Calibration of Micro-Simulation Models to Account for Safety and Operation Factors for Traffic Conflict Risk Analysis. In *Proceeding of 3rd International Conference on Road Safety and Simulation (RSS2011)*, Indianapolis, Indiana, USA, September 14-16.

H. Yang, K. Ozbay, and B. Bartin (2012). Effects of the Open Road Tolling on Safety Performance of Freeway Mainline Toll Plazas. Accept by *the Transportation Research Board (TRB) 91st Annual Meeting*, Washington D. C., January 22-26, 2012.

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Chapter 1 Introduction

This chapter introduces the research topic and presents background information necessary to understand the significance of the proposed research problem. The introduction is divided into three sections: background, problem description, and objectives of the proposed research.

1.1 Background

Road traffic safety is a global concern. It is characterized by the presence of numerous crashes of road users. According to the World Health Organization (Peden *et al.*, 2004), about 1.2 million fatalities and 50 million injuries are experienced worldwide each year due to traffic crashes. Road traffic crashes are ranked 11th as a major cause of death and account for 2.1 percent of all lives lost globally. The total number of deaths and injuries due to crashes is projected to rise by some 65 percent between 2000 and 2020 unless there are increased prevention efforts and new safety related initiatives.

Undoubtedly, traffic safety has become one of the world's largest public health challenges, attracting extensive focus and awareness within different authorities and agencies. For instance, in recognition of the importance of road safety, transportation authorities in the United States have made a variety of efforts to improve road safety since the first officially recorded automobile accident occurred in New York City in 1896 (Kane, 1933). A series of legislations, such as the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA), Transportation Equity Act for the 21st Century (TEA-21), and the "Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users" (SAFETEA-LU) passed in 2005, raised more public concern and promoted more projects to cope with the safety issues of surface transportation. The number of accidents per total miles traveled has been reduced due to countermeasures such as speed regulation, better enforcement, and improved highway geometry. According to the 2008 traffic safety facts of the National Highway Traffic Safety Administration (NHTSA), the number of traffic fatalities decreased by 9.1 percent from 37,435 in 2007 to 34,017 in 2008. The number of injuries decreased from 1,711,000 in 2007 to 1,630,000 in 2008. Both the fatality rate and injury rate per 100 million vehicle miles of travel have significantly dropped since 1966 (NHTSA, 2008a).

Despite the gradual reduction in fatality and injury rates over the past years, automobile crashes remain one of the leading causes of death in the United States. While traffic crashes ranked 9th overall as a cause of death, they ranked 3rd in terms of years of life lost, behind only malignant neoplasm and heart disease (NHTSA, 2008b). The annual economic cost associated with these traffic crashes was estimated to be approximately $230 billion, which was nearly 2.3 percent of the nation's gross domestic product (NHTSA, 2006). These statistics prompted researchers to conduct comprehensive research projects to improve road and traffic safety.

As shown in Figure 1.1, a transportation system represents the interaction among people, vehicles and road infrastructure, subject to legislation, traffic rules and weather conditions. Motor vehicle crashes thus happen as a consequence of a very specific combination of all of these factors. The frequency and severity of crashes depends on the magnitude of these interactions. Knowing the underlying factors is thus indispensable when planning effective crash reduction or prevention measures. However, knowledge about causes cannot always be easily captured, thereby limiting the accuracy and reliability of road safety analysis. To reach a higher level of road safety goal attainments, a series of programs associated with vehicles, roadways, humans, and their interaction should be activated.

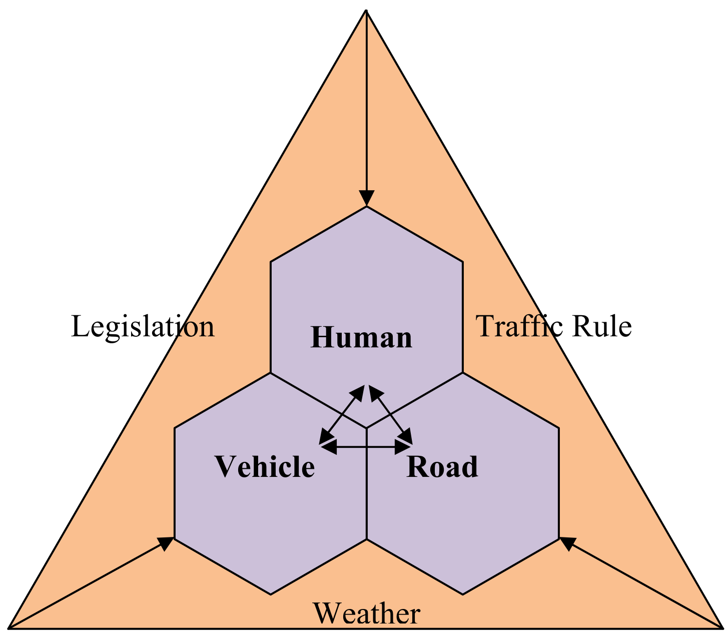


Figure 1.1 Interactions in a transportation system

It is important to conduct rigorous before-and-after studies of safety programs to make sure that the most effective decisions are made. Usually, three major tasks are needed to make effective decisions: (a) screen and diagnose traffic safety deficiencies; (b) propose countermeasures; and (c) assess the effectiveness of the safety measures undertaken. It is obvious that the first and the third tasks both require safety evaluation. Safety evaluation results are crucial to specify black spots, crash factors, countermeasures, and so on. Accordingly, the limited resources of different stakeholders can then be allocated to maximize safety improvements. Therefore, developing a robust evaluation approach to assess potential safety improvements and prioritize safety measures is essential.

1.2 Safety Evaluation Problem

Most of the traditional traffic safety evaluation approaches are carried out based on observed accident data using various types of statistical approaches, mainly before-and-after comparisons of observed data and/or anticipatory estimation studies based on safety audits. However, several problems have been identified while using these methods.

The first problem is associated with the commonly used statistical modeling approaches. Existing approaches for estimating safety range from simply using accident rates to complex prediction models that relate crash frequency to several contributing factors. Since the relationship between crash frequency and exposure is often nonlinear, one of the major concerns is that the crash rate is not always regarded as an appropriate representative of safety (Hauer, 1986). High crash rates may occur in locations with low values for exposure factors such as low population, low registered vehicles and low vehicle miles of travel (Datta *et al.*, 2001). Therefore, prioritizing based on crash or injury rates alone might give a false indication of the hazard. Moreover, even though the overall crash rate is high, segregating by location, time, and type may generally result in low rates per section, period, and/or type. The task of deriving statistically significant inferences on safety performance based upon this low rate then is subject to bias.

Approaches representing more complex crash prediction models such as regression models are also frequently questioned even though currently they constitute the primary tools for evaluating road safety. As traffic crashes are rare and random events, crashes may not be able to be adequately modeled using these models. The variables in the models are usually limited to some easily observable factors such as AADT, speed, and geometric features. They might however fail to take into account other important explanatory factors such as driver behavior and errors which in fact are the critical causes of accidents (Hankey *et al.*, 1999; Stanton and Salmon, 2009). The selection of a better model from a set of candidates is another challenge. Sometimes it is difficult to judge the goodness of fit of these models based on statistical measures. For instance, R-square is frequently used to make decisions and comparisons of crash prediction models, including the Poisson and negative binomial regression models. Because the models are non-normal and functional forms are typically nonlinear, Miaou *et al.* (1996) indicated that R-square is not an appropriate measure to make goodness-of-fit decisions and comparisons mentioned above. Therefore, statistical issues related to crash modeling deserve further attention and more effort should be made toward addressing these issues adequately if the models are to be used to make real world decisions.

Another major problem is related to historical crash data, which are always used as the primary source of data to conduct safety evaluations. In the majority of safety evaluation studies, crash records have been used as the fundamental information. However, this has not always been appropriate, as crash statistics are frequently questioned in terms of their availability, quality, and so forth. The most common limitations of using crash data as a single measure to assess traffic safety are summarized as follows:

Availability: Crashes are not always uniformly reported by police, and this can hinder the availability and reliability of information used to conduct safety studies. Some countries consider reporting only those crashes that involve injuries or property damage above a certain cost (Zegeer and Deen, 1978), while others may heavily under-register some minor crashes (Berntman, 1994). Indeed many crashes, especially those involving no injury, may not be reported at all. Results from a number of studies (James, 1991; Simpson, 1997) indicated that in developed countries under-reporting of fatalities was about 2 to 5 percent whereas 25 to 50 percent of those road crashes were underreported by the police in developing countries. Antov (1990) presented that about 96 percent of all traffic accidents were registered by the police in Soviet Union because it was obligatory for a person who was involved in an accident to inform the police. Jacobs *et al.* (2000) showed that road-crash data were seldom available or were usually several years out of date in many African countries. In principle, relying on these incomplete crash reports is prone to produce biased conclusions and might prevent practitioners from addressing all of the safety problems in a comprehensive manner.

Collection Cycle: Due to the low frequency and random variations inherent in traffic crashes, a relatively long observation duration is needed to gather sufficient data to produce estimates or conduct before-and-after comparisons with acceptable statistical properties (Chin and Quek, 1997). It is impossible to collect enough crash data within weeks or months. Zegeer and Deen (1978) suggested that up to 2 years of crash data are necessary to ensure reliability when diagnosing black spots. It also takes several more years to prove the effectiveness of a specific improvement based on crash records. Some studies (Nicholson, 1985; Parker and Zegeer, 1989b) have even recommended a typical period of study of 3 years before and after an improvement for its adequate assessment.

This also raises the important ethical problem that a large number of crashes have to take place in order to make a proper evaluation.

Data Quality: Crash reports are usually filled out by police in the field. A description of an accident in a report prepared by police can help to clarify possible causes of the crash. The crash report documents the roadways, vehicles, people, environmental characteristics, and consequences involved in a crash. Therefore, the success of the safety analysis is governed by the quality of the accident information. Unfortunately, in many cases the statements of parties involved in a crash tend to be vague and subjective, which makes it difficult for the police to accurately depict the actual causes. Antov (1990) found out that some 25 percent of traffic accident registration cards were filled incompletely and that 7 percent of them were impossible to use for traffic safety analysis because of a lack of some general information. For instance, one of the single biggest problems with the quality of crash data in Abu Dhabi has been failed to identify and record the precise location of a crash, as there has been no formal system of location to which to refer (Khan *et al.*, 2004). This has been acknowledged for a long time as a fundamental deficiency in crash records. Such incomplete data can thus jeopardize the success of safety analysis.

Data Integration: The occurrence of a crash is mainly attributable to individual vehicular interactions (Chin and Quek, 1997). Aggregated data such as weekly or monthly frequency often do not adequately capture individual characteristics. Though it is useful to give an overview of the crash trend, such information is sometimes not enough for traffic safety professionals to identify the detailed causes of accidents and take corresponding measures. Moreover, arbitrarily separating crashes by roadway segments, driver ages, and so on can only satisfy the specific requirements of a safety evaluation project. Including behavioral data related to individual interactions could significantly enhance crash modeling. However, as Park *et al.* (2008) indicated, few research efforts towards this goal have been made due to limitations in obtaining and using individual vehicular data. Data such as corresponding vehicle conditions and weather factors are also not easy to identify and obtain for analysis.

The elaboration of crash data quality and availability together with the development of extensive but statistically sound models can lead to high quality safety evaluation. However, attempts to address the aforementioned problems as well as some other issues such as regression-to-mean effect (Barker and Baguley, 2001) are still needed in the long run. Even with a perfect model, the use of crash data based on statistical analysis is only a reactive approach that still cannot avoid the ethical issue of waiting to obtain data. These problems have encouraged traffic professionals or practitioners to seek more proactive approaches. For instance, the use of safety audits to help make safety improvement decisions could potentially be a beneficial approach, but the level of audits' success depends heavily upon the auditors' experience and individual preferences. Moreover, some safety studies have been conducted using so-called 'real-time' traffic data from surveillance or monitoring systems. These studies mainly model the pre-crash traffic status on the basis of traffic flow change. Factors such as geometry have usually not been taken into account by these models (Pham *et al.*, 2008). Data extraction, processing, and system coverage have also sometimes limited the use of such studies to specific sites. Therefore, there is a need to develop more practical methods that can be used without being subject to many of these limitations.

Alternatively, far better surrogate safety evaluation approaches have been proposed with the development of the traffic conflict technique (TCT). This technique originated in the USA in the 1960's and was quickly transformed into a prevalent technical support tool to complement safety evaluation in various places. Previous research studies have shown that there is a high correlation between crash rates and conflicts, with the latter occurring at a much higher frequency. The conflict provide opportunities to capture dynamic characteristics of the road (FHWA, 1990). An impressive amount of work, for instance, on developing an automated detection system, has been done to enhance the technique. However, there are various limitations such as data collection cost and validation that have hampered wider use of the TCT.

This issue has led to the development of a new approach, namely the micro-simulation-based approach, for assessing the safety of a particular road section. Currently, some researchers are paying increasing attention to the use of traffic micro-simulation models to support TCT for deriving surrogate safety measures employing the same model used for operational performance analysis (Archer and Kosonen, 2000). Though there is still a limited amount of work in this area, micro-simulation models have proven to be potential tools to achieve at least some of the proactive evaluation goals. Micro-simulation is especially ideal for assessing a large number of new facility designs or improvement options even before they are considered. Assessment can be made quickly without risking any real crash occurrences or expensive project costs.

Nevertheless, the concept of simulation-based safety evaluation is still not fully developed due to a number of shortcomings of the underlying simulation models. Most of the researchers working on this topic have only been using special-purpose simulations such as access management or truck lane restrictions. Lack of efficient safety indicators, problems with realistic calibration, and related to validation techniques for the micro-simulation models are sources of the motivation for the research described in this study.

1.3 Objective and Scope

To overcome the aforementioned shortcomings of traditional safety analysis methods, this dissertation explores the potential of using micro-simulation models for transportation safety evaluation. Specifically, the main objectives of this dissertation can be summarized as follows:

Review the development of the well-known traffic conflict technique, study its potential, and identify obstacles to using it in combination with micro-simulation models for safety assessment, especially for analysis with few crash records.

Investigate various microscopic indicators that have the potential to describe unsafe interactions among road users. Develop new safety indicators that can be obtained from micro-simulation models given the availability of vehicle trajectory information.

Explore the potential of the micro-simulation platform and develop a robust framework for safety evaluation given the selected simulation tool. Propose a calibration and validation approach to identify the optimal input parameters for simulation models when used for the safety evaluation.

Use high resolution vehicle trajectory data to test the performance of the proposed surrogate safety measure and calibration algorithm. This is done by examining the relationship between the simulation results and the observations.

Conduct safety analysis through case studies to demonstrate the use of the proposed surrogate safety indicator and the micro-simulation-based safety evaluation approach.

Chapter 2 Literature Review

This chapter starts with a review of the traffic conflict technique, concept of the technique, its development, and applications. Following that, critical issues associated with the technique are discussed. The recent trend of integrating the traffic conflict technique in the micro-simulation model is given, followed by a discussion of its challenges. In addition, comments on the traffic conflict technique and simulation approach are briefly summarized at the end of this chapter.

2.1 Principle of Traffic Conflict Technique

Perkins and Harris (1967) at General Motors (GM) Corporation pioneered the traffic conflict concept. It was a procedure aimed to test whether GM cars performed more safely in comparison with those of other auto-makers. The procedure, which finally came to be called the traffic conflict technique (TCT), is systematically observing or qualifying evasive actions such as sudden lane-changing or hard braking as a clue to deduce critical situations. A critical situation is composed of at least two components: at least one road user (vehicle or person) is in imminent danger of a collision or interaction between two or more users, and at least one involved user has to perform an emergency evasive manipulation to avoid the potential collision.

Subsequent studies have followed the GM study but with some other theoretically specific conflict event formations (!!! INVALID CITATION !!!). A milestone in scientific progress on TCT was the first international workshop held in Oslo in 1977, where an unified definition of a traffic conflict was introduced (Amundsen and Hyden, 1977):

> *"A Traffic conflict is an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged."*

By definition, this kind of conflict analysis does not account for single-vehicle crashes. The concept is illustrated in Figure 2.1 for an interaction involving two vehicles. With minor modifications this definition remains a general basis for discussions of conflicts.

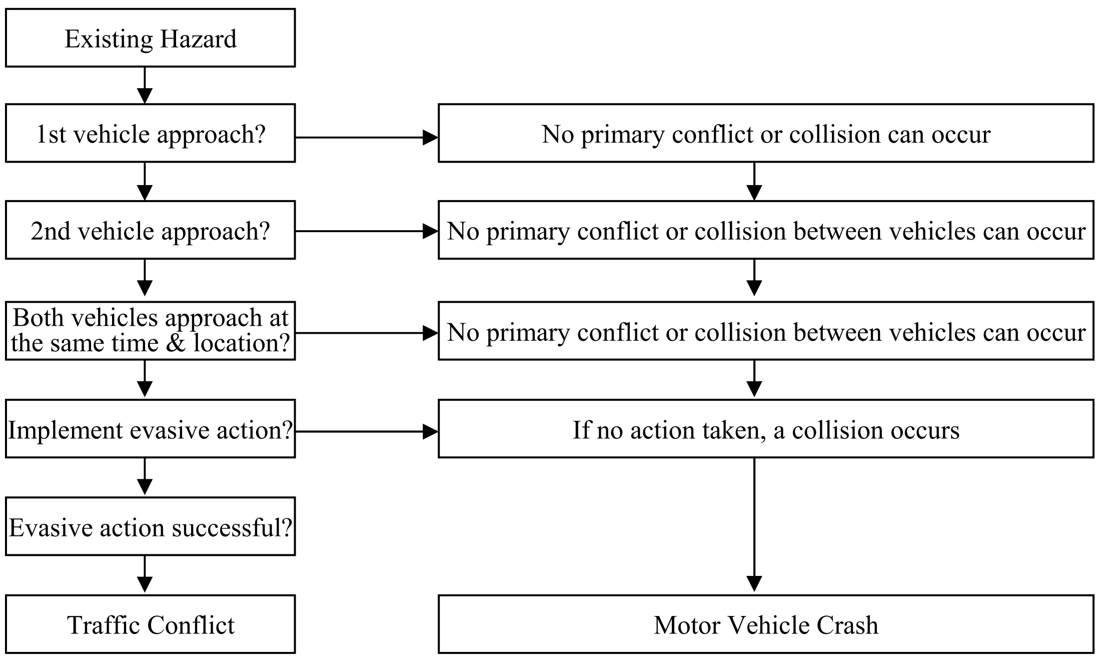
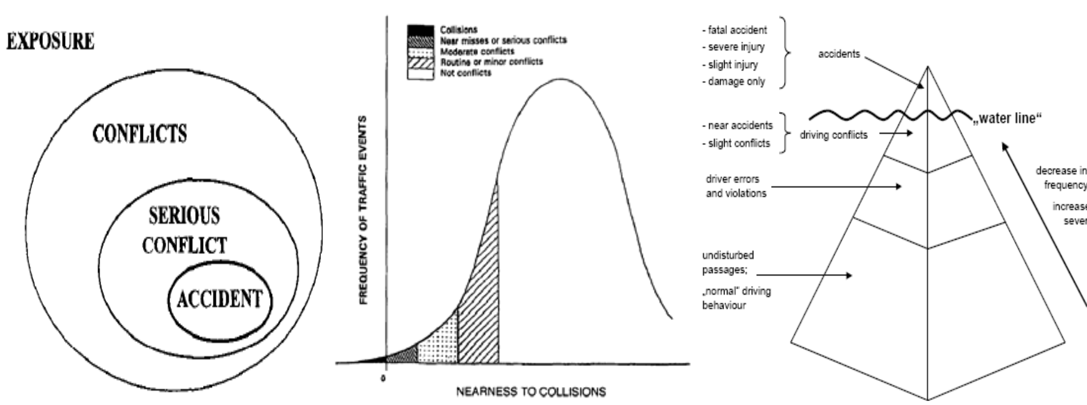


Figure 2.1 Traffic conflict concept (Ho, 2004)

Essentially, the TCT definition indicates that conflicts must precede accidents but there have a lower level of danger. If an evasive action is successfully taken, a primary traffic conflict occurs; otherwise, by definition, a collision occurs. The conflict-collision process suggests a hierarchical continuum representation between conflicts and collisions. Several typical models have been used to describe the continuum representation, as shown in Figure 2.2. For instance, Amundsen and Hyden (1977) described accidents as a subset of serious conflicts, which in turn are a subset of less serious conflicts from a universal set of exposure, shown in Figure 2.2(a). As a further development, Glauz and Migletz (1980) presented a distribution function in terms of nearness to a collision to order severity scales; see Figure 2.2(b).

More recently, Hyden (1987) introduced a well-known pyramidal visualization of the hypothesized continuum for road-user interactions from normal passage to a fatal accident. Accidents are placed at the top level and very safe driving with few interactions is placed at the bottom level; see Figure 2.2(c). Serious conflicts between accidents and safe driving describe the fundamental traffic safety problem, namely the breaking down of driver-driver and driver-environment interactions. The pyramidal ranking is based upon the severity of traffic interactions and reflects the sum of the individual behaviors of road users (Svensson, 1998). It also shows that non-conflicts are the major proportion of interactions, while the likelihood of occurrence decreases with increasing severity. The continuum representation of interactions results in a conclusion that there exists a relationship between the number of serious conflicts and accidents, varying with regard to type and definition of conflict (OECD, 1998).



(a) Conflicts in relation to exposure (Amundsen and Hyden, 1977) (b) nearness to collision (Glauz and Migletz, 1980) (c) safety pyramid (Hyden, 1987)

Figure 2.2 Safety continuum depicted traffic events

With constant development and refinement of the technique, TCT has been built as a set of relatively standardized procedures for safety assessment and for diagnostic purposes. This technique gained wide acceptance as a surrogate for assessing traffic safety problems for two main reasons. First, it provides supplemental information to accident data, for issues that may be suspected to exist or unavailable for safety studies. Accidents are statistically rare events, whereas conflicts are 5,000 to 10,000 times more frequent (OECD, 1998). Cooper and Ferguson (1976) reported that, on average, the ratio of crash versus serious conflict lies in the ratio of 1:2000. Second, the technique provides opportunities for proactively improving the safety of facilities instead of waiting for more accidents to occur. The more frequent nature of the occurrences enables trained observers to collect conflict data in a limited time period. A large amount of conflict data provides a more valid basis for investigating accident potential and deficiencies of facilities. In addition, it is possible to disaggregate and examine safety problems by conflict types, users, places, and so forth.

2.2 Theoretical Issues related to TCT

Validity and reliability are two critical issues strongly connected to the practicality of TCTs. Validity in this context means that conflict observations are, to a reasonable extent, successful in describing the traffic phenomenon of interest. External reliability is ensured when conflict observers are all able to distinguish conflicts from other events in the same way, and, of course, in accordance with the conflict criteria or definitions. However, traditional TCTs have created much controversy over these two issues.

Attempts to relate traffic conflict numbers with crash numbers have met with varying success, which may often be due to inaccurate crash data collection. Glauz and Migletz (1980) identified 33 previous studies that (partially) dealt with the conflict-accident relationships. Some studies illustrated a good relationship between conflicts and accidents, particularly between serious conflicts and injury accidents. Spicer (1972) investigated the variation of accidents and conflicts, and observed a high correlation between them. His further study of six intersections indicated that serious conflicts and the frequency of accidents involving injuries at different intersections were positively related (Spicer, 1973). Hyden (1975) compared reported accidents involving injury with observed serious conflicts at 50 intersections, and found a correlation between conflicts and accidents based on parameters such as speed. Migletz *et al.* (1985) showed that normal conflict studies could produce estimates of average accident frequency that were at least as accurate as those based on historical accident data. Subsequent work (Allen *et al.*, 1978; Svensson, 1992; Muhlrad, 1993; Sayed and Zein, 1999; Kaub, 2000) also illustrated that the relative statistics for conflicts and accidents are in agreement despite environmental differences. It should be noted that most of the aforementioned studies connecting actual crashes and conflicts were limited to intersection studies.

However, there has also been much criticism of the validity of TCT when determining the correlation between conflicts and crashes. For example, Glennon *et al.* (1977) and Williams (1981) seriously doubted the validity of TCT and called for a reassessment of the entire concept of traffic conflicts, claiming that both good correlation and poor correlation concurrently exist. Since both conflicts and accidents are randomly distributed events, it would be highly improbable to predict the exact number of accidents at a site (Sharma *et al.*, 2007). Instead of establishing regression models or correlation coefficients between conflicts and accidents, Glauz *et al.* (1985) argued that the proper use of conflict would be to estimate the expected rate of accidents. Fruhman (1993) suggested that the possibility of crash prediction based on traffic conflicts observed depends on focal marginal conditions and the probability of the occurrence of particular crash and conflict types. Tiwari *et al.* (1998) explored the relationship between fatal crashes and conflict rates mid-block at 14 locations in Delhi, India and the studies showed a weak crash-conflict association. There was no conclusive relationship between conflicts and accidents.

Without rejecting the technique thoroughly, some studies suggested a restrictive use of TCT or preferred to address the issue of validity more fundamentally rather than merely seeking a good statistical relationship between conflicts and accidents. Hauer and Gårder (1986) indicated that trying to validate conflicts in the sense of accuracy in predicting accidents is just as random as rolling dice. They argued for a new definition in which validity is a matter of degree that can serve as a yardstick to judge the quality of a particular conflict technique. Oppe (1986) further argued that it is necessary to classify conflicts and accidents according to type as well as severity level to examine correlations consistently. This point can be illustrated with the results of some studies. For instance, Lord (1996) investigated conflict between pedestrians and left-turning vehicles and examined the relationship between those conflicts and the expected number of accidents at eight sites in Hamilton, Ontario. He found that the relationship did indeed differ depending on the conflict technique applied. Brown (1994) investigated the traffic conflicts observed and recorded at intersections over three summer periods and evaluated these data against 5-year crash records. The overall correlation between conflicts and crashes was weak. However, when both data were stratified into different categories including left-turn/opposing, left-turn/crossing, rear-end, crossing, weaving, and right turn, the stratification yielded statistically sounder results, though no explicit relationship was established. Segregating conflicts and crashes, however, raises some concerns about sample size and may make comparison between conflicts and crashes even more difficult.

Reliability is another major concern about TCT. Traditionally, TCT rely on human observation which raises the issue of distinguishing various conflict situations subjectively.

TCT is criticized by many researchers (Guttinger, 1982; Chin and Quek, 1997) for inconsistency in observers' subjective judgments. Data collection can be cumbersome and requires highly trained manpower. Observers have to witness many real-time events at conflict sites and have to identify and record the precursors of conflict in a limited time period. Human factors such as fatigue and lack of training potentially introduce additional uncertainty into conflict measurements (Older and Spicer, 1976; Lightbum and Howarth, 1979; Shinar, 1984). A number of manuals and training packages were developed to overcome some of these problems (Parker and Zegeer, 1989a; Pfleger, 1993; ICBC, 1996; Almqvist and Ekman, 2001). However, the reliability of systematically trained field observers was still questioned. For example, Brown and Cooper (1990) monitored and documented observers' reliability under a training procedure. They showed that the training observers only produced about 75 percent reliability and that incorrect recognition or scoring of conflict events was unavoidable.

Many studies (Grayson *et al.*, 1984; Van der Horst, 1990; Kruysse, 1991) have applied the quantitative measurement method, whereby conflicts are measured by using surrogate safety measures, to improve the quality of conflict data collection. However, measurements such as absolute and relative speed, distance, and potential conflict point are sometimes difficult to estimate or project. Regarding these problems, video recordings and reviewing have been used as complements to interpret these uncertain measurements. Constraints, such as two dimensions, and coverage of the camera still limit the accuracy of video analysis (Archer, 2005). Researches on developing more efficient and accurate data collection methods, such as video sensors and computer vision techniques, are ongoing (Saunier *et al.*, 2007; Ismail *et al.*, 2009).

In general, traffic conflicts can provide a larger pool of data for assessing safety effects, but care must be taken to adopt stringent investigations that limit the variance inherent in conflict measurements. Even though the relationship between conflicts and crashes is sometimes inconclusive, integrating TCTs with some modern methods, such as the micro-simulation model, may offer wider perspectives in understanding traffic safety problems.

2.3 Safety Evaluation Using Micro-simulation

To date, micro-simulation models have been developed primarily for analysis, evaluation, management and optimization of traffic operations. The concept of using micro-simulation models for traffic safety evaluation is still a challenging topic in the traffic research community. Nevertheless, a number of researchers have put forward the potential of using a micro-simulation approach for safety evaluation in recent years. Since its initial recognition by Darzentas *et al.* (1980), this approach has gained increasing attention. Studies (Young *et al.*, 1989; Algers *et al.*, 1997) have revealed that micro-simulation models can capture driver behavior and individual interactions of vehicles to be studied, and many parameters used in the models have some implications for the safety issues of the interactions.

The essential nature of using micro-simulation models for safety assessments is to apply TCTs for traffic conflicts analysis in the same simulation models that have been used for operational performance analysis. By extending traditional TCTs, micro-simulation-based approach uses vehicle trajectory information produced during the simulation to automate conflict analysis and analyzes frequency and character. The overall lack of safety then can be determined by some safety performance function or surrogate safety measures that determine potential traffic conflicts of vehicles in real time. The simulation-based approach provides a proactive safety evaluation technique to quickly and economically diagnose traffic safety problems and apply appropriate remedial measures. It requires the least human involvement to extract conflict information and therefore avoids the main source of subjective error as encountered by traditional TCTs. The simulated results can provide evidence of association between simulated traffic safety indicators and driver attributes with the likelihood of conflict or collision (Sayed *et al.*, 1994; Muchuruza, 2006).

Because of its advantages, researchers have advocated the use of the simulation-based approach in various types of studies, such as an intersection safety evaluation by Sayed (1992) and a freeway safety analysis by Fazio *et al.* (1993). Since the earlier 2000s, the potential of micro-simulation for safety assessment has been further demonstrated and refined. Archer and Kosonen (2000) modified HUTSIM to investigate conflicts in a safety indicators (SINDI) project that focused on safety problems between different road users at urban intersections. Previous studies (Mehmood *et al.*, 2001; Gettman and Head, 2003b) also provided important insights into micro-simulation-based approaches for modeling relationships among highway geometric features, traffic flow variables, and highway safety. A recent FHWA-sponsored research project investigated the potential for deriving surrogate measures of safety from existing traffic simulation models (Gettman and Head, 2003a), as an attempt to advance this promising methodology further. This FHWA project provided a relatively thorough framework and insightful fundamentals for new research.

A detailed review of literature on the simulation-based evaluation approach identified VISSIM, Paramics and AIMSUN as the most frequently used tools that are capable of performing safety evaluation functions in practice. For example, AIMSUN has been modified to produce safety measurements of conflicts at ramp merging sections (Barceló *et al.*, 2003; Torday *et al.*, 2003; Huguenin *et al.*, 2005). Eisele and Toycen (2005) used VISSIM to identify operation and safety performance for access management. They also identified directions for future work, such as discussing cutoff values of safety indicators and calibrating results to crash data. Vanderschuren (2008) evaluated safety improvement through ITS in South Africa using Paramics. Liu and Garber (2007) followed the concept and process set out in the aforementioned FHWA report (Gettman and Head, 2003a) but adjusted it to assess the impact of freeway truck-lane restrictions on traffic safety. El-Tantawy *et al.* (2009) extended a similar idea to include the analysis of dedicated truck lanes as well as restricted lanes in a real-network application. For both truck-lane studies, Paramics simulation software was used as the test platform for lane-changing, merging, and rear-end conflicts analysis. Both studies found that geometric and traffic characteristics had a significant impact on freeway safety and operation.

Most recently, some projects have been working to enhance the simulation-based approach for safety assessment. For example, Abdoelbasier (2005) performed preparatory work toward the development of a working simulation model for calculation of surrogate safety measures. The research project at Netherlands Organization for Applied Scientific Research is attempting to develop a demonstration of a test bed for the evaluation of safety performance measures on the basis of a multi-agent real-time simulator framework coupled with Paramics (Klunder *et al.*, 2006). Some other projects such as developing and applying a more enhanced surrogate safety assessment model in simulation are also ongoing (Gettman *et al.*, 2008; Kim and Sul, 2009).

2.4 Simulated Safety Indicators

Various surrogate indicators have been used to determine traffic conflicts in simulation. Table 2.1 summarizes the potential traffic conflict indicators that have been applied to highway safety analysis. During the period 1991~2001, there were few deployment cases for the indicators. In recent years, such indicators have been more frequently used. This is possibly due to the development of technologies such as video image analysis and sensors to collect more detailed vehicle trajectory information in support of the indicators' derivation.

Table 2.1 Potential Traffic Conflict Indicators for Highway Safety Analysis

Indicator	Unit	Description	Reference
TTC	s	Time-to-collision	(Eisele *et al.*, 2003; Garber and Liu, 2007)
C_{max}	1/s	Inverse of time-to-collision	(Chin *et al.*, 1991)
UD	N/A	Unsafe density	(Barceló *et al.*, 2003; Huguenin *et al.*, 2005)
PICUD	m	Potential index for collision with urgent deceleration	(Uno *et al.*, 2002; Bin *et al.*, 2003)
J-value	N/A	An accumulative safety indicator	(Pham *et al.*, 2007)
CI	m^2/s^2	Criticality index	(Chan, 2006)
TET	s	Time exposed time-to-collision	(Minderhoud and Bovy, 2001)
TIT	s^2	Time integrated time-to-collision	(Minderhoud and Bovy, 2001)
CP	s	Crash potential	(Saccomanno and Cunto, 2006)
H	s	Headway of vehicle i and ahead vehicle i-1	(Vogel, 2003)
DRAC	m/s^2	Deceleration rate to avoid the crash	(Saccomanno *et al.*, 2008)
PMD	m	Predicted minimum distance	(Polychronopoulos *et al.*, 2004)
CI	N/A	Crash index	(Ozbay *et al.*, 2008)

Time-to-Collision (TTC) has been one of the frequently used surrogates of conflict measures in the models. For example, the Texas Transportation Institute (TTI) investigated the use of TTC in VISSIM to test the safety performance of several corridors. Proof of concept for this test was illustrated by TTI and reported by Eisele *et al.* (2003) and Eisele and Frawley (2004). This work presented preliminary results of applying the TTC for the analysis of the conflict and safety impacts of access management for the corridors. Similarly, Garber and Liu (2007) collected TTC information from Paramics models so as to identify the impact of different truck-restriction strategies. They concluded that simulated TTC was helpful for analyses of different strategies for truck lane restrictions.

Considering the limitation of the traditional TTC indicator, Minderhoud and Bovy (2001) described time exposed TTC (TET) and time integrated TTC (TIT) based on TTC. In the same study, they were shown to be useful safety measures in micro-simulation studies that focus on safety impacts. Furthermore, these two indicators are also integrated in a VISSIM model to analyze improvement in performance of an improved incident reduction function for the driver's dilemma at an actuated signal control intersection (Al-Mudhaffar *et al.*, 2004). When the safety performances of different route choice decisions in road networks are compared, two network-wide safety measures, namely TExT-IT and TInT-VR, are obtained by dividing TET and TIT by the number of involved vehicles counted during the simulation period (Dijkstra *et al.*, 2007).

Besides the above time-based researches, several other studies have proposed specific indicators in support of safety analyses through micro-simulation models. For instance, the Possibility Index for Collision with Urgent Deceleration (PICUD) was proposed as a new index to evaluate the possibility that two consecutive vehicles might collide, under the assumption that the leading vehicle applied its emergency brake (Uno *et al.*, 2003). The researchers who conducted this study concluded that PICUD is more suitable than TTC for evaluating the danger of collision of consecutive vehicles with similar speeds, because it captures the effect of the dynamically changing distance between these two vehicles (Uno *et al.*, 2002). This was also consistent with the results of a subsequent research study indicating that PICUD might detect the change in traffic conditions and conflicts more sensitively than TTC (Bin *et al.*, 2003). Furthermore, European researchers proposed unsafe density (UD) parameter and applied it in AIMSUN to obtain levels at which the links are unsafe (Barceló *et al.*, 2003). It was indicated that this parameter in itself is meaningless and should be used only for comparisons of different countermeasures (Huguenin *et al.*, 2005). UD is limited to the probability of linear collisions and does not provide information about conflicting trajectories that are encountered at intersections.

Other measures such as post-encroachment time (Archer, 2005) and crash potential (Saccomanno and Cunto, 2006) could also be simulated for safety analysis. Details about the concepts and algorithms for some surrogate safety indicators are addressed in further sections in this dissertation.

2.5 Comments on the Simulation-Based Approach

Although great efforts have been made toward deriving surrogate safety measures through microscopic simulation for safety assessment, most of the aforementioned studies focused only on a typical case study. Limited effort has been made to modify or enhance existing, general-purpose microscopic simulations toward traffic safety analysis. Questions related to traffic safety evaluation are still quite difficult problems and challenges for micro-simulation.

One of the primary concerns is the accuracy of driver behavior models within the simulation models. Most micro-simulation models currently focus on traffic flow simulation and have a crash avoidance mechanism. The internal car-following, gap-acceptance and lane-changing models generally have a rather simplified and limited character due to a lack of fundamental knowledge (Lu, 2007). They are not sufficient to represent the detailed and diverse driver interactions required for safety evaluation. This sometimes results in some unrealistic conflict cases if used without any caution (Abdoelbasier, 2005). In order to evaluate safety performance one might need more complicated driver behavior models which that allow for mimicking realistic conflict situations at high fidelity.

Another critical issue as encountered by traditional TCT that has to be addressed is the valid connectivity between the simulated surrogates and the crashes. The simulation approach is often hampered by its reliance on the premise that the simulated outputs can be linked to real crash risk. Logical linkage has not been widely addressed, which therefore lessens the utility of the simulation approach. This leads to the central question: which surrogate can lead to a more appropriate representative of the true risk? For a functionally appropriate surrogate, irrespective of the type of safety measures, which can be time-based, distance-based or speed-based indicators, further validation is needed to conclude positively that the simulated results are reasonable and consistent with real traffic conditions. Though some studies were occupied with these remaining voids (Vogel, 2003; Gettman and Pu, 2006), there would inevitably be a lengthy process to bridge the gap between simulated surrogates and crash risk.

Moreover, the calibration of the micro-simulation models remains an open question. Driver behaviors are determined via sub-models representing car-following, gap-acceptance and lane-changing behavior. These models are, in turn, dependent on input parameters that are deemed to encapsulate the relevant aspects of driver behavior. One of the major steps in applying simulation thus is to ensure that input parameters tune up based on observational data and that models replicate safety performance that can be verified from field observations (Cunto and Saccomanno, 2008). It has been recognized that input parameters can have a direct effect on the resulting safety measures from simulations (Klunder *et al.*, 2006). Thus, in order to adapt the simulation model, a calibration effort needs to be made. For safety evaluation, there is less calibration experience from previous practices compared to traffic flow simulation. The calibration process is even more intensive, expensive, and time-consuming when the objective of safety evaluation is combined with operational analysis. A systematic method should be developed to find the optimal parameters and enhance their transferability.

Last but not least, expanding the capability of simulators deserves more effort. Simulators such as VISSIM, Paramics, and AIMSUN have been frequently used. However, there is no agreement about the suitability of any one simulator for safety analysis. It is safe to conclude that different simulators have different strengths and weaknesses vis-à-vis the type of simulation-based safety analysis.

Chapter 3 Development of Surrogate Safety Measures

Many studies have been undertaken to better address and improve traffic safety. One research direction involves using surrogate safety indicators as alternatives to characterize traffic situations for investigating the safety performance of transportation systems and taking necessary countermeasures to reduce risk. There are several types of indicators proposed and used in the literatures to describe safety status of a road facility. This chapter summarizes the typical time-based surrogates with their definitions, algorithms, and discussion. A new indicator is also proposed and derived for further study.

3.1 Time-Based Indicators

3.1.1 Time Headway (THW)

THW is defined as the time difference (in seconds) between two consecutive vehicles in the same lane. It can be formulated as follows:

$$THW = t_i - t_{i-1} \qquad \textbf{(3-1)}$$

where t_i and t_{i-1} denote the time the following vehicle and the leading vehicle pass a given point in space, respectively.

If the relative space gap Δd (ft), the difference in position between two consecutive vehicles, is known, given the travel speed V_F (ft/s) of the following vehicle, THW can be further derived as follows:

$$THW = \frac{\Delta d}{V_F} \quad \textbf{(3-2)}$$

THW with different critical values is interpreted as a measure of driver risk. Some practices indicate that the time gap of less than 1 second is likely to be unsafe. For instance, when studying the relationship between headway in high flow freeway traffic and crash involvement, Evans and Wasielewski (1982) collected data on headways, historical records of crash involvement and traffic violations of drivers through photographs of vehicle license plates. It was found that crash involved drivers were more likely to follow with short headways that were less than 1 second. A similar relationship was also found in comparing drivers with and without traffic violations. Helliar-Symons (1983) described "dangerously closely" and "imprudently closely" as less than 0.7 seconds and less than 1 second, respectively. Ohta (1993) defined a THW range of between 1.1 and 1.7 seconds as a "comfortable" gap, while less than 0.6 seconds is the "danger" zone. Taieb-Maimon and Shinar (2001) reported in an experiment that the median choice for a minimum safe THW was 0.7 seconds. However, a drivers' survey showed that the responses tended to be much greater.

On the other hand, Evans (1991) pointed out that headway of less than 2 seconds should not be considered safe enough to prevent possible conflicts with the leading vehicle. This claim is in accordance with the findings of Michael *et al.* (2000). They suggested that headways of less than 2 seconds were defined as tailgating, which was mentioned as the contributing cause of rear-end crashes. Similarly, many road administrations in European countries recommend a safe THW of 2 seconds, according to Vogel (2003), but there is no complete agreement on safety time margins when following another vehicle.

3.1.2 Time-to-Accident (TA)

Time-to-Accident (TA) is the time between when an evasive action was taken and when a collision would have occurred if the conflicting road users had continued with unchanged speeds and direction (Hyden, 1987). The value is recorded only once at the time when evasive action is first taken by a conflicting road user. Given the approaching speed of the following road user, assuming that user can successfully stop just at the collision point, the minimal TA for a car braking maximal to come to stop just at the collision point is calculated:

$$TA = \frac{\Delta d}{v_i} \quad \textbf{(3-3)}$$

Assuming the user applies a constant deceleration rate α, the travel distance $\Delta d = d_f - d_i$ satisfies:

$$v_f^2 = v_i^2 + 2\alpha(d_f - d_i) \quad \textbf{(3-4)}$$

Given a user stopped at final position d_f with $v_f = 0$ and $\alpha < 0$,

$$\Delta d = \frac{v_i^2}{2\alpha} \quad \textbf{(3-5)}$$

The friction force F can be expressed as:

$$F = \mu mg = m\alpha \quad \textbf{(3-6)}$$

So the deceleration can be written as:

$$\alpha = \mu g \tag{3-7}$$

Base on the above equations, it follows that:

$$TA = \frac{\Delta d}{v_i} = \frac{v_i^2}{2\alpha} \times \frac{1}{v_i} = \frac{v_i}{2\alpha} = \frac{v_i}{2\mu g} \tag{3-8}$$

Suppose we have the friction coefficient as a function of the mean speed:

$$\mu = 0.85 \times \exp(-0.0306 \times v_m) \tag{3-9}$$

Hyden (1987) assumed that the deceleration is linear and that therefore the mean speed during braking is half the initial speed. In addition a safety margin of half the necessary braking time is built in. Therefore, the final TA calculation is formulated as:

$$TA = 1.5 \times \frac{v_i}{16.7 \times \exp(-0.0306 \times 0.5 v_m)} \tag{3-10}$$

where Δd is the distance to the collision point at the start of an evasive maneuver (distance between initial evasive location d_i and collision point d_f; v_i is the initial speed at d_i; v_f is the final speed at d_f; α is the deceleration rate; μ is the friction coefficient; m is the mass of the road user; and g is gravitational acceleration.

TA values are used in determination of the scale of conflict seriousness based on a threshold function (Archer, 2005). A single TA value of 1.5 seconds was initially used to distinguish serious conflict and slight conflict (Hyden, 1977). This was subsequently refined to a boundary that took the speed into account. Shbeeb (2000) indicated that the 1.5 seconds limit appeared to work well in urban areas when the speed was rather low, but not in rural areas where speed is higher. Gårder (1982) used a safety margin of 0.5 seconds, which was later confirmed by Hyden (1987) as an appropriate limit. Based on equation 3-10, a uniform severity level in red has been drawn in TA-speed Figure 3.1(a).

By adding the additional fixed safety margin of 0.5 seconds, the uniform severity level is adjusted to Figure 3.1(b). From this level, parallel lines can be drawn to graphically represent how the severity increases from non-serious conflict to serious conflict in the upper left of the figure. Svensson (1998) further introduced the concept of a severity hierarchy by dividing severity levels into subgroups.

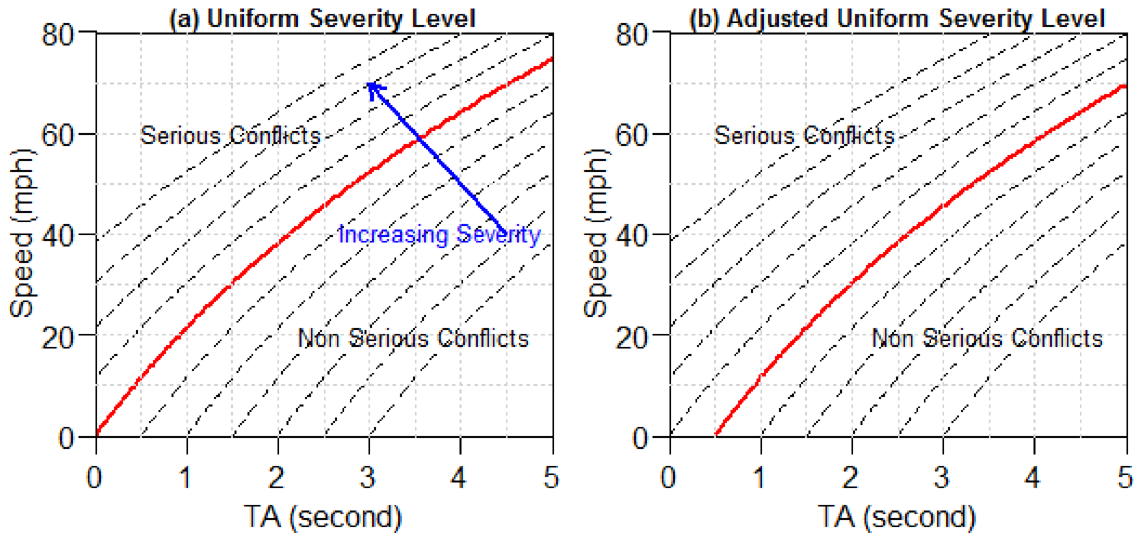


Figure 3.1 Limit between serious and non-serious conflicts (Hyden, 1987; Archer, 2005)

3.1.3 Post-Encroachment Time (PET)

The concept of Post-Encroachment Time (PET) was first introduced by Allen *et al.* (1978). PET was defined as the slight time difference it takes for two road-users with no necessary collision course to pass over a common spatial zone. More specifically, Songchitruksa and Tarko (2006) illustrated it as the time from the end of right-of-way infringement of the first user to the second vehicle reaching the conflict spot, measured from the rear bumper of the first vehicle to the front bumper of the second vehicle as shown in Figure 3.2. PET is calculated as:

$$PET = t_2 - t_1 \tag{3-11}$$

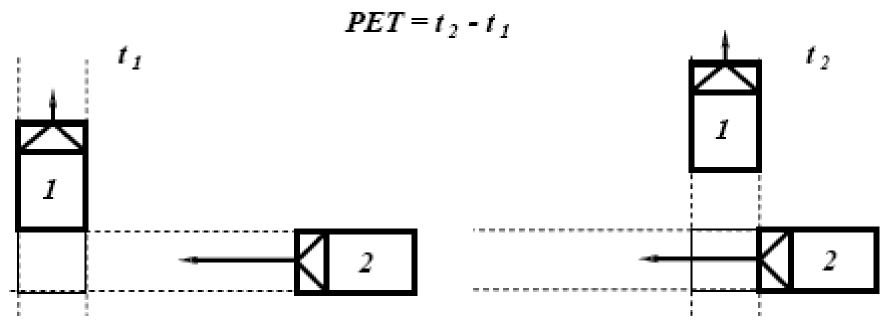


Figure 3.2 Concept of Post-Encroachment Time (Van der Horst, 1990)

The idea behind PET is that small PET values correspond to a greater risk of collision. Typically, it is assumed that a value less than 1.0 or 1.5 seconds can be regarded as critical (Kraay *et al.*, 1986; Archer, 2005). Preliminary evaluation of PET revealed that it was more appropriate than time-to-collision (TTC) for intersecting conflicts (Allen *et al.*, 1978; Van der Horst, 1990; Gettman and Head, 2003a; Archer, 2005; Songchitruksa and Tarko, 2006). PET can be easily extracted, as there is no need to estimate distance or speed, which are often subjective. Tarko and Songchitruksa (2005) indicated a potential relationship between PET distributions and right-angle crashes. They implied that driver behaviors interact with other users, or traffic elements, and that this makes it a desirable surrogate measure.

However, as the measure is collected on a fixed common spatial zone, PET is only useful in the case of transversal (i.e., crossing) trajectories and cannot reflect changes with the dynamics of safety-critical events over a larger area (Abbas and Khan, 2007). It also does not take into account the impact of a conflict.

3.1.4 Time-to-Collision (TTC)

TTC is defined as the time that remains before two road users collide unless one of them takes an avoiding manipulation such as braking or changing lanes, or unless an event occur such as a pedestrian stopping or stepping out of the way to change their present physical parameters. The concept was initially introduced by Hayward (1972) and was subsequently applied in many studies aimed at assessing the risk associated with car-following maneuvers. For two successive road users, if the following user (i) conflicts with the preceding user (i-1) at time t, TTC is a projection into the future of current condition and is calculated based on the following and preceding users' speeds and the gap distance between them. Figure 3.3 illustrates the concept. The equation for the calculation of TTC is as follows:

$$TTC_i(t) = \frac{X_{i-1}(t) - X_i(t) - L_i}{V_i(t) - V_{i-1}(t)} \qquad \forall V_i(t) > V_{i-1}(t) \qquad \textbf{(3-12)}$$

The distance between the two users is $V_i(t) \cdot G_i$. Then the TTC can be calculated by:

$$TTC_i(t) = \frac{V_i(t) G_i}{V_i(t) - V_{i-1}(t)} \qquad \forall V_i(t) > V_{i-1}(t) \qquad \textbf{(3-13)}$$

where X denotes the position of the users at time t, V is the speed, L is the vehicle length, and G is the time gap between the two users.

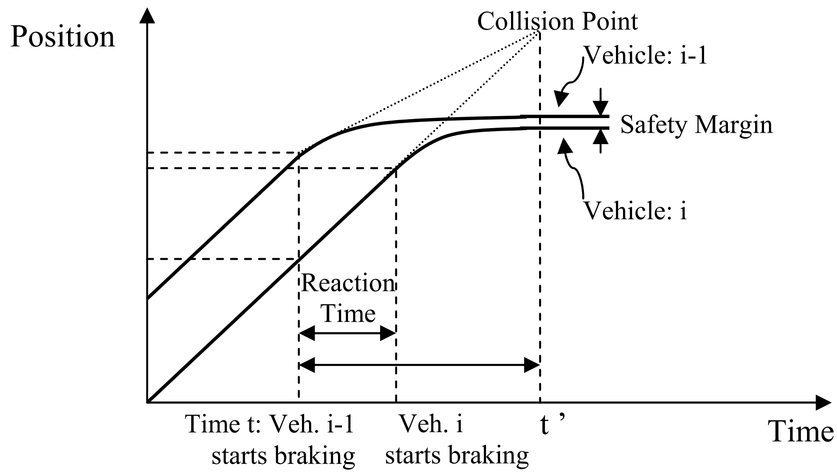


Figure 3.3 Vehicle trajectories and TTC

The traditional TTC expression assumes constant speed and does not consider user accelerations (Van der Horst, 1990), so it is only meaningful if a positive speed difference exists between the follower and its predecessor. Otherwise, the collision never occurs. When the relative speed is null, TTC is at infinity and a collision will not occur in this situation, either. When a collision course is determined, the TTC-value becomes finite and decreases with increasing crash proximity if there is no change in speed and path. To differentiate risky encounters from situations in which the driver remains safely in control, an appropriate threshold or critical value TTC^* must be defined. Generally, TTC lower than the perception and reaction time should be considered risky. For instance, typical choices for TTC^* may vary between 2 and 4 seconds (Hirst and Graham, 1997; Minderhoud and Bovy, 2001). However, various critical values of TTC can be argued for due to the variance of driver perception, reaction, and other driving conditions. The number of the critical value is still an important validation parameter.

Compared to PET or TA, TTC is far more frequently used in part because of theoretical issues (road users are not by definition on a conflicting path with PET) and in part because of issues with reliability (see, for example, Lord (1996), who found that PET measures could not be correlated with accidents because they were too scattered). Grayson *et al.* (1984) also confirmed that TTC rather than PET was the common index. Archer (2005) concluded that overall TTC was more informative than PET about safety problems in part because PET was not applicable to certain interactions. Thus, many automobile collision avoidance systems or driver assistance systems have used TTC as an important warning criterion (Gettman and Head, 2003a; Riener and Ferscha, 2009).

However, there are also some shortcomings associated with the use of the TTC measure. TTC can provide the magnitude of crashes but not their severity (Muchuruza, 2006). For instance, it cannot differentiate between the severity of two conflicting events with the same TTC values but with different traveling speeds. This implies that all minimum TTC values--for example, those below 1.0 second--are regarded as having an equal level of severity, which contradicts with actual case. This is irrespective of the speed used in the calculation (Archer and Young, 2010). Obtaining the field speed of both users and the distance gap in an evolution process is another difficulty and has to rely on other approaches, such as computer vision techniques, which may not be widely applied in such contexts due to time, cost, view coverage constraints, and so on.

TTC values with respect to the preceding user for a target user (i.e., vehicle) in every time step are recorded. Thus, the TTC evolution process for an individual user can be extracted. Therefore, two extended indicators based on the TTC concept proposed by (Minderhoud and Bovy, 2001) can be used: Time Exposed Time-to-Collision (TET) and Time Integrated Time-to-Collision (TIT). The TET indicator expresses the total time spent in safety-critical situations, characterized by a TTC value below the threshold value

TTC^*. For calculation purposes, it is assumed that TTC, at an instant t, is kept constant for a small time step τ_{SC}. For the considered time period H, there are t_{i-1} time instants, to which the summation is extended while calculating the TET value. For a single road user (vehicle) i, we have:

$$TET_i^* = \sum_{t=0}^{T} \delta_i(t) \cdot \tau_{SC} \qquad \delta_i(t) = \begin{cases} 1, \forall 0 \le TTC_i(t) \le TTC^* \\ 0, otherwise \end{cases} \tag{3-14}$$

The superscript * indicates that the parameter has been calculated with respect to a predefined threshold value TTC^*. This indicates a disadvantage of TET indicators, in that any TTC value lower than the threshold value is assumed to have the same weighting in the calculation. To properly reflect the impact of the TTC value, the TIT indicator was developed.

The TIT indicator, evaluating the entity of the TTC lower than threshold TTC^*, allows one to express the severity associated with the different conditions of approach that take place in time; it represents a measure of the integral of the TTC value during the time it is below the threshold. For each driver i, we have:

$$TIT_i^* = \int_{t=0}^{T} [TTC^* - TTC_i(t)]dt \qquad \forall 0 \le TTC_i(t) \le TTC^* \tag{3-15}$$

Or using a discrete time calculation, we have:

$$TIT_i^* = \sum_{t=0}^{T} [TTC^* - TTC_i(t)] \cdot \tau_{SC} \qquad \forall 0 \le TTC_i(t) \le TTC^* \tag{3-16}$$

For N users, the total TET^* and TIT^* are calculated:

$$TET^* = \sum_{i=1}^{N} TET_i^* \tag{3-17}$$

$$TIT^* = \sum_{i=1}^{N} TIT_i^* \tag{3-18}$$

The calculation modalities for the two TTC-based safety indicators are illustrated in Figure 3.4. The TTC trajectory overtime for user i in the figure is displayed for three closing-in situations with finite TTC. Two of these profiles become safety critical because TTC values below the threshold value TTC* were collected. The TET indicator for the user i is the sum of the time travelled over the considered time period H with subcritical TTC value; the TIT indicator is the sum of the shaded areas.

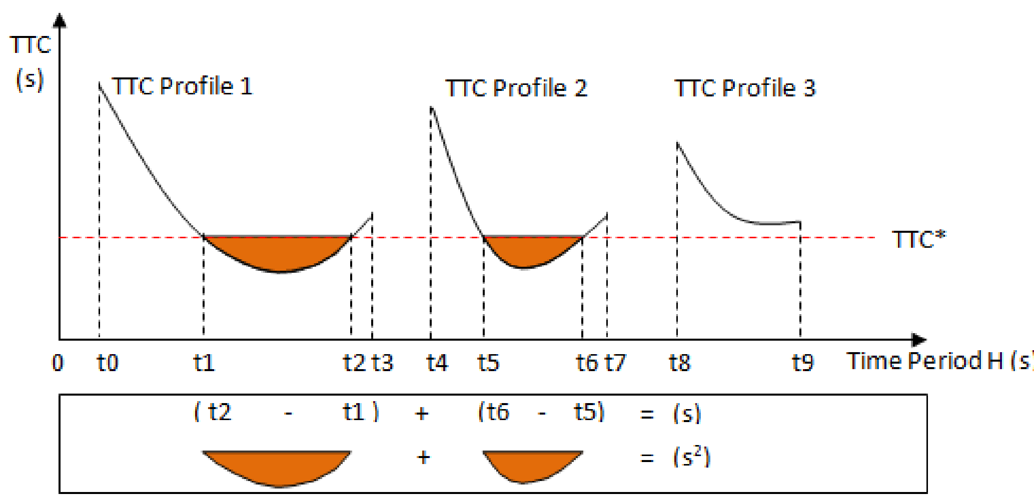


Figure 3.4 Extended safety indicators based on TTC (Minderhoud and Bovy, 2001)

3.2 Derivation of New Surrogate Safety Measures

To evaluate the risk of a traffic accident, microscopic vehicle behaviors are analyzed from the viewpoint of traffic conflict. Though some research (Glennon *et al.*, 1977; Williams, 1981) has suggested that there is only a medium correlation between the number of traffic accidents and traffic conflicts, this study adopts the methodology to evaluate the risk of traffic collision due to the difficulty in observing the actual traffic crash itself.

As mentioned in the previous section, one of the frequently used surrogate safety measures to characterize a potential rear-end conflict is time-to-collision (TTC). This indicator is adopted as a fundamental concept to derive the new surrogate measures in this study. Originating with auto manufacturers, TTC represents the remaining time that it would take a subject vehicle to collide with the tail of the vehicle in front if the speed and direction of the vehicles did not change (Hayward, 1972). This can also be explained as the time needed to avoid a collision by taking certain countermeasures. Figure 3.5 illustrates a possible rear-end conflict if the following vehicle took no or improper countermeasures to respond to the leading vehicle's deceleration.

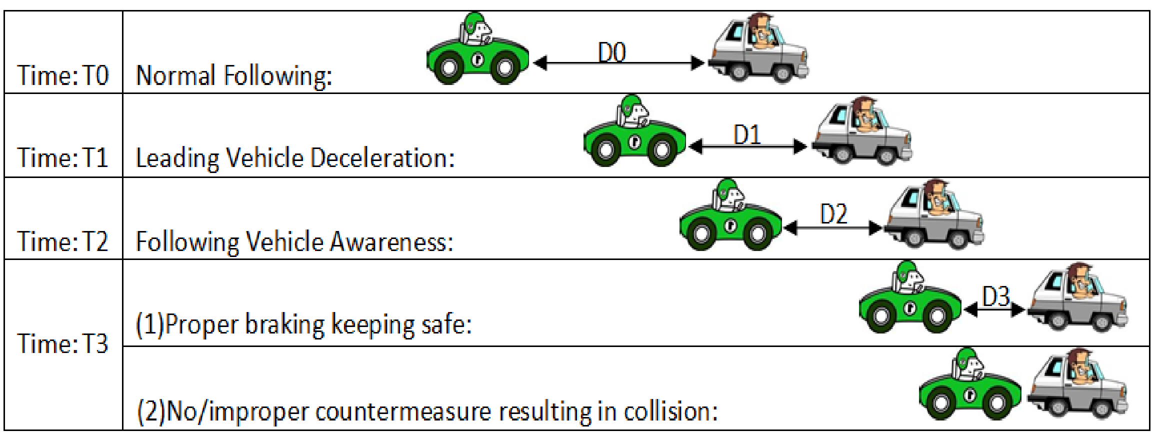


Figure 3.5 Typical car-following and rear-end collision scenario

As shown in the previous section, TTC can be formulated as in equations 3-12 or 3-13. These equations simply assume that only if the speed of the subject vehicle is larger than that of the preceding vehicle on the same lane can a collision occur. In the case when the preceding vehicle is faster than the subject vehicle, the traditional TTC index cannot be computed as a meaningful positive number. This is a practical weak point of the TTC indicator. It disregards many potential conflicts because of ignoring the discrepancies in acceleration or deceleration of the consecutive vehicles. Considering the impact of acceleration, Table 3.1 indicates all possible situations where the potential conflict may or may not occur (Ozbay *et al.*, 2008). In Table 3.1, V_S, V_P, a_S, and a_P are the speed and acceleration of the subject and its preceding vehicle, respectively.

Table 3.1 Description of Possible Scenarios between Two Consecutive Vehicles

V	$V_S > V_P$			$V_S \le V_P$		
a	a_P>0	a_P<0	a_P=0	a_P>0	a_P<0	a_P=0
a_S>0	P	C	C	P	C	P
a_S<0	P	P	P	I	P	I
a_S=0	P	C	C	I	C	I

Note: C-Conflict occurs; P-Possible Conflict; I-Impossible conflict with each other.

Formulas (3-19) and (3-20) can be used to mathematically describe the underlying relationships that determine the occurrence of the conflict shown in Table 3.1. They are based on the trajectory projection of the two consecutive vehicles given their relative distance, speed and acceleration information. These formulas are proposed as a modification of the traditional TTC to capture extra potential conflict cases considering acceleration.

$$V_S t + \frac{1}{2} a_S t^2 \ge D_{SP} + V_P t + \frac{1}{2} a_P t^2 \qquad \textbf{(3-19)}$$

$$\frac{1}{2}\Delta a t^2 + \Delta V t - D_{SP} \ge 0 \qquad \textbf{(3-20)}$$

where V_S is the speed of the subject vehicle (ft/s), V_P is speed of the preceding vehicle (ft/s), a_S is the acceleration of subject vehicle's (ft/s^2), a_P is the acceleration of preceding vehicle (ft/s^2), ΔV is the relative speed (ft/s), $\Delta V = V_S - V_P$, Δa is the relative acceleration (m/s^2), $\Delta a = a_S - a_P$, D_{SP} is the initial relative distance (ft), and t is time (s).

In order to calculate Time-to-Collision accurately, computational logic that selects the specific expression for TTC under different circumstances is proposed. Thus, based on the equations (3-21), (3-22), and (3-23), a minimum TTC can be computed for a rear-end collision for each vehicle pair. This modified surrogate safety measure is named Modified Time-to-Collision (MTTC). It is clear from the discussion above that MTTC is better than the traditional definition of TTC. A case study in the next section will further illustrate the effect of using MTTC versus TTC.

The computational logic of MTTC is described as follows:

If ($\Delta a \neq 0$)

{ $t_1 = \dfrac{-\Delta V - \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}$ and $t_2 = \dfrac{-\Delta V + \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}$

If ($t_1 > 0 \,\&\, t_2 > 0$)

{ If ($t_1 \geq t_2$) { $MTTC = t_2$ }

Else If ($t_1 < t_2$) { $MTTC = t_1$ }

}

Else If ($t_1 > 0 \,\&\, t_2 \leq 0$)

$$\{MTTC = t_1 = \frac{-\Delta V - \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}\} \qquad \textbf{(3-21)}$$

Else If ($t_1 \leq 0 \,\&\, t_2 > 0$)

$$\{MTTC = t_2 = \frac{-\Delta V + \sqrt{\Delta V^2 + 2\Delta a D}}{\Delta a}\} \qquad \textbf{(3-22)}$$

}

$$\text{If}(\Delta a = 0 \,\&\, \Delta V > 0)\{MTTC = \frac{D}{\Delta V}\} \tag{3-23}$$

Generally, if MTTC is relatively short, a crash potential would arise because there might not be enough time for the subject vehicle to respond in a safe manner, such as braking and changing lanes to avoid the collision. However, the question of "how short is really short" is difficult to determine, as different drivers have different response times, and they also might take different actions depending upon the vehicle's performance, prevailing traffic conditions, and so forth. Studies in the literature have offered different suggestions for the selection of a threshold value for TTC to identify critical conflict. For instance, a TTC value of 4 seconds was suggested to distinguish between safe and uncomfortable situations on the roads (Farber, 1991; Van der Horst, 1991). On the other hand, Hogema and Janssen (1996) suggested a minimum TTC of 3.5 seconds for drivers without an automatic cruise control system and 2.6 seconds for drivers with equipped vehicles. Arguably there is no unique threshold value of TTC below which all drivers face a potential collision situation.

Considering the fact that the shorter MTTC is, the higher the risk of conflict is, this study adopts an exponential decay function as an alternative for defining a single threshold value to identify the potential risk of conflict. Then the conflict probability (CP) is proposed as the new surrogate measure. The function of the i^{th} type of potential conflict probability (CP_i) associated with the subject vehicle is shown in equation 3-24 and it is a continuous monotonic decreasing function of MTTC such that as MTTC $\in [0, +\infty)$, CP $\in [1, 0)$. When MTTC is 0, the two consecutive vehicles definitely conflict with each other. When MTTC is relatively large, the conflict risk is small. The same MTTCs may not indicate the same chance of conflict under different traffic conditions. Therefore, a parameter λ is used to adjust the impact of MTTC at different traffic conditions such as arterials versus minor streets.

$$CP_i = \Pr(Conflict \mid MTTC_i) = Exp(\frac{-MTTC_i}{\lambda}) \qquad \textbf{(3-24)}$$

The parameter λ has to be specified in practice. As an example, assume that a MTTC of 4 seconds corresponds to a conflict probability of 0.5. The λ thus can be set to 5.77. If assuming a shorter MTTC of 3 seconds corresponds to a conflict probability of 0.5, then λ can be set to 4.32. Figure 3.6 shows an example of the exponential decay curve using these assumed parameters. As MTTC increases, the conflict probability will decrease. The same MTTC will correspond to a higher conflict probability if a larger parameter λ is used. The sensitiveness of the parameter λ will be tested in the following study.

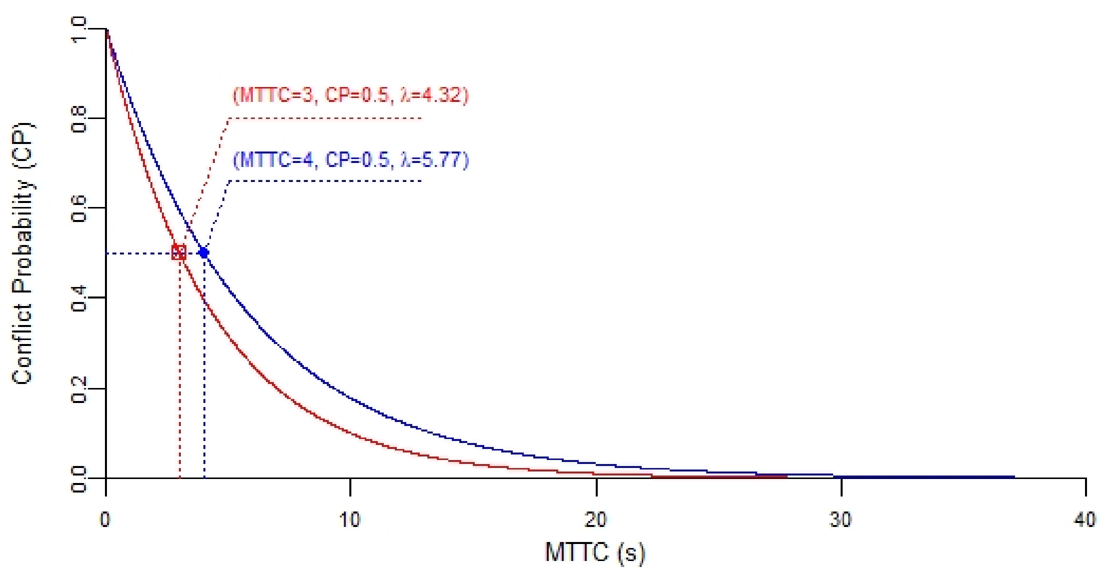


Figure 3.6 Example of exponential decay function to describe conflict probability

3.3 Indicator Comparison Using Trajectory Data

A trajectory dataset, "I-80 Dataset," generated by the Next Generation Simulation (NGSIM)[1] program is used to investigate the difference when analyzing traffic conflicts using the presented indicator above. The schematic illustration of the data collection site is shown in Figure 3.7. The dataset was collected at a segment of Interstate I-80 in Emeryville (San Francisco), California. It represented 45 minutes of data collection during the afternoon peak period on April 13, 2005. A total of 5,648 vehicle trajectories with a time increment of 1/10 second were collected. The data were integrated into three independent 15-minute datasets separately. Data of (A) 16:00~16:15 represent the transitional traffic conditions to congestion. Data of (B) 17:00~17:15 and (C) 17:15~17:30 represent congested traffic conditions. The detailed trajectory information provides important attributes such as vehicle longitudinal position, speed, preceding and following vehicles, spacing and time headway, which are important elements for traffic conflict analysis using different surrogate measures.

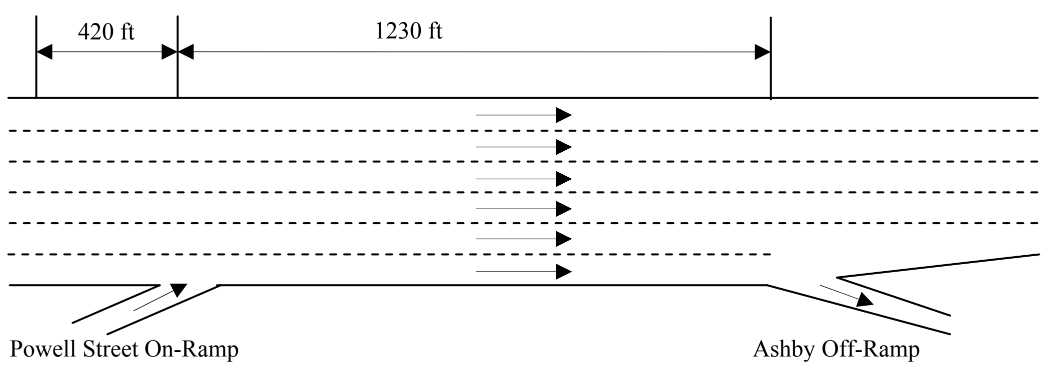


Figure 3.7 Study area schematic of I-80

[1] NGSIM is a research project let by the US FHWA to provide resolution and high-quality driver behavior data and algorithms. All its datasets are available at the NGSIM official website: http://www.ngsim.fhwa.dot.gov.

A program developed in the statistical software R[2] is implemented to process the trajectory data query, filter, computation, and final results analysis[3]. Since millions of trajectory records are included in each period, it is impractical to analyze all of them. As the time step used to collect the vehicle trajectory data was 0.1 second, the time series of vehicle trajectory information, at least part of it, is expected to be auto-correlated. For instance, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of headway time series in Figure 3.8 show that there are some lags, which means the series is not stationary and have inter-correlations and interventions for different time steps. This is expected because in such a short time step, vehicles' headways do not change considerably. Therefore, to make it computable without continuously analyzing all the trajectories, one percent (sampling every 10 seconds, with more than 10,000 samples obtained) of the original dataset for each time period was randomly sampled to calculate different surrogate measures.

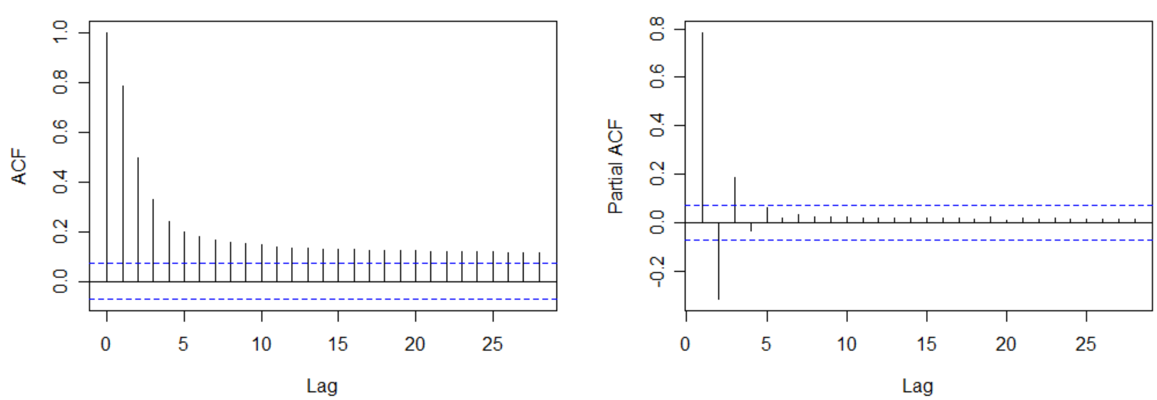


Figure 3.8 Example of ACF and PACF of a vehicle headway time series (time step=0.1 seconds)

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[2] R is a free software environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows, and MacOS. http://www.r-project.org/

[3] The original dataset in text format is about 150 MB for each 15-minute period.

Figure 3.9 shows observed TTC and MTTC (that are less than 10 seconds) of the sampled trajectories. Given a threshold of 4 seconds, using TTC as the surrogate measure detects fewer conflicts than using MTTC as the surrogate measure. This confirms the argument in the previous section that MTTC can explain more conflict scenarios by considering acceleration/deceleration influence. For surrogate measures like TTC, MTTC, and THW, the determination of the threshold value is critical. The number of conflicts directly relies on the threshold value. It will give biased results if a threshold value is not well defined. For instance, if the threshold value is too large, many safe car-following scenarios will be judged as unsafe conflict scenarios, and vice versa. The difficulty lies in defining a single threshold value. There is no clue to choose the value. In the meantime, it will lose lots of information by ignoring those observations that are above the threshold value. Especially for those weakly above the threshold line , it may not suggest completely safe cases.

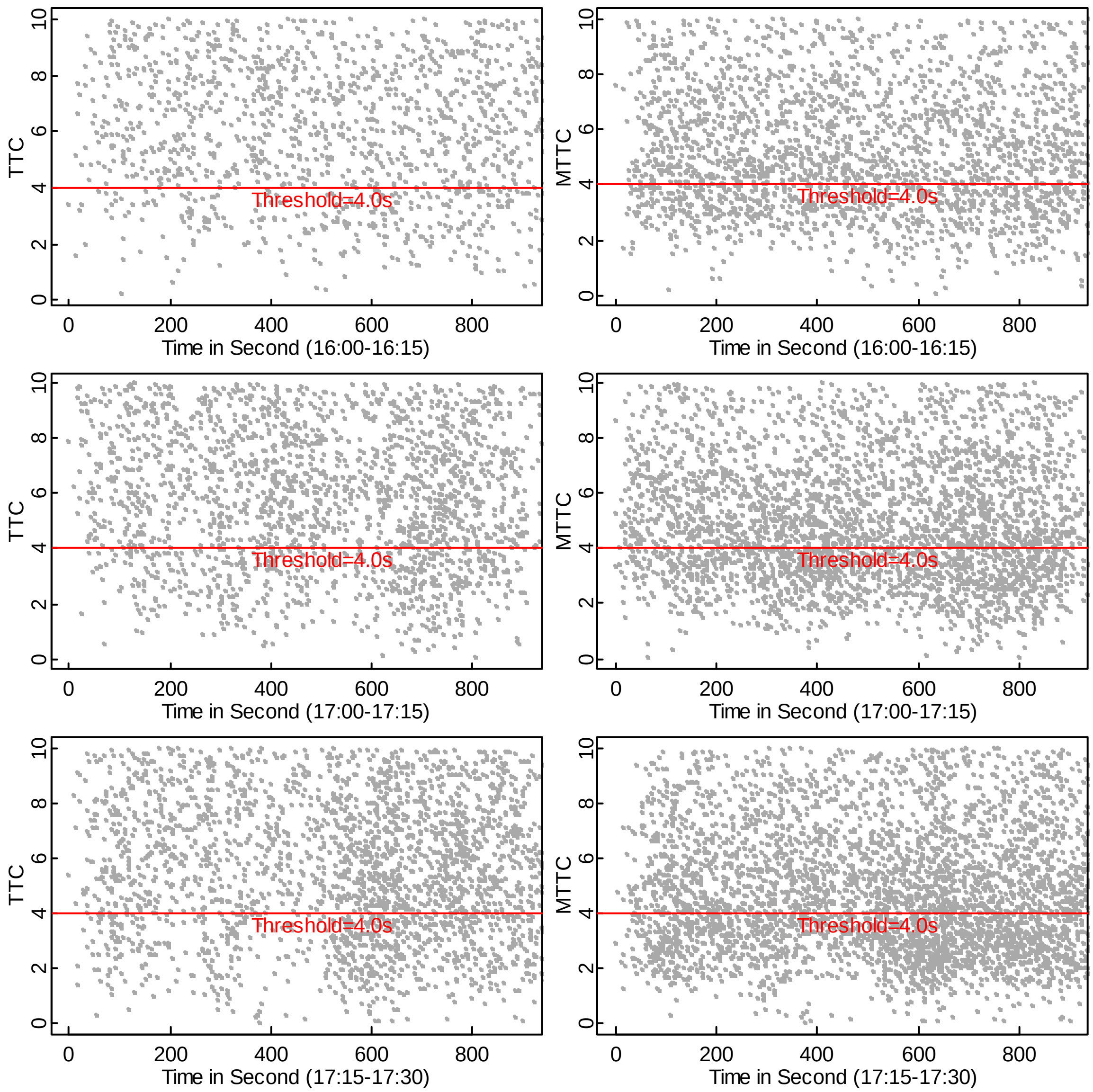


Figure 3.9 Observed TTC and MTTC of different time periods

When CP is used as the surrogate measure, it takes advantage of MTTC to explain more conflict scenarios. In the meantime, all observed information is utilized. It preserves the characteristic that small MTTC means high risk and there is no risk-free case as long as the MTTC exists. For instance, we can say that the case of MTTC=2.0 seconds is risker compared to the case of MTTC=4.5 seconds. However, it is inappropriate to argue that the latter case (MTTC=4.5s) is safe while the formal case (MTTC=2.0s) is certainly unsafe. Another important characteristic of CP is the exponential decay function that distinguishes those high-risk scenarios from very low-risk ones. As shown in Figure 3.6, when the observed MTTC increases, the corresponding risk quickly decreases. When MTTC is relatively large, say 20 seconds, the risk exists but is very close to zero. Instead of using an uncertain threshold value, the decay function of CP provides a way to consider all observed MTTCs.

3.4 Summary

This chapter has investigated the major time-based surrogate safety measures. Their concept and derivation have been presented. In consideration of the characteristics and limitations of current measures, a new surrogate safety indicator in terms of measuring the relative conflict probability (CP) has been proposed. The computational logic of CP has been presented. Some of the important features of the time-based surrogate measures have been investigated through analysis of an actual vehicle trajectory dataset. The advantages of using CP have also been discussed.

Chapter 4 Simulation Modeling and Calibration Approach

This chapter introduces a calibration approach to set simulation model for safety analysis. Using Paramics as an example, information about its underlying behavioral models is presented. Since the behavioral models are linked with a number of internal parameters, it is necessary to figure out which ones should be calibrated so that the simulation results can match the observations. Therefore, a statistical method is introduced to screen important parameters, and a stochastic calibration approach is used to estimate their values.

4.1 Simulation Platform

4.1.1 Overview of the Program

Former studies have given some insights about the strengths and weaknesses of various simulation software used to support safety analysis. However, there are still no definitive conclusions about the selection criteria for available traffic software packages specific to safety analysis. In the absence of this kind of guidance, Paramics (Parallel Microscopic Simulation) is selected as the traffic simulation platform in this research. It is a suite of high-performance microscopic simulation tools originally developed at the Edinburgh Parallel Computing Center in Scotland. The suite includes Processor, Analyser, Designer, Converter, Estimator, and Modeller. Modeller is the core simulation tool of the suite that is used in this study.

Similar to other microscopic simulators, Paramics is built on car-following theory and is inherently stochastic. Different random seeds are used to randomly generate vehicles and probabilistically assign attributes to vehicle characteristics. As a stochastic, microscopic, time-step, and behavior-based simulation model, it provides a number of advanced modeling and data extraction features. Paramics allows users to gather representative average results of multiple runs. The small time-step characteristics help researchers to explore the transitional behavior of individual drivers with specific attributes for various network traffic conditions, during various time periods.

Another important feature Paramics has is that it provides a way to customize underlying simulation models and variables through the Application Programming Interface (API), which is a significant advantage over most other similar simulators. Since the default models such as car-following and lane-changing may not always satisfy needs, using APIs allows users to access and develop new algorithms. Moreover, it allows Paramics to interface with other software and simulate some special cases. For our studies, customized APIs that gather detailed parameters about simulated vehicle trajectories such as time step, speed, acceleration, and position, can be implemented into the Paramics model to compute and collect the proposed surrogate safety measures. These features make Paramics a good choice for safety analysis.

4.1.2 Car-Following Model

Different microscopic models have been used to imitate individual driver behavior in simulation. The car-following model is one of these crucial tactical-level models used to replicate the longitudinal actions of driver-vehicle units (DVUs) in reality (i.e., vehicle velocity and acceleration). Figure 4.1 shows a typical car-following case.

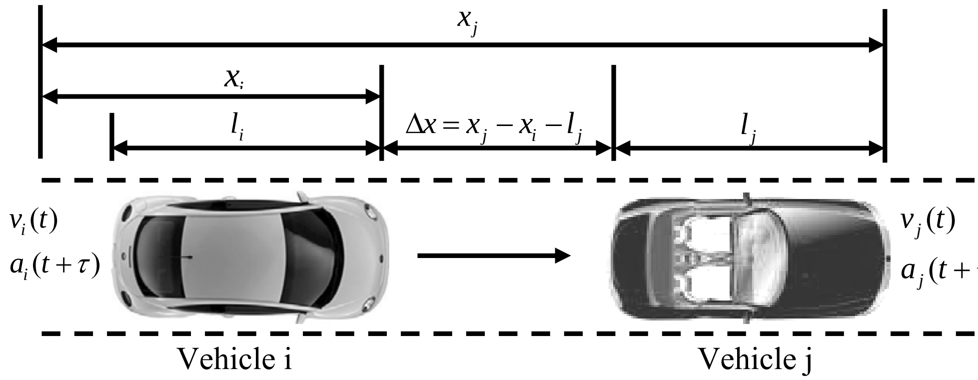


Figure 4.1 Example of car-following scenario

As shown in the above figure, a vehicle i is classified as following when it is constrained by a leading vehicle j. The constraint usually requires the following vehicle to adjust its acceleration to maintain a safe following course. Different models have been developed to describe such adjustment. Xin *et al.* (2008) suggested that most classical car-following models can be generalized using the following equations:

$$a_i(t+\tau) = f(\Delta x, v, \Delta v, \Delta a, a_i \mid t) \quad \textbf{(4-1)}$$

$$a_i(t+\tau) = f(\Delta x, v, \Delta v, \Delta a, a_i \mid t) + \varepsilon \quad \textbf{(4-2)}$$

$$\Delta x(t) = x_{i-1} - l_{i-1} - x_i(t) \quad \textbf{(4-3)}$$

$$\Delta v = v_{i-1}(t) - v_i(t) \quad \textbf{(4-4)}$$

$$\Delta a(t) = a_{i-1}(t) - a_i(t) \quad \textbf{(4-5)}$$

where a represents the acceleration of a vehicle; v is the velocity of a vehicle at time t; x is the position of a vehicle; l is the vehicle length; Δx is the space headway between two vehicles; Δv is the difference in velocity; Δa is the difference in acceleration; τ is the reaction time of the following vehicle; and ε is the noise term used to create a stochastic model 4-2 based on the deterministic equation 4-1.

Specifically, the car-following model utilized in Paramics is a modified version of the psycho-physical model developed by Fritzsche (1994). This is a discrete, stochastic, and microscopic model, where a DVU is defined as a single entity. In the model, the car-following process is based on the assumption that a DVU can be perceived in one of the five driving regimes: the free driving state, following I state, following II state, closing-in state, and danger state. Figure 4.2 shows an observed car-following diagram of the five driving regimes.

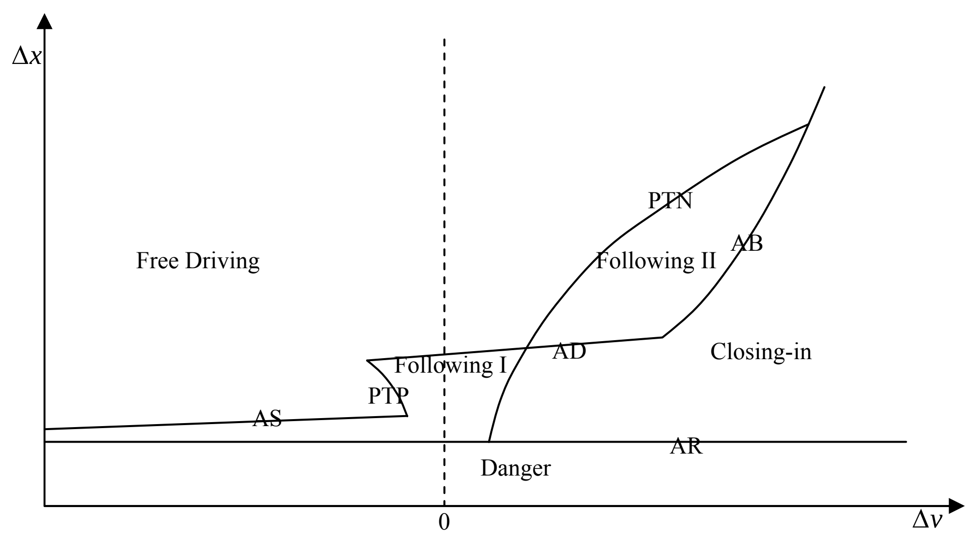


Figure 4.2 Fritzsche's car-following regimes and thresholds (Fritzsche, 1994)

To classify the driving state into the named regimes, thresholds are defined in a relative space/speed diagram of a follower-leader vehicle pair. Specifically, two speed-based thresholds and four distance-based thresholds are introduced. When the following vehicle is slower than its leading vehicle, the thresholds for perception of positive (PTP) speed differences is used. Otherwise, the threshold for the perception of negative (PTN) speed differences is used. These two speed-based thresholds are described as follows:

$$\Delta v_{PTP} = k_{PTP}(\Delta x - A_0)^2 + f_x \quad \textbf{(4-6)}$$

$$\Delta v_{PTN} = -k_{PTN}(\Delta x - A_0)^2 - f_x \quad \textbf{(4-7)}$$

where Δx is the distance between the leading and the following vehicles; A_0 is the standstill distance; and k_{PTP}, k_{PTN}, and f_x are the model parameters. The following car will not perceive differences in speed below the thresholds Δv_{PTP} and Δv_{PTN}.

In addition to the thresholds for speed differences, the Fritzsche model introduced four thresholds regarding the distance between the two consecutive vehicles. These thresholds include desired distance (AD), risky distance (RD), safety distance (AS), and braking distance (AB):

$$AD = A_0 + T_d \cdot v_i \quad \textbf{(4-8)}$$

$$AR = A_0 + T_r \cdot v_j \quad \textbf{(4-9)}$$

$$AS = A_0 + T_s \cdot v_i \quad \textbf{(4-10)}$$

$$AB = AR + \frac{\Delta v^2}{\Delta b_m}, \ with\ b_m = |b_{\min}| + b_j \quad \textbf{(4-11)}$$

where v_i and v_j are the velocities of the following and leading vehicles, respectively; Δv is the velocity difference between the two vehicles; and T_d, T_r, and T_s are the time headways for desired, risky, and safety distance, respectively. These time headways have to satisfy $T_d > T_s > T_r$. $b_{\min}$ and b_j are model parameters controlling maximum deceleration.

The above thresholds are illustrated in Figure 4.2. Panwai and Dia (2005) discussed the following vehicle's response in terms of acceleration and deceleration. In a danger state ($\Delta x \le AR$), the following vehicle has to decelerate as much as possible to avoid a collision. In a closing-in state, the following vehicle drives faster than the leading vehicle. Given $\Delta v \le \Delta v_{PTN}$ and $AR < \Delta x \le AD$, the following vehicle has to decelerate until it is not faster than the leading one. When $\Delta v_{PTN} < \Delta v \le \Delta v_{PTP}$ and $AR < \Delta x < AD$ or given $\Delta v \ge \Delta v_{PTP}$ and $\Delta x < AS$, the following vehicle is in following I state and there is no need for action. If $\Delta v < \Delta v_{PTN}$ and $AD < \Delta x$, then the vehicle is in following II state and there is no need for action. At free driving state, the follower accelerates with a normal acceleration, given $\Delta v > \Delta v_{PTN}$ and $AD < \Delta x$, or $\Delta v > \Delta v_{PTP}$ and $AS < \Delta x$.

Paramics simulation software was created from scratch mainly based on the above model. However, according to Brockfeld *et al.* (2003), the differences or similarities between the published version of the Fritzsche model and the version used in Paramics are not quite clear. For reasons of commercial confidentiality, details of the Paramics model have not been revealed. Only a brief description of car-following model was discussed in Duncan (1998) and Quadstone (2004). Generally, car-following behavior was summarized by three modes: cruising, braking, and accelerating. For the cruising mode, the vehicle is in the following traffic situations:

- A following vehicle's current headway is less than its target value, and it attempts to achieve the desired speed as quickly as possible when the physical constraints (i.e., maximum speed) are allowed.
- The leading vehicle moves faster, and the following vehicle is pulled away.
- All vehicles are in constant separation or coming together.

Based on the perception of the distance between the vehicle pair, the following vehicle either brakes or accelerates to interact with the leading vehicle's maneuver. When the leading vehicle is observed to decelerate over a certain threshold, the following vehicle will brake to increase the distance between vehicles. If the leading vehicle is perceived to accelerate at a high rate and is more than the following vehicle's safe stopping distance away, the following vehicle's acceleration is set to the maximum value (Quadstone, 2004).

4.1.3 Lane-Changing Model

In addition to the car-following model, an understanding of the lateral movements of vehicles is necessary to allow an accurate representation of traffic movement in simulation. Lateral movements are usually described using lane-changing models. These models control how vehicles merge, wave, and make lane changes in multilane situations. As far as lane-changing is concerned, a vehicle will attempt to change lanes in two typical situations: mandatory lane changes (i.e., when a lane is dropped or blocked) and discretionary lane changes (i.e., when a vehicle is impeded by a slower vehicle). These lane-changing maneuvers in Paramics are modeled using a gap-acceptance policy and a historical record of suitable gap availability (Duncan, 1998).

Figure 4.3 illustrates an example of a lane-changing situation in which the subject vehicle is impeded by a slower lead vehicle and desires to move into the fast lane.

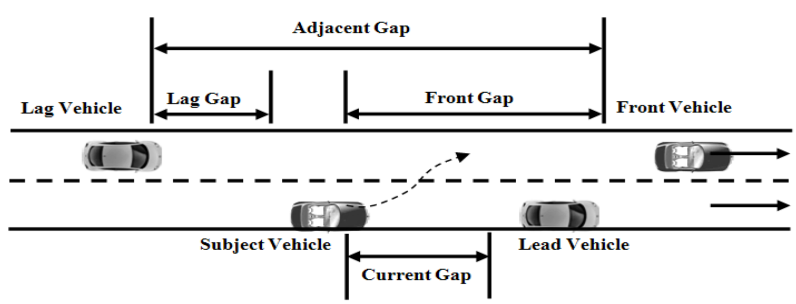


Figure 4.3 Example of potential lane-changing scenario

For the gap-acceptance policy, when a subject vehicle desires to change lanes it must find an acceptable gap between the lag vehicle and front vehicle in the target lane. Duncan (1998) indicated that this gap-acceptance policy is linked with the car-following model because the accepted gap is based on target headway. Target headway for a vehicle varies around the specified mean target headway and depends on many other factors such as the aggressiveness of the driver. In Paramics, the following conditions must be satisfied for the lane change to take place (Quadstone, 2004):

$$g_1 > d_{\Delta v_1} + hv_1 \quad \textbf{(4-12)}$$

$$g_2 > d_{\Delta v_2} + hv_2 \quad \textbf{(4-13)}$$

$$d_{\Delta v_1} = t_{r_0} + \frac{\Delta v_1}{D_0} = t_{r_0} + \frac{v_1 - v_0}{D_0} \quad \textbf{(4-14)}$$

$$d_{\Delta v_2} = t_{r_0} + \frac{\Delta v_2}{D_2} = t_{r_0} + \frac{v_0 - v_2}{D_2} \quad \textbf{(4-15)}$$

where h is the target headway. $v_0, v_1, and\, v_2$ are the current velocities of the subject vehicle, front vehicle and lag vehicle, respectively. $g_1\, and\, g_2$ are the front gap and lag gap, respectively. t_{r_0} is the reaction time of the subject vehicle. $D_0\, and\, D_2$ are the maximum deceleration rates of subject vehicle and lag vehicle in the target lane, respectively.

The lane-changing maneuver is enabled if the above conditions are continuously satisfied for a period of T_{LC} seconds. Drivers have to check the historical record gaps to make sure that the gap lasts long enough to implement a safe lane change. Duncan (1998) suggested that the typical value of T_{LC} is in the range of 3 to 6 seconds. It varies depending on behavior and location parameters. In light or moderate traffic conditions, acceptable T_{LC} can be easily obtained. However, when there are heavy merging or weaving movements, T_{LC} is difficult to guarantee. A vehicle may be forced to change lanes and cause irregularities in the simulation.

4.2 Simulation Model Parameters

Generally, when a driver-vehicle unit (DVU) is generated in a simulation model, a set of parameters associated with physical and behavioral information is assigned to it. For instance, the physical parameters include length and width of the vehicle, while behavioral parameters include driver awareness, reaction time, and so on. These parameters control the detailed motion of the vehicle through these behavioral models and have to be calibrated so that the simulation model can mimic the observed traffic data. Different simulators have different underlying parameters. In Paramics, these parameters can be grouped into two general categories: (i) global parameters and (ii) local parameters. The global parameters include mean reaction, mean target headway, driver alertness, driver awareness, speed memory, and so forth. The local parameters include link headway factor, link reaction factor, curve factor, minimum queue gap, speed memory, signpost, and so on. Table 4.1 lists major parameters in Paramics. Explanation of each parameter can be found in the Paramics Manual (Quadstone, 2010). To reflect the actual situation, the values of the parameters should be bounded to a certain range. The feasible range of each parameter in Table 4.1 was based on the practice and experience of the author.

Table 4.1 Major Parameters in Paramics

Factor	Parameters	Default Value	Feasible Range
A	Mean Target Headway (s)	1.0	0.5 to 3.0
B	Mean Driver Reaction Time (s)	1.0	0.5 to 2.0
C	Minimum Gap (ft)	5.00	1.0 to 9.0
D	Queue Gap Distance (ft)	32.81	5.0 to 40.0
E	Queue Speed (mph)	4.47	1.0 to 8.0
F	Link Headway Factor	1.0	0.5 to 2.0
G	Link Reaction Factor	1.0	0.5 to 2.0
H	Signpost (ft)	696..2	1.0 to 1500.0
I	Speed Memory	5	1 to 20
J	Driver Aggressiveness	4	1 to 8
K	Driver Awareness	4	1 to 8

Instead of using default values, reliable configuration (input) of the parameters has to be determined. Due to limited resources and background information, not all the values of parameters can be carefully identified. Only some important ones are considered. Table 4.2 summarizes some previous studies in which various Paramics parameters were selected according to the simulation calibration targets. It shows that some of the parameters such as mean headway and mean reaction time seem to be critical in all studies. Some of the others such as curve speed factor and ramp headway factor are only relevant in specific studies. The selection of potential parameters in previous studies seems to be arbitrary, as different selections were made though the calibration targets were similar. In this study, a methodology to select the important parameters is presented in next section.

Table 4.2 Example of Selected Parameters in Previous Paramics Calibration Studies

Study	Calibration Targets	Potential Parameters	
Ma and Abdulhai (2002)	Link Counts	Mean Headway (s)	Mean Reaction Time (s)
		Feedback	Familiarity (%)
		Perturbation Factor (%)	
Gardes *et al.* (2003)	OD	Mean Headway (s)	Mean Reaction Time (s)
		Time Step	Speed Memory
		Ramp Headway Factor	Minimum Ramp Time (s)
Chu *et al.* (2004)	OD, Volume, Travel Time	Mean Headway (s)	Mean Reaction Time (s)
		Familiarity (%)	Perturbation Factor (%)
Park and Qi (2004)	Travel Time	Mean Headway (s)	Mean Reaction Time (s)
		Speed Memory	Curve Speed Factor
		Visibility (ft)	Headway Factor
Liu *et al.* (2006)	Capacity	Mean Headway (s)	Mean Reaction Time (s)
		Time Step	Speed Memory
Ma *et al.* (2007) Zhang *et al.* (2008)	Link Capacity, Critical Occupancy	Mean Target Headway (s)	Mean Reaction Time (s)
		Driver Aggressiveness	Driver Awareness
		Link Headway Factor	Link Reaction Factor
		Ramp Headway Factor	Minimum Ramp Time (s)
		Signposting (ft)	Ramp Awareness Distance (ft)
Nezamuddin and Al-Deek (2008)	Volume	Mean Target Headway (s)	Mean Reaction Time (s)
		Minimum Gap (ft)	Queue Gap Distance (ft)
			Queue Speed (mph)
Abdel-Aty *et al.* (2008)	Flow and Speed	Mean Target Headway (s)	Mean Reaction Time (s)
		Queue Gap Distance (ft)	Queue Speed (mph)
Lee and Ozbay (2009)	Flow and Speed	Mean Target Headway (s)	Mean Reaction Time (s)

4.3 Key Parameters Selection Method

As mentioned above, there are a number of parameters in the simulation model. Depending on simulation objectives and constraints of resources, only some of the important parameters may be of great interest. The selection of these key parameters to be tuned and the methodology followed play critical roles in simulation modeling. The challenge is that knowledge about the importance of parameters is usually limited. It is necessary to screen their sensitivities on simulation results and determine their roles for calibration. Traditional methods usually use a one-parameter-at-a-time strategy to study the effect of a parameter, as it is statistically relatively simple to manipulate. However, some simulation parameters may be interdependent, and it is impractical to use the traditional strategy. Therefore, this section introduces the factorial design method to help design simulation experiments to determine parameter effects as well as their interactions.

4.3.1 Full Factorial Design

When running a simulation model, a specific configuration of the parameter set has to be determined. Such a configuration is a treatment with a given level (value) of parameter setting from a statistical standpoint. When there is a clear description of the level of each parameter, the configurations have a factorial structure. Assume there are two parameters A and B, for instance, time headway and reaction time in Paramics, with a and b levels (i.e., $a = 3, b = 4$ given time headway can be 0.50, 0.75, or 1.00 seconds, and reaction time can be 0.50, 0.70, 0.90, or 1.10 seconds, respectively). The simulation model is then run n times for each combination of the parameters (A_i, B_j). Thus, there are $a*b*n$ runs in total. This is a full factorial design of an experiment for running the simulation model with two parameters. Table 4.3 shows the factorial parameter structure of this factorial design.

Table 4.3 Example of Factorial Parameter Structure

Parameter Level	B_1 (Reaction=0.50)	B_2 (Reaction=0.70)	B_3 (Reaction=0.90)	B_4 (Reaction=1.10)
A_1 (Headway=0.50)	$y_{111}, y_{112}, \ldots, y_{11n}$	$y_{121}, y_{122}, \ldots, y_{12n}$	$y_{131}, y_{132}, \ldots, y_{13n}$	$y_{141}, y_{142}, \ldots, y_{14n}$
A_2 (Headway=0.75)	$y_{211}, y_{212}, \ldots, y_{21n}$	$y_{221}, y_{222}, \ldots, y_{22n}$	$y_{231}, y_{232}, \ldots, y_{23n}$	$y_{241}, y_{242}, \ldots, y_{24n}$
A_3 (Headway=1.00)	$y_{311}, y_{312}, \ldots, y_{31n}$	$y_{321}, y_{322}, \ldots, y_{32n}$	$y_{331}, y_{332}, \ldots, y_{33n}$	$y_{341}, y_{342}, \ldots, y_{34n}$

Define the "$\bullet$" in the subscript as all samples in a cell (given $ij\bullet$), row (given $i\bullet\bullet$), or column (given $\bullet j\bullet$), or as all samples in the table ($\bullet\bullet\bullet$). Denote $\overline{y}_{ij\bullet}$ as the observed mean of all n outputs in a combination (A_i, B_j) in Table 4.3. $\overline{y}_{i\bullet\bullet}$ is the average of all simulation output having level i for parameter A. It represents the row mean in Table 4.3. Similarly, $\overline{y}_{\bullet j\bullet}$ is the average of all simulation outputs having level j for parameter B. It is the average of each column in Table 4.3. $\overline{y}_{\bullet\bullet\bullet}$ is the overall mean of all output in Table 4.3. Assuming there is a linear relationship between the parameters and the simulation output Y (i.e., travel time), the above parameter structure can be modeled as:

$$y_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \varepsilon_{ijk} \qquad \textbf{(4-16)}$$

where $i = 1,2,...,a$; $j = 1,2,...,b$; $k = 1,2,...,n$; μ is the overall mean effect; α_i is the main effect of the i^{th} level of the parameter A; β_j is the main effect of the j^{th} level of the parameter B; $\alpha\beta_{ij}$ represents the interaction of parameter A and B at the corresponding levels; and ε_{ijk} is independent and normally distributed with a zero mean and variance σ^2. According to Oehlert (2000), the following set of restrictions on the parameters is used:

$$\sum_{i=1}^{a} \alpha_i = \sum_{j=1}^{b} \beta_j = \sum_{i=1}^{a} \alpha\beta_{ij} = \sum_{j=1}^{b} \alpha\beta_{ij} = 0 \qquad \textbf{(4-17)}$$

The estimators of the main and interaction effects are then given in following equations:

$$\hat{\mu} = \overline{y}_{\bullet\bullet\bullet} \qquad \textbf{(4-18)}$$

$$\widehat{\alpha}_i = \overline{y}_{i\bullet\bullet} - \widehat{\mu} = \overline{y}_{i\bullet\bullet} - \overline{y}_{\bullet\bullet\bullet} \quad \textbf{(4-19)}$$

$$\widehat{\beta}_j = \overline{y}_{\bullet j\bullet} - \widehat{\mu} = \overline{y}_{\bullet j\bullet} - \overline{y}_{\bullet\bullet\bullet} \quad \textbf{(4-20)}$$

$$\widehat{\alpha\beta}_{ij} = \overline{y}_{ij\bullet} - \widehat{\mu} - \widehat{\alpha}_i - \widehat{\beta}_j = \overline{y}_{ii\bullet} - \overline{y}_{i\bullet\bullet} - \overline{y}_{\bullet j\bullet} + \overline{y}_{\bullet\bullet\bullet} \quad \textbf{(4-21)}$$

We are interested in finding out how the main effect and interaction of parameters affect simulation output. For instance, does increasing time headway change the simulation results? Do larger headway and larger reaction time change the results? In general, the following hypothesis tests can be used to answer the questions:

$$\begin{aligned} &\textit{Null Hypothesis}\, H_0 : \alpha_1 = \alpha_2 = ... = \alpha_a = 0 \\ &\textit{Alternative Hypothesis}\, H_1 : \textit{not all}\, \alpha_i = 0 \end{aligned} \quad \textbf{(4-22)}$$

$$\begin{aligned} &\textit{Null Hypothesis}\, H_0 : \beta_1 = \beta_2 = ... = \beta_b = 0 \\ &\textit{Alternative Hypothesis}\, H_1 : \textit{not all}\, \beta_j = 0 \end{aligned} \quad \textbf{(4-23)}$$

$$\begin{aligned} &\textit{Null Hypothesis}\, H_0 : \alpha\beta_{11} = \alpha\beta_{12} = ... = \alpha\beta_{ab} = 0 \\ &\textit{Alternative Hypothesis}\, H_1 : \textit{not all}\, \alpha\beta_{ij} = 0 \end{aligned} \quad \textbf{(4-24)}$$

Analysis of variance (ANOVA) is used to test the aforementioned null hypotheses. The following ANOVA table summarizes the computation of test statistics:

Table 4.4 ANOVA Table for Two-Factor Factorial Design

Term	Sum of Squares	Degree of Freedom	Mean Square	F-statistic
A	$SS_A = b \times n \times \sum_{i=1}^{a} (\widehat{\alpha}_i)^2$	$a-1$	$MS_A = SS_A / (a-1)$	MS_A / MS_E
B	$SS_B = a \times n \times \sum_{j=1}^{b} (\widehat{\beta}_j)^2$	$b-1$	$MS_B = SS_B / (b-1)$	MS_B / MS_E
AB	$SS_{AB} = n \times \sum_{i=1}^{a} \sum_{j=1}^{b} (\widehat{\alpha\beta}_{ij})^2$	$(a-1)(b-1)$	$MS_{AB} = SS_{AB} / [(a-1)(b-1)]$	MS_{AB} / MS_E
Error	$SS_E = \sum_{i=1}^{a} \sum_{j=1}^{b} \sum_{k=1}^{n} (y_{ijk} - \overline{y}_{ij\bullet})^2$	$ab(n-1)$		
Total	$SS_T = \sum_{i=1}^{a} \sum_{j=1}^{b} \sum_{k=1}^{n} (y_{ijk} - \overline{y}_{\bullet\bullet\bullet})^2$	$abn-1$		

If the computed F-statistic of a given term is larger than the critical statistic of the corresponding F-test, the null hypothesis would be rejected. In other words, the term probably has notable effect on the simulation output. In a calibration process, this term should be well calibrated.

The above part uses two factors to illustrate the concept of the factorial design. For simulation with more than two parameters, similar analysis can be used. More information about multi-way factorial design can be found in many statistics books (Oehlert, 2000; Montgomery, 2009).

4.3.2 Fractional Factorial Design

Factorial design can allow us to analyze main effects and interactions, but the problem is complicated when it is applied to a simulation model. First, it is difficult to define the levels of either discrete or continuous parameters in simulation models. Usually, only the lower and upper limits of the parameters are unknown. Second, factorials can be become extremely large even if we only define 2 levels (lower and upper limits) for each parameter. For instance, there are $2^8 = 256$ treatments (combinations) for eight parameters. It is not practical to run simulation model with such a large number of parameter sets. In addition, it is hard to investigate the main effect and interactions, as there are many high-order interactions. To overcome these difficulties, 2^{k-p} fractional factorial design, an experimental design method, is used to reduce the number of treatments to a feasible amount while still reasonably screening the main effects and low-order interactions of parameters.

Assume there are 3 parameters (A , B and C) in the simulation model, the upper limit of a parameter is represented by "+1", and the lower limit is "-1." To test the effect of the parameters, we have to run $2^3 = 8$ times. The relationship between the level of a parameter and the simulation output y can be expressed as a regression model $y \sim x$:

$$y = \beta_0 + \beta_1 x_A + \beta_2 x_B + \beta_3 x_C + \beta_4 x_A x_B + \beta_5 x_B x_C + \beta_6 x_A x_C + \beta_7 x_A x_B x_C + \varepsilon \qquad \textbf{(4-25)}$$

where β_0 represents the overall mean effect, and β_i represents either the main effect of the parameter or the interaction of multiple parameters. As x is "+1" or "-1," the following design matrix in Table 4.5 can be used to represent full factorial designs:

Table 4.5 Design Matrix for 2^3 Factorial Design

Intercept	Main Effect			Interaction				Observations
I	A	B	C	AB	BC	AC	ABC	$\bar{y}$
+1	+1	+1	+1	+1	+1	+1	+1	$\bar{y}_{abc}$
+1	+1	+1	-1	+1	-1	-1	-1	$\bar{y}_{ab}$
+1	+1	-1	+1	-1	-1	+1	-1	$\bar{y}_{ac}$
+1	+1	-1	-1	-1	+1	-1	+1	$\bar{y}_{a}$
+1	-1	+1	+1	-1	+1	-1	-1	$\bar{y}_{bc}$
+1	-1	+1	-1	-1	-1	+1	+1	$\bar{y}_{b}$
+1	-1	-1	+1	+1	-1	-1	+1	$\bar{y}_{c}$
+1	-1	-1	-1	+1	+1	+1	-1	$\bar{y}_{(1)}$

For the last column, $\bar{y}_{(1)}$ denotes observation when all parameters are at their lowest level (-1). Similarly, $\bar{y}_a$ denotes observation when parameter A is at its highest level (+1) while other parameters at their lowest level (-1). A similar pattern applies to other parameters. If we can only run half of the full design, we can choose a factorial effect to confound with blocks. For instance, if we choose ABC to confound the design matrix to two blocks shown in Table 4.6 and Table 4.7, then for each of the blocks, it is impossible to measure the effect of this high-order interaction. However, we can still estimate the main effects and other low-order interactions. The effect, ABC defines contrast and $I = ABC$ and $I = -ABC$ are defining relations for the design. The new design using either Table 4.6 or Table 4.7 is called a 2^{3-1} fractional factorial design.

Table 4.6 Design Matrix for 2^{3-1} Factorial Design (I=ABC)

Intercept	Main Effect			Interaction				Observations
I	A	B	C	AB	BC	AC	ABC	$\overline{y}$
+1	+1	+1	+1	+1	+1	+1	+1	$\overline{y}_{abc}$
+1	+1	-1	-1	-1	+1	-1	+1	$\overline{y}_a$
+1	-1	+1	-1	-1	-1	+1	+1	$\overline{y}_b$
+1	-1	-1	+1	+1	-1	-1	+1	$\overline{y}_c$

Table 4.7 Design Matrix for 2^{3-1} Factorial Design (I= -ABC)

Intercept	Main Effect			Interaction				Observations
I	A	B	C	AB	BC	AC	ABC	$\overline{y}$
+1	+1	+1	-1	+1	-1	-1	-1	$\overline{y}_{ab}$
+1	+1	-1	+1	-1	-1	+1	-1	$\overline{y}_{ac}$
+1	-1	+1	+1	-1	+1	-1	-1	$\overline{y}_{bc}$
+1	-1	-1	-1	+1	+1	+1	-1	$\overline{y}_{(1)}$

To measure the main effect of a parameter or its interactions, we can subtract the average observations where A is the lowest level (-1) from the average observations where A is the highest level (+1). Taking Table 4.6 as an example, the main effects of parameters A, B, and C are:

$$\beta_1 = \frac{(\overline{y}_{abc} + \overline{y}_a)}{2} - \frac{(\overline{y}_b + \overline{y}_c)}{2} \quad \textbf{(4-26)}$$

$$\beta_2 = \frac{(\overline{y}_{abc} + \overline{y}_b)}{2} - \frac{(\overline{y}_a + \overline{y}_c)}{2} \quad \textbf{(4-27)}$$

$$\beta_3 = \frac{(\overline{y}_{abc} + \overline{y}_c)}{2} - \frac{(\overline{y}_a + \overline{y}_b)}{2} \tag{4-28}$$

The effect of interactions, AB, BC, and AC are:

$$\beta_4 = \frac{(\overline{y}_{abc} + \overline{y}_c)}{2} - \frac{(\overline{y}_a + \overline{y}_b)}{2} \tag{4-29}$$

$$\beta_5 = \frac{(\overline{y}_{abc} + \overline{y}_a)}{2} - \frac{(\overline{y}_b + \overline{y}_c)}{2} \tag{4-30}$$

$$\beta_6 = \frac{(\overline{y}_{abc} + \overline{y}_b)}{2} - \frac{(\overline{y}_a + \overline{y}_c)}{2} \tag{4-31}$$

Equations 4-26 and 4-30 have the same results; equation 4-27 is the same as equation 4-31; and equation 4-28 is identical to equation 4-29. Such an effect is called alias of treatments. For instance, $\frac{(\overline{y}_{abc} + \overline{y}_a)}{2} - \frac{(\overline{y}_b + \overline{y}_c)}{2}$ estimates both the main effect of A and the interaction of BC, which can be denoted as:

$$\beta_1 + \beta_5 = \frac{(\overline{y}_{abc} + \overline{y}_a)}{2} - \frac{(\overline{y}_b + \overline{y}_c)}{2} \tag{4-32}$$

A and BC are aliased to each other. Using the defining relation, one can easily determine which effects are aliased. The rule is to multiply all elements of the defining relation by an effect and reduce exponents mod 2 (Oehlert, 2000). For instance, given defining relation $I = ABC$, we have:

$$A = A \times I = A \times ABC = A^2BC = BC$$

$$B = B \times I = B \times ABC = AB^2C = AC$$

$$C = C \times I = C \times ABC = ABC^2 = AB$$

Note that any effect multiplied by I remains the same, i.e., $A = A \times I$, and an effect multiplied by itself results in I, i.e., $A \times A = A^2 = I$.

If we run the simulation model using design matrix in Table 4.7, the definition relation is $I=-ABC$. Similarly, we can obtain all aliases $A=-BC$, $B=-AC$, and $C=-AB$. In turn, the following equation can be obtained to estimate both the main effect of A and the interactions of BC:

$$\beta_1-\beta_5=\frac{(\bar{y}_{ab}+\bar{y}_{ac})}{2}-\frac{(\bar{y}_{bc}+\bar{y}_{(1)})}{2} \tag{4-33}$$

If equations (4-31) and (4-32) are used together, we can de-alias the main effects of parameter A and BC interaction:

$$\beta_1=\frac{1}{2}\left[\frac{(\bar{y}_{abc}+\bar{y}_{a})}{2}-\frac{(\bar{y}_{b}+\bar{y}_{c})}{2}+\frac{(\bar{y}_{ab}+\bar{y}_{ac})}{2}-\frac{(\bar{y}_{bc}+\bar{y}_{(1)})}{2}\right] \tag{4-34}$$

$$\beta_5=\frac{1}{2}\left[\frac{(\bar{y}_{abc}+\bar{y}_{a})}{2}-\frac{(\bar{y}_{b}+\bar{y}_{c})}{2}-\frac{(\bar{y}_{ab}+\bar{y}_{ac})}{2}+\frac{(\bar{y}_{bc}+\bar{y}_{(1)})}{2}\right] \tag{4-35}$$

When both Table 4.6 and Table 4.7 are used, the design is called fold-over design. This can be implemented by reversing the signs of the main effects and interactions in a design matrix to obtain another design matrix.

The above illustrates the concept of a fractional factorial design for a 3-parameter example. Generally, if we confound additional effects, we can obtain a smaller design matrix. For a k-parameter simulation model, the 2^k full factorial design can be confounded into 2^q blocks of size 2^{k-q}. There are q generators. The defining relation includes the generators, and their multi-way interactions. This is called 2^{k-q} fractional factorial design. For example, assume that there are six parameters A, B, C, D, E, and F and we plan to do 8 runs instead of $2^6=64$ runs. Assuming the generators are ABD, ACE, and BCF, the defining relation is then:

$$I = ABD = ACE = BCF = BCDE = ACDF = ABEF = DEF$$

The alias structure can be obtained according to the aforementioned rule. The number of parameters in the shortest term (except I) in the defining relation is defined as a design resolution. In this case, the resolution is III , and the design can be denoted as 2_{III}^{6-3} . The resolution determines how the main effects are confounded with others. For screening design, the resolution should be at least III in order to investigate all main effects.

4.4 Algorithm for Parameter Estimation

4.4.1 Stochastic Approximation

Simulation models have many input parameters, and only part of these parameters can be determined directly on the basis of existing knowledge. After one has identified the critical parameters, estimations for their unknown values are needed. The estimating process usually requires running the simulation model for different parameter configurations and comparing the simulated results of the trials with the available observations. The black-box nature and stochastic output of the simulation model make quantifying precise parameter estimates very difficult. The process generally results in an optimization problem of a given cost function (the goodness-of-fit of the model) that has the following characteristics:

1. Calculation of the cost function is computationally time-consuming or expensive.
2. Exact first-order partial derivatives of the cost function cannot be computed.

3. Numerical approximation of the gradient of the cost function is impracticably expensive or slow.

Assume that $\Theta \subset R^p$ and $\theta \in \Theta$ is a vector with components representing the parameters of our simulation model. Let $L(\theta)$ be the loss function of interest. Assume the measurements of $L(\theta)$ are $z(\theta)$, which are available at any given θ with the stochastic zero-mean noise ε of the system, where

$$z(\theta) = L(\theta) + \varepsilon(\theta) \tag{4-36}$$

For example, $L(\theta)$ may represent the mean response with input parameters θ, and $z(\theta)$ may represent the outcome of one simulation experiment at θ. In some problems, exact loss-function measurement is available, and the corresponding noise is set to $\varepsilon = 0$. When the exact values of the loss-function are unavailable and are estimated, our objective is to minimize the loss function:

$$\begin{aligned} \min \quad & L(\theta) \\ s.t. \quad & \theta \in \Theta \end{aligned} \tag{4-37}$$

In this study, we consider the stochastic approximation (SA) approach to estimate the parameters in equation 4-37. The SA approach is a cornerstone of the stochastic optimization technique. The general form of the algorithm takes the following iterative form:

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k g_k(\hat{\theta}_k) \tag{4-38}$$

where $g_k(\hat{\theta}_k)$ is the gradient of $L(\theta)$ at parameter vector $\theta = \hat{\theta}_k$, and a_k is a positive gain sequence of step sizes.

The SA approach attempts to mimic the gradient search method used in deterministic optimization. Based on equation 4-38, the recursive procedure must obtain the gradient of the objective function in order to update the parameters in the kth iteration. The Robbins-Monro algorithm (Robbins and Monro, 1951) can be used to perform parameter updates when the gradient of the loss-function is available. However, our simulation model does not allow the computation of $g(\theta) = \partial L(\theta) / \partial \theta$. Thus, it is necessary to get an approximation to $g(\theta)$. When a finite-difference (FD) method (Dennis and Schnabel, 1989) is used to approximate the gradient, the well-known form of SA called the Kiefer-Wolfowitz algorithm (Kiefer and Wolfowitz, 1952) is obtained. Considering the problem of minimizing the objective function shown in equation 4-37, the general iterative form is developed as:

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \hat{g}_k(\hat{\theta}_k) \qquad \textbf{(4-39)}$$

where a_k is a positive gain sequence of step sizes, and $\hat{g}_k(\hat{\theta}_k)$ is the approximation of $g(\theta)$ at each iteration.

To obtain the approximation, two types of FD approximation $\hat{g}(\hat{\theta}_k)$ can be used: the one-sided gradient approximation involving measurements $z(\theta)$ and $z(\theta + perturbation)$ shown in equation 4-40; and the two-sided approximation involving measurements $z(\theta \pm perturbation)$ shown in equation 4-41.

$$\hat{g}_k(\hat{\theta}_k) = \begin{bmatrix} \dfrac{z(\hat{\theta}_k + c_k \xi_1) - z(\hat{\theta}_k)}{c_k} \\ \cdots \\ \dfrac{z(\hat{\theta}_k + c_k \xi_p) - z(\hat{\theta}_k)}{c_k} \end{bmatrix} \qquad \textbf{(4-40)}$$

$$\hat{g}_k(\hat{\theta}_k) = \begin{bmatrix} \dfrac{z(\hat{\theta}_k + c_k\xi_1) - z(\hat{\theta}_k - c_k\xi_1)}{2c_k} \\ \cdots \\ \dfrac{z(\hat{\theta}_k + c_k\xi_p) - z(\hat{\theta}_k - c_k\xi_p)}{2c_k} \end{bmatrix} \quad \textbf{(4-41)}$$

where ξ_i denote a p-vector with a 1 in the ith place and 0 elsewhere; c_k are gain sequences.

The FD method is widely used in practice. However, it is not computationally efficient as the number of parameters increases. For instance, the one-sided FD approximation needs $p+1$ functions calculations, and the two-sided FD approximation needs $2p$ functions calculations. The computation effort increases linearly with the parameter size p. To address this difficulty, we will use the simultaneous perturbation stochastic approximation (SPSA) algorithm as the alternative to the FD method. The SPSA algorithm was developed by Spall (1987, 1988, 1992), and it requires only two function evaluations to estimate the gradient at each recursion, regardless of the dimension of the parameters vector θ. Details about the algorithm are presented in the next section.

4.4.2 SPSA Calibration Algorithm

The simultaneous perturbation SA (SPSA) algorithm was introduced by Spall (1987, 1988, 1992) and expanded in subsequent work (Fu and Hill, 1997; Sadegh, 1997; Kunde, 2002; Bhatnagar and Borkar, 2003; Lee and Ozbay, 2009). Beginning with the generic SA form in equation 4-41, we now present the simultaneous perturbation form of the gradient approximation. Unlike the FD method, all components of parameter vector

γ are randomly perturbed together to obtain measurements $z(\cdot)$ of the loss function for SPSA. For the two-sided SP gradient approximation involving $z(\theta \pm perturbation)$, this corresponds to the following form (Spall, 1992):

$$\hat{g}_k(\hat{\theta}_k) = \begin{bmatrix} \dfrac{z(\hat{\theta}_k + c_k\Delta_k) - z(\hat{\theta}_k - c_k\Delta_k)}{2c_k\Delta_{k1}} \\ \cdots \\ \dfrac{z(\hat{\theta}_k + c_k\Delta_k) - z(\hat{\theta}_k - c_k\Delta_k)}{2c_k\Delta_{kp}} \end{bmatrix} = \frac{z(\hat{\theta}_k + c_k\Delta_k) - z(\hat{\theta}_k - c_k\Delta_k)}{2c_k} \begin{bmatrix} \Delta_{k1}^{-1} \\ \Delta_{k2}^{-1} \\ \cdots \\ \Delta_{kp}^{-1} \end{bmatrix} \quad \textbf{(4-42)}$$

As the numerator in equation 4-42 is the same for each component of $\hat{g}_k(\hat{\theta}_k)$, the number of function evaluations needed to estimate the gradient in SPSA is only two. This provides the potential for a large improvement of the overall efficiency of optimization analysis. At iteration step k, we take a random perturbation vector:

$$\Delta_k = [\Delta_{k1}, \Delta_{k2}, \ldots, \Delta_{kp}]^T \quad \textbf{(4-43)}$$

where Δ_{ki} denote a sequence of independent, identically, symmetrically distributed, bounded random variables satisfying certain conditions (Spall, 1992). A standard perturbation can be a sequence Δ_{ki} of Bernoulli ± 1 distribution with probability $P(\Delta_{ki} = +1) = 1/2$ and $P(\Delta_{ki} = -1) = 1/2$.

The convergence of the gradient approximation has been proven and documented in the literature (Spall, 1992; Kushner and Yin, 1997). Generally, the gain sequences should monotonically decrease to zero at a certain rate that is neither too fast nor too slow. They are used to balance the algorithm stability. Some standard conditions imposed on the two gain sequences are given below:

$$
\begin{aligned}
&a_k, c_k > 0 \forall k \\
&a_k \to 0, c_k \to 0 \qquad as\, k \to \infty \\
&\sum_k a_k = \infty \\
&\sum_k (\frac{a_k}{c_k})^2 < \infty
\end{aligned}
\tag{4-43}
$$

Common gain sequences of a_k and c_k are positive with the form of power functions shown in equations (4-44) and (4-45):

$$a_k = \frac{a}{(1 + A + k)^{\alpha}} \tag{4-44}$$

$$c_k = \frac{c}{(1 + k)^{\gamma}} \tag{4-45}$$

where a, c, α, γ, and A are the coefficients. a and c control the noise setting. A is a constant introduced to stabilize the optimization process. The exponents α and γ control the speed of the convergence. Li *et al.* (2006) presented typical constraints for α and γ shown in equation 4-46.

$$
\begin{aligned}
&a, c > 0 \\
&A \geq 0 \\
&0 < \gamma < \alpha < 1 \\
&\alpha - 2\gamma > 0 \\
&3\gamma - a / 2 \geq 0
\end{aligned}
\tag{4-46}
$$

For more practical use, these coefficients can be determined based on some guidelines given by Spall (1998). For instance, practically effective and theoretically valid values for α and γ can be 0.602 and 0.101, respectively.

The step-by-step implementation of the modified SPSA algorithm as part of the simulation calibration approach is summarized below:

Step 1: Initialization and Parameter Selection

Set the iteration index k=0. Pick initial guess $\hat{\theta}_0$ for equation 4-4. In our simulation model, we can use the default values as an alternative. Select the nonnegative algorithmic coefficients a , c , α , γ , and A .

Step2: Generation of Simultaneous Perturbation Vector

Generate a p -dimensional random perturbation vector Δ_k , where each of the p components of Δ_k is independently generated from a Bernoulli ± 1 distribution with probability of 0.5 for each ± 1 outcome.

Step 3: Loss Function Evaluations

Run the simulation model with perturbed parameters $\hat{\theta}_k \pm c_k \Delta_k$ based one c_k and Δ_k from Step 1 and Step 2. Obtain two measurements of the loss function: $z(\hat{\theta}_k + c_k \Delta_k)$ and $z(\hat{\theta}_k - c_k \Delta_k)$.

Step 4: Gradient Approximations

Compute the simultaneous perturbation approximation to the unknown gradient $\hat{g}_k(\hat{\theta}_k)$ according to equation 4-7.

Step 5: Update Parameter Estimation $\hat{\theta}_k$

Use the recursive equation 4-4 to update $\hat{\theta}_k$ to a new value $\hat{\theta}_{k+1}$. Check for the violation of constraints and modify the updated θ if necessary.

Step 6: Check Convergence

Check whether the maximum number of iterations has been reached or the convergence criterion has been met. If not, return to Step 2 with iteration $k+1$. If so, terminate the algorithm and report the optimal values of parameters θ .

To make the SPSA algorithm more suitable for the analysis in this study, several enhancements have been made:

(1) original simulation parameters have been normalized to 0-1.0 for perturbation in step 3, and inverse scaling of the perturbed parameters has been performed when running the simulation ,

(2) multiple simulation runs with different random seeds have been conducted to obtain the average gradient in step 4, and

(3) multiple initial parameters for the simulation were tested and compared to obtain better parameters.

4.5 The Effect of Random Seeds

When running the simulation model, considering the stochastic nature of the simulation model, a relatively large number of runs must be conducted in order to capture a more accurate representation of traffic conditions. Paramics uses random seeds to assign different driver behavior parameters to each simulated DVU. For instance, a simulation run with a random seed of 121 may assign an awareness value of 7 to a vehicle. If a different random seed is used, the awareness value may be changed. Different random seeds finally result in different traffic operations and simulated measures of effectiveness.

To get statistically robust results from the simulation experiments, the number of simulation scenarios with different random seeds is identified to meet a stated objective. Based on these considerations, a sequential approach is used for determining the number of replications required in the simulation analysis. This statistical procedure aims at obtaining the mean $\mu = E(X)$ of the selected measures of effectiveness (MOE) X, within a specified precision. If we estimated $\bar{X}$ such that $|\bar{X} - \mu| / |\mu| = \gamma$, then γ is called the relative error of $\bar{X}$. The specific objective of this approach is to obtain an estimated μ with a relative error of γ and a confidence level of $100(1-\alpha)$ percent. Denote the half-length of the confidence interval by $\delta(n,\alpha)$. Further details about the approach are as follows (Law and Kelton, 2000):

(1) Make an initial number of n_0 replications of the simulation and set $n = n_0$, then calculate initial (crude) estimates $\bar{X}(n)$ and $S^2(n)$ from $X_1, X_2, ..., X_n$;

(2) Decide the size of allowable relative error $\gamma = |\bar{X} - \mu| / |\mu|$;

(3) Calculated the adjusted relative error $\gamma' = \gamma / (1-\gamma)$;

(4) Decide the level of significance α;

(5) Calculate half-length of the confidence interval $\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{S^2(n)/n}$;

(6) If $\delta(n,\alpha)/|\bar{X}(n)| \le \gamma'$, use $\bar{X}(n)$ as the point estimate for μ and stop, or else make one more replication and set $n = n+1$, then go back to step 2.

This approach assumes identical, independent (IID) outcomes, but they need not be normally distributed. Thus the estimates of $\bar{X}(n)$ and $S^2(n)$ for the mean and variance, as well as the estimation of the confidence interval, will become better with the incremental iteration.

4.6 Model Calibration Framework

The previous sections presented important components when calibrating a simulation model. Figure 4.4 shows the framework of how to systematically implement a calibration procedure. Briefly, at the first stage the simulation model is developed according to the actual geometric configuration of the facilities, and important background information is collected. At the second stage, the important parameters are identified through statistical experiments. Then the SPSA algorithm is applied to estimate the input value of the selected parameters. This is an iterative process until acceptable values are determined. Finally, validations are conducted to further confirm the reliability of the calibrated parameters.

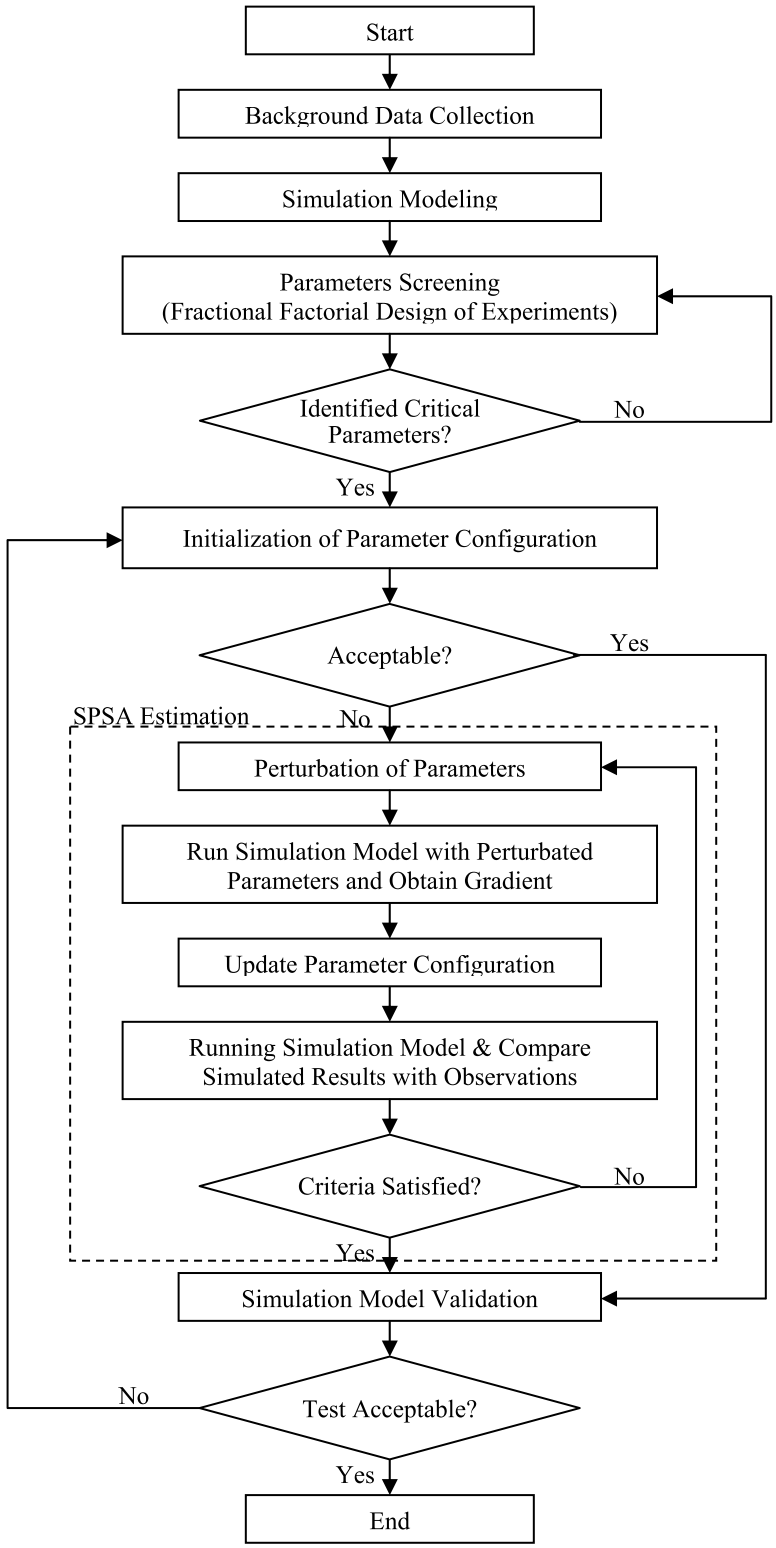


Figure 4.4 Proposed process for the simulation model calibration

Chapter 5 Calibration of Microscopic Simulation Model Using Trajectory Data

The main objective of this section is to test the validity of the proposed surrogate safety measure based on simulation and the efficiency of the proposed calibration approach. The stochastic approximation approach proposed in the previous chapter and the multi-criteria optimization method are used to estimate optimal parameters, and high-resolution vehicle trajectory data are used as major sources of observed data. The proposed calibration approach is further validated by comparing simulated results with actual observations of additional trajectory data not used for calibration.

5.1 Multi-criteria Optimization

Calibration of a micro-simulation model can be defined as the problem of finding a set of optimal parameters to optimize the difference between simulation output and corresponding observations. The simulation output can be a set of measurements such as flow, speed, and travel time. The difference between each simulated measurement and its observation can be used to quantify a performance criterion. Essentially, calibration is a multi-objective optimization problem, though only one of the performance criteria is frequently studied in practice. Mathematically, the problem of calibration can be described as finding the parameter set $\theta^* = [\theta_1^*, \theta_2^*, ..., \theta_n^*]$ that can optimize the objective function set $z(\theta)$:

$$z(\theta) = [z_1(\theta), z_2(\theta), ..., z_m(\theta)]^T \quad \textbf{(5-1)}$$

Here, "optimize" means that the optimal parameter set θ^* can yield the solution of each performance criterion $z_i(\theta)$ at a defined acceptable level. For example, one criterion is to find θ^* to minimize the difference between simulated and observed traffic counts, and another is to reduce the difference of simulated and observed travel times to less than 5 percent. Specifically, the objective function defined as $z(\theta)$ in this paper consists of both safety and operational performance criteria. It should be noted that these performance criteria may be in conflict with each other. In other words, it is rarely the case that a single set θ^* can simultaneously optimize all of the performance criteria. There is no choice but to search somehow the "space of tradeoffs" among the safety and operational performance criteria. The search process is complicated and challenging, as the space of tradeoffs is usually not small. In this study, we use the idea of multi-criteria optimization approaches, the point estimate weighted-sums method (Steuer, 1986), to simplify the typical calibration problem in terms of minimizing differences between simulated output and observations.

The point estimate weighted-sums method can be described as follows:

$$\min\ z(\theta) = \omega_1 z_1(\theta) + \omega_2 z_2(\theta) + \ldots + \omega_m z_m(\theta) \qquad \textbf{(5-2)}$$

where ω_i is a user defined non-negative scalar weight of the i^{th} performance criterion $z_i(\theta)$. $z(\theta)$ becomes the aggregated objective function. Θ is the possible domain of parameters to be calibrated. If there is no interest to calibrate the specific $z_k(\theta)$, one can set $\omega_k = 0$. Otherwise, a positive scalar weight has to be assigned to each performance criterion. Without loss of generality, we can assume that $\omega_1 + \omega_2 + \ldots + \omega_m = 1$. The method looks straightforward to aggregate safety and operational performance measures.

By using the scalar weights, the multi-objective of the optimization problem is converted into a single criterion problem that is easier to analyze. Moreover, each ω_i can be modified to reflect the importance attached to this individual criterion by the model or other users of the model.

5.2 Description of Vehicle Trajectory Data

A field vehicle tracking dataset namely the "I-101 Dataset" generated by the NGSIM program was obtained to demonstrate the implementation of the proposed methodology. The dataset is "*specifically collected to improve the quality and performance of simulation tools, promote the use of simulation for research and applications, and achieve wider acceptance of validated simulation results" (FHWA, 2005)*. The data were collected at a segment of southbound of U.S. Highway 101 in the Universal City neighborhood of Los Angeles, California. A schematic illustration of the location is shown in Figure 5.1. The length of the segment used for data collection was approximately 2100 feet. The length of the auxiliary lane for on-ramp vehicle merging and vehicle diverging is about 698 ft. About 6,000 vehicle trajectories were collected based on video data with a 0.1-second time increment. This amount of detailed trajectory data is unique compared with previous traffic studies and provides a better basis to objectively investigate real-world traffic conflicts. The dataset was also separated into three 15-minute periods representing transitional and congested flow conditions in the morning on June 15, 2005. Data between 08:05 AM and 08:20 AM were retrieved for model calibration, and data between 08:20 AM and 08:35 AM were used for validation.

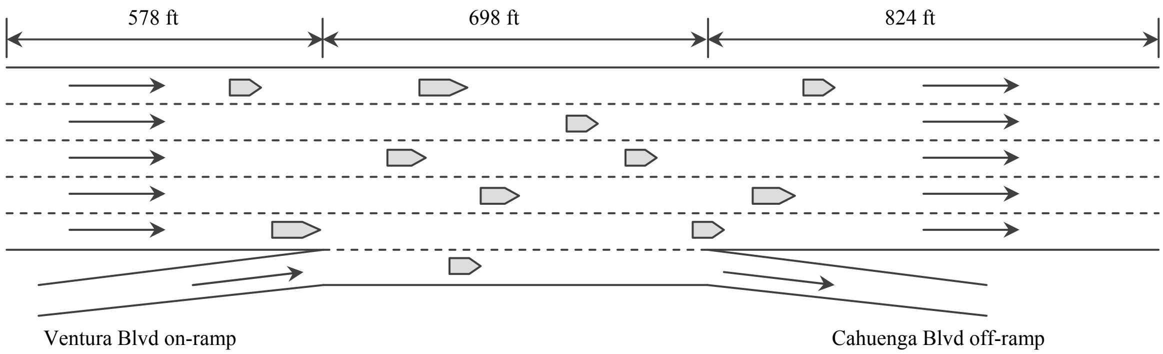


Figure 5.1 Study area schematic of I-101

5.3 Defining Objective Functions

Both safety performance and operational performance of the section are considered using the multi-criteria optimization approach. The operational performances are measured through traditional traffic measures including flow, speed, and lane change. Safety performance is described by the proposed surrogate measure CP. Depending on the objective, CP of vehicles can be aggregated by time and space to describe the conflict risk of the facility. In this study, the conflict risk C_m is represented by aggregating the simulated CPs over the m^{th} section (100 ft) and simulation time period (15 minutes).

Specifically, the following objective functions in terms of root mean square percentage error (RMSPE) have been defined as $z(\theta)$ to calibrate the simulation model:

$$\min\ z_1(\theta) = \sqrt{\frac{1}{M}\sum_{m=1}^{M}\left[\frac{C_m^s - C_m^o}{C_m^o}\right]^2} \tag{5-3}$$

$$\min\ z_2(\theta) = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left[\frac{L_n^s - L_n^o}{L_n^o}\right]^2} \tag{5-4}$$

$$\min\ z_3(\theta) = \sqrt{\frac{1}{I}\sum_{i=1}^{I}\left[\frac{F_i^s - F_i^o}{F_i^o}\right]^2} \quad \textbf{(5-5)}$$

$$\min\ z_4(\theta) = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\left[\frac{V_j^s - V_j^o}{V_j^o}\right]^2} \quad \textbf{(5-6)}$$

Based on the point estimate weighted-sums method, we defined the aggregate objective function $z(\theta)$ as follows:

$$\begin{aligned}\min z(\theta) &= \omega_1 z_1(\theta) + \omega_2 z_2(\theta) + \omega_3 z_3(\theta) + \omega_4 z_4(\theta) \\ &= \omega_1\sqrt{\frac{1}{M}\sum_{m=1}^{M}\left[\frac{C_m^s - C_m^o}{C_m^o}\right]^2} + \omega_2\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left[\frac{L_h^s - L_h^o}{L_h^o}\right]^2} + \omega_3\sqrt{\frac{1}{I}\sum_{i=1}^{I}\left[\frac{F_i^s - F_i^o}{F_i^o}\right]^2} + \omega_4\sqrt{\frac{1}{J}\sum_{j=1}^{J}\left[\frac{V_j^s - V_j^o}{V_j^o}\right]^2}\end{aligned} \quad \textbf{(5-7)}$$

where $z(\theta)$ quantifies the overall error of the simulation and $z_1(\theta)$, $z_2(\theta)$, $z_3(\theta)$, and $z_4(\theta)$ are criteria that quantify the performance of traffic conflict, lane change, traffic count and speed, respectively. C_m^o, L_n^o, F_i^o, and V_j^o are observations of traffic conflict risk, lane change, traffic count, and speed value, respectively. C_m^s, L_n^s, F_i^s, and V_j^s are the corresponding simulated values. M, N, I, and J are total numbers of observations. Calibrations have been separately implemented considering each single objective function and the aggregated objective function.

5.4 Screening Key Parameters

The Paramics simulation tool is selected as our test platform to model the study section mainly because of our previous experience with this tool as well as its relatively superior customization potential. The simulated trajectory information obtained through the Application Programming Interface (API) facility of Paramics provides vehicle position, speed, and acceleration for a user-defined small time resolution. These simulated data provide sufficient information to numerically compute the surrogate safety measure and other operational measures. Major parameters of the simulation model have been summarized in Table 5.1. The search space defined by factors ranging from A to K consists of an eleven-dimensional hyperplane. It is difficult to enumerate all possible parameter sets on the hyperplane and to run a simulation model with all the sets.

Table 5.1 Potential Parameters to Be Analyzed

Factor	Parameters	Default Value	Feasible Range	Low Level (-1)	High Level (+1)
A	Mean Target Headway (s)	1.0	0.5 to 3.0	0.5	3.0
B	Mean Driver Reaction Time (s)	1.0	0.5 to 2.0	0.5	2.0
C	Minimum Gap (ft)	5.00	1.0 to 9.0	1.0	9.0
D	Queue Gap Distance (ft)	32.81	5.0 to 40.0	5	40
E	Queue Speed (mph)	4.47	1.0 to 8.0	1.0	8.0
F	Link Headway Factor	1.0	0.5 to 2.0	0.5	2.0
G	Link Reaction Factor	1.0	0.5 to 2.0	0.5	2.0
H	Signpost (ft)	696..2	1.0 to 1500.0	1.0	1500.0
I	Speed Memory	5	1 to 20	1	20
J	Driver Aggressiveness	4	1 to 8	1	8
K	Driver Awareness	4	1 to 8	1	8

Instead of using the enumeration method, the key parameter selection method presented in the last chapter has been used to investigate some important parameters. The upper limit and lower limit of each parameter have been described as high level “+1” and low level “-1,” as shown in Table 5.1. To investigate the main effects and low-order interactions of parameters, we use ABCF, BCDG, CDEH, ACDI, ADEJ, and BDEK as generators to construct a 2_{IV}^{11-6} fractional factorial design of an experiment of 32 runs. The structure of the design is shown in Appendix A. The defining relations are I = ABCF=BCDG=CDEH=ACDI=ADEJ=BDEK=all aliases of these generators (Note: here, “ I ” means defining relation, and “I” is parameter “I” in Table 5.1). The aliases can be found using the rule presented in the last chapter. As a design of resolution IV, no main effects are confounded with any 2-factor interactions in this experiment. They are only confounded with 3-factor or higher interactions.

When one is running the simulation, the parameter set is configured according to the experiment design presented in Appendix A. All 32 runs are conducted in random order. Considering the random effect in the simulation model, nine simulation replications are carried out for each run to reduce the random effects of different simulation seeds. The average results of these simulation replications are summarized in Appendix B1. To investigate the effect of parameters, ANOVA tables have been presented in Appendix B2-B5 according to the performance measures. Depending on the performance measure, the parameters play different roles. For instance, when the conflict risk measure is used as the simulation measure, the queue gap distance's effect is not significant. However, it will significantly affect other simulation measures.

If more performance measures are considered, few parameters can be ignored. In our case, though each parameter may affect operational and/or safety performance, calibration of the last three discrete parameters is outside the scope of this study. The SPSA-based approach is then used to search acceptable parameter sets in a faster manner.

5.5 Simulation Results and Discussion

5.5.1 Calibration Results

NGSIM provides summarized lane change and speed information for each sub-section (100-ft) of the entire segment (2100-ft) in its summary reports (FHWA, 2005). These values are used as baseline data when computing $z_2(\theta)$ and $z_4(\theta)$, respectively.

The simulated throughput and the reported 15-minute throughput are compared to obtain $z_3(\theta)$. To obtain $z_1(\theta)$, traffic conflict probability is calculated using the original trajectory data and the simulated trajectories. Only one percent of all car-following scenarios are sampled. This is equivalent to screening the status of an individual vehicle every 10 seconds. The conflict probability of each sample is then calculated using equation 3-24 and aggregated by sub-section. $z(\theta)$ is computed based on equation 5-7.

To confirm the need for adequate model calibration, initial runs with default input parameters and 13 sets of guessed input parameters were also conducted. The simulation results based on these input parameter sets are presented in Table 5.2. No matter which performance measure is used, simulation results are found to be unstable. For instance, $z_1(\theta)$ ranges from 0.176 to 0.706, and $z_2(\theta)$ varies from 0.243 to 1.820. The large variance of these performance measurements suggests that neither default values nor guessed parameter sets can definitely yield optimal results. It is thus necessary to calibrate the parameters.

Table 5.2 Simulation Results based on Different Parameter Guesses

Initial Inputs	Value of Parameters (θ)								Simulation Results				
	A	B	C	D	E	F	G	H	$z_1(\theta)$	$z_2(\theta)$	$z_3(\theta)$	$z_4(\theta)$	$z(\theta)$
Default	1.00	1.00	6.56	32.81	4.47	1.00	1.00	696.20	0.353	0.243	0.056	0.155	0.202
Guess 1	0.90	1.60	6.00	10.00	2.80	1.50	0.70	700.00	0.364	0.309	0.184	0.230	0.272
Guess 2	1.45	0.75	7.30	27.00	7.50	1.20	1.10	800.00	0.176	0.416	0.179	0.144	0.229
Guess 3	0.90	0.90	6.20	15.00	7.00	1.70	1.70	1450.00	0.529	0.508	0.239	0.123	0.350
Guess 4	0.70	0.70	4.50	22.81	4.90	1.50	1.50	570.00	0.292	0.300	0.053	0.102	0.187
Guess 5	1.80	1.50	6.60	29.00	6.40	1.20	1.20	1350.00	0.571	1.029	0.397	0.168	0.541
Guess 6	1.68	1.45	3.30	24.00	6.50	1.20	1.20	570.00	0.595	1.111	0.349	0.154	0.552
Guess 7	1.60	1.30	7.70	40.00	5.00	1.00	1.00	800.00	0.302	0.264	0.256	0.212	0.259
Guess 8	1.70	1.30	4.20	36.00	5.20	1.35	1.85	1000.00	0.706	1.820	0.456	0.143	0.781
Guess 9	1.25	1.05	4.30	28.00	3.15	1.30	0.50	630.00	0.194	0.440	0.099	0.153	0.222
Guess 10	1.75	1.35	5.20	15.00	4.75	1.40	0.70	300.00	0.324	0.360	0.307	0.177	0.292
Guess 11	0.75	1.70	6.00	10.00	2.80	1.50	0.75	720.00	0.592	0.301	0.171	0.225	0.322
Guess 12	1.50	1.50	7.30	32.00	5.90	1.20	1.00	900.00	0.417	0.340	0.314	0.197	0.317
Guess 13	2.40	1.70	6.00	19.00	5.50	1.00	1.00	1200.00	0.555	1.187	0.457	0.283	0.621

The SPSA-based extended calibration approach described in the previous section of this paper is employed to calibrate the input parameters. Initially, the simulation model is calibrated just using a single objective function in terms of the measurements of conflict risk, lane change, throughput, or speed (shown in equations 5-3 to 5-6). After calibrating the simulation model using a single performance criterion, the model is then calibrated based on the aggregated multi-criteria objective function shown in equation 5-7. Figure 5.2 (a) illustrates an example of the convergence diagram using the measurements of conflict risk as the calibration objective function $z_1(\theta)$. Despite using different initial guessed parameter sets, the fitted values of $z_1(\theta)$ converged after a number of iterations using SPSA. Similarly, Figure 5.2 (b) shows the convergence diagram of the fitted value of $z(\theta)$. The converged value of $z(\theta)$ is about 0.15.

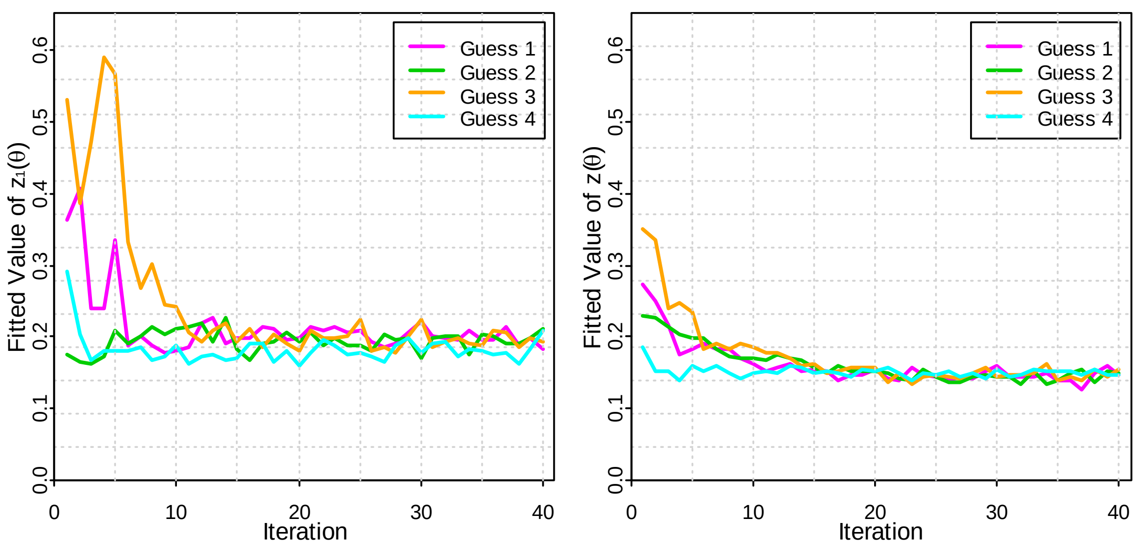


Figure 5.2 Calibration convergence diagram: a) single criterion (left), b) multi-criteria (right)

Table 5.3 presents an example of the final calibrated results when running a simulation with the initial input parameters of guessed vector 4 (listed in Table 5.2).

Similarly, Table 5.4 summarizes the results of guessed vector 5. The parameter set is either calibrated by minimizing a single objective function, $z_i(\theta)$ (i=1, 2, 3, and 4), or the multi-criteria objective function, $z(\theta)$. When an objective function is minimized, the corresponding measurements of the other four performance functions are also obtained. For instance, the first row in Table 5.4 shows that $z_1(\theta)$ is the objective function and its minimized value is 0.137. In the meanwhile, the measured $z_2(\theta)$, $z_3(\theta)$, $z_4(\theta)$, and $z(\theta)$ are calculated as 0.403, 0.117, 0.143, and 0.200, respectively, for this specific calibration scenario.

Table 5.3 Calibration Results Using Different Objective Functions (Initial: Guess 4)

Objective Function	Calibrated Value of Parameters (θ)								Simulation Results				
	A	B	C	D	E	F	G	H	$z_1(\theta)$	$z_2(\theta)$	$z_3(\theta)$	$z_4(\theta)$	$z(\theta)$
$\min z_1(\theta)$	0.50	0.50	6.72	17.47	4.08	1.40	1.06	522.73	0.210	0.273	0.051	0.079	0.153
$\min z_2(\theta)$	0.72	0.52	5.83	15.10	5.26	0.69	1.27	934.07	0.216	0.269	0.051	0.088	0.156
$\min z_3(\theta)$	0.50	0.58	4.33	20.37	5.04	1.35	1.32	551.50	0.177	0.322	0.051	0.077	0.157
$\min z_4(\theta)$	0.50	0.53	4.27	23.85	5.37	1.40	1.47	599.39	0.204	0.288	0.052	0.077	0.155
$\min z(\theta)$	0.50	0.50	3.38	18.36	3.86	1.19	1.22	769.03	0.174	0.290	0.051	0.076	0.148

Table 5.4 Calibration Results Using Different Objective Functions (Initial: Guess 5)

Objective Function	Calibrated Value of Parameters (θ)								Simulation Results				
	A	B	C	D	E	F	G	H	$z_1(\theta)$	$z_2(\theta)$	$z_3(\theta)$	$z_4(\theta)$	$z(\theta)$
$\min z_1(\theta)$	1.28	0.63	8.27	13.81	6.40	1.21	0.75	1452.26	0.137	0.403	0.117	0.143	0.200
$\min z_2(\theta)$	1.96	0.80	3.39	35.97	5.98	1.75	0.57	536.59	0.426	0.330	0.332	0.152	0.310
$\min z_3(\theta)$	0.58	0.92	7.15	27.13	6.37	0.87	1.03	1036.37	0.196	0.299	0.051	0.087	0.158
$\min z_4(\theta)$	1.51	1.13	7.59	31.94	5.82	1.54	1.40	1239.80	0.520	0.331	0.376	0.125	0.338
$\min z(\theta)$	0.50	0.99	8.50	35.80	5.98	1.61	0.71	1137.27	0.191	0.271	0.052	0.091	0.151

The difference between the final calibrated parameters across the tables suggests that there are multiple quasi-optimal solutions for simulation models and that SPSA is still a local optimization algorithm that can find one of the many possible quasi-optimal solutions. To obtain optimal results, use of multiple initial input parameter sets is recommended. The calibrated results in both tables also suggest that minimization of safety performance function cannot guarantee the minimization of the operational performance functions, and vice versa. For instance, when the safety criterion $z_1(\theta)$ is the selected objective function, the corresponding value of lane-change criterion $z_2(\theta)$ is 0.403 in Table 5.4. However, lower values of 0.330 can be obtained if $z_2(\theta)$ is selected as the objective function. By comparing two tables we found that when $z(\theta)$ is the objective function, the measurement of each performance function is more stable than that of using a single objective function $z_i(\theta)$. The minimized values of $z(\theta)$ are about 0.15 in both tables. The corresponding $z_1(\theta)$ is about 0.19, $z_2(\theta)$ is about 0.29, $z_3(\theta)$ is about 0.05, and $z_4(\theta)$ is about 0.09. Though not all of the criteria are simultaneously minimized, $z(\theta)$ avoids the cases of minimizing a single criterion by significantly deteriorating the performance of other criteria. Therefore, $z(\theta)$ is the preferred approach because when $z(\theta)$ is minimized all of the four performance functions can be equally considered.

5.5.2 Validation Test

To evaluate the performance of the calibration model, optimized input parameters are tested using NGSIM trajectory data collected between 08:20 AM and 08:35 AM. The data were collected at the same peak hour as the data used for parameter calibration. Thus, it is expected that the calibrated parameters should be applicable to this period. The simulated conflict risk, lane changes, speed, and throughput are then compared with the computed results using the actual trajectory data. Figure 5.3 illustrates validation results when using calibrated input parameters. Apparently, simulated results can accurately capture observed conflict risk, lane change, and speed along the 2100-ft segment. Both simulated results using the calibrated parameter set and actual results show that: (a) conflict risks are higher for the upstream of the weaving section; (b) the majority of lane changes occur at the weaving section; and (c) speed when approaching the weaving section is lower, whereas the speed of its downstream is higher. Table 5.5 compares simulation results based on the calibrated parameter set with the original guessed set. The RMSPE of traffic conflict risk is reduced from 0.566 to 0.123. Similarly, the RMSPE of other measures is also greatly reduced. Observed throughput is 1915 vehicles, and simulated throughput using a calibrated parameter set is 1847 vehicles. These findings suggest that the calibrated model shows generally good performance in comparison with actual observations.

Table 5.5 Validation Results Using a Calibrated Parameter Set

Parameter Set	Parameters (θ)								RMSPE				
	A	B	C	D	E	F	G	H	$z_1(\theta)$	$z_2(\theta)$	$z_3(\theta)$	$z_4(\theta)$	$z(\theta)$
Guess	1.80	1.50	6.60	29.00	6.40	1.20	1.20	1350.00	0.566	4.165	0.350	0.094	1.294
Calibrated	0.50	0.99	8.50	35.80	5.98	1.61	0.71	1137.27	0.123	0.582	0.035	0.054	0.199
Difference (%)									78.27	86.03	90.00	42.55	84.62

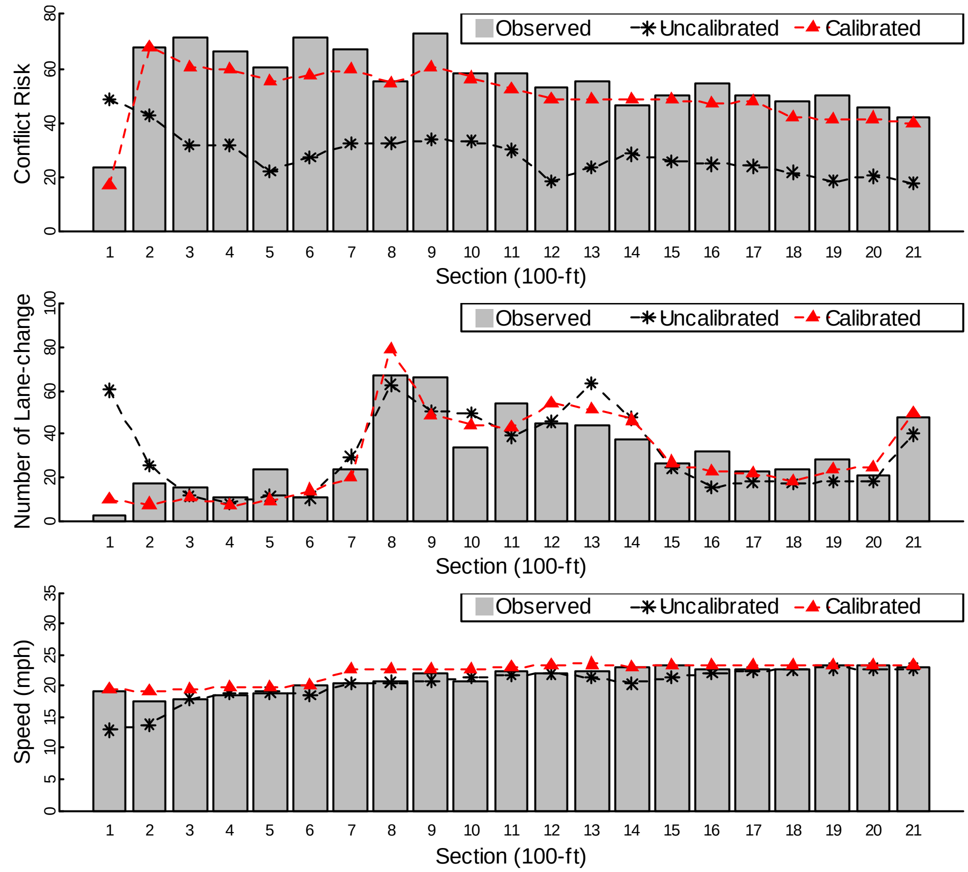


Figure 5.3 Simulation results using uncalibrated parameters and calibrated parameters versus observations: conflict risk (top), lane-change (middle), speed (bottom)

5.6 Summary

This chapter uses the proposed approach presented in the previous chapter to calibrate the micro-simulation model for traffic conflict analysis. It has been found that neither default parameters in the simulation model nor randomly guessed parameters can guarantee the accuracy of the simulation model. Moreover, calibration of the simulation model using a single criterion may cause deterioration of other important criteria. When one is simulating traffic conflict risk, the accuracy of safety performance is of great interest. However, calibration solely based on safety criteria can be in conflict with other operational performance criteria such as speed and traffic counts. Instead of solely calibrating to optimize the model's estimates in terms of safety performance and ignoring operational criteria, this study adopted the concept of multi-criteria optimization by simultaneously considering all of these criteria together. The weighted-sums method is then used to simplify the calibration problem by developing an aggregated objective function. Since there are many input parameters that need to be calibrated, it is impossible to enumerate all possible combinations and run the simulation model for all these combinations. To efficiently find the optimal parameters of the highly stochastic simulation model, the SPSA approach is used to perturbate and to update all parameters in the searching process. The approach has been shown to be able to find the acceptable parameter set in a relatively fast manner. The proposed SPSA-based multi-criteria calibration approach is implemented using the Paramics traffic simulation platform for a study network for which vehicle trajectory data are available through the NGSIM program (FHWA, 2005). In the case study, this stochastic and gradient-based calibration approach is shown to be able to identify input parameters that make the aggregate objective function quickly converge to a stable, almost optimal value. The consistency of the calibrated parameters has been further validated by using additional 15-minute vehicle trajectory data that were not used for calibration. The results show that the fine-tuning of parameters can greatly improve the performance of simulation models to describe traffic conflict risk as well as the operational measures quantified using the field data.

Chapter 6 Applications to Traffic Risk Analysis

6.1 Estimating Traffic Conflict Risk Using the New Indicator

This section proposes a methodology for estimating rear-end conflict risk of merging vehicles on freeway merge sections as a probabilistic measure. The methodology consists of two major components. The first part estimates the merging probability of a vehicle given its position in a merge lane. Detailed vehicle trajectory data from the Next Generation Simulation (NGSIM) program are used to find the underlying probability density function of merging decisions. The second part derives the probabilistic risk of a merging vehicle conflicting with vehicles around it as a function of the proposed surrogate safety measure, namely modified time-to-collision (MTTC). Combining these two parts, the derived surrogate measure conflict probability (CP) is used to describe the conflict risk of each merging vehicle at each time step. By aggregating the conflict risk over time and space, it is possible to create a risk map for describing the level of conflict risk. A case study demonstrates the implementation of the proposed method for traffic conflict analysis in detail. The results of this study can be used to evaluate the safety level of merge sections and to develop real-time traffic control strategies to reduce conflicts associated with merging traffic.

6.1.1 Introduction

Highway vehicle collisions are one of the most important concerns for traffic systems all over the world. One major source of vehicle collisions is merge sections. For instance, lane changing/merging collisions constituted about 4.0 percent of all police-reported collisions in 1991, and accounted for about 0.5 percent of all fatalities (Wang and Knipling, 1994). The 1999 National Automotive Sampling System/General Estimates System (GES) crash database of the National Highway Traffic Safety Administration showed that 19, 000 crashes occurred because of merging (Sen *et al.*, 2003). A merging vehicle is required to execute a mandatory lane-change maneuver along a limited length of a merge lane. By controlling the timing of the merge, a merging vehicle either successfully resolves the unsafe conflict with other vehicles or gets involved in a collision.

Traffic engineers are looking for ways to redesign merge sections or control merging traffic to reduce collisions associated with merging vehicles. For instance, Cirillo (1970) studied accident experiences among 700 weaving sections in 20 states based on data gathered in the early 1960s, and determined that shorter acceleration lanes exhibited higher accident rates for merging traffic, and that the effect of increasing the length of acceleration lanes appears to be substantial when the percent of merging traffic is greater than 6 percent. Some case studies of freeways in major U.S. cities have shown that ramp metering can reduce the crash rate and more specifically rear-end and sideswipe crashes by regulating access of merging traffic to the mainline (Piotrowicz and Robinson, 1995; Cleavenger and Upchurch, 1999; Lee *et al.*, 2006). These historical crash-data-based studies have suggested some effective countermeasures. However, it is difficult to evaluate the effects of traffic safety countermeasures in terms of the change in the number of traffic crashes in many cases. For instance, it is difficult to evaluate the safety performance of the new proposed facility designs or traffic control measures at the initial operation stage. Traditional analysis methods such as before-and-after comparison may not be implemented. One reason is that crashes are rare events and may not be observed in a short time period (Chin and Quek, 1997); the use of historical crash statistics as a measure of safety requires a relatively long period for data accumulation, and it is only a reactive approach (Ismail *et al.*, 2009). In addition, there are also concerns about the quantity and quality of the crash data (Antov, 1990; Svensson and Hyden, 2006). Consequently, there is a need to develop alternative methods for identifying safety performance in a shorter time period and perhaps in a proactive manner.

The objective of this study is to develop a novel methodology for estimating the risk of traffic conflicts associated with merging vehicles on a highway merge section. The risk is estimated on the basis of investigating the potential conflicts caused by mandatory lane-changes of merging vehicles. Whether merging or not, merging vehicles interact with both vehicles on the merge and through lanes. Given the uncertainty of interactions, the merging decision is described in a probabilistic manner. Risks of potential conflict scenarios under each merging decision are then exploited by using the proposed surrogate safety indicator.

The methodology is presented in detail in the next section. It is followed by a case study demonstrating the application of the methodology. The major findings are then summarized, and suggestions are offered regarding several research topics that require future study.

6.1.2 Proposed Methodology

Vehicles merging on a highway continuously interact with neighboring vehicles on the current merge lane and adjacent through lane, which actually generate car-following and lane-changing events. Based on the driver's judgment of the environment, the subject vehicle either keeps traveling in the merge lane or changes lanes. Figure 6.1 indicates the typical situation of a merging vehicle to be studied in this paper. As shown in Figure 6.1, the decision of the subject vehicle will lead to four potential conflicts between the subject vehicle and its surroundings: conflict with the preceding vehicle, conflict with the following vehicle in the merge lane, conflict with the leading vehicle in the target lane, and conflict with the lagging vehicle in the target lane. In order for the subject vehicle to avoid these conflicts, it has to adjust its speed or position to interact with others in a safe manner.

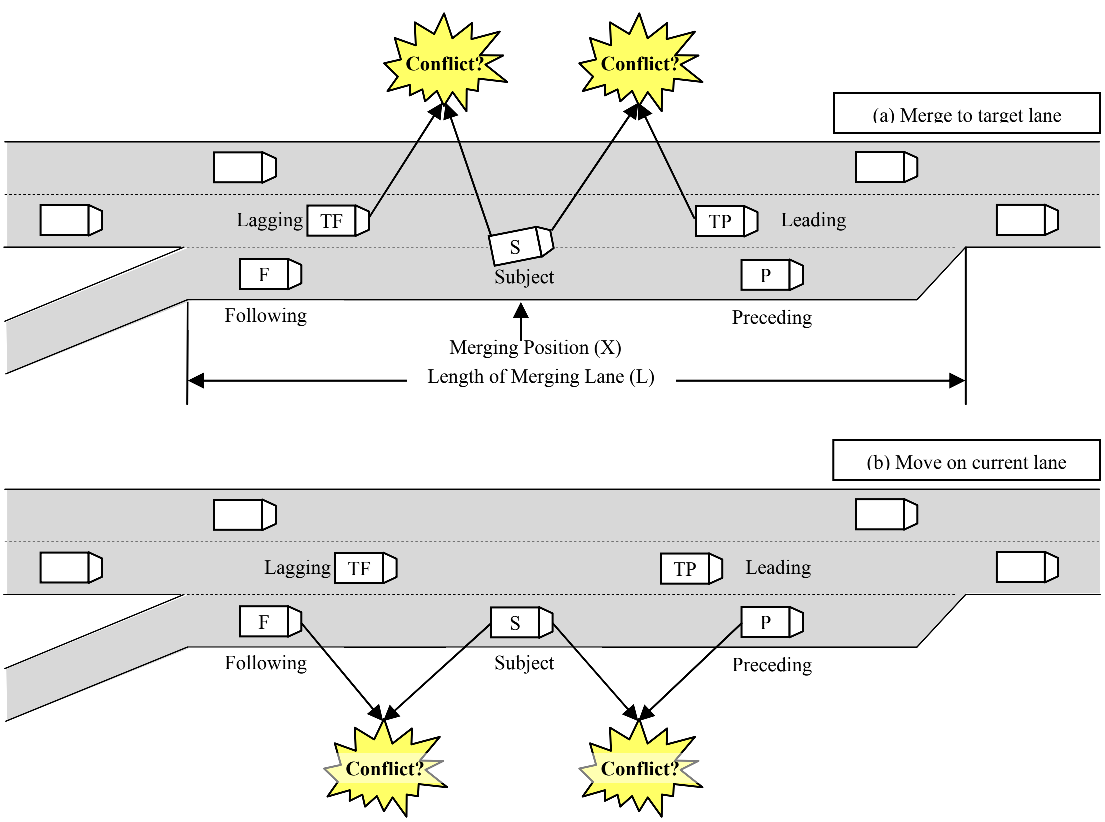


Figure 6.1 Merging vehicle and its potential conflicts with other vehicles

Figure 6.2 presents the structure of estimating the conflict risk associated with the subject vehicle under different conflicting scenarios shown in Figure 6.1. It consists of two major parts: estimating the merging probability and estimating the potential risk under each possible interaction scenario. For the first part, the merging decision depends on many factors such as gaps between vehicles, relative speed, and vehicle types. A generalized model can be presented as a probabilistic model (6-1) in which *X* represents a class of factors and *f* defines the relational model on X to predict merging probability.

$$\Pr(Merge \mid X) = f(X) \quad \textbf{(6-1)}$$

One of the typical examples of such a model is the gap acceptance model in terms of a binary logistic regression model similar to the one presented by (Kita, 1993). However, there is no unique model that can be applied to all merging behaviors under different traffic conditions because influencing factors in the model can vary from location to location. The approach of this study is purely empirical, and thus no attempt is made to develop or validate any existing analytical gap acceptance model applicable to a merging process. Rather, emphasis is placed on the elementary empirical analysis of merging probability based on the collected traffic data. This approach will be demonstrated in the case study section.

For the second part, in order to evaluate the risk of a traffic crash, microscopic vehicle behaviors are analyzed from the perspective of a traffic conflict. Though some research studies (Glennon *et al.*, 1977; Williams, 1981) have suggested that there is only a medium correlation between the number of traffic accidents and traffic conflicts, many other studies (Migletz *et al.*, 1985; Svensson, 1992; Muhlrad, 1993; Sayed and Zein, 1999; Kaub, 2000) suggested agreement between these statistics. Therefore, this study adopts the methodology to evaluate the risk of a traffic collision due to the difficulty in observing the actual traffic collision itself.

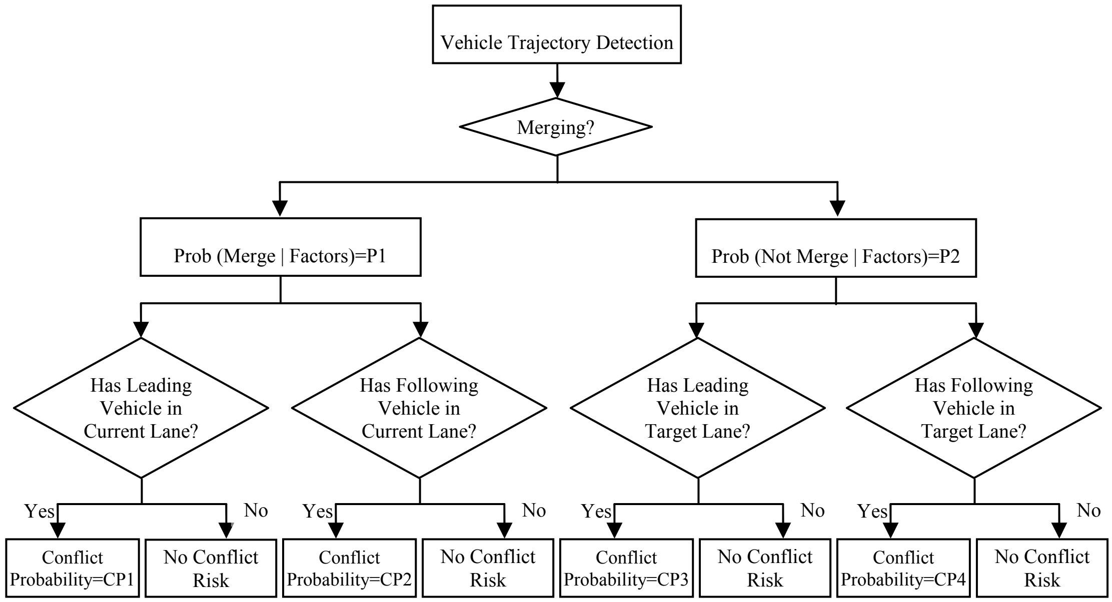


Figure 6.2 Proposed structure for estimating conflict risk of merging vehicles

The function of the i^{th} type of potential conflict probability (CP_i) associated with the subject vehicle is shown in the equation below.

$$CP_i = \Pr(Conflict \mid MTTC_i) = Exp(\frac{-MTTC_i}{\lambda}) \quad \textbf{(6-2)}$$

where, MTTC represents modified time-to-collision and λ is an adjust factor.

There are four possible conflict risks denoted as CP_1, CP_2, CP_3, and CP_4, as shown in Figure 6.2. Given the uncertainty of merging behavior, at each time step, the overall potential conflict risk (CR_j) associated with the jth subject vehicle in merging process can be written as shown in the equations 6-3 and 6-4:

$$CR_j = \Pr(Merge \mid X) \times (CP_1 + CP_2) + \Pr(NotMerge \mid X) \times (CP_3 + CP_4) \quad \textbf{(6-3)}$$

$$\begin{aligned} CR_j &= \Pr(Merge \mid X) \times \left[Exp(\frac{-MTTC_1}{\lambda}) + Exp(\frac{-MTTC_2}{\lambda}) \right] + \Pr(NotMerge \mid X) \times \left[Exp(\frac{-MTTC_3}{\lambda}) + Exp(\frac{-MTTC_4}{\lambda}) \right] \\ &= \Pr(Merge \mid X) \left[Exp(\frac{-MTTC_1}{\lambda}) + Exp(\frac{-MTTC_2}{\lambda}) \right] + [1 - \Pr(Merge \mid X)] \times \left[Exp(\frac{-MTTC_3}{\lambda}) + Exp(\frac{-MTTC_4}{\lambda}) \right] \end{aligned} \quad \textbf{(6-4)}$$

To describe the conflict risk involving all N merging processes at a given segment during certain period T, equation 6-5 can be used as an index to identify the overall level of conflict risk (LOCR).

$$LOCR = \frac{1}{T \times N} \sum_{t=1}^{T} \sum_{j=1}^{N} CR_{jt} \quad \textbf{(6-5)}$$

where CR_{jt} is the potential conflict risk of merging associated with the jth subject vehicle at each time step t.

6.1.3 Case Study

The field vehicle tracking dataset, namely the "I-101 Dataset" generated by the NGSIM program, is used to demonstrate the applicability of the proposed methodology for the study of traffic conflicts. As mentioned by NGSIM program (FHWA, 2005), the dataset is *"specifically collected to improve the quality and performance of simulation tools, promote the use of simulation for research and applications, and achieve wider acceptance of validated simulation results."* The data were collected at a segment of southbound direction of U.S. Highway 101 in the Universal City neighborhood of Los Angeles, California. A schematic illustration of the location is shown in Figure 6.3.

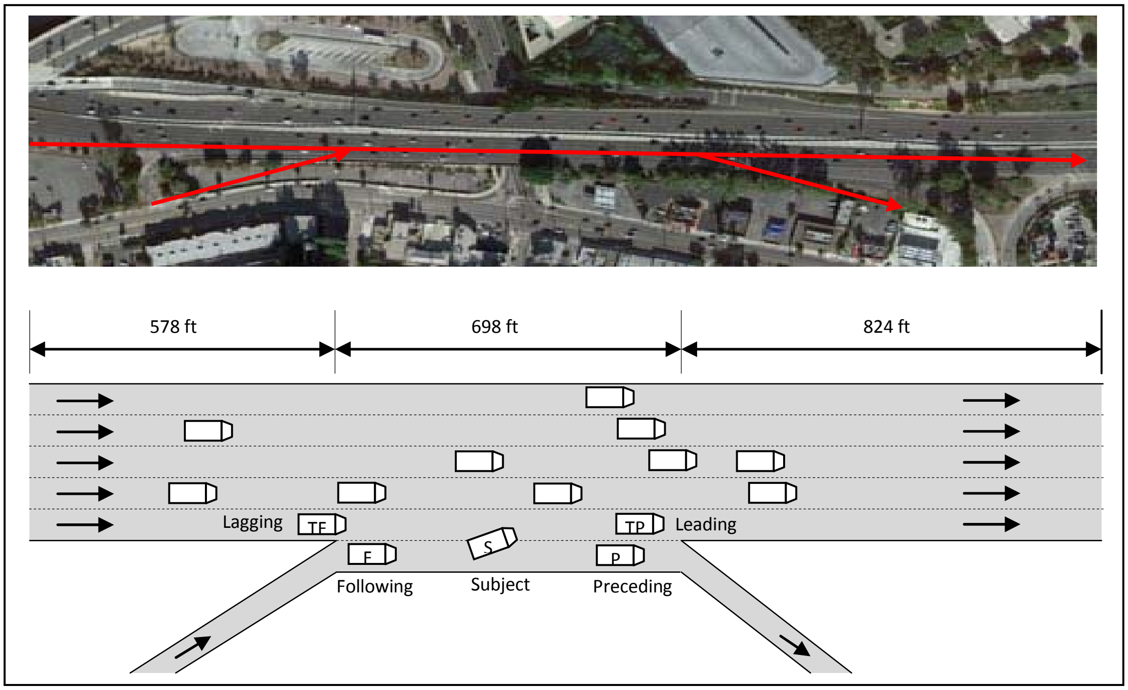


Figure 6.3 Weaving section schematic of I-101

The objective range of data collection was approximately 2100 feet in length. The auxiliary lane for on-ramp vehicle merging and vehicle diverging is about 698 ft. About 6,000 vehicle trajectories were collected based on video data with a 0.1-second time increment. The data were separated into three 15-minute periods representing transitional and congested flow conditions in the morning, on June 15, 2005: (a) 07:50~08:05, (b) 08:05~08:20, and (c) 08:20~08:35. Vehicle trajectories associated with merging vehicles and their surroundings in the auxiliary lane and adjacent through lane are retrieved for further analysis.

Statistical software package R is used to analyze NGSIM vehicle trajectory data. Instead of the merging decisions being modeled using a gap acceptance model, the merging behaviors along the auxiliary lane are investigated based on the observed data. Data for time periods (a) and (c) are used as training data to identify the merging probability at each location along the merge lane. It is found that the merging probability can be fitted as a lognormal distribution, which is shown in Figure 6.4 (a). The probability model developed in this study with the estimated parameters is shown in equation 6-6. To test the goodness of fit, χ^2 test is used. The test statistic is 13.076, which is less than the critical value of 15.507 given the significance level of 0.05. Thus, it is reasonable to assume that the merging probability along the auxiliary lane comes from the fitted lognormal distribution. To further verify the validation of the fitted model, empirical data for time period (b) are used as test data. The Kolmogorov-Smirnov test is used to decide if the testing data can also be assumed to come from a population with the specified lognormal distribution. The null hypothesis that the testing data also follow the lognormal distribution is accepted because the p-value (=0.1513) of the test is higher than significance levels of 0.05. Therefore, the merging probability model (6-6) is used for the following study.

$$\Pr(Merge \mid X = Position) = f(X) = \frac{\exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right]}{x\sigma\sqrt{2\pi}} = \frac{\exp\left[-\frac{1}{2}\left(\frac{\ln x - 5.3785}{0.9173}\right)^2\right]}{0.9173 \times \sqrt{2\pi} \times x} \quad \textbf{(6-6)}$$

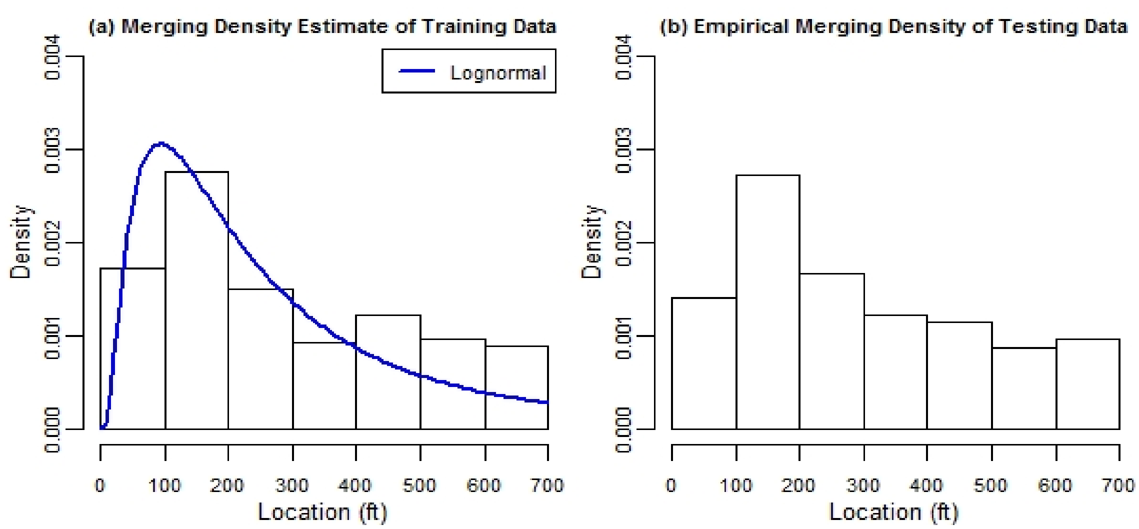


Figure 6.4 Merging density of training and testing data

As mentioned in the Chapter 3, the exponential decay function is adopted to model conflict probability. To do this, the parameter λ has to be specified. As an example in this study, assuming MTTC of 4 seconds corresponds to a conflict probability of 0.5. The parameter λ thus can be set to 5.77. If a shorter MTTC of 3 seconds is assumed, then this would correspond to a conflict probability of 0.5, and λ can be set to 4.32. Figure 6.5 shows an example of the exponential decay curve using the assumed parameters. The model using λ=5.77 can be written as equation 6-7. As MTTC increases, the conflict probability will decrease. Figure 6.5 shows that the same MTTC will have higher conflict probability if a larger parameter λ is used. Arguably the value of the parameter λ deserves more consideration to adjust the shape of the curve for different traffic conditions.

$$CP_i = \Pr(Conflict \mid MTTC_i) = Exp(\frac{-MTTC_i}{5.77}) \tag{6-7}$$

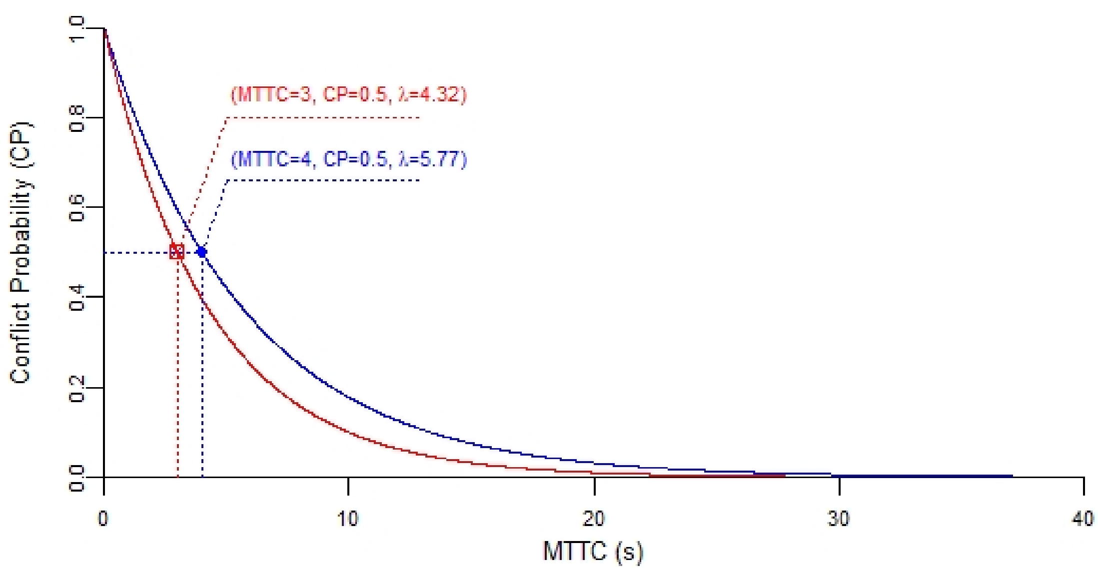


Figure 6.5 Example of conflict probability curve

MTTCs between the subject vehicle and vehicles in the merge lane and adjacent through lanes are computed using the method presented in Chapter 3. Assuming λ=5.77, the conflict probability associated with the merging vehicle at each time step can be estimated by equation 6-8:

$$
\begin{aligned}
CR_j &= \Pr(Merge|X)\times\left[Exp(\frac{-MTTC_1}{\lambda})+Exp(\frac{-MTTC_2}{\lambda})\right]+\Pr(NotMerge|X)\times\left[Exp(\frac{-MTTC_3}{\lambda})+Exp(\frac{-MTTC_4}{\lambda})\right] \\
&= \Pr(Merge|X)\times\left[Exp(\frac{-MTTC_1}{\lambda})+Exp(\frac{-MTTC_2}{\lambda})\right]+[1-\Pr(Merge|X)]\times\left[Exp(\frac{-MTTC_3}{\lambda})+Exp(\frac{-MTTC_4}{\lambda})\right] \\
&= \frac{\exp\left[-\frac{1}{2}(\frac{\ln x-5.3785}{0.9173})^2\right]}{0.9173\times\sqrt{2\pi}\times x}\times\left[Exp(\frac{-MTTC_1}{\lambda})+Exp(\frac{-MTTC_2}{\lambda})\right]+ \\
&\left[1-\frac{\exp\left[-\frac{1}{2}(\frac{\ln x-5.3785}{0.9173})^2\right]}{0.9173\times\sqrt{2\pi}\times x}\right]\times\left[Exp(\frac{-MTTC_3}{\lambda})+Exp(\frac{-MTTC_4}{\lambda})\right]
\end{aligned}
\qquad \textbf{(6-8)}
$$

When one aggregates the computed conflict risks from equation 6-8, the overall level of conflict risks over time and space can be computed by equation 6-5. Figure 6.6 illustrates maps of the level of conflict risk (LOCR) over a 1-minute time interval and 50-feet spatial interval aggregation using the NGSIM data. Figure 6.6 (a) shows the estimated risk using assumed parameter λ=5.77. As a sensitivity comparison, the risk map using a relatively smaller λ=4.32 is also presented in Figure 6.6 (b). The overall level of conflict risk for Figure 6.6 (b) is smaller because crash risk computation model 6-4 is an increasing function of the parameter λ given a fixed MTTC. Both maps suggest that the conflict risk associated with merging vehicle increases when traffic flow becomes more congested in the last 15 minutes. This may be due to the fact that shorter gaps available for merging increase under high traffic density and it is riskier to merge into these gaps. The risk maps also show that the LOCR is lower at the end of the auxiliary lane. This is due to fewer vehicles merging at the end of the auxiliary lane and vehicles having more chances to find acceptable gaps when travelling farther in the merge lane.

Some of the larger LOCRs occurring at the end of the merge lane may be a result of those forced merging behaviors.

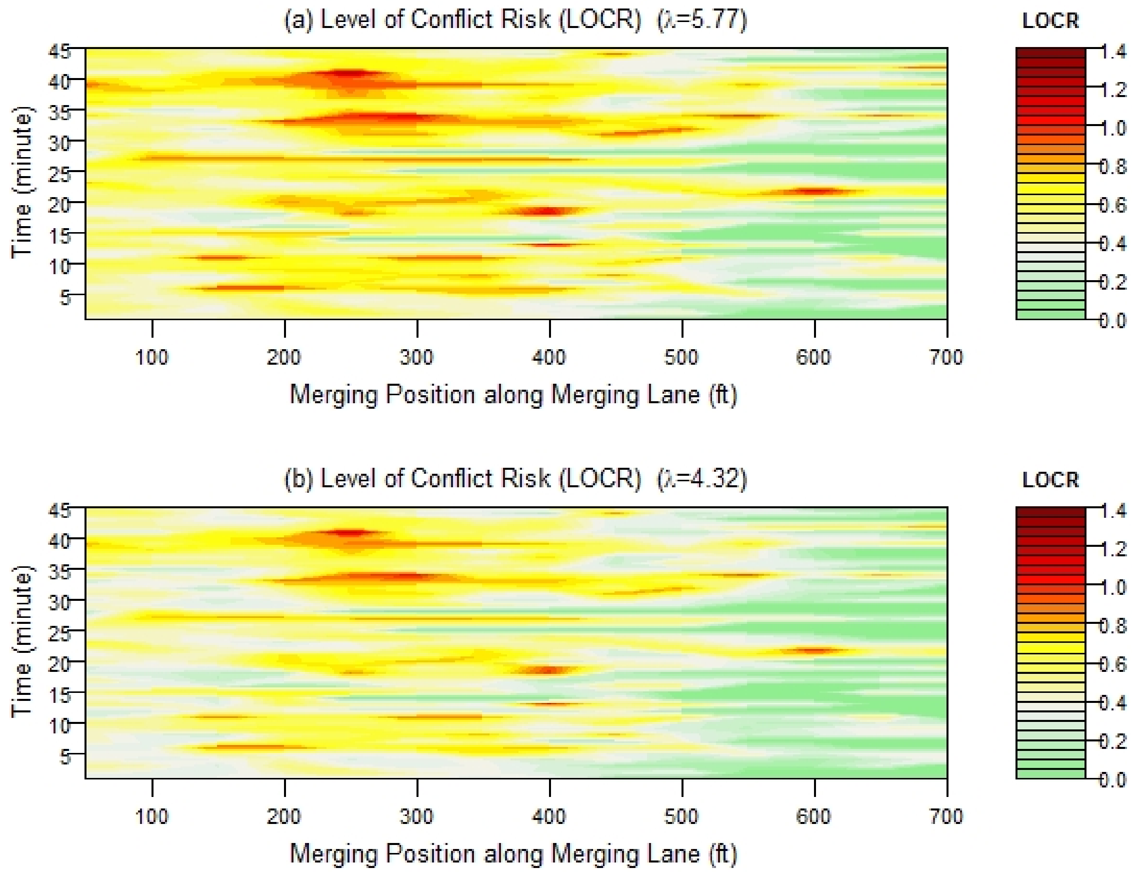


Figure 6.6 Example of level of conflict risk associated with merging vehicles

It should be noted that the value of the LOCR itself does not have a practical meaning. It only acts as a measure to describe the potential conflict risk of different traffic conditions. Rather than predicting actual crashes, it can be used as an index for real-time traffic control to reduce conflicts associated with merging vehicles. For instance, on-ramp merging flow can be regulated (i.e., by ramp metering) when the LOCR is relatively higher than that of normal traffic conditions.

6.1.4 Remarks

Merge sections are locations where traffic collisions frequently occur. In terms of the short-term evaluation of safety performance of countermeasures available for merging collision reduction, the crash-data-based safety evaluation approach is not always practical because the number of crashes may be relatively low and safety engineers have to wait for years to collect such crash data. This study proposes an alternative methodology for estimating the conflict risk associated with merging vehicles on freeway merge sections. Four types of conflicts are studied: conflict with the preceding vehicle, conflict with following vehicle in the merge lane, conflict with the leading vehicle in the target lane, and conflict with the lagging vehicle in target lane. The structure of the proposed methodology consists of two major parts: estimating the merging probability and estimating the conflict probability when the subject vehicle interacts with its surrounding vehicles. Detailed vehicle trajectory data obtained from the NGSIM dataset are used to find the underlying probability density function of merging decisions. The new surrogate safety measure MTTC recently proposed by Ozbay *et al.* (2008) is used to capture the potential conflict probability (CP) through an exponential decay function. Combining these two parts, a conflict risk (CR) index is computed to describe the potential risk associated with a merging vehicle at each time step. By aggregating the conflict risk of all the merging vehicles, the overall level of conflict risk (LOCR) is computed for the specific merge section. A case study using NGSIM data illustrates the application of the proposed methodology. The map of LOCR can be used to visually highlight the potential conflict risk associated with vehicles over time and space and to develop real-time traffic control measures to prevent potential accidents at merge sections.

Although the feasibility of the proposed method is demonstrated using real data, further research is needed to fully implement this methodology in the real world. The method mainly describes the linear conflicts between consecutive vehicles, so it does not take other types of collisions into account. More analysis of the merging probability model should also be conducted through additional trajectory data. The determination of the model parameter in the exponential decay function also deserves more detailed study.

6.2 Link between Surrogate Indicator and Crashes

6.2.1 Simulation Modeling

To test the performance of the new surrogate measure CP, a comparison between simulation results and real crash records is conducted. The proposed measure is tested based on a simulation model of a 15-mile-long section of an interstate highway (New Jersey Turnpike). The modeled section is located between Interchanges 3 and 5 in the northbound section of the highway. The segment between Interchanges 3 and 4 has two lanes, and there are three lanes between Interchanges 4 and 5. The section has a posted speed limit of 65 mph. The schematic of the section is shown in Figure 6.7.

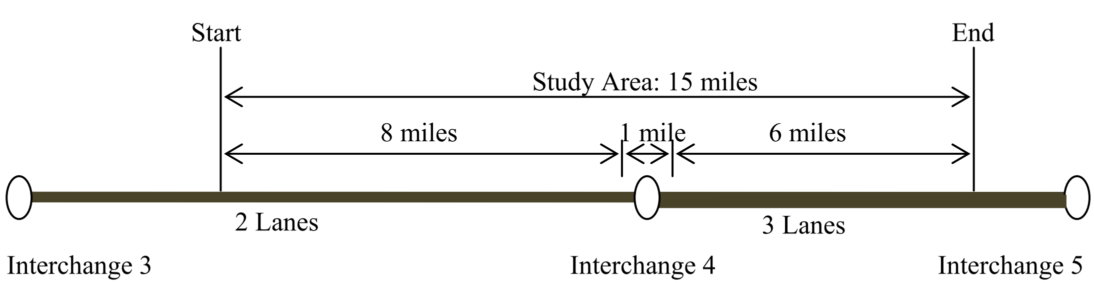


Figure 6.7 Schematic of the studied section

Considering the experience and customizable potential of Paramics, it is selected as our test platform to simulate the study section. The simulated trajectory information through the Application Programming Interface (API) provides the vehicle's position, speed, and acceleration for a user-defined small time resolution. Therefore, it provides sufficient data to numerically compute the surrogate safety measure.

The test section is carefully modeled in Paramics using aerial photographs and other geometric data. All important geometric configurations are matched with the actual ones. In order to represent the actual traffic flow conditions, daily traffic counts are collected through the New Jersey EZ-Pass system. The processed data of 24-hour traffic volumes with variation (mean ± standard deviation of each hour) are coded using the application programming interface (API) as the basic simulation input so that the random fluctuation features of real traffic flow can be captured. The GEH statistic is used to test the calibration of simulated link volumes versus observed. The final model is calibrated, and three main parameters in Paramics are adjusted: mean headway (=1.21), reaction time (=0.55), and curve speed factor (=1.50).

The algorithm of the new surrogate safety measure is also programmed and integrated in the simulation model using the API. After running the simulation model with the API, the output is extracted. To obtain statistically valid results from micro-simulation models, multiple repetitions with different random seeds are required to mitigate random errors. The average results of 25 replications with different random seeds are used for final analysis.

Crashes reported by police from 2001 to 2005 are obtained through the New Jersey Department of Transportation (NJDOT) accident database for the study section.

The records consist of detailed information on each accident, including type, time, location, and some other information. Considering that the surrogate measure can only describe rear-end conflicts, only the major types of crashes, including rear-end and sideswipe accidents occurring on the highway mainline, are extracted from the dataset. The data are aggregated by 1-mile segments from the start point to the end of the target section shown in Figure 6.7. The aim is to distinguish the segment containing Interchange 4 from other segments. The crash distribution of each segment is shown in Figure 6.8. About 80 crashes occurred within the segment that contains Interchange 4. This figure is about 2.2 times higher than the average number of crashes per mile. Higher crash frequency is expected to occur at the interchange segment because of serious weaving interactions. If the new surrogate safety measure is reliable, the simulated results should also be able to identify this relatively high-risk segment. Therefore, the performance of the simulated safety analysis using the new surrogate measure is verified in next section.

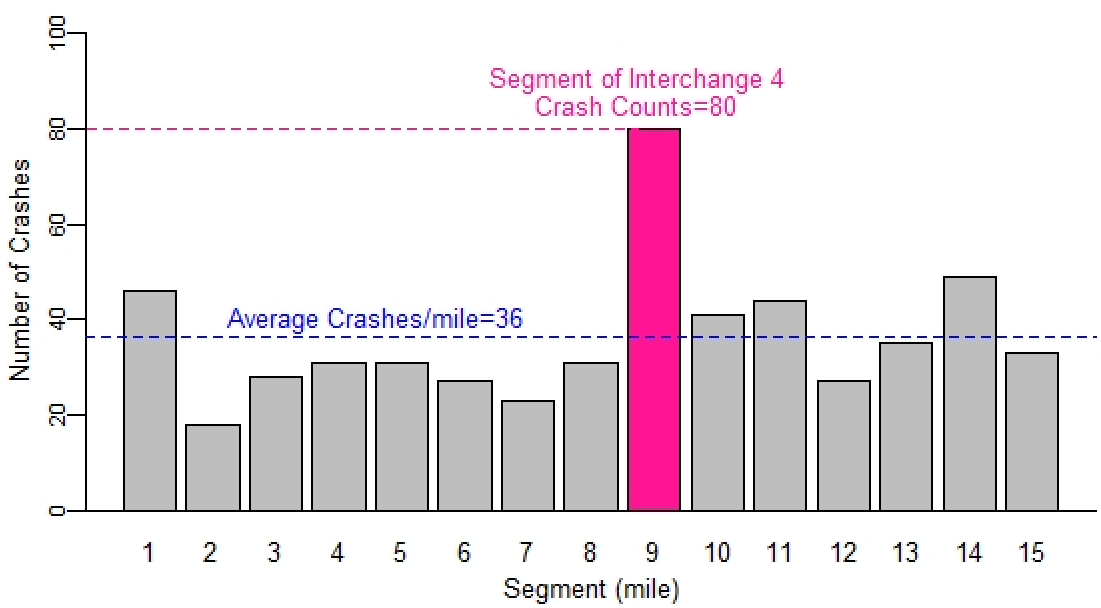


Figure 6.8 Crash distributions along the studied section

6.2.2 Results and Discussion

MTTCs of all conflicts are obtained from simulation output. Then the conflict risk for each vehicle-to-vehicle conflict is calculated by equation 6-2 given in section 6.1. The conflict risk of each 1-mile segment is obtained by aggregating risks associated with those conflicts occurring within that segment. Then comparisons between actual crashes and simulated conflict risks are conducted. The aim is to find the relationship between the observed crashes and the simulated results. If the simulation results are valid, the simulated conflict risks are expected to reflect the actual level of segment safety illustrated by crash counts. In other words, the higher the conflict risk is, the more crashes should be observed. To measure the degree to which these two variables are related to each other, the Pearson product-moment correlation coefficient (called Pearson's correlation for short) is used. Pearson's correlation can range from -1 to +1, where +1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and zero means no linear relationship. In our case, the positive relationship is expected.

When one is calculating the conflict risk using equation 6-2, the parameter λ has to be tuned. The appropriate parameter is assumed to be the one that can yield the highest correlation coefficient between simulated conflict risks and actual crashes. We searched λ from values of 2 to 6 with an incremental step of 0.1. The following Table 6.1 lists the sensitive analysis of λ. A positive relationship between the simulated conflict risks and the crash counts is confirmed. More specifically, it has been identified that by using $\lambda=4.1$, the highest Pearson's correlation is obtained as 0.8619. The small difference between other correlations suggests that the parameter λ can partially adjust the results but not completely change the results.

Table 6.1 Sensitive Analysis of Parameter λ

Scenario	Value of Parameter λ	Pearson's Correlation
1	λ=2.0	0.8107
2	λ=2.5	0.8318
3	λ=3.0	0.8464
4	λ=3.5	0.8574
5	λ=4.0	0.8616
6	**λ=4.1**	**0.8619**
7	λ=4.2	0.8616
8	λ=4.3	0.8612
9	λ=4.4	0.8601
10	λ=4.5	0.8590
11	λ=5.0	0.8472
12	λ=5.5	0.8264
13	λ=6.0	0.7969

Figure 6.9 is a visualization of the spatial distribution of crashes and the associated simulated conflict risks along the studied section based on parameter λ=4.1. Though several segments such as segments 3 and 13 do not exactly match, the simulated conflict risk is in good agreement with the observed safety pattern along this test section for the great majority of the segments. Most importantly, the simulated results can detect the high-risk segment of Interchange 4. The conflict risk of this segment is about 2.3 times higher than the average for the section. This result is comparable to the frequency of actual crashes at this segment, which is 2.2 times higher, as illustrated in Figure 6.8.

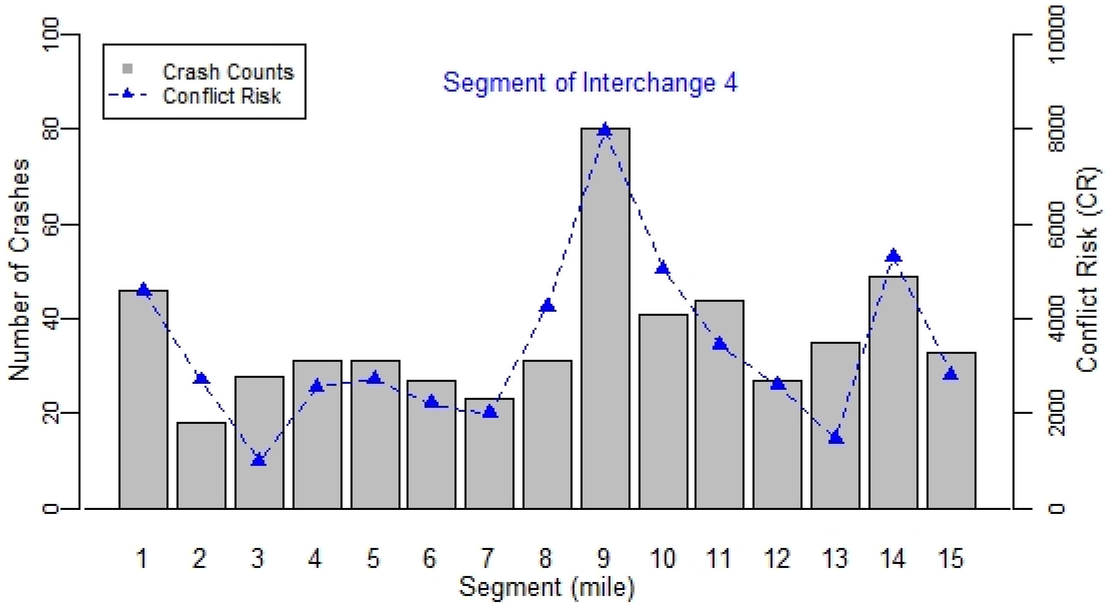


Figure 6.9 Simulated conflict risks versus observed crashes

A simple regression model is estimated to link the two measures because of the highly linear relationship between simulated conflict risks and actual crashes. Figure 6.10 shows the regression line. The intercept is not used in the model, assuming no crash occurs if the conflict risk is zero. The regression model is specified as: Crash=0.00998×ConflictRisk. The R-squared value of the estimated model is 0.94.

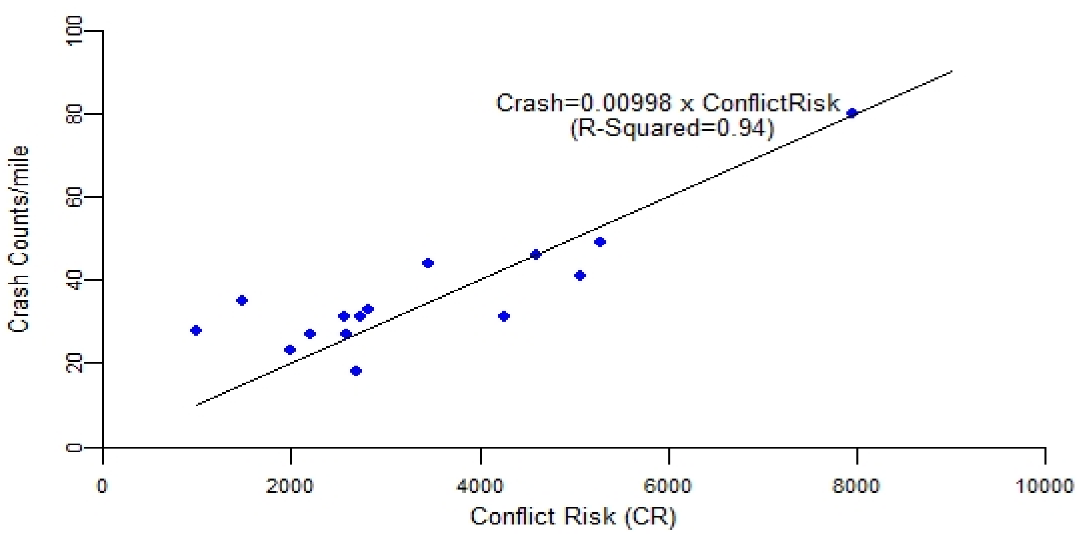


Figure 6.10 Correlate conflict risks with crashes

The above comparison between simulated conflict risk and actual crashes illustrates the potential of simulation-based conflict risk (CR) as a new surrogate safety measure for highway safety analysis. The simulation model captures the linkage between crashes and the surrogate measure as a case study. It should be noted that the model built here does not aim to establish a final model to predict the exact number of crashes using the surrogate measure. It might be used as an alternative approach to evaluate the effectiveness of different traffic safety countermeasures applied to facilities where crash information is not available or not sufficient.

6.2.3 Remarks

The logic of the proposed surrogate safety analysis was incorporated into the Paramics micro-simulation model to extract the data required for the quantification of the new surrogate measure. The integrated microscopic simulation model was successfully applied to a 15-mile-long section of the New Jersey Turnpike. In order to investigate the performance of the new measure, 5-year real crash records associated with the studied section were obtained from the NJDOT accident database. Then their spatial characteristics were directly compared with CR data obtained from the simulation. As shown in Figure 6.9, the overall spatial predictions of conflict risks matched well with the level of risk predicted by actual crash data. The most high-risk segment illustrated by historical crash data was successfully identified by the simulated conflict risk measure. The Pearson's correlation coefficient between simulated conflict risks and actual historical crashes among segments is found to be approximately 0.86. A linear relationship was also established to link the two risk measures together. Given the agreement between the levels of accident risk predicted by historical crash data and simulation results, it is possible to use the proposed surrogate measure obtained from the micro-simulation model as an alternative approach for highway safety analysis.

Although potential for surrogate safety analysis is illustrated in this chapter, some limitations of this proposed methodology have to be noted. The new surrogate measure is derived based on information related to two consecutive interacting vehicles. It mainly takes into account potential rear-end conflicts. Therefore, it is useful for link or network-scale analyses of rear-end crashes only. Moreover, even though the relationship between simulated conflict risks and historical crashes is established, our results may not be necessarily applicable to other facilities with different geometric or traffic characteristics. The parameter used to calculate the conflict risk also needs to be determined using more field data. Additional validation studies should be carried out to further validate transferability and validity of the results.

6.3 Safety Evaluation of Open Road Tolling

6.3.1 Introduction

Open road tolling (ORT) is a new generation of tolling solution that will eventually lead to a conversion of conventional toll plazas to barrier-free electronic toll collections in the future. By design, ORT consisting of high-speed (express) electronic toll collection (ETC) lanes allows vehicles to electronically and automatically pay tolls without slowing down from highway speeds. Typically, there are two types of implementation of ORT (Klodzinski *et al.*, 2007). The first type is all-electronic ORT, which completely replaces barrier tollbooths with express ETC lanes (Mendoza *et al.*, 1999; Stewart, 1999). Without the presence of tollbooths, this type of ORT design enables automatic debiting via in-vehicle transponders (i.e., E-ZPass tags) or other automatic vehicle identification (AVI) technologies. The second is the interim type of ORT implementation, which is being deployed by many toll authorities. It installs express ETC lanes by retrofitting existing tollbooths to permit high-speed non-stop toll collection for ETC users and other registered users only (Klodzinski and Al-Deek, 2004; Klodzinski *et al.*, 2007). Cash or coin users are still diverted to use remaining barrier booths off the express ETC lanes.

In the United States, many highway authorities in states like New Jersey, Florida, and Illinois have implemented the ORT concept in recent years (Muriello and Jiji, 2004; Suarez and Hoeflich, 2005; Kovacs and Abou-Sabh, 2008). Demonstration projects have shown that the implementation of ORT is an effective means of relieving congestion. For example, Klodzinski *et al.* (2007) evaluated the addition of ORT to a mainline toll plaza in Florida and found that the installation of express ETC lanes reduced delays by 49.8 percent for cash users and by 55.3 percent for automatic coin machine (ACM) users. According to Levinson and Odlyzko (2008), express ETC lanes of ORT can increase throughput, from 350 to 400 vehicles per hour per lane with manual collection up to 2200 vehicles per hour per lane. The use of ORT has also been shown to significantly reduce emissions. For instance, Lin and Yu (2008) quantified various ORT deployment scenarios on Illinois toll highways and suggested that the near-roadside carbon monoxide concentration levels and diesel particulate matter emissions can be reduced by up to 37 percent and 58 percent, respectively.

While ORT can sharply reduce transaction-related delays and pollution at toll plazas, the safety impacts of retrofitting existing toll plazas and installing express ETC lanes, however, are still not clear. ORT systems can be deemed safer, since high-speed tolls avoid the safety deficiency of barrier toll plazas as they eliminate much stop-and-go traffic, as well as dangerous interactions and distractions (Siegel *et al.*, 2004). On the other hand, diverging and merging of vehicles that use express ETC lanes at higher speeds might increase traffic conflicts (Tri-State Transportation Campaign, 2000; Benda *et al.*, 2009). Cash and coin users must exit to use the barrier tollbooths and then merge with high-speed users on express lanes. These maneuvers may raise more safety issues. Unlike those easily measurable benefits such as capacity improvement and reduction of costs in toll collection (Weinstein, 2001; Ciszewski, 2004; Ciszewski *et al.*, 2005; Raczynski and Finn, 2005), it is difficult to evaluate the safety performance of the new tolling solution shortly after its implementation because of the random and rare occurrence of motor vehicle crashes. Quantifying safety performance of ORT requires long-term crash data collected at toll plazas with and without the deployment of ORT.

This study aims to use the simulation-based safety evaluation approach to evaluate the impact of implementing ORT on safety performance at mainline toll plazas on Garden State Parkway in New Jersey.

6.3.2 Open Road Tolling in New Jersey

The Garden State Parkway (GSP) is a 172.4-mile limited-access toll parkway with 359 exits and entrances. Over 380 million vehicles travel the GSP, which stretches the length of New Jersey (NJ) from the New York (NY) state line at Montvale to Cape May at the southern tip of the state. Tolls are collected at 50 locations, including 11 mainline toll plazas and 39 on entrance and exit ramps (NJTA, 2011c). It is among America's busiest highways, serving users from NJ and NY's most marketable communities (Currie and Walker, 2011; Travelers' Market, 2011).

The GSP operator (GSP was operated by the NJ Highway Authority [NJHA] until 2003 and later by the NJ Turnpike Authority [NJTA]) always focused on using new toll collection technologies to improve tolling efficiency and reduce congestion. After the first toll collected manually in 1954, automatic coin machines (ACM) were introduced in the early 1950s and had spread to most toll plazas and ramps on the Parkway by 1959 (Toll Road News, 2008). When a toll increased beyond a quarter, tokens were introduced in the early 1980s. They continued to be available until January 2002 and ceased to be accepted as payment in January 2009 (Toll Road News, 2008). A regular (low-speed) ETC system was implemented in 1999. The entire ETC system was completed in August 2000 (Currie and Walker, 2011). The ETC system has been widely adopted by travelers, with an ETC penetration rate beyond 70 percent on GSP (NJTA, 2011b).

In 2001, the state government issued an order to promote a 10-year congestion relief plan for the GSP (Weinstein, 2001). Under the plan, elimination of mainline barriers in one direction and use of express ETC lanes of ORT in the other were recommended. By 2010, all mainline barriers except Toms River had been converted into one-way tolling (express ETC lanes were added to both directions at the Toms River toll plaza). Between 2004 and 2006, the open road tolling program was implemented. Express ETC lanes of ORT have been installed at a number of toll plazas listed in Table 6.2.

Table 6.2 ORT Operation at the Mainline Toll Plazas on the GSP (NJTA, 2011a)

Toll Plaza	Milepost	ORT Operation Date	No. of Express ETC Lanes
Cape May NB	19.4	May 2006	2
Toms River NB	84.7	May 2005	2
Toms River SB	84.7	May 2005	2
Asbury Park NB	104.0	May 2005	3
Raritan SB	125.4	May 2005	5
Pascack Valley NB	166.1	January 2004	2
Pascack Valley SB	166.1	January 2004	2

The conventional toll plaza with seven tollbooths in one direction was retrofitted to an interim version of the ORT system, which allows ETC drivers to drive at 55mph through the two high-speed lanes in each direction. Figure 6.11 shows an example of the layout of the converted Cape May toll plaza. Signs are installed upstream of the toll plaza to guide the selection of tollbooths. Upon the operation of such an ORT system, electronic readers mounted on the gantry automatically charge ETC users. Meanwhile, overhead cameras capture the license plates of vehicles without transponders (i.e., E-ZPass tag). Cash and coin users are diverted to use barrier tollbooths. The new ORT system has been widely accepted, as over 90 percent of E-ZPass vehicles use the high-speed lanes on the GSP. It is estimated that the express ETC lane can process about 800 more vehicles per hour than traditional ETC lanes (Siegel *et al.*, 2004). Compared to the observed benefits such as capacity improvement and reduction of costs in toll collection (Weinstein, 2001; Siegel *et al.*, 2004; Raczynski and Finn, 2005), little information about the safety impact of the deployed ORT system is available.

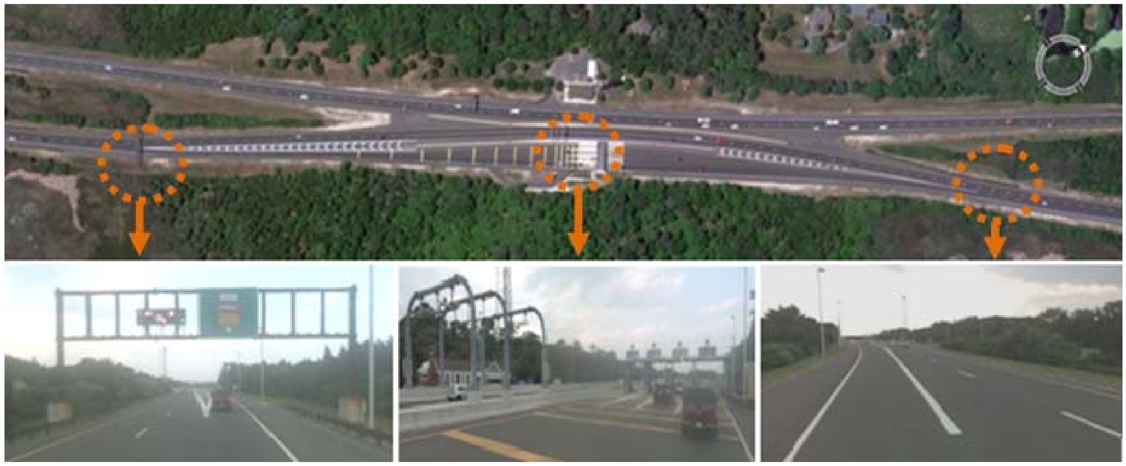
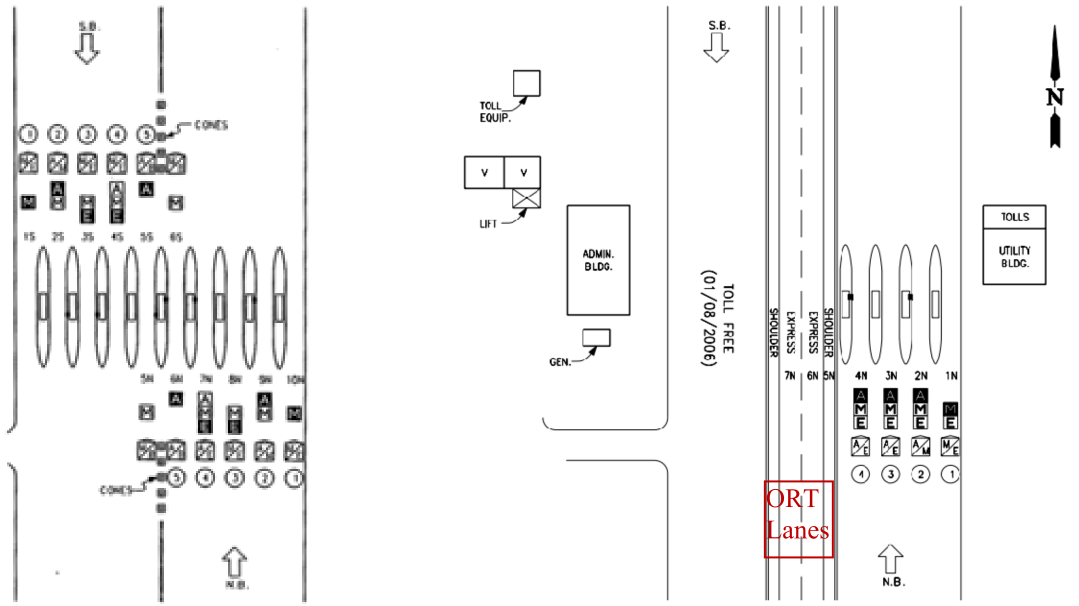


Figure 6.11 Separation between barrier tollbooths and express E-ZPass lanes at Cape May Northbound toll plaza *(Source: Google Map)*

The main objective of this study is to evaluate the safety efficiency of the ORT system using the Cape May toll plaza as a case study. The safety efficiency is investigated based on the estimated reductions of traffic conflict risks through the proposed simulation-based approach. In the meantime, the crash data are explored to investigate the accuracy of the simulation results.

6.3.3 Toll Plaza Simulation Modeling

Simulation models of the Cape May toll plaza before and after installing ORT were developed in Paramics using the satellite images as overlays. Information about the toll lanes configurations (EZ-Pass, ACM, and cash) was adopted from the toll schematics shown in Figure 6.12. For the traditional barrier booths, there were 5 tollbooths consisting of 2 regular ETC lanes, 2 ACM lanes, and 1 cash lane. After conversion, the toll plaza has two express ETC lanes, 3 ACM lanes, and 1 cash lane.



(a) Traditional barrier booths (b) ORT deployed

Figure 6.12 Tollbooth configuration of the Cape May toll plaza (*Source: GSP Toll Schematics, 2004-2006, from NJTA (2011a)*)

Notes on Figure 6.12: (1) dark boxes at the toll lanes indicate the primary mode of payment; (2) character “A” represents an automatic coin machine, “M” means manual, and “E” is EZ-pass.

Toll transaction data between April and May, 2008 provided by the NJTA were used to create an OD demand matrix of the simulation model. The transaction dataset consists of the individual vehicle-by-vehicle entry and exit time data. It also consists of information regarding the lane through which each vehicle was processed (EZ-Pass, cash, and ACM users). Lane usage is used as one of the calibration objectives. Hourly volume is used as another calibration objective.

Service time information on each type of toll lane is critical input for toll plaza modeling. Services times used in the simulation runs of the Cape May toll plaza model were adopted from the data collected for the Union toll plaza on the GSP. Vehicles using the express EZ-pass lanes do not wait to pay tolls. As to cash and ACM lanes, the service time distribution observed at the Union toll plaza is expected to apply at the Cape May toll plaza, because (1) service times in ACM lanes are not location specific, and (2) the same toll fee, one dollar, is being collected at both toll plazas, which would yield similar service time distributions.

Service times for cash and ACM users of the Union Toll plaza were collected on April 10, 2009. Service times of 81 cash users and 78 ACM users were extracted. Kolmogorov-Smirnov and Anderson-Darling goodness-of-fit tests show that toll processing times follow a lognormal probability distribution for $\alpha = 0.05$ with parameters $\mu = 1.659$, $\sigma = 0.625$ for cash users and $\mu = 1.391$, $\sigma = 0.665$ for ACM users.[4] These service times were incorporated into the toll plaza model using the API capability in Paramics, thus obtaining a more representative toll plaza model. Cash and ACM users slowed down at the toll gates to zero speed and were randomly assigned a service time based on the service time distribution. Once they spent the assigned service time at the toll gate, they accelerated and exited the plaza. EZ-Pass vehicles, on the other hand, drove through the two ORT lanes and exited the plaza.

The Cape May toll plaza was modeled in Paramics microscopic traffic simulation software based on the guidance of Ozbay *et al.* (2006). The following Figure 6.13 shows an overview of the simulation model in Paramics. Vehicles' lane selection algorithm at the toll plaza was implemented in the simulation using the Paramics API according to Mudigonda *et al.* (2009). The model was then calibrated to reflect the actual conditions.

[4] It should be noted that these values are in log-scale. Mean values of service times for cash and ACM users are 6.7 and 5.0 seconds, respectively.

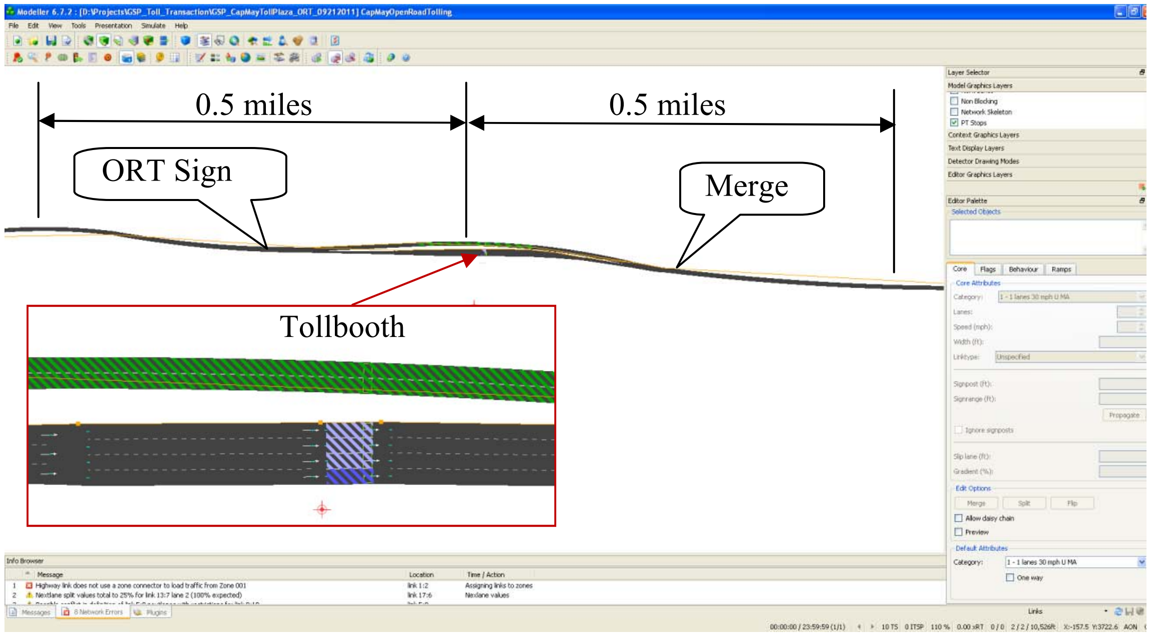


Figure 6.13 Overview of simulation model for the Cape May toll plaza

The observed and simulated lane utilization as well as traffic volume are compared. Figure 6.14 illustrates the simulated traffic volumes versus the observations extracted from toll transaction data. The average difference between simulated and observed hourly traffic volume is about 4.4 percent. The observed average daily traffic for the toll plaza is about 14339 vehicles per day. The simulated daily traffic is about 14038, which is close to the observation. Figure 6.15 compares the simulated lane usage with actual observed usage. Lane 1 is used by cash users. Lanes 2, 3, and 4 are for ACM users. Lanes 6 and 7 are ORT lanes. Figure 6.15 suggests that the simulation model captures the existing lane usage at the toll plaza. Thus, the calibrated model is used as the basis to develop new simulation scenarios to compare different concept designs.

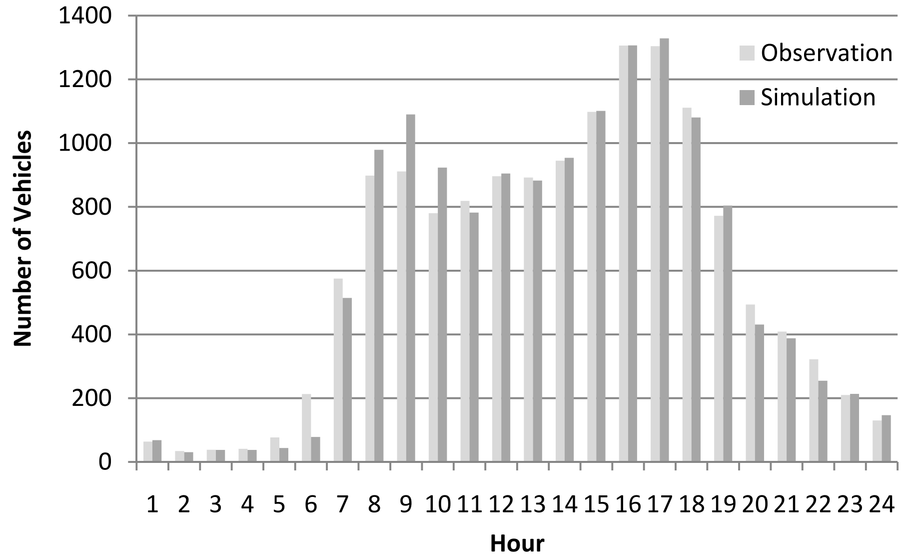


Figure 6.14 Comparison of observed and simulated hourly traffic volumes

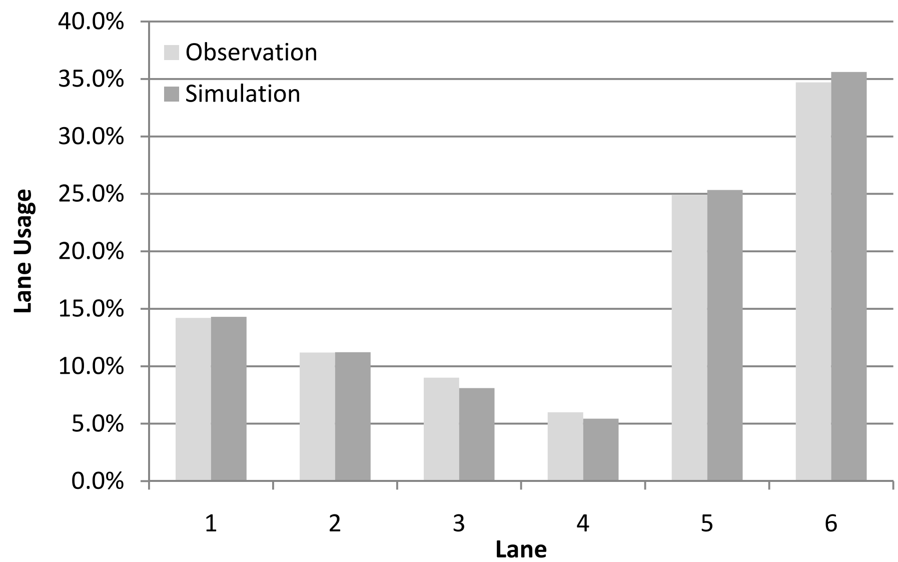


Figure 6.15 Comparison of observed and simulated lane usage

6.3.4 Simulated Results

The simulation models for the traditional barrier toll plaza and the deployment of ORT both have been run 29 times with different random seeds based on the approach presented in section 4.5 to account for the random effects. The simulated traffic conflict risk of the toll plaza with ORT is about 19303.4. Assume the toll plaza has not been converted to ORT, the simulated conflict risk of the traditional barrier toll plaza is about 16285.7, which suggests that the conflict risk was increased by about 18.5 percent given the deployment of ORT.

The actual numbers of crashes between 2001 and 2010 have been reviewed. To eliminate the construction influence, crash data between 2005 and 2006 were excluded from analysis. During the operation of the traditional barrier toll plaza (2001-2004), there were 25 crashes around the toll plaza. However, after the ORT system was installed, there were 29 crashes between 2007 and 2010. Figure 6.16 shows the annual crash counts. The four-year before-and-after comparison suggests that the number of crashes increased by about 16 percent. To address the impact of traffic volumes on crash, the AADTs of the toll plaza were explored. Figure 6.17 shows that the AADTs at the toll plaza were about 15000 before and after the installation of the ORT system. Therefore, the deployment of the ORT system arguably did not clearly cause a positive effect on the safety performance of the toll plaza. The change of simulated conflict risk also reflected a similar finding.

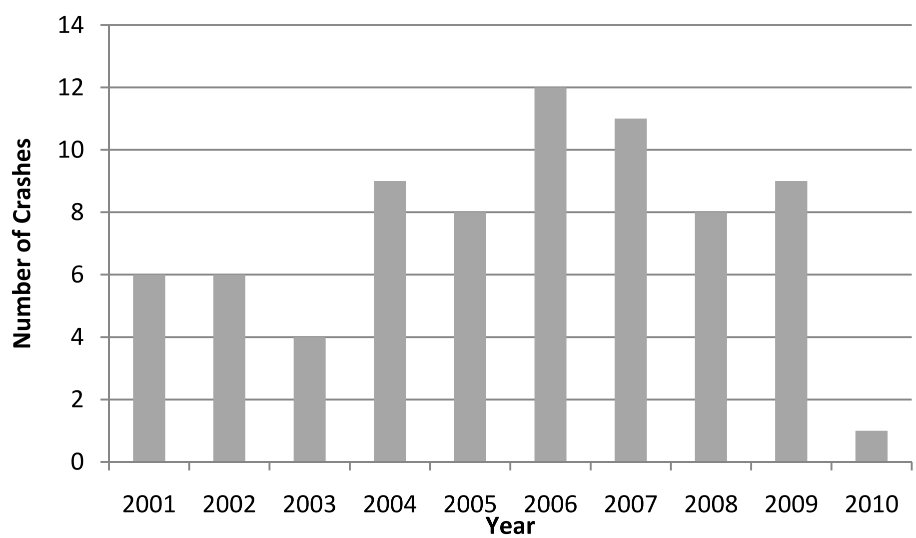


Figure 6.16 Observed crashes of the northbound of Cape May toll plaza

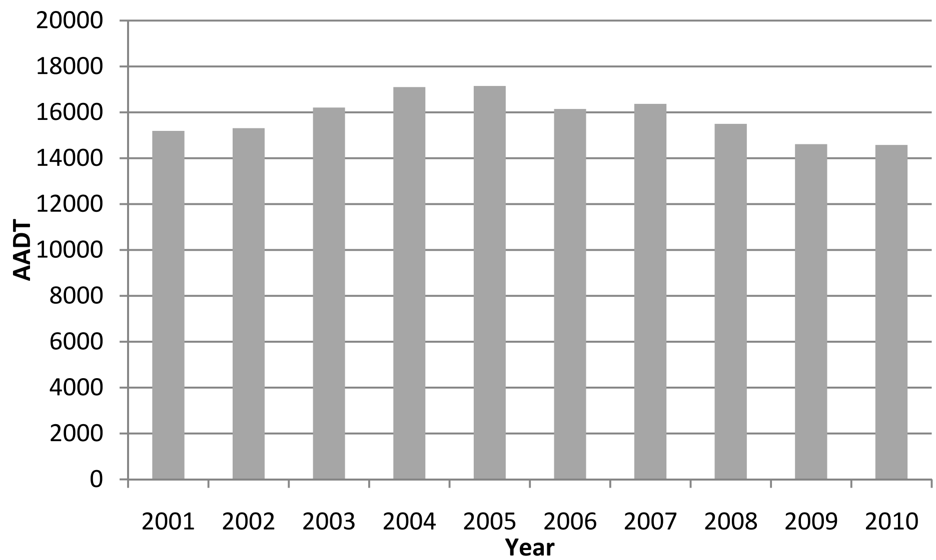


Figure 6.17 AADT of the northbound of Cape May toll plaza

Figure 6.18 and Figure 6.19 investigate the spatial distribution of simulated traffic conflict risk along the 1-mile toll plaza section. Notably, Figure 6.18 suggests that the segments before the ORT signs have higher conflict risk compared to other segments around the toll plaza. The simulated conflict risk within these segments was about 59.4 percent of the total conflict risk. Such a high number is expected as more vehicles have to change their lanes to either select ORT lanes or divert to barrier booths. More interactions among vehicles occur before the diversion. Moreover, the conflict risk around the tollbooths was reduced as many vehicles were diverted to the ORT lanes. Figure 6.19 illustrates the distribution of the simulated conflict risk for a traditional barrier toll plaza and suggests that the approach segment has the highest percentage of conflict risk compared to others. For the traditional toll plaza, vehicles have to make lane changes to select proper payment before approaching the tollbooths. In the meantime, there is a lot of stop-and-go traffic caused by cash/ACM users, which may result in more rear-end conflicts.

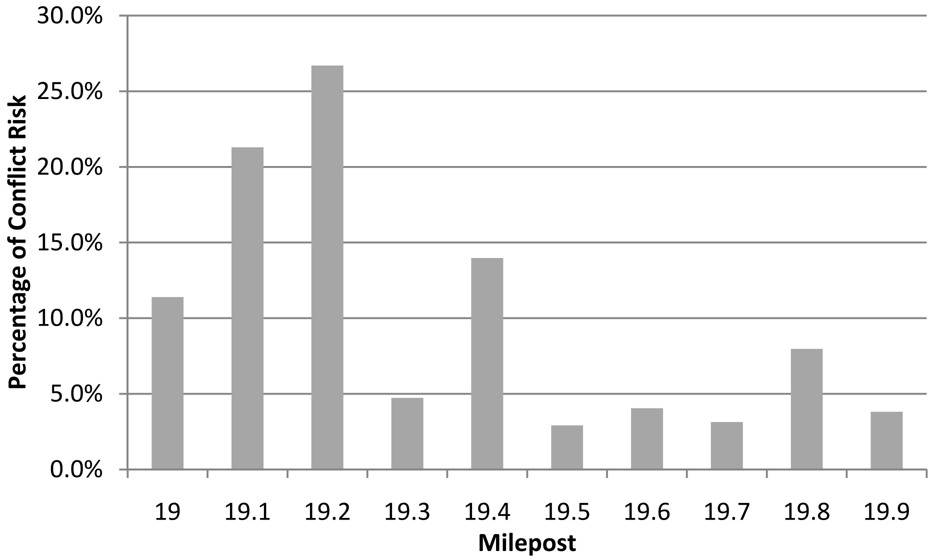


Figure 6.18 Distribution of simulated conflict risk with ORT

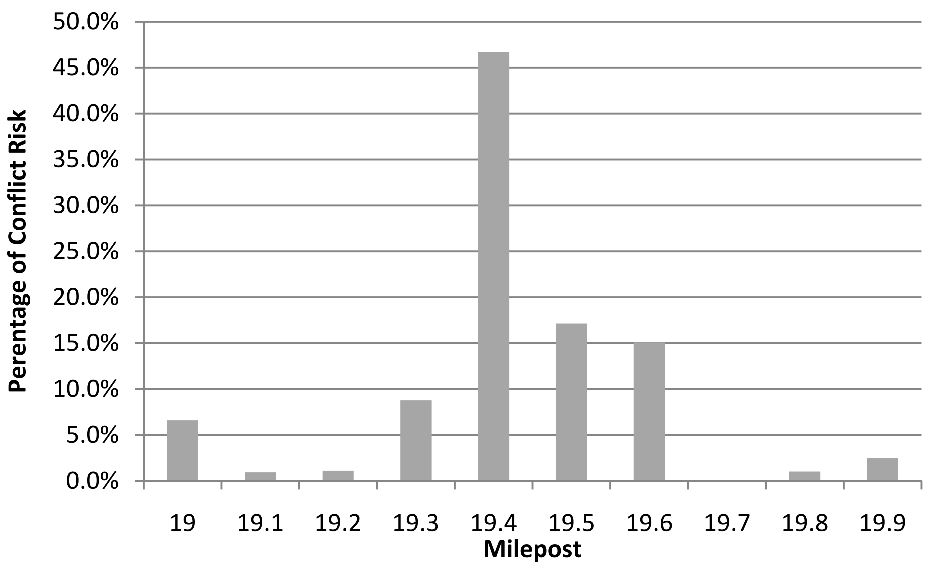


Figure 6.19 Distribution of simulated conflict risk without ORT

A more careful review of the reported crashes at the toll plaza was conducted. Figure 6.20 shows the spatial distribution of the reported crashes before and after the ORT system was deployed. As seen from Figure 6.20(a), more than 45 percent of the crashes occurred at the approach segment during 2001 and 2004. This result confirms our finding based on the simulated conflict risk in previous Figure 6.19. The high correlation

(0.961) between the distribution of the simulated conflicts and actual crashes suggests that the simulated conflict risk can reflect the safety characteristics of the toll plaza. Similarly, Figure 6.20(b) confirms the finding based on the distribution of the simulated conflict risk in Figure 6.18 that the segments before the ORT signs are riskier. The correlation between the distribution of the simulated the conflict risk and actual crashes is about 0.665.

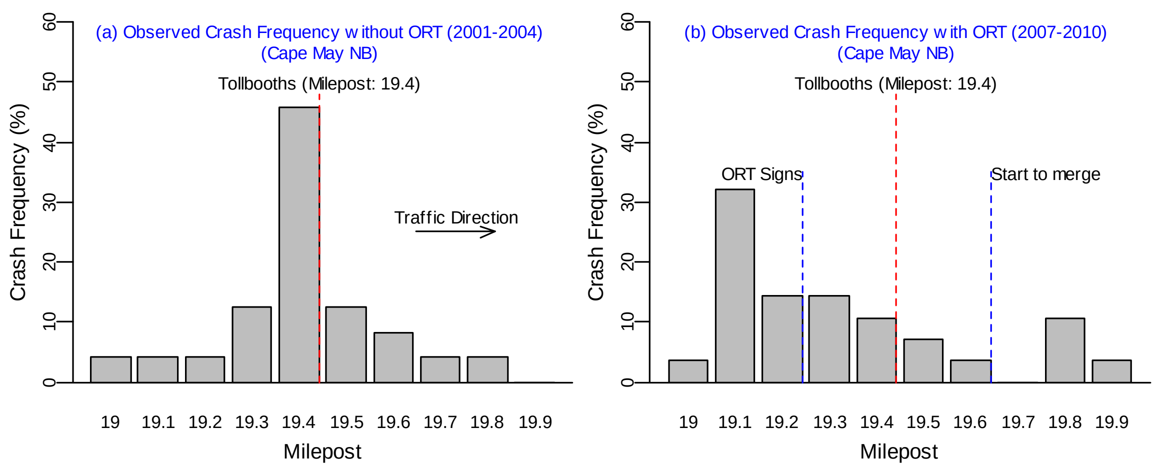


Figure 6.20 Spatial distribution of observed crashes before-and-after deploying ORT

For both cases, the simulated conflict risk can capture important information on safety characteristics. However, it should be noted that simulated conflicts cannot completely match the pattern suggested by observed crash data. This might be due to two factors: (1) the location information of crash data were not perfectly reported; and (2) the simulation results can only reflect the linear conflict risk. Therefore, enhancement of simulation models as well as crash data collection are needed to conduct additional validation studies in the future.

6.3.5 Remarks

This section aims to evaluate the impact of open road tolling (ORT) on the safety performance of mainline toll plazas using a simulation model. The Cape May northbound toll plaza on the Garden State Parkway (GSP) in New Jersey was used as a case study. Crash data, related traffic data and toll plaza configurations between 2001 and 2010 were used to conduct the analysis. The simulated conflict risk suggested that the deployment of ORT at the toll plaza did not improve the safety performance of the toll plaza. The simulated results provided comparable manner as the actual crash data did to capture the change of safety performance of the toll plaza before and after the deployment of the ORT system.

6.4 Summary

This chapter conducted three case studies to show examples of (1) the use of the proposed surrogate safety indicator; (2) linking simulated conflicts to safety performance analysis; and (3) the use of the simulation-based approach to conduct the safety evaluation of new traffic engineering countermeasures. The first case study illustrated the use of the proposed conflict probability (CP) measure to analyze the traffic conflict risk for merging vehicles on highway merging/weaving sections given that trajectories data are available. Given the lack of field trajectory/crash data in many cases, it is usually difficult to directly analyze safety performance. Thus the simulation approach was tested in the second case study to show whether the simulated conflict risk can reveal similar safety characteristics as crash data do. The results suggest that simulated conflict risk can help to capture safety features. Therefore, the approach was further applied in the third case study to evaluate the effectiveness of different traffic safety countermeasures for an actual toll plaza improvement project. These studies suggest that the proposed measures implemented with simulation models can be an alternative to conducting safety analysis.

Chapter 7 Conclusions and Future Research

This chapter summaries the major contributions of this dissertation and discusses directions for future research in the field of using the simulation-based safety evaluation approach.

7.1 Conclusions

Road safety is a critical issue for transportation systems. The use of crash data-based methodologies to analyze traffic safety problems has been problematic due to shortcomings such as unavailability and low quality of historical crash data. Other than crash data-based analysis, development of micro-simulation models in conjunction with surrogate safety measures has been shown to complement traditional safety analysis.

Micro-simulation models have been developed primarily for analysis, evaluation, and optimization of traffic operations. The concept of using micro-simulation models for traffic safety evaluation is still a challenging and relatively unexplored topic. Essentially, using micro-simulation models for safety assessments can be thought of as employing traditional traffic conflict techniques (TCT) in conjunction with the same simulation models used for operational performance analysis of traffic. Traditional TCTs are extended to use simulated vehicle trajectory information to automate conflict analysis based on traffic simulation data. The overall level of safety under certain operational conditions can then be determined by using surrogate safety measures. A simulation-based approach using surrogate safety measures provides a proactive safety evaluation technique to diagnose traffic safety problems in order to select and quantify appropriate remedial measures. It requires less human involvement to extract conflict information and therefore avoids one of the main sources of error encountered when using traditional TCT.

Although great effort has been made toward using microscopic simulation models for safety assessment, questions related to the use of this approach still exist. One issue is the lack of reliable surrogate indicators that can be simulated and observed. Another major concern is the calibration of the micro-simulation models. In a microscopic simulation model, driver behaviors are captured via sub-models representing car-following, gap-acceptance, and lane-changing behavior of each driver in the simulation. These models are in turn dependent on input parameters deemed to represent relevant aspects of driver behavior. Thus, one of the major steps in using simulation models is to ensure that input parameters are determined based on observational data, so that the models replicate the safety performance of a given facility under a given operational condition, and can be verified from field observations. These realistic input parameters can be determined through a robust calibration process that incorporates safety-related aspects of traffic through the use of relevant observed safety data, such as observed conflicts and accidents. Unfortunately, there is limited simulation calibration experience with an emphasis on safety evaluation. In fact, the calibration process can even be more demanding, expensive, and time-consuming, when the objective of safety evaluation is combined with traditional operational performance-related objectives.

The major objectives of this dissertation were focused on the development of a simulation-based framework to support safety evaluation when traditional statistical approaches are not applicable. The major achievements and contributions can be highlighted as follows:

(1) a new surrogate safety measure that can be simulated, observed, and validated for collecting traffic conflict information was developed;

(2) an efficient procedure for calibrating traffic model input parameters was proposed and tested to analyze traffic conflict risks; and

(3) the use of the surrogate safety measure along with the simulation-based approach was further demonstrated through case studies.

7.1.1 Derivation of New Surrogate Safety Measure

The major concern of incorporating the traffic conflict technique (TCT) into micro-simulation for safety evaluation is how to identify potential conflicts. Other than depending on subjective observation and judgment, alternatively, objective measures have to be developed. Generally, such alternative measures can be classified into four groups: time-based, distance-based, deceleration-based, and other composite measures. These alternative measures should be measurable both in actual and simulation conditions. Moreover, the simulated measures have to be verified by actual observations.

In this dissertation, a time-based surrogate safety measure has been derived. Initially, all possible conflict scenarios under car-following condition were investigated. These conflict scenarios were then mathematically described by the kinematic models. The modified time-to-collision (MTTC) measure was derived based on these kinematic models. MTTC extends the definition of TTC by taking into account the influence of accelerations of the consecutive vehicles. It avoids the assumption that a conflict will occur only if the speed of the following vehicle is greater than that of the leading vehicle. Therefore, the derived MTTC can capture more potential conflicts due to acceleration or deceleration discrepancies.

Like other time-based surrogate measures such as TTC and PET, a short value of MTTC generally suggests that a conflict potential will arise because there might not be enough time for the subject vehicle to respond in a safe manner, such as braking and changing lanes to avoid a collision. However, the answer to the question of “how short is really short” is difficult to determine since different drivers have different response times, and they also might take different actions depending upon the vehicle’s performance, prevailing traffic conditions, and so forth.

When using surrogate measures such as MTTC, TTC, and PET in a simulation model to collect conflicts, the determination of the threshold value is critical. The number of simulated conflicts directly relies on the threshold value. It will give biased results if a threshold value is not well defined. For instance, if the threshold value is too large, many safe car-following scenarios will be judged as unsafe conflict scenarios, and vice versa. The difficulty lies in defining a single threshold value. Arguably, there is no unique threshold value of MTTC to distinguish the safe and conflict situation. In addition, there is no clue to choose the value in the micro-simulation model. In the meantime, one will lose lots of information by ignoring those observations that are above the threshold value. Especially for those weakly above the threshold line they may not suggest completely safe cases.

Therefore, considering the fact that the shorter MTTC is, the higher risk of conflict is, this dissertation proposed an exponential decay function as an alternative to define a single threshold value for MTTC to identify the potential risk of the conflict. Then the conflict probability (CP) is proposed as an enhanced surrogate measure on the basis of MTTC. It is a continuous monotonic decreasing function of MTTC. When MTTC is zero, the two consecutive vehicles definitely conflict with each other. When MTTC is relative large, the conflict probability will be small. Thus, CP is a rational indicator to describe the conflict scenarios.

7.1.2 Development of Calibration Procedure

Given the availability of the new surrogate safety indicator, the simulated conflict risk can be obtained for safety evaluation. However, simulation models are not specifically designed for safety analysis. Neither default parameters in the simulation model nor randomly guessed parameters can guarantee the accuracy of the simulated results for safety analysis. Moreover, calibration of the micro-simulation model using a single criterion may cause deterioration of other important criteria. When simulating traffic conflict risk, the accuracy of the safety-related performance of the simulation model is of great interest. However, calibration solely based on safety criteria can be in conflict with other operational performance criteria such as speed and traffic counts. To achieve a high fidelity of simulation output for safety evaluation, it is important to develop a reliable and efficient calibration procedure.

In this dissertation, a numerical optimization approach to calibrate a traffic simulation model for rear-end traffic conflict risk analysis has been proposed. Since there are many input parameters that need to be calibrated, it is impossible to enumerate all possible combinations and run the simulation model for all these combinations. To efficiently find the quasi-optimal parameters of the highly stochastic simulation model, the factorial design method was used to help design simulation experiments to screen key parameters before a final calibration attempt. For instance, with 32-run design, we can screen eleven simulation parameters. Then the simultaneous perturbation stochastic approximation (SPSA) based approach was developed to estimate the quasi-optimal parameters of stochastic traffic simulation models. Instead of solely calibrating to optimize the models' estimates in terms of safety performance and ignoring operational criteria, the concept of multi-criteria optimization by simultaneously considering all of these criteria together was considered. The weighted-sums method was then used to simplify the calibration problem by developing an aggregated objective function.

The proposed approach has been implemented on the selected traffic simulation platform to test its performance. Simulated operational measurements and traffic conflict risk in terms of surrogate safety measures are quantified and compared with observations derived from real-world vehicle trajectory data from the Next Generation Simulation (NGSIM) program. This stochastic and gradient-based calibration approach is shown to be able to identify input parameters that make the aggregate objective function quickly converge to a stable quasi-optimal value. For instance, Figure 5.2 illustrated that with about 40 iterations, we can achieve a relatively stable result. However, it is difficult to use a trial-and-error procedure to search the acceptable parameter combinations when there are three or more parameters. The consistency of the calibrated parameters has been further validated by using additional vehicle trajectory data that were not used for calibration. The results show that the fine-tuning of parameters can greatly improve the performance of simulation models to describe traffic conflict risk as well as the operational measures quantified using the field data. For example, the RMSPEs for most performance criteria have been reduced by about 80 percent.

7.1.3 Link with Safety Evaluation Practices

Traditional ad-hoc approaches to safety evaluation are not useful in many conditions. The use of surrogate safety measures and the simulation-based approach provide a proactive safety evaluation technique to quickly and economically diagnose traffic safety problems and apply appropriate remedial measures.

To illustrate the benefits of the proposed surrogate safety measure and the simulation-based approach, three case studies were conducted in this dissertation: (1) the use of the proposed surrogate safety indicator to describe the traffic conflict risk in real time; (2) linking simulated conflicts to crash characteristics; and (3) the use of the simulation-based approach to conduct safety evaluations for new traffic engineering countermeasures.

The first case study illustrated the use of the proposed surrogate safety measure conflict probability (CP) to analyze the traffic conflict risk for merging vehicles on highway merging/weaving section if trajectory data are available. The results based on trajectory data analysis highlight the potential conflict risk associated with vehicles over time and space. It can be used to develop real-time traffic control measures to prevent potential accidents at merge sections. Given the lack of field trajectory/crash data in many cases, it is usually difficult to directly analyze safety performance. Thus, the simulation approach was tested in the second case study to show whether the simulated conflict risk revealed safety characteristics as crash data did. The results suggested that simulated conflict risk can help to capture safety features. Therefore, the approach was further applied in the third case study to conduct a safety evaluation of new countermeasures applied to an actual toll plaza improvement project. The study showed that the overall change of safety then can be determined by the simulated conflict risk using the proposed surrogate safety measures. The comparison with crash data confirmed that the proposed surrogate safety measures implemented with simulation models can be a useful alternative to conduct safety evaluation in case crash data are not available.

7.2 Future Research Directions

Although the proposed surrogate safety measure and the calibration approach presented in this dissertation illustrated the potential of using micro-simulation models to perform traffic safety evaluation, future research is needed to fully implement this methodology in the field. One research direction is the further validation of the proposed surrogate safety measure. Due to the limited amount of trajectory data, only limited calibration efforts have been made to examine the performance of the proposed indicator. Given the availability of more detailed vehicle trajectory data, large-scale validation studies should be conducted to extensively test the soundness and feasibility of the surrogate safety measures. Moreover, more comparisons between the proposed surrogate safety measure and other surrogate measures are necessary. There are a number of surrogate measures introduced in the literature, but comparisons of these measures to the proposed measure as well as among themselves have not been widely conducted. To identify the reliable indicators for different objectives of safety evaluation, such comparisons are immediately needed.

Another research direction is the investigation of the linkage between simulated conflict risk and crash counts. This dissertation explored a potential link between the simulation conflict risk and the observed crash data by comparing their spatial distribution characteristics. However, no clear linkages between the number of simulated conflicts and the crash counts for all types of accidents could be established, as our work only focused on rear-end crashes at a limited number of facility types. It is important to establish such a relationship by analyzing more crash data and corresponding simulated conflicts so that the crash frequency of different types of accidents at different facilities can be predicted based on these simulated conflicts.

Another research direction lies in the enhancement of micro-simulation models as well as the surrogate safety measures. Current micro-simulation models are not developed for safety analysis. When the surrogate safety measures are used in the simulation models, only limited types of conflict risks can be described. For instance, the proposed surrogate measure in this dissertation can only capture the major linear conflicts (i.e., rear-end conflicts) between vehicles. It is difficult to describe single vehicle conflicts (i.e., fixed-object conflicts) due to the capacity of current simulation models and surrogate measures. Therefore, the internal driver-behavior models need to be improved to capture scenarios such as sideswipe, fixed-object, and non-fixed-object interaction. In the meantime, aggregation of different surrogate safety measures may be applied to describe more conflict situations.

Appendix A1

Table of 2_{IV}^{11-6} Fractional Factorial Design of Experiment

Run	A	B	C	D	E	F	G	H	I	J	K
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
2	-1	-1	-1	-1	1	-1	-1	1	-1	1	1
3	-1	-1	-1	1	-1	-1	1	1	1	1	1
4	-1	-1	-1	1	1	-1	1	-1	1	-1	-1
5	-1	-1	1	-1	-1	1	1	1	1	-1	-1
6	-1	-1	1	-1	1	1	1	-1	1	1	1
7	-1	-1	1	1	-1	1	-1	-1	-1	1	1
8	-1	-1	1	1	1	1	-1	1	-1	-1	-1
9	-1	1	-1	-1	-1	1	1	-1	-1	-1	1
10	-1	1	-1	-1	1	1	1	1	-1	1	-1
11	-1	1	-1	1	-1	1	-1	1	1	1	-1
12	-1	1	-1	1	1	1	-1	-1	1	-1	1
13	-1	1	1	-1	-1	-1	-1	1	1	-1	1
14	-1	1	1	-1	1	-1	-1	-1	1	1	-1
15	-1	1	1	1	-1	-1	1	-1	-1	1	-1
16	-1	1	1	1	1	-1	1	1	-1	-1	1
17	1	-1	-1	-1	-1	1	-1	-1	1	1	-1
18	1	-1	-1	-1	1	1	-1	1	1	-1	1
19	1	-1	-1	1	-1	1	1	1	-1	-1	1
20	1	-1	-1	1	1	1	1	-1	-1	1	-1
21	1	-1	1	-1	-1	-1	1	1	-1	1	-1
22	1	-1	1	-1	1	-1	1	-1	-1	-1	1
23	1	-1	1	1	-1	-1	-1	-1	1	-1	1
24	1	-1	1	1	1	-1	-1	1	1	1	-1
25	1	1	-1	-1	-1	-1	1	-1	1	1	1
26	1	1	-1	-1	1	-1	1	1	1	-1	-1
27	1	1	-1	1	-1	-1	-1	1	-1	-1	-1
28	1	1	-1	1	1	-1	-1	-1	-1	1	1
29	1	1	1	-1	-1	1	-1	1	-1	1	1
30	1	1	1	-1	1	1	-1	-1	-1	-1	-1
31	1	1	1	1	-1	1	1	-1	1	-1	-1
32	1	1	1	1	1	1	1	1	1	1	1

Appendix B1

Summary of Simulation Results Based on the Design of Experiment

Run	A	B	C	D	E	F	G	H	I	J	K	$z_1(\theta)$	$z_2(\theta)$	$z_3(\theta)$	$z_4(\theta)$
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1.0480	0.9696	0.0860	0.2984
2	-1	-1	-1	-1	1	-1	-1	1	-1	1	1	0.1395	0.5957	0.0318	0.0391
3	-1	-1	-1	1	-1	-1	1	1	1	1	1	0.1519	0.5039	0.0314	0.0391
4	-1	-1	-1	1	1	-1	1	-1	1	-1	-1	0.4510	0.5990	0.0763	0.1718
5	-1	-1	1	-1	-1	1	1	1	1	-1	-1	0.2623	0.4243	0.2301	0.1776
6	-1	-1	1	-1	1	1	1	-1	1	1	1	0.1349	0.7515	0.0323	0.0338
7	-1	-1	1	1	-1	1	-1	-1	-1	1	1	0.1329	0.9172	0.0330	0.0352
8	-1	-1	1	1	1	1	-1	1	-1	-1	-1	0.1922	0.4445	0.2055	0.2357
9	-1	1	-1	-1	-1	1	1	-1	-1	-1	1	1.0062	0.4579	0.3971	0.2374
10	-1	1	-1	-1	1	1	1	1	-1	1	-1	1.5499	0.3903	0.3590	0.2226
11	-1	1	-1	1	-1	1	-1	1	1	1	-1	1.4780	0.4575	0.2670	0.3710
12	-1	1	-1	1	1	1	-1	-1	1	-1	1	0.3947	0.5696	0.0736	0.1731
13	-1	1	1	-1	-1	-1	-1	1	1	-1	1	0.5848	0.2899	0.0772	0.2283
14	-1	1	1	-1	1	-1	-1	-1	1	1	-1	0.3837	2.2708	0.3404	0.1902
15	-1	1	1	1	-1	-1	1	-1	-1	1	-1	0.6446	1.2304	0.4409	0.2171
16	-1	1	1	1	1	-1	1	1	-1	-1	1	0.3729	0.5134	0.2761	0.2639
17	1	-1	-1	-1	-1	1	-1	-1	1	1	-1	0.4896	0.7704	0.3292	0.1162
18	1	-1	-1	-1	1	1	-1	1	1	-1	1	0.6755	0.5425	0.5375	0.2041
19	1	-1	-1	1	-1	1	1	1	-1	-1	1	0.7644	0.5723	0.5951	0.1825
20	1	-1	-1	1	1	1	1	-1	-1	1	-1	0.7283	1.6197	0.5272	0.1129
21	1	-1	1	-1	-1	-1	1	1	-1	1	-1	0.5208	1.4084	0.3344	0.2559
22	1	-1	1	-1	1	-1	1	-1	-1	-1	1	0.5086	0.5593	0.5075	0.4045
23	1	-1	1	1	-1	-1	-1	-1	1	-1	1	0.4930	0.4658	0.4797	0.4276
24	1	-1	1	1	1	-1	-1	1	1	1	-1	0.6590	0.4297	0.2261	0.3170
25	1	1	-1	-1	-1	-1	1	-1	1	1	1	0.9564	0.7552	0.1540	0.2071
26	1	1	-1	-1	1	-1	1	1	1	-1	-1	0.6696	0.4677	0.6473	0.4666
27	1	1	-1	1	-1	-1	-1	1	-1	-1	-1	0.8680	0.5302	0.6554	0.5371
28	1	1	-1	1	1	-1	-1	-1	-1	1	1	1.7054	0.8903	0.3101	0.3817
29	1	1	1	-1	-1	1	-1	1	-1	1	1	0.6421	0.3957	0.4280	0.0840
30	1	1	1	-1	1	1	-1	-1	-1	-1	-1	0.7577	0.6414	0.7034	0.3847
31	1	1	1	1	-1	1	1	-1	1	-1	-1	0.8343	0.5858	0.7722	0.3866
32	1	1	1	1	1	1	1	1	1	1	1	0.6736	0.4891	0.4525	0.0562

Appendix B2

ANOVA Table for Simulated Conflict Risks

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significant
A	1	2.5628	2.5628	90.6166	< 2.2e-16	***
B	1	10.7065	10.7065	378.5648	< 2.2e-16	***
C	1	7.837	7.837	277.1052	< 2.2e-16	***
D	1	0.013	0.013	0.4581	0.499102	
E	1	0.2183	0.2183	7.7172	0.005867	**
F	1	0.0881	0.0881	3.1145	0.078766	.
G	1	0.0483	0.0483	1.7089	0.192272	
H	1	0.0608	0.0608	2.1481	0.143949	
I	1	1.4741	1.4741	52.1206	5.70E-12	***
J	1	0.3448	0.3448	12.1932	0.000563	***
K	1	1.3613	1.3613	48.1352	3.13E-11	***
A:B	1	0.751	0.751	26.5542	5.06E-07	***
A:C	1	0.8542	0.8542	30.2048	9.24E-08	***
B:C	1	1.3492	1.3492	47.7054	3.77E-11	***
A:D	1	2.1998	2.1998	77.7807	< 2.2e-16	***
B:D	1	0.1108	0.1108	3.9188	0.0488	*
C:D	1	0.0113	0.0113	0.3993	0.527988	
A:E	1	1.7566	1.7566	62.1123	8.82E-14	***
B:E	1	0.005	0.005	0.1764	0.674822	
C:E	1	0.0001	0.0001	0.0027	0.958933	
D:E	1	0.0706	0.0706	2.4947	0.115444	
D:F	1	0.2053	0.2053	7.2597	0.007509	**
E:F	1	0.0044	0.0044	0.156	0.69317	
E:G	1	0.1696	0.1696	5.9985	0.014976	*
A:H	1	0.6634	0.6634	23.4558	2.19E-06	***
F:H	1	4.4636	4.4636	157.8264	< 2.2e-16	***
Errors	261	7.3815	0.0283			

*Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Appendix B3

ANOVA Table for Simulated Lane Changes

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significant
A	1	0.0193	0.0193	0.3861	0.534877	
B	1	0.1148	0.1148	2.298	0.130754	
C	1	0.3562	0.3562	7.128	0.008065	**
D	1	0.2139	0.2139	4.2808	0.039529	*
E	1	0.3041	0.3041	6.0854	0.014273	*
F	1	1.6881	1.6881	33.7772	1.80E-08	***
G	1	0.0061	0.0061	0.1227	0.726412	
H	1	8.8167	8.8167	176.418	< 2.2e-16	***
I	1	0.8748	0.8748	17.5034	3.92E-05	***
J	1	7.73	7.73	154.6719	< 2.2e-16	***
K	1	4.4338	4.4338	88.7182	< 2.2e-16	***
A:B	1	1.8819	1.8819	37.6554	3.12E-09	***
A:C	1	3.3899	3.3899	67.8301	8.64E-15	***
B:C	1	2.0054	2.0054	40.1266	1.04E-09	***
A:D	1	0.2576	0.2576	5.1537	0.024012	*
B:D	1	0.0013	0.0013	0.0254	0.873485	
C:D	1	1.7003	1.7003	34.0222	1.61E-08	***
A:E	1	0.1492	0.1492	2.9852	0.085211	.
B:E	1	1.1476	1.1476	22.9628	2.78E-06	***
C:E	1	0.0213	0.0213	0.4267	0.514208	
D:E	1	0.0583	0.0583	1.1671	0.281004	
D:F	1	3.3195	3.3195	66.4213	1.53E-14	***
E:F	1	0.1358	0.1358	2.718	0.100423	
E:G	1	1.2837	1.2837	25.686	7.62E-07	***
A:H	1	2.0415	2.0415	40.8485	7.53E-10	***
F:H	1	0.046	0.046	0.9203	0.338286	
Errors	261	13.0439	0.05			

*Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Appendix B4

ANOVA Table for Simulated Traffic Counts

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significant
A	1	6.2183	6.2183	3516.088	< 2.2e-16	***
B	1	1.2298	1.2298	695.4027	< 2.2e-16	***
C	1	0.0598	0.0598	33.7909	1.79E-08	***
D	1	0.0145	0.0145	8.1899	0.004554	**
E	1	4.81E-06	4.81E-06	0.0027	0.958469	
F	1	0.4522	0.4522	255.6762	< 2.2e-16	***
G	1	0.3098	0.3098	175.1612	< 2.2e-16	***
H	1	0.0024	0.0024	1.3324	0.249431	
I	1	0.3808	0.3808	215.3226	< 2.2e-16	***
J	1	1.1506	1.1506	650.6108	< 2.2e-16	***
K	1	0.8947	0.8947	505.8893	< 2.2e-16	***
A:B	1	0.2373	0.2373	134.1946	< 2.2e-16	***
A:C	1	0.0077	0.0077	4.3518	0.037941	*
B:C	1	0.177	0.177	100.0626	< 2.2e-16	***
A:D	1	0.0781	0.0781	44.1452	1.77E-10	***
B:D	1	0.0009	0.0009	0.4979	0.48104	
C:D	1	0.016	0.016	9.0469	0.002888	**
A:E	1	0.0309	0.0309	17.447	4.03E-05	***
B:E	1	0.0008	0.0008	0.4714	0.492953	
C:E	1	0.0028	0.0028	1.5755	0.210532	
D:E	1	1.4243	1.4243	805.3496	< 2.2e-16	***
D:F	1	0.0468	0.0468	26.4557	5.30E-07	***
E:F	1	0.0283	0.0283	16.019	8.18E-05	***
E:G	1	0.0063	0.0063	3.5708	0.059913	.
A:H	1	0.0025	0.0025	1.4185	0.234729	
F:H	1	0.0291	0.0291	16.4594	6.57E-05	***
Residuals	261	0.4616	0.0018			

*Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

Appendix B5

ANOVA Table for Simulated Speed

Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)	Significant
A	1	0.71125	0.71125	946.0141	< 2.2e-16	***
B	1	0.51711	0.51711	687.7977	< 2.2e-16	***
C	1	0.00109	0.00109	1.4504	0.229558	
D	1	0.03604	0.03604	47.9382	3.41E-11	***
E	1	0.00576	0.00576	7.6615	0.006045	**
F	1	0.57665	0.57665	766.9878	< 2.2e-16	***
G	1	0.09716	0.09716	129.23	< 2.2e-16	***
H	1	0.00268	0.00268	3.5586	0.060349	.
I	1	0.03	0.03	39.8973	1.15E-09	***
J	1	1.24131	1.24131	1651.04	< 2.2e-16	***
K	1	0.60253	0.60253	801.4089	< 2.2e-16	***
A:B	1	0.04273	0.04273	56.8399	7.82E-13	***
A:C	1	0.0219	0.0219	29.1284	1.52E-07	***
B:C	1	0.64011	0.64011	851.3945	< 2.2e-16	***
A:D	1	0.01111	0.01111	14.7778	0.000152	***
B:D	1	0.03924	0.03924	52.195	5.52E-12	***
C:D	1	2.03E-06	2.03E-06	0.0027	0.958563	
A:E	1	0.04613	0.04613	61.3592	1.20E-13	***
B:E	1	0.00379	0.00379	5.0453	0.02553	*
C:E	1	0.0238	0.0238	31.6537	4.74E-08	***
D:E	1	0.19136	0.19136	254.529	< 2.2e-16	***
D:F	1	0.00835	0.00835	11.1013	0.000988	***
E:F	1	0.01033	0.01033	13.736	0.000257	***
E:G	1	0.0114	0.0114	15.1602	0.000126	***
A:H	1	0.08142	0.08142	108.2944	< 2.2e-16	***
F:H	1	0.01183	0.01183	15.738	9.41E-05	***
Residuals	261	0.19623	0.00075			

*Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1*

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