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Microscopic Safety Evaluation and Prediction for Special Expressway Facilities

Ling Wang
University of Central Florida

MICROSCOPIC SAFETY EVALUATION AND PREDICTION FOR SPECIAL EXPRESSWAY FACILITIES

by

LING WANG

B.S., Hunan University, China, 2010
M.S., Tongji University, China, 2013

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Major Professor: Mohamed A. Abdel-Aty

ABSTRACT

Expressways are of great importance and serve as the backbone of a roadway system. One of the reasons why expressways increase travel speeds and provide high level of services is that limited access is provided to permit vehicles to enter or exit expressways. Entering and exiting of vehicles are accomplished through interchanges, which consist of several ramps, thus the spacing between ramps is important. A weaving segment might form when an on-ramp is closely followed by an off-ramp. The geometric design of ramps and the traffic behavior of weaving segments are different from other expressway segments. These differences result in distinct safety mechanisms of these two expressway special facilities. Hence, the safety of these two facilities needs to be addressed.

The majority of previous traffic safety studies on expressway special facilities are based on highly aggregated traffic data, e.g., Annual Average Daily Traffic (AADT). This highly aggregated traffic data cannot represent traffic conditions at the time of crashes and also cannot be used in the study of weather and temporal impact on crash occurrence. One way to solve this problem is microscopic safety evaluation and prediction through hourly crash prediction and real-time safety analysis. An hourly crash study averages one or several hours' traffic data in a year and also aggregates crash frequencies in the corresponding hour(s). Then it applies predictive models to determine the statistical relationship between crashes and hourly traffic flow characteristics, such as traffic volume. Real-time safety analysis enables us to predict

crash risk and distinguish crashes from non-crashes in the next few minutes using the current traffic, weather, and other conditions.

There are four types of crash contributing factors: traffic, geometry, weather, and driver. Among these, traffic parameters have been utilized in all previous microscopic safety studies. On the other hand, the other three factors' impact on microscopic safety has not been widely analyzed. The geometric factors' influence on safety are generally excluded by previous researchers using the matched-case-control method, because the majority of previous microscopic safety studies are on mainlines, where the geometric design of a segment does not change much and geometry does not have a significant effect on safety. Not enough studies have adopted weather factors in microscopic safety analysis because of the limited availability of weather data. The impact of drivers on safety has also not been widely considered since driver information is hard to be obtained. This study explores the relationship between crashes and the four contributing factors. Weather data are obtained from airport weather stations and crash reports which record weather and roadway surface conditions for crashes. Meanwhile, land-use and trip generation parameters serve as surrogates for drivers' behavior.

Several methods are used to explore and quantify the impact of these factors. Random forests are used in discovering important and significant explanatory variables, which play significant roles in determining traffic safety, by ranking their importance. Meanwhile, in order to prevent high correlation between independent variables, Pearson correlation tests are carried out before model estimations. Only the variables which are not highly correlated are selected. Then, the selected variables are put in logistic regression models and Poisson-lognormal models to respectively estimate crash risk and crash frequency for special expressway facilities. Meanwhile, in case of correlation among observations in the same segment, a multilevel modeling structure has been implemented. Furthermore, a data mining technique–Support Vector Machine (SVM)–is used to distinguish crash from non-crash observations.

Once the crash mechanisms for special expressway facilities are found, we are able to provide valuable information on how to manage roadway facilities to improve the traffic safety of special facilities. This study adopts Active Traffic Management (ATM) strategies, including Ramp Metering (RM) and Variable Speed Limit (VSL), in order to enhance the safety of a congested weaving segment. RM regulates the entering vehicle volume by adjusts metering rate, and VSL is able to provide smoother mainline traffic by changing the mainline speed limits. The ATM strategies are carried out in microscopic simulation VISSIM through the Component Object Model (COM) interface. The results shows that the crash risk and conflict count of the studies weaving segment have been significantly reduced because of ATM.

Furthermore, the mechanisms of traffic conflicts, a surrogate safety measurement, are explored for weaving segments using microscopic simulation. The weaving segment conflict prediction model is compared with its crash prediction model. The results show that there are similarity and differences between conflict and crash mechanisms.

Finally, potential relevant applications beyond the scope of this research but worth investigation in the future are also discussed in this dissertation.

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LIST OF ACRONYMS/ABBREVIATIONS

AADT	Annual Average Daily Traffic
ADT	Average Daily Traffic
AIC	Akaike Information Criterion
ALINEA	Asservissement Linéaire d'Entrée Autoroutière
ATM	Active Traffic Management
ATT	Average Travel Time
AUC	Area Under the Curve
CARS	Crash Analysis Reporting System
CC0	Stand Still Distance
CC1	Following Headway Time
CC2	Following Variation
CFX	Central Florida Expressway Authority
CI	Confidence Interval
CMF	Crash Modification Factor
COM	Component Object Model
DIC	Deviance Information Criterion
DLCD	Desired Lane Change Distance
DMS	Dynamic Message Signs
DZ	Drizzle
F+I	Fatal and Injury Crash
F+S	Fatal and Severe Injury Crash
FARS	Fatality Analysis Reporting System
FDOT	Florida Department of Transportation

FHWA	Federal Highway Administration
GEH	Geoffrey E. Havers
GES	General Estimates System
HCM	Highway Capacity Manual
HGV	Heavy Goods Vehicle
HSM	Highway Safety Manual
ISAT	Interchange Safety Analysis Tool
ITS	Intelligent Transportation Systems
MCMC	Markov Chain Monte Carlo
MCO	Orlando International Airport
MP	Milepost
MV	Multi-Vehicle
MVDS	Microwave Vehicle Detection System
NCDC	National Climate Data Center
NOAA	National Oceanic and Atmospheric Administration
OR	Odds Ratio
ORL	Orlando Executive Airport
PDO	Property Damage Only Crash
PET	Post-Encroachment Time
RA	Rain
RCI	Road Characteristics Inventory
RITIS	Regional Integrated Transportation Information System
RM	Ramp Metering
RM-VSL	Integrated Ramp Metering and Variable Speed Limit

S4A	Signal Four Analytics
SAS	Statistical Analysis System
SPF	Safety Performance Function
SR 408	State Roads 408
SR 417	State Roads 417
SR 528	State Roads 528
SSAM	Surrogate Safety Assessment Model
SV	Single-vehicle
SVM	Support Vector Machine
SWTAZ	Statewide Traffic Analysis Zone
TS	Thunderstorm
TTC	Time-to-Collision
USNO	United States Naval Observatory
V/C	Volume-to-Capacity-Ratio
VBA	Visual Basic for Application
VMT	Vehicle-miles Traveled
VSL	Variable Speed Limit

CHAPTER 1: INTRODUCTION

1.1 Overview

Expressways play a vital role in serving megacities. They increase the travel speed and reduce the travel time for daily traffic, mid- and long-trips in particular. One of the reasons for the efficiency of the expressway system is that access is only permitted at limited locations where interchanges are provided. There are two types of interchanges: service interchanges and system interchanges. A service interchange is an interchange between a freeway and a non-freeway, such as a local street; a system interchange connects two freeways and it is also called freeway-to-freeway interchange (Ray et al., 2011; HCM, 2010). An interchange consists of several ramps. The geometric design of ramps is different from mainlines, e.g., smaller radii. Furthermore, compared to service interchange ramps, freeway-to-freeway interchange ramps need to provide free-flow movements, and the ramps may be grade separated, thus going over or under each other. Hence, traffic conditions on freeway-to-freeway interchange ramps are more complicated than on other ramps, and the safety of freeway-to-freeway interchange ramps need to be separately studied.

Meanwhile, the spacing between two ramps is important. Previously studies have found that there exist significant relationship between ramp spacing and safety (Le and Porter, 2012). Expressways whose on-ramps are closely followed by off-ramps would have a weaving problem. This phenomenon often occurs at the downtown areas where there are dense expressway entrances and exits. When the length of a weaving segment is limited, merging and diverging maneuvers cannot be operated independently. Vehicles entering and exiting expressways have to weave with each other and compete for lane-changing opportunities. Thus, the safety of weaving segments could be a concern (Kim and Park, 2016).

In order to understand the crash mechanisms on these two expressway facilities (ramps and weaving segments), there has been a significant number of related studies on identifying crash factors and developing crash prediction models to estimate crash frequency. Among these research efforts, plenty of them are based on highly aggregated traffic data, for example, Annual Average Daily Traffic (AADT) or Average Daily Traffic (ADT). Using highly aggregated traffic data may cause three problems. First, average flow cannot represent traffic conditions at the time of a crash. An expressway with high traffic flow during peak hours would have a different crash potential than an expressway with the same AADT but whose flow is evenly spread out during the day. Second, the impact of weather on traffic safety cannot be explored. Diver behavior under fog conditions is different from that under clear conditions. Hence, different weather conditions should have different impacts on traffic safety. Third, it is impossible to know the impact of temporal factors on crash occurrence, such as daytime and nighttime (Mensah and Hauer, 1998).

These problems can be solved by microscopic safety studies based on high resolution traffic data at short time intervals from well-developed traffic management and information systems. There are mainly two types of microscopic safety studies: hourly safety studies and real-time crash analyses. The hourly crash study averages one or several hours' worth of traffic data in a year and also aggregates crash frequencies in the corresponding hour(s). Then it applies predictive models to determine the statistical relationship between crashes and hourly traffic flow characteristics, such as traffic volume (Lord et al., 2005). In an hourly crash study, the impact of peak traffic and temporal factors on crash frequency can be captured.

Meanwhile, with the development of technologies which analyze and manage considerable data, crash mechanisms can be explored using real-time crash studies, which are from a more microscopic aspect than hourly crash studies. Conditions that occur just before crashes, such as traffic and environmental situations, are considered to be crash causes. By comparing crash conditions with non-crash conditions, crash precursors which are relatively more "crash prone" than others can be identified. Then, real-time crash analysis builds models using these crash precursors to estimate crash risk for each time interval and then distinguish hazardous traffic conditions.

Because of the advantages of microscopic safety analyses, they have already been applied to freeway mainline segments by several previous researchers. Nevertheless, there has not been enough microscopic safety research on expressway special facilities. Therefore, the objective of this study is microscopic safety evaluation and prediction for special expressway facilities, i.e., ramps, freeway-to-freeway interchange ramps, and weaving segments. Generally, there are four crash contributing factors: traffic, geometry, weather, and driver, among which traffic parameters are widely used in microscopic safety analyses. But studies that utilize the other three factors in microscopic safety analyses are limited.

Previous microscopic safety analyses for expressways have focused on mainlines, whose geometric design does not change much and whose geometry does not have a significant impact on safety. Hence, these safety studies intentionally exclude geometric factors. However, the geometry designs of expressway special facilities are site-specific and should have a significantly influence on the occurrence of crashes. As for weather factors, though the effect of weather on safety has been found, there are not enough microscopic safety studies which have had weather as a variable. The main reason is the limited availability of weather data which are generally provided by weather stations. This study intends to propose a new method which combines weather information from airport weather stations and also from crash reports.

The driver factor is seldom considered in real-time safety study. In real-time safety studies, crash reports can provide driver information for crash observations; but for non-crash observations, driver information cannot be obtained from available data sources. Hence, it is difficult to directly study driver characteristics' impact on crash risk. On the other hand, although driver information is not available, there are some surrogates: trip generation and land-use factors. These two types of factors can reflect driver behavior and affect traffic safety. For crashes which happen on ramps, the origins or destinations of the vehicles involved are very likely to be in nearby zones. Hence, if the trip generation and land-use information of the zone where a ramp lies in can be captured, this information might act as surrogates for driving behavior of vehicles on ramps.

All of the impacts of these four factors on safety is explored and quantified in this study using statistical models and data mining methods. Furthermore, after the crash mechanisms are uncovered by real-time safety analyses, the safety of expressway facilities can be enhanced by adopting Active Traffic Management (ATM), which is able to dynamically manage roadway facilities based on the prevailing and predicted traffic conditions. To be more specific, the safety of a congested weaving segment is improved by Ramp Metering (RM) and Variable Speed Limit (VSL) strategies in microscopic simulations. RM is capable to adjust entering vehicles on on-ramps using ramp signals, and VSL can smoothen traffic conditions on mainlines through changing mainline speed limits.

In addition to crash mechanisms, the conflict mechanism is also explored from a microscopic aspect of view. The conflict count has been proven to be a valid crash frequency surrogate in previous studies (Sayed and Zein, 1999; Sacchi and Sayed, 2016). However, there are limited studies which confirm that the conflict mechanisms are similar to crash mechanisms using real-time safety analyses. Meanwhile, very few studies have utilized conflicts to evaluate the safety of special facilities.

1.2 Research Objectives

The dissertation focuses on microscopic safety evaluation and prediction for special expressway facilities, and utilizing ATM to improve safety in real-time. The specific objective will be achieved by the several tasks:

1. Real-time safety analysis for expressway ramps;
2. Microscopic safety prediction for freeway-to-freeway interchange ramps;
3. Real-time crash prediction for expressway weaving segments;
4. Implementation of ATM to enhance the safety of a congested weaving segment, and;
5. Exploring conflict mechanisms in real-time.

The first objective has been achieved in Chapters 3 and 4 by the following sub-tasks:

a) Exploring the crash contributing factors for sing-vehicle (SV) and multi-vehicle (MV) crashes for expressway ramps. The contributing factors include traffic, geometry, weather, land-use, and trip generation parameters.
b) Building Bayesian logistic regression models to estimate crash risks for SV and MV crashes.
c) Appling a data mining technique–Support Vector Machine (SVM)–to achieve

better model performance for the real-time ramp crash prediction model.

d) Ranking the importance of significant crash precursors to provide suggestions to practitioners on how to efficiently improve ramp safety.

The second objective has been achieved in Chapter 5 by the following sub-tasks:

e) Developing Bayesian Poisson-lognormal models to predict SV and MV crash frequency for freeway-to-freeway interchange ramps based on 3-hour interval.

f) Building Bayesian logistic regression models to predict crash risk based on real-time analysis for SV and MV crashes.

g) Utilizing weather data from crash reports to enrich weather data source and to help understanding crash mechanisms.

The third objective has been achieved in Chapter 6 by the following sub-tasks:

h) Understanding crash characteristics of weaving segments and giving a primary analysis of the impact of geometric configuration on weaving segment safety.

i) Building a Bayesian logistic regression model to estimate crash risk on weaving segments in real-time.

j) Providing suggestions on how to enhance the safety of weaving segments.

The fourth objective has been achieved in Chapter 7 by the following sub-tasks:

k) Finding the ATM strategies which can potentially improve safety of weaving segment based on the crash mechanisms of weaving segments found in

Chapter 6.

l) Proposing a novel RM algorithm to improve the safety of a congested weaving segment.

m) Applying ATM strategies in microscopic simulation using the Component Object Model (COM) interface.

n) Evaluating the safety impact of several ATM strategies, i.e., RMs, VSLs, and integrated strategies, on the studied weaving segment.

The fifth objective has been achieved in Chapter 8 by the following sub-tasks:

o) Calibrating and Validating weaving segments' microscopic simulation networks using volume, speed, and field crashes.

p) Building conflict prediction models for weaving segments to find conflict mechanisms.

1.3 Dissertation Organization

The organization of the dissertation is as follows: following this chapter, existing studies on safety analysis for freeway special facilities, microscopic traffic safety analysis, the implementation of ATM, etc. are reviewed and summarized in Chapter 2. Chapter 3 presents real-time safety analysis for different crash types on expressway ramps and ranks the importance of identified significant variables. Chapter 4 adopts SVMs to improve the real-time safety analysis model. In addition to traffic, weather, and geometry parameters, land-use and trip generation factors are utilized in real-time safety study for expressway ramps. Chapter 5 focuses on investigating crash mechanisms for freeway-to-freeway interchange ramp segments using microscopic analyses, that is: crash frequency prediction based on 3-hour intervals and real-time safety analysis. Meanwhile, the flexibility of using weather information from crash reports in real-time safety studies is also explored in Chapter 5. Chapter 6 analyzes crash characteristics on weaving segments and builds a model to estimate crash risks in real time. Based on the crash mechanisms found in Chapter 6, Chapter 7 proposes a new RM strategy and implements several ATM strategies to improve the safety of a congested weaving segment in microsimulation. Chapter 8 intends to explore conflict mechanisms based on simulated weaving segment networks. Finally, Chapter 9 summarizes the dissertation and raises potential improvement for future applications and proposes studies in microscopic safety analyses for expressway special facilities.

CHAPTER 2: LITERATURE REVIEW

The literature review includes six parts, i.e., safety studies on special expressway facilities, microscopic safety analyses, ATM strategies, microscopic simulations, conflict studies, and summary. In the first part, the previous studies on safety of special facilities are summarized to illustrate why these facilities are important. In the second part, microscopic safety analyses, including hourly crash frequency estimation and real-time crash analysis, are synthesized. Meanwhile, the methods used in microscopic safety studies are also summarized. The third part presents the ATM strategies which might be used to enhance the safety of roadway facilities. The fourth part reviews the implementation of microscopic simulation in weaving segments, and also the relationship between the safety in simulation and in the field. The fifth part sums up the conflict related studies.

2.1 Safety Studies on Special Facilities

2.1.1 Ramps

The safety of interchange ramps has been examined. Torbic et al. (2007) examined Fatality Analysis Reporting System (FARS) and General Estimates System (GES) from 2000 to 2004. The FARS showed that 3.2% of fatal crashes on interchanges and 17.9% freeway system crashes were interchange related, and GES showed that 3.5% of fatal crashes on interchanges. They also concluded that the average interchange crashes was 12.5 crashes per year. FARS data demonstrated that there were more fatal single-vehicle crashes than fatal multiple-vehicle crashes on ramps. In addition to gain a general background about the safety of interchanges, researchers investigated the specific impact of ramp configuration, type, and location on crash frequency and crash characteristics.

Researchers have found that the ramp configuration has a significant impact on crash frequency. The common ramp configurations include diamond, free-flow loop, outer connection, etc. A study by Chen et al. (2013) evaluated the safety performance of four off-ramp configurations (diamond, directional, loop and outer connection) using models and web-based surveys. Both the model and survey showed that diamond off-ramp was the safest type; while a loop off-ramp was the most dangerous type. Hence, crash adjustment factor for ramp configuration was added to display the influence of ramp configuration on crash count (Bauer and Harwood, 1998; Lord and Bonneson, 2005).

In addition to ramp configuration, the ramp type (on- and off-ramp) is one of the most important crash contributing factors. A study by Lundy (1965) reveals that off-ramps have about 42% more crashes than on-ramps, given the same traffic volume and ramp configuration. Later the study by Bauer and Harwood (1998) also indicated that there were about 65% more crashes on off-ramps. From the data reported by Khorashadi (1998), it can also be found that the crash rate of off-ramps was about 1.77 times of that of on-ramps. Lord and Bonneson (2005) found more crashes were on off-ramps than on-ramps by a ratio of 1.5. The crash severity on different ramp type also vary. Geedipally (2014) stated that the percentage of Fatal and Incapacitated injury (K+A) crashes on off-ramps was 16.4%, but was 11.8% on other ramps, including on-ramps and freeway-to-freeway interchange ramps. Meanwhile, the severe crash percentage of off-ramp is also higher than other roadway facilities (Chen et al., 2013).

Meanwhile, the location of ramp (rural or urban) is also found to be significant crash explanatory variables. There are higher crash rates on rural ramps than on urban ramps (Lord and Bonneson, 2005). But the study by Bauer and Harwood (1998) build Negative Binomial models and found that urban ramps experienced more crashes than rural ramps. The K+A crash percentage on rural ramps was found to be 4.7% higher than urban ramps, this might be attributed to higher operating speeds on rural ramps (Geedipally et al., 2014).

The different geometric design of ramps results in distinctive crash characteristics. The most common crash types for ramps are run-off-road and rear-end crashes. McCartt et al. (2004) summarized that 48% ramp crashes were run-off-road crashes and 36% were rear-end crashes. With regard to the crash type of on- and off-ramps, run-off-road was the most common crash type for off-ramp crashes, rear-end was the most common type for on-ramp crashes. Furthermore, single- and multi-vehicle fatal crashes also have their own predominate crash type. FARS and GES showed that the predominated single-vehicle crash type was collision with fixed object, and the main multiple-vehicle crash type was angle and rear-end crash (Torbic et al., 2007).

The ramp studies do not just concentrate on linking a single parameter, for example, ramp configuration, with crashes. Researchers also utilized negative binomial models to predict ramp crash frequencies using several significant factors (Garnowski and Manner, 2011). The result indicated that ramp ADT, truck percentage, ramp curvature, lane width, right and left shoulder width, etc. were positively related the ramp crash number. Sun et al. (2014) explored crashes factors for off-ramps on Shanghai expressways. The significant variables were ramp AADT, number of off-ramp lanes, ramp slope, etc.

Researchers built models to predict crash frequency with respect to different crash severities and crash types separately. Parajuli et al. (2006) developed Safety Performance Functions (SPFs) for different crash severities for ramp using negative binomial model with 7 years data from 1545 ramps. The variables put in model estimation were only ramp AADT and ramp length. Bonneson et al. (2012) developed several SPFs and Crash Modification Factors (CMFs) to estimate the expected crashes for interchanges ramps with respect to five severity levels and to multi- and single-vehicle crash. Ramp AADT was used in the calculation of SPFs. The CMFs included the CMF of median width, outside barrier, shoulder rumble strip, etc.

Under different lighting conditions, crash mechanisms might differ. Yu et al. (2015) collected 5-year nighttime crashes from 224 ramps in 3 states. The authors built two negative binomial models to estimate the SPFs of interchange ramps under lighting and unlighting condition separately. The result showed that for lighted interchange ramps, number of lanes and ramp AADT were significant variables. When number of lanes and ramp AADT increase, the crash frequency decreases. For unlighted interchange ramps, the ramp AADT and ramp type (on-ramp and off-ramp), right shoulder width, left shoulder width and lane number were significant variables. The increase of right or left shoulder width, and lane number would decrease the unlighted crashes.

Once the crash mechanisms of ramps have been explored, researchers developed several software models to help engineers to estimate crash counts in advance. Torbic et al. (2007) developed a software program called Interchange Safety Analysis Tool (ISAT). The SPFs were a function of area type (rural and urban), ramp type, ramp configuration, severity level, ramp ADT, ramp length, etc. Federal Highway Administration (FHWA) used the data from 4 states to develop a set of software tools for safety management of specific highway sites, known as SafetyAnalyst (Harwood et al., 2010). It contained the SPFs for three types of facility, i.e., roadway segments, intersections, and ramps. SafetyAnalyst predicted ramp crash number using ramp AADT or ADT and ramp length. The analyses in SafetyAnalyst include the prediction of total crash, fatal and injury (F+I), fatal and severe injury crash (F+S) and Property Damage Only Crash (PDO).

There are substantial ramp safety studies. The general conclusion is that, off-ramp is more danger than on-ramp; diamond ramp is the safest ramp. The traffic data the majority studies utilized were AADT or ADT, very few studies applied real-time or hourly traffic data to estimate the safety of ramps.

2.1.2 Weaving Segments

Weaving segments have already gained considerable attention from researchers since the publication of the first Highway Capacity Manual (HCM) in 1950. The capacity, level of service, weaving behavior and geometric design of weaving segments have been a major focus of traffic analysis (Stewart et al., 1996; Kwon et al., 2000; Roess and Ulerio, 2000; Lertworawanich and Elefteriadou, 2001, 2003; Roess and Ulerio, 2009). However, few previous researches were on the safety performance of weaving segments. This subsection below presents a summary of literatures on safety of weaving segments, and also on the safety studies are related to weaving segment.

Weaving segments experience more crashes comparing to other mainline segments. A report by Glad (2001) indicates that during peak hours the crash number of the studied weaving segment was higher than other segments, except for the segment which was just upstream of the weaving segment. Meanwhile, the report stated that during off-peak hours, the number of sideswipe and rear-end crash was increased in weaving segment. Kim and Park (Kim and Park, 2016) also found that the crash number on weaving segments were larger than other parts of the studied interstate highway. Pulugurtha and Bhatt (Pulugurtha and Bhatt, 2010) explained that the greater crash number might be due to crossing of entry and exit traffic over a short distance.

The lane distribution of weaving segment crashes was explored by Glad (2001). Glad found that most crashes (two thirds of rear-end and one third of sideswipe crashes) occurred in the auxiliary lane of the studies weaving segment. Both this study and a study by Golob et al. (2004) indicated that sideswipe collision was the predominated crash type in weaving segment. However, studies by Kim and Park (2016) and Pulugurtha and Bhatt (2010) indicates that the rear-end crash was the leading crash type.

The configuration of weaving segment is highly correlated with crash type and severity. Golob et al. (2004) studied crash data for 55 weaving segments, which include Type A, Type B, and Type C weaving segments. The definition of weaving segment type was accordance with HCM 2000. The results showed that a type A weaving segment crash was less severe than other two types and was more lively to occur on wet road surfaces; Type B weaving section was more likely to result in injuries and was less likely to be rear-end crashes; Type B and Type C weaving segment crashes were strongly related vehicle miles of travel, but Type A weaving segment was not. However, their study results showed that there was no significant difference between total crash rate of different segment types. Their result is not consistent with what Pulugurtha and Bhatt (2010) found: Type A weaving segment tends to be safer than other weaving segment types.

The weaving segment length has been found to be an important factor in deciding crash counts. Cirillo (1970) uncovered that increasing weaving segment length could reduce crash rate when

ADT was higher than 10,000 vehicles; but when ADT was below 10,000 vehicles, there was no significant relationship between crash rate and weaving segment length. Meanwhile, Bonneson and Pratt (2008) developed a CMF for weaving segment with the data from Texas. The CMF was a function of weaving segment length. The longer the segment, the lower CMF, indicating lower crash count. The same phenomenon has also been discovered by Qi et al. (2014) and Pulugurtha and Bhatt (2010).

Additionally, Cirillo (1970) also investigated the impact of percentage of merging or diverging traffic on crash rate, and found higher percentage increased crash rate. The higher percentage, the denser merging, diverging, and weaving maneuvers, and resulting more traffic turbulence and higher crash potential. The same positive relation between percentage of weaving vehicles and crash count has also been found by Iliadi et al. (2016).

To estimate weaving segment crash frequency based on several factors, Qi et al. (2014) quantified the impact of significant explanatory variables on weaving segment safety. Their results showed that shorter segment length, more required lane changes for diverging vehicles, higher diverging traffic volume and lower merging traffic volume resulted in higher crash rates. Iliadi et al. (2016) also built models to estimate crash frequency of weaving segments using length of weaving segment, AADT, percentage of weaving vehicles, etc.

There are several studies which do not directly focus on weaving segment, but very related to weaving segment. Liu et al. (2009) analyzed 3 years crash data at 66 freeway segments on which on-ramps were closely (less than 0.5 miles) followed by off-ramps. They compared the crash frequency, crash rate, severity and type for different segments. The results were similar with that for weaving segments: crash rate and severity was highly related to segment configuration. But they found the dominate crash type on those segments was rear-end crash. Le and Porter (2012) tried to quantify the relationship between ramp spacing and freeway safety. In their study, the average spacing was 2.348 mile, with 0.501 as the minimum and 10.412 as the maximum. The overall sample size was 404 freeway segments in two states. The result showed that the presence of an auxiliary lane would decrease crash number for a given ramp spacing. Hence, compared to a merging shortly followed by a diverging area without auxiliary lane(s), a weaving segment with auxiliary lane(s) is preferred.

From the review above, it can be found that there are limited safety studies on weaving segments. Weaving segment configuration, length, and weaving traffic percentage have significant impact on crash type, crash number and crash severity. Meanwhile, predominate crash type on weaving segments are sideswipe and rear-end.

2.2 Microscopic Safety Analyses

2.2.1 Hourly Crash Studies

The hourly crash prediction has been proven to be better than crash studies based on ADT. Gwynn (1967) collected 5 years data from a 3.8-mile US Route, on which there were no traffic signals and grade crossings. The study investigated the relationship between hourly volume and accident rates. The result indicated that highest crash rates occurred in the low and high volume level, and lowest crash rate in the mediate volume level. If the author did not use the hourly volume but use the ADT, it was hard to find the result. The whole section had a same traffic exposure (i.e., ADT) since it did not have any access. Persaud and Dzbik (1993) used a generalized linear model to estimate freeway crash frequency by traffic flow, expressed both as

ADT and hourly volume. The result showed that hourly volume was more appropriate than ADT, because it took the traffic condition at the time of crashes into consideration. The authors also claimed that ADT was often used in the crash prediction models though the advantage of using hourly volume, because the accurate hourly volume was hard to obtain.

In addition to hourly volume, the relationship between volume-to-capacity-ratio (V/C) and crash rates has also been explored. Zhou and Sisiopiku (1997) examined the relationship on an urban freeway with the consideration of day of week (weekday and weekend), crash type (turnover, rear-end, and fixed object), severity (PDO, F+I). The result showed that the relationship between total accident rates and hourly V/C ratio followed a general U-shaped pattern. That is to say, the accidents rates were high when V/C was very low and very high, but low when V/C was moderate. Chang et al. (2000) also explored the relationship between accident rate and hourly V/C with 5 years freeway data. In their research, three freeway segments were studied: basic freeway section, tunnel section, and toll gate section. The similar U shape relationships were also been found for these three sections. However, the U shape of these three sections was not the same, e.g., the toll gate section U-shape was above other two (when the V/C was the same, crash rate of toll gate section was higher). The authors suggested the inclusion of more geometric and other traffic factors in the model since the R^2 values (0.4209 to 0.5161) were low. Lord et al. (2005) investigated how the crashes on rural and urban freeway segments were affected by hourly traffic parameters, e.g., volume, density and V/C ratio. The result showed that the higher density and V/C ratio, the more crash count.

Additionally, hourly speed and hourly density are also linked to hourly crash rate. Kononov et al. (2012) studied the relationship between hourly crash rate and hourly speed along with density for urban freeways. The result showed that when density was between low and moderate, and speed was high, crash rate remained stable; when density was high and speed did not decrease, crash rate would increase.

One of the advantage of hourly crash research is that it can take temporal factors into consideration. Persaud and Mucsi (1995) utilized the hourly traffic volumes for estimating accident number on 2,015 two-lane rural roads. The models were calibrated for different time periods (all day, daytime and nighttime) and geometric characteristics (e.g., shoulder width, lane width) for total crashes and for F+I. The result proved that effect of day/night was different for single- and multi-vehicle crash. Martin (2002) collected 2 years traffic and crash data from 2,000 kilometers French interurban motorways. The study linked the crash rates with hourly traffic volume, time of day (night or day), day of week (weekday and weekend) and number of lanes. The result showed when traffic was lightest (under 400 vehicles/hour) the PDO and injury crash rates were highest; whatever the traffic; there were more severity crashes at night when the hourly traffic was light.

The previous researches proved that the crash prediction models based on hourly traffic were better than the ones which used the AADT or ADT. Meanwhile, a few researchers suggested building the SV and MV crash model separately. Nevertheless, the study objects of are mainly mainlines, no researches focused on other facilities.

2.2.2 Real-time Crash Studies

Since 1995 (Madanat and Liu, 1995), there have been numerous studies on real-time crash prediction models which intended to link real-time crash likelihood with microscopic traffic data.

The assumption underlying these studies is that the traffic and weather parameters which are called crash precursors are relatively more ‘crash prone’ than others. Generally, researches were on four types of freeway segment, i.e., general mainlines, basic mainlines, ramp vicinities, and ramps. Since the basic mainline and ramp vicinities were studied in the same papers together, they are integrated.

General Mainlines. Most of researches focused on exploring factors which had significant impact on the crash risk on general mainline, which did not consider whether the mainline was influenced by ramp or not. Madanat and Liu (1995) were the first to use traffic and weather data to develop a Binary Logit model to predict crashes in real-time. However, the traffic parameters were not significant in their model. They found that visibility and rain would affect crash occurrence. Later, Oh et al. (2001) applied non-parametric Bayesian to compare normal traffic condition and disruptive traffic condition, and found standard deviation of speed was the most significant crash precursor. Garber and Wu (Garber and Wu, 2001) proved that the geometric variables, e.g., curvatue, lane width, grade, had significant impact on crash risk.

Lee et al. (2002) estimated crash frequency in 5 minutes. They concluded that the significant crash predictors were: weather condition, speed variation along the segment, speed difference across lanes, and traffic density. The weather condition was a binary variable which indicated whether it was severe or not.

Abdel-Aty et al. (2004) and Pande et al. (2005) matched designed the experiment to exclude the impact of road geometry, day of week and time of day. Their results showed that crash risk was highly related to average lane occupancy, variation of speed, coefficient of variation in speed, etc.

Abdel-Aty and Pande (2005) successfully adopted Probabilistic neural network classifiers to identify more than 70% of crashes in the next 10-15 minutes using coefficient of variation in speed from three stations.

The crash mechanism might be not the same under different traffic condition. Abdel-Aty et al. (2005) built two different matched case-control models which predicted the crash risk under low and high speed. It was found that multivehicle crashes under high- and low-speed were different in severity and crash mechanism, e.g., the speed standard deviation at the station closest to the crash location at 5-10 minutes before the crash had significant impact on crash risk in low-speed regime, but not significant in high-speed regime.

Zheng et al. (2010) studied the impact of traffic oscillations, which was also known as stop-and-go driving, on freeway crashes in real-time. The matched case-control model showed that speed deviation was a significant variable, and it had positive impact on crash occurrence.

There were also numerous studies put the weather factors in the mainline crash prediction model. Golob and Recker (2003) applied linear and nonlinear multivatiate statistical analyses to determine how the traffic, weather and lighting condition related to crash types. The result showed that rear-end collisions were more likely to occur on dry roads during daylight. Abdel-Aty and Pemmanaboina (2006) added the hourly rainfall information in a matched case-control logit model for crash prediction. Ahmed et al. (2014) first used airport weather data in real-time crash risk assessment based on Bayesian logistic regression. The results indicated that airport weather information was valid. Christoforou et al. (2011) also entered the binary weather condition and lighting condition in the model and found that the crash type could be predicted by the traffic and other parameters shortly before crash occurrence on freeways, e.g., multi-vehicle sideswipes crashes are related to high speeds, daytime and flat freeways. Xu et al. (2013b) collected 902 expressway crashes under clear, rainy and reduced visibility condition and built three Bayesian logistic regression models for each weather condition separately. The result showed that the significant variables and the impact of significant variables on real-time crash risk were not the same under different weather condition.

With more and more effort in real-time crash study, researchers began to investigate crash precursors for different crash type, severities, and time. Lee et al. (2006a) identified the factors with the odds of sideswipe crashes relative to rear-end crashes. Authors also proposed a surrogate measure of lane change named overall average flow ratio. The new variables were significant higher for sideswipe than rear-end crashes at a 95% confidence interval. Qu et al. (2012) developed a Support Vector Machine model to predict rear-end crash potential by using the 5 minutes traffic data from loop detectors. Xu et al. (2013a) predicted the crash likelihood at different levels of crash severity with a sequential logit model and elasticity analysis. The finding showed that different crashes had different precursors, e.g. PDO crash rate was positively related to congested traffic flow with a high speed variance and frequent lane changes. Yu et al. (2016) separately built models to estimate the risk of weekday peak hour crashes, weekday non-peak hour crashes, and weekend non-peak hour crashes to investigate different crash contributing factors. Their studies found that during different time period the crash contributing factors varied.

Basic Mainlines and Ramp Vicinities. The real-time crash studies above took the freeway mainline as a whole, and didn't distinguish the mainline was influenced by ramp or not. However, some researchers discovered that the crash mechanisms of different segments were not the same. Hossain and Muromachi (2012, 2013a, 2013b) studied the basic mainline segments and ramp vicinities. They concluded that congestion index and speed difference between upstream and downstream had the biggest impact on crash number and crash type for basic segments; on the other hand, ramp volume had the highest influence in determining crash types within ramp vicinities.

Hourdos et al. (2006) built a real-time crash prone condition detection model for mainline high-crash locations, which were in ramp vicinities. The crash data and traffic, environmental factors, e.g., pavement condition (wet or dry), visibility (clear or reduced) and sun position (night, cloudy, sun in back or side, and sun in front), were used in the study. All data were collected by video. The data revealed that 63% of crashes occurred when the sun was facing the drivers. The result proved environmental was also a factor for crash.

Ramps. Besides mainline, ramp is also an important facility of freeways. Lee and Abdel-Aty (2006) estimated the crash risk on freeway ramps and at ramp-street junction using log-linear models. They found that higher volumes and lower speeds would result in higher crash risk. They also found that crash rates on loop and outer connection ramps were higher than on diamond ramps. The traffic explanatory variables in the models were daily ramp volume or estimated hourly ramp volume.

Abdel-Aty et al. (2007b) built matched case-control models to real-time estimate crash likelihood for mainline and ramp. A two-level nested logit model was developed to model the ramp crashes, which were defined as the crashes at ramp and ramp-arterials junction. Traffic data in ramp model were the volume difference between ramp’s upstream and downstream mainline volume. The ramp model showed that mainline speed downstream of ramp would decrease off-ramp crash risk and increase on-ramp crash risk, etc.

Lee and Abdel-Aty (2008b) collected 627 ramp crash data to build a two-level nested logit model and a multinomial logit model. The models were used to identify traffic condition which was highly related to crash occurrence by type (on- or off-ramps) and configurations (diamond, loop, etc.). There was no detector on ramps, hence, the ramp volume was estimated by the mainline detectors and other traffic parameters were also from mainline detectors. The result showed that: for off-ramps, high speed difference in upstream and downstream of a ramp, lower ramp volume and lower upstream mainline volume increased the crash risk; crash risk was high on loop ramps; high crash risk on diamond ramps was due to the high crash number at ramp-street junction; etc. The result also proved that nested logit model was better than multinomial logit model.

Traffic and weather factors are significant in crash risk. The study objects of real-time crash prediction are general mainlines, basic mainlines, ramp vicinities, and ramps. Among these objects, ramp real-time crash prediction models were based on the mainline traffic data or highly aggregated traffic data, but not based on real-time ramp traffic information.

2.2.3 Methods

To analytically explore crash mechanisms using microscopic analyses, several statistical methods have been implemented. These methods link hourly crash frequency or risk with short term traffic parameters, geometric, and other factors.

Crash frequencies commonly follow Poisson (Jovanis and Chang, 1986; Joshua and Garber, 1990) or Negative binomial distributions (Maycock and Hall, 1984; Hauer and Hakkert, 1988). Therefore, the Poisson and Negative binomial models are widely used in hourly safety analysis, and plenty of statistical methods are extensions of these two models.

Persaud et al. (1993, 1995) estimated hourly crash frequency per kilometer per unit of time by hourly traffic volume and two model parameters which are needed to be estimated. In their studies negative binomial errors were specified. Martin (2002) found that Negative binomial distribution fit the research data best. Hence, the researcher applied Negative binomial models to find the relationship between crash ratio and traffic flow. Poisson regression model was used by Lord et al. (2005) to study the relationship between hourly crash number on urban and rural freeway segments and hourly volume, density, and V/C ratio separately. In their studies, a Generalized Estimating Equations procedure was used to handle temporal correlations between same site observations.

Ma et al. (2014) adopted Poisson, Negative binomial model, zero-inflated Poisson, and zero-inflated Negative binomial models to examine the relationship between hourly crash and traffic for consecutive downgrade roadway sections. Their results did not reach an agreement about which model was best in estimating hourly crashes. The selection of the best model depended on the data collecting method.

Other methods were also used. Polynomial trend lines were adopted to investigate the relationship between V/C and crash rates by Zhou and Sisiopiku (1997) for weekdays and weekends, different crash types (single- and multi-vehicle crashes), different crash severities, etc.

In addition to statistical models, data mining method was also used in the hourly safety analysis prediction. Kononov et al. (2012) adopted neural networks to link hourly crash rate with hourly speed and density. The safety performance functions were different in two regimes, which were decided by density and speed.

For real-time safety analysis, the target variable is generally binary outcome: crash or non-crash. Thus, logistic regression model has been adopted in numeric real-time crash prediction studies (Hourdos et al., 2006). There are a lot of real-time safety analysis models are based on logistic regression. In order to exclude the impact of geometric factors on crash likelihood several researches implemented matched case-control model in real-time crash estimation (Abdel-Aty et al., 2004; Abdel-Aty and Pemmanaboina, 2006; Zheng et al., 2010). Meanwhile, aiming at investigate the impact of traffic parameters' impact on crash risk under different season, multilevel logistic regression model was used by Yu and Abdel-Aty (2013a). The binary outcome was also distinguished by two-level nested logit model (Lee and Abdel-Aty, 2008b), Bayesian belief net (Hossain and Muromachi, 2012, 2013a, 2013b), Multilayer perceptron neural network models (Pande et al., 2011), Probabilistic neural network (Abdel-Aty and Pande, 2005), and Support Vector Machine (Qu et al., 2012).

Some researchers did not only intend to calculate crash risk but also were interested in crash risks for different crash severities and types. Hence, the target variable is treated as categorical variables whose level is more than two. A sequential logit model was used to link crash likelihood of KA, BC, and PDO to various traffic flow parameters (Xu et al., 2013a). A multivariate probit model was applied in crash type, such as rear-end crashes, propensity identification (Christoforou et al., 2011).

A few researchers also considered the target variable as categorical outcome, but as integrate outcome. In their studies, the crash frequency but not crash risk in real-time was estimated. Lee et al. (2002) and Lee and Abdel-Aty (2006) applied Log-linear models to investigate the relationship between the expected crash number on ramps in a 5-minute interval and independent variables, for example, ramp geometry and ramp traffic volume.

There are several models used in hourly crash frequency prediction and real-time crash prediction study. In general, the dominate model for hourly crash frequency prediction is Negative Binomial model, the main model for real-time crash prediction is logistic regression model.

2.3 ATM Strategies

2.3.1 Ramp Metering

RM is a traffic signal which is installed on freeway on-ramps to control the rate of entering flow by temporarily storing entering traffic on ramps. In the 1960s, it was first applied on the Eisenhower Expressway in Chicago and later in plenty of metro areas in the United States, and it has been proven to be a cost-effective strategy both from operation and safety aspects (FHWA, 2016a).

There are two types of RM: fixed time and traffic responsive control. The fixed time RM cannot adjust the ramp signal timing according to current traffic conditions, but use pre-defined signal timing. It might be less efficient and result in more ramp delays (Chen, 2011; Yin et al., 2012). The traffic responsive RM utilizes real-time traffic data from traffic sensors installed on freeways to decide metering signal timing in real-time. The traffic response control consists of local control and system-wide control, among which the local control decide metering rate only based on traffic condition at current ramp and its adjacent mainline. On the other hand, in addition to one ramp and one mainline segment, system-wide control also takes adjacent ramps and mainline segments into consideration (Chilukuri et al., 2015).

RM algorithms have been largely enriched by several researchers. The basic RM algorithm is Asservissement Linéaire d'Entrée Autoroutière (ALINEA). It belongs to local control and its metering rate is based on the occupancy data collected from mainline detectors located downstream from the meter (Papageorgiou and Kotsialos, 2000). Xu et al. (2013c) successfully utilized a fuzzy logic local control based RM to minimize a cost function based on weighted total-time spent. In their study, the ramp queue length was considered in the algorithm. Some other studies did not only concentrate on one ramp or ramp's downstream mainline. Kan et al. (2016) propose a Proportional-Integral extension of ALINEA to handle the case of far-downstream bottlenecks. Chilukuri et al. (2015) proposed a Genetic Algorithm to metering parameters in a System-Wide Adaptive Ramp Metering control in order to optimize the travel time of network system. Faulkner et al. (2014) developed a system-wide control–HERO–based on ALINEA to coordinate local controls. Their results show that the HERO significantly improved traffic throughput and travel times of networks, compared t0 the previously used fixed-rate RM.

One reason for the effectiveness of RM is its ability to break up the entering traffic platoons. Hence, vehicles is able to merge onto the mainline more smoothly and safer. Arnold (1998) has found that there was a reduction in crash in merging areas. Another reason is that it can control entering vehicle rate to reduce the need for mainline vehicles to reduce speed, resulting an increased travel speed (Piotrowicz and Robinson, 1995). Because its capability of smoothing traffic and increasing speed, RM has proven to be significantly and long-term facilitate freeway operations in the following aspects: alleviating traffic congestion (Haj-Salem and Papageorgiou, 1995), increasing capacity (Cassidy and Rudjanakanoknad, 2005), decreasing travel time and increasing travel time reliability (Bhouri and Kauppila, 2011), etc.

Additionally, RM controls entering vehicle rate to prevent extremely high occupancy and to further avoid traffic flow breakdowns. Fewer breakdowns will significantly decrease number of stops. Michalopoulos et al. (2005) have inferred the reduced number of mainline stops might contribute to the safer freeways. Hence, the safety influence of RM is also investigated. Piotrowicz and Robinson (1995) summarized the effect of RM in the North American: crash number was reduced by 43% during peak hours in Oregon; crash number and crash rate were reduced by 24% and 38% respectively during peak hours in Minnesota; the crash rate was decreased by 39% in Washington; rear-end and sideswipe crashes declined by 5% in Denver; total number of crashes and injury crashes were lowered by 50% and 71% in Michigan; etc. The Minnesota Department of Transportation (Cambridge Systematics Inc., 2001) has found that a 26% increase of crash frequency after the RMs were off.

To improve the safety of freeway in real-time, several studies have explored the safety impact of RM from a microscopic aspect as well. Lee et al. (2006b) was the first to quantify the effects of local traffic-responsive ALINEA RMs on freeway real-time safety, and have concluded that RMs have reduced crash potential by 5–37%. Later, Abdel-Aty et al. (2007a) have adopted RMs on a congested freeway, and have found that RMs have significantly decreased crash risk. Abdel-Aty and Gayah (2008) also have successfully adopted uncoordinated ALINEA and a coordinated Zone Ramp Metering algorithm to mitigate real-time crash risk.

The previous RM studies adjusted metering rate based on traffic operation parameters, such as occupancy and queue length. The results have proven that RM is capable to improve traffic operation, for example, reducing average travel time. Meanwhile, RM also can improve network safety. However, no study has incorporated crash risk in a RM algorithm, and no study has applied RM in the safety of expressway special facilities.

2.3.2 Variable Speed Limit

VSL (FHWA, 2016b) are changeable speed limit whose value is based on road, traffic, and weather conditions. VSL system utilizes several sensors to monitor traffic or weather conditions or both, and then posts appropriate speed limits on dynamic message signs. The common conditions that implement VSL are traffic congestion, work zone and increment weather. In case where VSL is used to mitigate traffic congestion or enhance safety, the recommended speed limit is generally a function of traffic parameters, such as occupancy and average speed, and intends to smooth traffic by reducing speed variation (Li et al., 2014; Lu et al., 2015). VSL under increment weather is usually decided by an algorithm which considers rainy, visibility, or other weather conditions (Goodwin and Pisano, 2003).

VSLs have potential benefits of improving traffic operations. Previous research has confirmed that the throughputs and capacity of networks have been increased because of VSLs (Kwon et al., 2007, Kang and Chang, 2011; Hoogendoorn et al., 2013). Some researchers (Lee et al., 2004; Kwon et al., 2011) have found that VSLs have increased travel times to a small extent, but several other studies have shown that VSLs have decreased travel times (Abdel-Aty et al., 2006; Nicholson et al., 2011; Li et al., 2014; Lu et al., 2015).

The implementation of VSL during less than ideal conditions, such as inclement weather, can enhance safety by reducing crash risks related to travelling speeds which are higher than appropriate speeds for the conditions (Katz et al., 2012). One of the other advantages of VSL is reducing the speed variance. Several experiments have studied the speed variance after implementing VSL through driving simulators (Lee and Abdel-Aty, 2008a; Van Nes et al., 2010) and simulations (Kang and Chang, 2011). These experiments' results were the same as what has been observed in the field (Rämä, 1999; Kwon et al., 2007): drivers drove at more homogeneous speeds with the VSL than with the static speed limits.

Reducing speed variance indicates a lower crash likelihood (Hossain and Muromachi, 2010), so VSL might improve safety. Saha and Young (2014) have collected six winter seasons' worth of data and have concluded that VSL has significantly reduced winter crashes by 0.67 crashes per week per 100 miles over that period. Yet collecting enough crash data is not practical in all cases since it takes a long time period because the occurrence of a crash is infrequent. Therefore, there have been several studies which have conducted safety studies of VSL in simulation (Lee et al., 2004; Abdel-Aty et al., 2006; Yu and Abdel-Aty, 2014a; Fang et al., 2015). These studies have utilized one or several precursors, such as speed variation, to calculate crash risk. Their results have demonstrated that VSL is an effective strategy to mitigate crash risk.

VSL has been proven to be effective in improving traffic operation and in enhancing traffic safety. The majority of previous studies did not use crash risk in VSL algorithms to determine posted speed limit. Meanwhile, the VSL has not been implemented in real-time enhancing the safety of expressway facilities.

2.3.3 Integrated Strategy

RM is able to control metering rates of on-ramps to reduce adverse impact of entering vehicles on mainline traffic; VSL adjust the speed limit on mainlines to improve traffic operation and safety of mainlines. Integrating RM and VSL strategies might cooperate ramp and mainline traffic, and result in better traffic operation and safety conditions than a single strategy.

Previous studies have found that compared to the RM and the VSL, the integrated RM and VSL strategy might result in a network which has a higher outflow or a significantly lower total travel time or both (Hegyi et al., 2005; Carlson et al., 2010; Carlson et al., 2012). Previous studies have found that the integrated strategy is able to significantly prevent congestion, improve stability, or reduce delays (Alessandri et al., 1998; Abdel-Aty and Dhindsa, 2007; Lu et al., 2011; Su et al., 2011).

Furthermore, the safety benefit of the integrated strategy is noteworthy. Abdel-Aty and Dhindsa (2007) have implemented VSLs and RMs on congested freeway segments. They have concluded that the integrated strategy outperforms VSLs or RMs alone in terms of safety, speed, and travel time. Later, Abdel-Aty et al. (2009) have also applied VSL and RM to reduce crash risk on freeway segments under congested and uncongested conditions. It has been found that the integrated strategy provides lower crash risk than VSL only at the 80% volume load.

The integrated RM and VSL strategy might outperform both RM and VSL by improving traffic operation and crash risk. Nevertheless, no study has focused on the safety effects of an integrated strategy on expressway weaving segments.

2.4 Microscopic Simulations

In order to evaluate the impact of ATM strategies on the safety of weaving segment, the microscopic simulation is implemented. It is one of the most widely used tools for roadway system operation, level of service, and safety analysis. Compared with other methods, simulation can test the impact of one treatment before it is put into practice. By doing this, the risk of negative impact of this treatment on safety or operation can be found in advance and may be avoided. Meanwhile, the simulation helps engineers in obtaining the safety or operation performance of a facility within a relatively short time period. On the other hand, if researchers intend to study crashes, three or more year crash data are needed because crashes are rare events.

Calibration and validation are two most important steps to ensure the simulated traffic can replicate the real world traffic condition at a great extent. There are a few previous weaving segments related studies applied microscopic simulations. In these studies several, simulation parameters were adjusted to well calibrate and validate weaving segment. The choosing of parameters' value depends on empirical observations (Koppula, 2002), optimizing validation targets, for example, minimizing speed difference, by attempting several sets of simulation parameters (Woody, 2006).

There are generally two types of driver behavior models in microscopic simulation: car following and lane change models. Car following model decides a simulated vehicle's longitude movements and lane change model determines a vehicle's lateral movements. The quality of the driver behavior models is essential to the accuracy of a traffic simulation model. Koppula (2002) claimed that the desired lane change distance (DLCD) for weaivng segments in VISSIM should be 1000 meters other than the default value which is 200 meters. This parameter DLCD defines the distance at which vehicles begin to attempt to change lanes in order to arrive their desinations. Wu et al. (2005) studied the Shanghai expressway weaving segments. They concluded that the most important parameters were DLCD, wait time before diffusion, stand still distance (CC0), following headway time (CC1) and following variation (CC2).Woody (2006) stated that the calibration and validation of freeway weaving segments were much more complicated than both merge and diverge facilities, and the most important driver behavior parameters in VISSIM simulation were DLCD and CC1. Jolovic and Stevanovic (2013) investigated the weaving segments under congested condition and showed a list of car following and lane change parameters which needed to be adjusted and give the values for these parameters.

In simulations, a facility's safety performance was generally based on safety surrogate measurements: conflict. The foundermental is that the positive relationship between conflicts and crashes is significant and conflicts are good indicator of crashes (Sayed and Zein, 1999). The idea of surrogate safety assessment software based on simulations was first proposed by FHWA (Gettman and Head, 2003). Later, the user manual of Surrogate Safety Assessment Model (SSAM) was available to the public (Pu and Joshi, 2008). The SSAM can automatically process vehicle trajectory data, which are outputs of simulations, and then provide conflict information, including conflict location, time, etc. In additon, three types of multi-vehicle conflicts, i.e., crossing, rear-end, and sideswipe, can be identified by SSAM. In the previous literature review, it is not hard to conclude that the major crash types at the weaving segment is rear-end and sideswipe crashes (Golob et al., 2004; Pulugurtha and Bhatt, 2010; Kim and Park, 2016). Hence, the SSAM is appropriate to be used in weaving segments.

One method for testing the validation of safety in simulation is comparing simulated conflict with real crash count. Gettman et al. (2008) compared 83 intersections' hourly simulated conflict number with average yearly crash frequency. The Spearman rank correlation coefficient was 0.463, which was significant at a 95% confidence interval. Shahdah et al. (2014) simulated the conflict for 53 signalized intersections and provided a link between simulated conflicts and observed crashes with negative binomial model. The result proved that there was significant relationship between conflict and crash. Saleem et al. (2014) used the simulated conflict and peak hour ratio to estimate the crashes. The result showed that conflict was a significant factor for all crash type and all crash severity models at a 95% confidence interval. The authors pointed that the use of simulated conflicts was a reliable and promising approach for intersection safety performance estimation.

The other way to validate the safety in simulation is comparing simulated conflict with real conflict number. Huang et al. (2013) developed a linear model for regressing the observad and simulated conflict to evaluate the accuracy of SSAM and VISSIM simulation for 10 intersections. The result shows the Spearman rank corrlation coefficient was 0.916. Vasconcelos et al. (2014) compared simulated conflict with obseved conflict from 4 intersections, and also compared simulated SSAM result with predicted injury. The authors concluded that SSAM could replicate the hourly evolution of conflict and could also help in identifying the hazardous area; SSAM was a very promising method to assess the safety, etc. Roach et al. (2015) collected video data at a roundabout to calibrate and validate SSAM. The result suggested that there might be strong correlation between simulated conflict and real conflict. The result indicated the appropriateness of using SSAM to test the roundabouts safety. However, the authors also pointed out that the actual and predicted conflicts number was pretty low, more roundabout data were needed.

From the research above, it is not hard to conclude that the parameters related to weaving segment driver behavior are DLCD, CC0, CC1, and CC2. However, in the process of their validation, only traffic parameters, i.e., volume and speed, were put into consideration. Hence, the validated VISSIM network might only duplicate the real world's traffic condition. If simulation is used in the safety study of weaving segment, the safety of the simulation network should also be validated. Several researchers evaluated the traffic safety in simulation, which is based on SSAM, and proven that the safety in simulation were accordance with that in field. But there is no study has applied SSAM in weaving segment safety study.

2.5 Conflict Studies

In the first conflict study by Perkins and Harris (1968) for intersections, conflicts were identified by evasive actions. Thus, conflicts have been related to those actions of vehicles: braking, swerving, noticeable deceleration, jerk, etc., (Fan et al., 2013; Tageldin et al., 2015). Additionally, with the development of technologies, more quantitative measurements have been adopted in conflict frequency analysis. The common measurements are Time-to-Collision (TTC), Post-Encroachment Time (PET), and gap time. There are also some several researchers proposed new conflict measurements, such as Conflict Propensity Metric, Aggregate Conflict Propensity Metric (Wang and Stamatiadis, 2016).

Once conflict could be identified using measurements, the conflict information can be obtained for further safety analyses. In order to validate the consistency between conflict and crash, some researchers tried to build a relationship between conflict and crash (Meng and Qu, 2012; El-Basyouny and Sayed, 2013; Shahdah et al., 2015; Sacchi and Sayed, 2016). Their studies have found that conflict count is a significant and positive explaining variable of crash frequency.

Since the conflict is a valid measurement of safety, some studies collected conflict count to uncover potential safety hazard, and then proposed countermeasures to improve safety (Van Der Horst et al., 2014). Additionally, several papers adopted conflict as an evaluation metric of countermeasures and new roadway designs, because the collection of conflict data is not time consuming. Cafiso et al. (2011) conducted conflict analysis to verify the safety improvement of crosswalks because of traffic calming devices, such as speed bumps and raised crosswalks. Autey et al. (2012) successfully implemented conflict to carry out a before-after safety evaluation of a new design for channelized right-turn lanes. Shahdah et al. (2014) estimated crash modification factors (CMFs) using simulated conflict, and concluded that the CMFs based on conflicts closely match those based on crashes. Zaki et al. (2016) collected and analyzed video data at signalized intersections, and recommended to maintain the current speed limit.

Meanwhile, several researches used conflict as a measurement to choose an optimal design. Kim et al. (2007) simulated a 4-leg intersection and tested whether changing the conventional signal intersection to superstreet intersection can bring safety and operation benefit. Their results indicated that the superstreet design with one U-turn lane was better than conventional signal intersection under high traffic volumes. Al-Ghandour et al. (2011) studied the conflict patterns at single-lane roundabouts with and without slip lanes by using SSAM and VISSIM. They concluded that installing a free-flow slip lane could improve the roundabouts' safety. Stevanovic et al. (2013) optimized signal timing for 12-intersection corridor and two smaller synthetic networks based on the balanced safety and efficiency. The result showed that the signal timing based on balanced safety and efficiency reduced conflict by 9% without a significant loss of efficiency (about 1%) comparing with considering efficiency only.

There are also studies that adopted conflicts to test the efficiency of traffic management strategies. Nezamuddin et al. (2011a) built a VISSIM network for expressway segments. They tested the beneficial of VSL and shoulder use during peak hour. The results showed that both strategies could improve the safety condition. Qi and Zhao (2014) tested the safety impact of using a signalized lane control strategy in a work zone by simulation. The result showed that proposing a signal control device in the work zone merge points would signficantly reduce conflict number.

Additionally, some researchers intended to find out the contributing factors of conflict. One factor is driver behavior. Habtemichael and de Picado-Santos (2013) concluded that high-risk drivers' freedom was highly related to safety: the increase of freedom rises conflict number. Furthermore, researchers also built functions to capture the impact of parameters on conflict frequency. El-Basyouny and Sayed (2013) built a negative binomial safety performance function to predict conflict counts using significant variables: hourly volume, area type, and geometric parameters. Sacchi and Sayed (2015) adopted Bayesian statistics to model the relationship between rear-end conflict at intersection approaches and explanatory variables: hourly volume and length. On the other hand, there is few research concentrated on the occurrence of each conflict from a microscopic aspect. At access points of primary roads, Manan (2014) investigated the effects of traffic and road environments attributes on the likelihood of serious motorcyclist conflicts using logistic regression. But, the traffic information used in that study is average daily traffic, which cannot sufficiently reflect the traffic condition at the time of conflicts.

Numerous studies have already proved that conflicts are a good surrogate of crashes and can be used to evaluate the safety of a roadway facility, such as intersections, roundabouts, and work zones. The majority of previous conflict related studies mainly focused on conflict count using average daily traffic or hourly volume. Nevertheless, the occurrence of conflict is more relevant to the time just before the conflict, maybe several minutes, than to the aggregated volume over hours or years. Hence, exploring the relationship between conflict likelihood and real-time explanatory variables might be worthwhile.

2.6 Summary

The safety of special facilities is a concern since there might be more crashes on special facilities and the crash type along with crash severity of special facilities are also different from other expressway segments. There are substantial ramp safety studies, but limited weaving segment safety related research. Meanwhile, the majority of previous special facilities safety studies were based on highly aggregated traffic data: AADT and ADT.

Compared to studies based on highly aggregated traffic data, the safety analysis utilizing microscopic traffic data, i.e., hourly and real-time traffic data, performs better in providing detail crash mechanisms. There are limited number of hourly safety studies and plenty of real-time crash analyses. However, the majority of them focused on freeway mainlines other than special facilities. For the methods used in microscopic safety analyses, the dominate model for hourly crash frequency prediction is Negative Binomial model, the main model for real-time crash prediction is logistic regression model.

The significant and positive impact of RM and VSL on traffic operation and safety has been proven by practitioner and researchers. Additionally, the integrated RM and VSL strategy might outperform both RM and VSL by improving traffic operation and crash risk. However, previous studies not consider real-time safety in RM and VSL algorithms. Meanwhile, very limited RM, VSL, and integrated strategies have been applied to the safety of expressway special facilities.

The impact of ATM strategies on the safety of a weaving segment will be tested in microscopic simulations. Hence, the microscopic simulation research is also reviewed. There are several studies simulated weaving segment in VISSIM and adjusted driver behavior parameters to validate the simulation network. However, the validations were only based on traffic but not on safety. The safety of simulation network can be captured by conflicts from SSAM. Researchers have already proven that the simulated conflicts are consistent with field crashes and field conflicts. Nevertheless, the majority of previous conflict related studies mainly focused on the number of conflict count not on the occurrence of individual conflict, which is more relevant to the time just before the conflict. Hence, exploring the relationship between conflict likelihood and explanatory variables in real-time might be worthwhile.

CHAPTER 3: REAL-TIME CRASH PREDICTION FOR RAMPS USING REAL-TIME TRAFFIC AND WEATHER DATA

3.1 Introduction

Though plenty of real-time safety analyses have been done for expressway mainlines, very limited research has been conducted on real-time crash prediction for ramps. The crash mechanisms of mainlines and ramps might differ (Lee and Abdel-Aty, 2009), since the geometric characteristics of mainlines and ramps vary, e.g., ramps may have smaller radii and/or steeper slopes than mainlines. Meanwhile, different crash types might have distinct contributing factors (Pande and Abdel-Aty, 2006; Yu and Abdel-Aty, 2013a), so it may be better to analyze each crash type separately if the crash sample size is enough. The two most important crash sub-groups are single-vehicle (SV) crashes and multi-vehicle (MV) crashes. Hence, for ramp safety, there is a need to distinguish significant factors and build separate crash estimation models for SV and MV crashes.

In general, primary crash contributing factors are environment, traffic, vehicle, and driver (Oh et al., 2001). The former two factors are considered to be more important for studies and can be more easily collected compared with the latter two. Environmental factors mainly include geometric design and weather. Traffic factors include volume, speed, lane occupancy, etc. Among these environmental and traffic variables, the influence of traffic variables on crash is analyzed by all real-time safety research, but the impact of weather on real-time safety has not been widely studied. However, weather is an important explanatory factor of crashes. On average, from 2002 to 2012 in the United States, 23% of crashes were weather-related, among which 74% of crashes happened on wet pavement (FHWA, 2014). Meanwhile, weather-related crashes have been shown to cause 94 million to 272 million hours of delay each year (Goodwin, 2002). As a result, in addition to traffic factors, weather also should be a potential explanatory variable in crash prediction model.

This chapter has two basic objectives: 1) to find factors, including weather parameters, which contribute to crashes on expressway ramps; 2) to develop Bayesian logistic regression models for real-time ramp crash likelihood. The studied ramp area in this study is the range between the painted gore point and ramp terminal intersection at crossroads.

This chapter is organized into five sections. The second section describes the research methodology. The third section describes the data used. The forth section shows the results of model estimations and variable importance analyses. Finally, the fifth section summarizes the findings and potential applications.

3.2 Methodology

This study built Bayesian logistic regression models to estimate ramp crash likelihood. The traditional and standard logistic regression models treat the variable coefficients as fixed values. However, Bayesian models assume that there are distributions for the coefficients. The Bayesian inference also makes use of the knowledge gained from observations to update the behavior of the coefficients and then assess their distributional properties.

In this study, Bayesian logistic regression models were used to estimate the relationship between the binary response variable (crash or non-crash) and explanatory variables. For i^{th} observation, its response (y_i) has two exclusive outcomes: crash (y_i =1) or non-crash (y_i =0). The two outcomes' possibilities are p_i (y_i=1) and 1- p_i (y_i=0), respectively. Bayesian logistic regression models are as follows,

$$y_i \sim Bernoulli(p_i) \tag{3-1}$$

$$\log(\frac{p_i}{1-p_i}) = \beta_0 + \sum_{r=1}^{R} \beta_r x_{ri} \tag{3-2}$$

where β_0 is the intercept, x_{ri} the value of r^{th} explanatory variable for i^{th} observation, β_r the coefficient of x_r, and R the total number of independent variables. A common choice for the β_0 and β_r distribution is normal distribution (Gelman et al., 2014):

$$\beta_0 \sim N(\mu_0, \sigma_0^2) \tag{3-3}$$

$$\beta_r \sim N(\mu_r, \sigma_r^2) \tag{3-4}$$

In general, there are three kinds of prior distribution. The implementation of a type of prior distribution depends on the availability of prior information. Informative prior distribution is used if the possible values of coefficients are known. When little or nothing is known about the coefficient values, or if a researcher intends to know what the data will provide as inferences, vague or non-informative priors are preferred. In this research, non-informative priors were used, since no similar studies using the same variables as this study have been carried out on ramps. The following are the prior distributions of coefficients:

$$\beta_0 \sim N(0, 10^6) \tag{3-5}$$

$$\beta_r \sim N(0, 10^6) \tag{3-6}$$

All real-time ramp crash prediction models were estimated by Bayesian inference which was carried out by Winbugs in R (Lunn et al., 2000; Sturtz et al., 2005). In each model, there were three chains of 10,000 iterations. The first half of simulation iterations were discarded in order to eliminate the concern that early values didn't represent the true posterior distribution (Gelman et al., 2014).

The deviance information criterion (DIC) is widely used for the selection of a better Bayesian model. A model with a smaller DIC implies that the model is able to better predict a replicate dataset that has the same structure as the current sample (Spiegelhalter et al., 2002). Additionally, analysis of the Area Under the Curve (AUC) was used to evaluate the prediction accuracy of the proposed model.

3.3 Experimental Design and Data Description

3.3.1 Experimental Design

To accomplish the study objectives, three expressways in Central Florida were chosen. They were State Road 408 (SR 408), State Road 417 (SR 417), and State Road 528 (SR 528). These three expressways are monitored by MVDS, and almost all ramps have an MVDS detector to provide ramp traffic information. On the other hand, the weather data of the expressway system can only be partially obtained since there are a limited number of weather stations in Central Florida. Hence, only 14.2 miles of SR 408, 26.9 miles of SR 417, and 7.6 miles of SR 528, which are covered by the Orlando International Airport's (MCO) and the Orlando Executive Airport's (ORL) 7.0-mile coverage buffer, were chosen for further analysis. Within the 7.0-mile buffer, the airport weather station can provide sufficiently accurate weather information for the crash and non-crash observations (Ahmed et al., 2014). In total, four datasets–crash, geometry, traffic, and weather–were collected during the study period of July 2013 to March 2014.

There are 141 ramps in the study area, and each ramp has four geometric characteristics: ramp type, ramp configuration, the presence of a toll booth, and ramp length. Seventy out of the 141 ramps are off-ramps, 71 are diamond ramps, and 39 with a toll booth, and the mean of ramp length is 0.347 miles. Nearly every ramp has one MVDS detector to collect traffic flow data. Furthermore, the real-time weather information can be provided by a nearby airport weather station.

In order to reduce data noise, the traffic data were aggregated into 5-minute intervals. The traffic data 0-5 minutes and 5-10 minutes prior to crash events were extracted. For example, if a crash occurs at 8:00 A.M., the traffic data extracted are from 7:55 to 8:00 A.M. and from 7:50 to 7:55 A.M. The traffic data which were 5-10 minutes prior to crash events were subsequently found to provide better model performance. Additionally, they could possibly increase the practical application of the model by providing sufficient time for the traffic management center to analyze, react, and announce warning information to drivers. Hence, in the following parts of this chapter, the crash traffic data utilized are 5-10 minutes prior to crash events.

The number of non-crash events was 11,207,808 (12 intervals × 24 hours × 276 days × 141 ramps), each event was also aggregated into 5-minute intervals, so each hour has 12 intervals in total. It was difficult to put all these non-crash events in analysis, so a case control design is used. A random sample of 0.05% of non-crash events are selected from the population of total non-crash events (11,207,808). Statistical Analysis System (SAS), a commercial software for data process, advanced analytics, predictive analytics, etc., was used to select the sampled non-crash events. Meanwhile, in order to ensure the purity of non-crash traffic flow data, a non-crash data point was excluded if any crash had happened within 2 hours of this point.

3.3.2 Data Description and Combination

There were 211 crashes and 5603 (11,207,808 × 0.05%) non-crash events were filtered out in the study area during the study period. Thirty four crash events were then eliminated from consideration because of the absence of complete information. Seventy nine SV crashes and 58 MV crashes were identified and collected. Among the SV crashes, sixty four (81%) were off road crashes, nine (11%) were rollover crashes, and six (8%) crashes were missing the type information. As for the MV crashes, there were forty five (78%) rear end crashes, ten (17%) sideswipe crashes, and three (5%) crashes with unknown type.

Integrating crash, traffic, geometric, and weather data together was an important work of this study. The processing of data integration is as follows. In the geometric data file, every ramp was first assigned an identification number (ID). Then, for every crash, the corresponding ramp ID was manually added as an additional variable. As for the traffic data, all traffic data at the same ramp were therefore given the same ID. Based on this ID variable, crash, geometric, and traffic data were combined. The next step was adding weather data into the formerly combined data. The weather data for a ramp was collected from the airport which was closest to it. Two weather variables were collected: visibility and road surface condition. As for the visibility parameter, all crash and non-crash events were matched with the visibility data whose time was the closest prior to the events. As for the road surface condition parameter, if for any time point a weather station record shows that the hourly precipitation is higher than zero, or the weather type contains TS (thunderstorm), RA (rain), or DZ (drizzle), it is assumed that the surface of a roadway, which is in the coverage buffer of this weather station, is wet in the following hour of this time point. Otherwise, the roadway surface condition of an event is considered to be dry.

Combining all the datasets together produced 137 crash observations and 4,907 non-crash observations. Each of them contained complete traffic flow, ramp geometric, and weather information. The non-crash observations are assigned to SV and MV crash analysis based on the number of SV and MV crashes. Two thousand eight hundred and thirty non-crash observations were randomly assigned to SV, and 2,077 were assigned to MV crashes. In total, the sample size of SV crashes model-building dataset was 2,909, and the sample size of MV crashes model-building dataset was 2,135. The detailed information of independent variables are shown in Table 3-1.

Table 3-1 Variables considered for the model

Data	Symbol	Description
Traffic*	Vehcnt	Vehicle count (veh/5minutes)
	Spd	Average speed (mile/h)
	Std_spd	Standard deviation of speed (mile/h)
	Occ	Average lane occupancy (%)
	Std_occ	Standard deviation of occupancy (%)
Geometry	Type	1=if the ramp is an off-ramp; 0=otherwise
	Configuration	1=if the ramp is a diamond-ramp; 0=otherwise (e.g., loop, direct connection)
	Toll	1=if there is a toll booth on the ramp; 0=otherwise
	Length	The length from the painted gore point to the intersection of the ramp and the street (mile)
Weather	Visibility	The distance at which an object or light can be clearly discerned (mile)
	Wet	1=if the road surface condition is wet; 0=otherwise

* All traffic data were based on a 5-minute interval

3.3.3 Descriptive and Exploratory Analysis

In order to explore the difference between different crash types, Table 3-2 separately summarizes the descriptive statistics of continuous variables for SV and MV crash events. The number of SV crash events is 79, and that of MV crash events is 58.

Table 3-2 Summary of continuous variables' descriptive statistics for crashes

	Spd		Std_spd		Log (Vehcnt)		Occ		Std_occ		Visibility		Length	
	SV	MV	SV	MV	SV	MV	SV	MV	SV	MV	SV	MV	SV	MV
Mean	56.5	56.5	3.3	4.5	3.2	3.2	3.7	3.8	1.6	1.5	4.4	7.9	0.5	0.4
Std.	6.3	7.8	2.2	5.2	0.8	0.7	3.6	3.9	1.8	1.1	3.9	3.5	0.5	0.3
Min	36.4	29.4	0.3	0.0	1.4	1.4	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1
Max	66.3	82.0	11.1	29.9	5.1	4.4	22.0	28.1	12.5	5.3	10.0	10.0	1.7	1.7
t-value	-0.00		-1.67		0.36		-0.02		0.39		-5.43		1.27	
p-value	0.9997		0.0992		0.7192		0.9855		0.7008		<0.0001		0.2062	

T-test shows that there was no significant difference for five variables: speed, Logarithm of vehicle count, occupancy, and ramp length. Yet, the speed standard deviation of MV crash events was significantly higher than that of SV crashes at a 90% confidence interval. This indicates that when the speed fluctuation is small, it is less likely to have an MV crash. Meanwhile, the mean of visibility of SV crashes was significantly less than that of MV crashes at a 95% confidence interval. These differences confirm that separately estimating SV and MV crash prediction models would be helpful in exploring the variables' different impact on the likelihood SV and MV crashes.

Additionally, the categorical variables of SV and MV crash events are analyzed in Table 3-3. This further confirms that dividing crashes into SV and MV crashes is better for model estimation.

Table 3-3 Exploratory statistics of crashes on categorical variables

Variables	SV crash	MV crash	Chi-square	P-value
Ramp type				
On-ramp	47	16	13.708	0.0002
Off-Ramp	32	42		
Ramp configuration				
Non-diamond ramp	71	31	23.330	<.0001
Diamond ramp	8	27		
Toll				
No toll booth on ramp	70	47	1.539	0.2148
With toll booth on ramp	9	11		
Roadway surface condition				
Dry	13	41	41.195	<.0001
Wet	66	17		

The Chi-square and p-value of Table 3-3 show that ramp type, ramp configuration, and road surface condition have played significant roles in determining crash type. The ratio of SV crashes on on-ramp to that on off-ramp is 1.469; the ratio of MV crashes on on-ramp to that on off-ramp is 0.381; the odds ratio of MV to SV crashes for on-ramps relative to off-ramps was 0.259. It could be inferred that MV crashes are more likely to happen at off-ramps than SV crashes. Vehicles at off-ramps need to decelerate to accommodate the speed of connecting streets, so a rear-end crash may occur if the following vehicles do not decelerate in time. The odds ratio of SV to MV crash at a curved ramp relative to diamond ramp was 7.730 and on a wet surface relative to dry surface was 12.244. These results suggest that SV crashes are more likely to happen on non-diamond ramps and wet surface ramps. On these ramps, the chance of vehicles skidding off the road and then being involved in a SV crash would increase significantly.

3.4 Model Estimation and Variable Importance

As mentioned earlier, the objective of this chapter is to estimate the relationship between the likelihood of a ramp crash and the independent variables: traffic, weather, and geometrics, while distinguishing different crash sub-groups. Two Bayesian logistic regression models were built, one was real-time SV crash prediction model, and the other was real-time MV crash prediction model. Both SV and MV crash model-building datasets were divided into training and validation datasets with a ratio of 70:30.

In order to prevent high correlation between traffic predictors for SV and MV crash prediction models, the Pearson correlation test was done before the model building. The result showed that, for both SV and MV dataset, occupancy was correlated with the Logarithm of vehicle count, speed, and also speed standard deviation; furthermore, the absolutes of the correlation coefficient values were higher than 0.3. Meanwhile, the standard deviation of occupancy was also correlated with the speed, and Logarithm of vehicle count for both SV and MV datasets. Additionally, in SV crashes, standard deviation of speed was found to be highly correlated with speed with a -0.45 correlation coefficient. After excluding variables which were highly correlated with other variables, only Logarithm of vehicle count and speed were taken into consideration in the real-time SV crash model; in the MV crash model, Logarithm of vehicle count, speed, and the standard deviation of speed were taken into consideration.

3.4.1 Real-time Single-Vehicle Crash Model

Estimation results for the real-time SV crash analysis model are shown in Table 3-4. Five variables were found to be significant in the model at a 95% confidence interval (CI). The AUC area for training and validation were 0.935 and 0.971, respectively. The overall accuracy for training and validation were 0.890 and 0.905, respectively, when the cutoff-point was 0.020, at which the specificity is similar to sensitivity.

Table 3-4 Real-time SV crash prediction model for ramps

Variables	Mean	Std.	95% CI	
Intercept	-8.805	2.113	(-13.400, -5.140)	
Log(Vehcnt)	0.959	0.262	(0.441, 1.507)	
Spd	0.061	0.027	(0.013, 0.121)	
Configuration	-1.737	0.479	(-2.723, -0.864)	
Visibility	-0.238	0.051	(-0.340, -0.145)	
Wet	3.087	0.476	(2.134, 4.036)	
	$\overline{D}$	p_D	DIC	
	247.222	6.324	253.547	
	AUC	Sensitivity	Specificity	Accuracy
Training	0.935	0.849	0.891	0.890
Validation	0.971	0.923	0.904	0.905

The Logarithm of vehicle count in 5-minute intervals was positive, indicating that high traffic volume increases the likelihood of SV crashes on ramps. Speed was found to be significant with a positive sign. When the vehicles are at high speed, if the driver are distracted or influenced by unexpected occurrences, they may suddenly brake or turn the wheel. Drivers may lose control of vehicles because ramp has a steep slope or small turning radius or both, and SV crashes may occur.

Ramp configuration was significant and proven to be negatively related to SV crashes, since non-diamond ramps have smaller turning radii compared to diamond ramps and can lead to a loss of vehicle control and result in SV crashes. Visibility was also statistically significant and found to be negatively related to SV crash occurrence, which suggests that SV crashes are more probable during poor visibility conditions. Furthermore, wet road surfaces have smaller friction and may result in longer braking distances than on dry surfaces. Consequently, wet road surfaces may contribute to an increased potential for SV crashes.

3.4.2 Real-time Multi-Vehicle Crash Model

Estimation results for the real-time MV crash-prediction model are shown in Table 3-5. In the model, four variables are significant at a 95% confidence interval, and the standard deviation of speed is significant at the 90% interval. AUC area for training and validation were 0.8134 and 0.8095, respectively. The overall accuracy for training and validation were 0.7644 and 0.7600 when the cutoff-point was 0.035, at which the specificity is similar to sensitivity.

Table 3-5 Real-time MV crash prediction model for ramps

Variables	Mean	Std.	95% CI	
Intercept	-8.959	1.493	(-12.070, -6.124)	
Log(Vehcnt)	1.157	0.221	(0.725, 1.589)	
Spd	0.048	0.019	(0.011, 0.085)	
Std_spd*	0.065	0.033	(-0.004, 0.1244)	
Type	0.845	0.348	(0.194, 1.546)	
Visibility	-0.147	0.052	(-0.243, -0.039)	
	$\overline{D}$	p_D	DIC	
	350.385	5.922	356.307	
	AUC	Sensitivity	Specificity	Accuracy
Training	0.813	0.750	0.765	0.764
Validation	0.810	0.643	0.764	0.760

* Variable significant at a 90% confidence interval

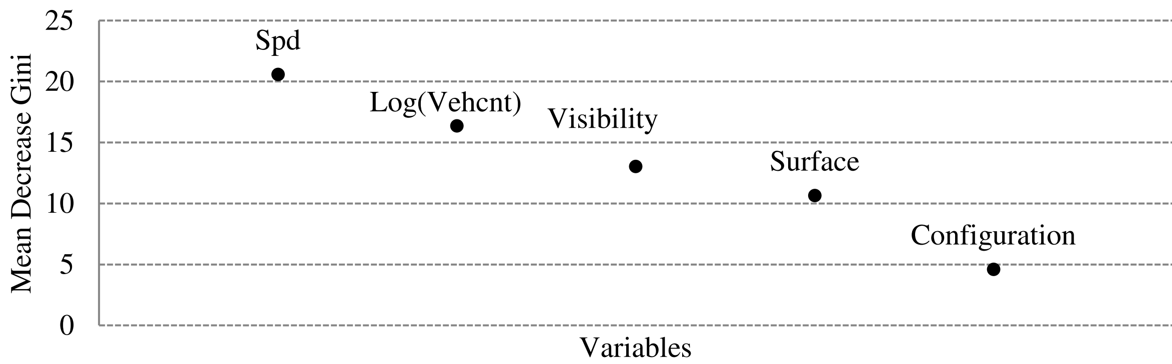
The performance of the MV crash estimation model is not as good as that of the SV crash model. A possible reason is that the variation of speed along the segment, one of the independent variables in the MV crash model, was not able to be collected since only one MVDS detector was located at each ramp. This variable has been proven to be a significant MV crash contributing factor (Lee et al., 2002). This is a potential restriction in our research, particularly for MV crashes.

The coefficient of Logarithm of vehicle count in a 5-minute interval was positive, which indicated that high volume might increase the total interactions between vehicles and then rise the likelihood of MV crashes. Speed was found to be significant with a positive sign. Since an increase of speed will definitely increase both the braking distance and the reaction distance, a vehicle travelling at a higher speed will more likely have a collision with the vehicle ahead of it. Hence, higher speed would significantly increase the possibility of MV crashes. The standard deviation of speed is a good indicator of traffic turbulence. When there is a significant speed difference, deceleration or acceleration action would need to be taken to keep acceptable following distances. The speed changing maneuvers, especially for decelerations, might result in rear-end crashes.

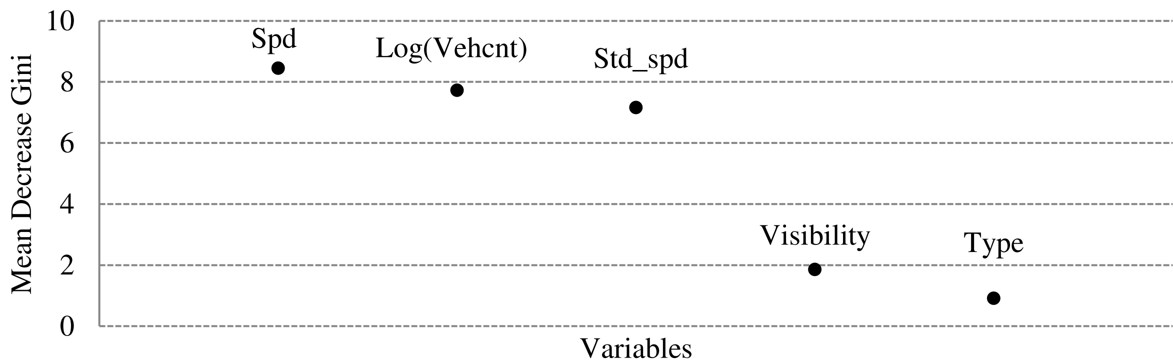
Ramp type was significant and proven to be positively related to MV crashes. Vehicles on the off-ramps need to slow down to adjust to the lower surface street speed. If a following vehicle does not react and decelerate in time, it will run into the leading vehicle, and then an MV crash occurs. Visibility was significant with a negative sign. Under poor visibility, car-following and lane-changing are much harder, so vehicles may have rear-end or sideswipe crashes.

3.4.3 Variable Importance

This study applied Random Forests to rank the importance of variables which were found to be significant contributing factors for SV and MV crashes in the Bayesian logistic regression models. In Random Forests, Gini importance, which measures how Gini impurity decreases in node split over all trees, for significant variables was collected. More important variables result in nodes with higher purity and have a higher decrease in Gini. The results are illustrated in Figure 3-1.



(a) SV Crash Model



(b) MV Crash Model

Figure 3-1 Variable importance in real-time crash prediction for ramps

From Figure 3-1, it is observed that traffic variables are more important than weather and ramp geometric variables for both SV and MV real-time crash models. Meanwhile, speed is the most important factor in both models. Thus, informing drivers to reduce speeds via Dynamic Message Signs (DMS) may be the most effective way to reduce crash likelihood. The impact of weather on real-time crashes is moderate. Warning drivers that the roadway surface is wet is able to significantly reduce SV crash likelihood, and informing drivers that they should be careful in low visibility areas may reduce the likelihood of both SV and MV crashes. Ramp geometric variables have significant, but the least, impact on the occurrence of SV and MV crashes. The effects of warnings about ramp type or configuration may not be as efficient as those warnings which regulates speed or informs the presence of severe weather.

To sum up, regardless of crash type (SV or MV), the essential factors used in real-time crash prediction on ramps are traffic variables, e.g., volume, speed, and standard deviation of speed. This is the reason why models in previous works provided good real-time crash predictions even only with traffic information. However, if real-time weather information along with geometric characteristics can be used in building crash prediction models, this would be better than just including traffic parameters, since weather and geometric variables might also be statistically significant and important factors in predicting crashes.

3.5 Summary and Conclusion

No research has been conducted on real-time crash prediction for expressway ramps with real-time traffic, weather, and geometric information. This chapter implements two Bayesian logistic regression models to predict in real time the likelihood of SV and MV crashes on expressway ramps based on MVDS traffic data, airport weather data, and ramp geometric information.

The descriptive and exploratory analyses show that crash types are linked to the standard deviation of speed, ramp type, ramp configuration, road surface condition, and visibility. This finding corroborates the importance of distinguishing between SV and MV crashes, since crash types are obviously not homogeneous across the traffic, geometric, and weather parameters. Non-diamond and wet roadway surface ramps are more likely to have SV crashes. There are more MV crashes on off-ramps.

The Bayesian logistic regression models show that the occurrences of SV and MV crashes are significantly influenced by the Logarithm of vehicle count, average speed in 5-minute intervals, and visibility. If the Logarithm of vehicle count increases, average speed increases, or visibility decreases, the likelihood of SV and MV crashes will considerably increase. When the Logarithm of vehicle count increases by one unit, the odds ratio of an SV crash is 2.6, and that of an MV crash is 3.18. This implies that the Logarithm of vehicle count has a greater positive impact on the occurrence of MV crashes. On the contrary, speed and visibility have greater impact on odds ratio of SV crashes than on that of MV crashes. The standard deviation of speed is only significant in the MV crash prediction model. When it increases, the likelihood of MV crashes increases significantly. As for the categorical variables, the Bayesian logistic regression models' results are the same as that of the exploratory analysis. Ramp configuration and road surface condition have significant impact on the occurrence of SV crashes, and ramp type would obviously influence MV crash occurrence.

Variable importance analysis indicates that the most important factors for SV and MV models are traffic variables; the least important but still significant factors are ramp geometric characteristics. In practice, when traffic conditions are poor and weather is also severe, traffic-related warning information should be given the priority on DMS. Additionally, since speed is the most important factor affecting crash occurrence for both SV and MV models, informing drivers of adapting their speed through DMS may be one of the most effective ways to reduce crash likelihood. Furthermore, real-time changing messages and colors based on the risk condition should also be considered.

Meanwhile, this chapter also concludes that MV and SV crashes on ramps have different precursors and also these precursors' impact on crash risk vary. In other words, the mechanisms of SV and MV crashes are not exactly the same. When implementing Intelligent Transportation Systems (ITS) to decrease crash risk on ramps, it is advisable to calculate the crash risk for both MV and SV crashes, and then show the warning information based on the higher risk value.

CHAPTER 4: IMPACT OF LAND-USE AND TRIP GENERATION PREDICTORS ON CRASH RISK FOR RAMPS

4.1 Introduction

There have been numerous studies on real-time crash prediction models with the intention to link real-time crash likelihood with various predictors. The underlying assumption of these studies is that some predictors, called crash precursors, are relatively more 'crash prone' than others. The primary crash factors are traffic, environment, vehicle, and driver (Oh et al., 2001).

Among the studied traffic predictors, the standard deviation of speed, traffic volume, and traffic density were common significant crash precursors (Lee et al., 2002; Abdel-Aty and Pande, 2005). Besides traffic parameters, several studies also explored the relationship between crash risk and weather. Hourly rainfall, visibility, and roadway surface conditions have been proven to have significant effect on crash risk (Abdel-Aty and Pemmanaboina, 2006; Yu and Abdel-Aty, 2013a; Wang et al., 2015b). Furthermore, geometric parameters also play important roles in the occurrence of crashes (Wang et al., 2015a).

However, the human factor (driver) has not been widely examined in real-time safety studies. For crash events, crash reports can provide information on drivers who are involved in a traffic crash. But for non-crash events, driver information cannot be obtained from available data sources. Hence, real-time crash risk analysis is unable to consider driver characteristics as explanatory variables. Trip generation and land-use factors can reflect driver behavior and their further effect on traffic safety. From a macroscopic perspective of view, trip generation and land-use have already been proven to be significant crash frequency contributing factors (Abdel-Aty et al., 2013; Lee et al., 2015a; Lee et al., 2015b). However, there has been no study that adopted trip generation and land-use factors in microscopic traffic safety analysis.

For crashes that happen on ramps, the origins or destinations of the vehicles involved in the crash are very likely to be nearby zones. Hence, if the trip generation and land-use information of the zone in which a ramp lies can be captured, these points of data might act as surrogates of driver characteristics and may be driving behavior on the ramp.

The logistic regression model has been widely used in the analysis of data whose target variable is categorical (Washington et al., 2010). It measures the relationship between the target variable and explanatory variables based on a logistic function. The model is easy for interpretation since the model results provide the coefficient value for each significant variable. However, the logistic regression assumes that the error term has a standard logistic distribution. In reality, this assumption may not be true. On the other hand, the data mining method may not be able to provide the impact of each independent variable on the target variable, but it does not have a restriction on the distribution of parameters. Among numerous data mining methods, Support Vector Machine (SVM) models have been applied in several transportation studies, because they can provide high accuracy (Qu et al., 2012).

The two main objectives of this part of the study are: 1) to find land-use and trip generation factors which contributes to crash risk for expressway ramps using a logistic regression model; 2) to build a real-time crash prediction model using land-use, trip generation, and other parameters. The chapter is organized into five sections. The second section presents the methodologies of logistic regression and SVM models. The third section describes the data and conducts descriptive analysis of collected variables. The fourth section shows the model results. The fifth section summarizes the findings, conclusions, and limitations of this study.

4.2 Methodology

4.2.1 Logistic Regression Model

For any given event *i*, it has two exclusive states: crash or non-crash. In this study, the binary responses, crash (y_i=1) and non-crash (y_i=0), are converted into probabilities p_i (y_i=1) and 1-p_i (y_i=0), respectively. The model is as follows,

$$y_i \sim Bernoulli(p_i) \tag{4-1}$$

$$\log it(p_i) = \beta_0 + \sum_{r=1}^{R} \beta_r x_{ri} \tag{4-2}$$

where β_0 is the intercept, β_r the coefficient of r^{th} predictors, x_{ri} the value of r^{th} explanatory variable for i^{th} observation.

4.2.2 Support Vector Machine

SVM is used for classification analysis by constructing a hyperplane or set of hyperplanes in a high- or infinite-dimensional space (Suykens and Vandewalle, 1999). The hyperplane with the largest distance to the nearest training-data point is chosen, indicating that it provides the largest separation between two types of events. There are two types of SVM: linear and nonlinear. The choice of SVM type is based on the data type, e.g., a linear SVM is better if data is linearly separated and so on. A nonlinear SVM is achieved by applying a kernel. By introducing a kernel, SVM is flexible in the choice of the separation form and can handle nonlinear data (Deng et al., 2012). In this study, a nonlinear SVM is applied.

The crash occurrence outcome y is either 1 (crash) or -1 (non-crash). Training data D is a set of n points of the form,

$$D = \left\{ \left(x_i, y_i \right) | \, x_i \in R^P, y_i \in \left\{ -1, 1 \right\} \right\}_{i=1}^{n} \quad (4\text{-}3)$$

where x is the matrix of independent variables which were identified by the logistic regression model and p is the number of significant variables. The decision function is

$$f(x) = sign(w^T x + b) \quad (4\text{-}4)$$

$$w = [\omega_1 \; \omega_{2 \ldots} \omega_p]^T \quad (4\text{-}5)$$

A hyperplane can be written as the set of points x satisfying

$$w^T x + b = 0 \quad (4\text{-}6)$$

$(w^T x_i + b)$ should be positive when y_i=1, and it should be negative when y_i=-1. To summarize, $y_i(w^T x_i + b) > 0$. The decision function is using a sign-function. This results in an uncertainty of distance or margin (Campbell and Ying, 2011). Hence, two parallel hyperplanes is constructed (Campbell and Ying, 2011):

$$w^T x + b = 1 \quad (4\text{-}7)$$

and

$$w^T x + b = -1 \quad (4\text{-}8)$$

The distance between these two hyperplanes is $\frac{2}{\|w\|}$. The target of SVM is to maximize the distance between the two hyperplanes by minimizing $\frac{1}{2}\|w\|^2$. In order to prevent data points from falling into the margin between two hyperplanes, the following constraint is added: for each observation i either

$$w^T x_i + b \geq 1, if \;\; y_i = 1 \quad (4\text{-}9)$$

or

$$w^T x_i + b \le -1, if \quad y_i = -1 \tag{4-10}$$

Combing Eq. (4-9) and (4-10), produce the following new constrain:

$$y_i(w^T x_i + b) \ge 1, for \quad all \quad i \tag{4-11}$$

This is a constrained optimization problem in which $\frac{1}{2}\|w\|^2$ is minimized subject to constrain (Eq. (4-11). The optimization problem can be reduced to the minimization of the following Lagrange function,

$$L(w,b) = \frac{1}{2}(w.w) - \sum_{i=1}^{n} \alpha_i [y_i(w.x_i + b) - 1] \tag{4-12}$$

where α_i are Lagrange multipliers, and α_i>0. The Eq. (4-12) is taken the derivatives with respect to b and w, and set these derivatives to zero:

$$\frac{\partial L(w,b)}{\partial b} = \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{4-13}$$

$$\frac{\partial L(w,b)}{\partial w} = w - \sum_{i=1}^{n} \alpha_i y_i x_i = 0 \tag{4-14}$$

Substituting Eq. (4-13) and (4-14) back into Eq. (4-12), the formulation is obtained,

$$\begin{aligned} W(\alpha) &= \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i.x_j) - \sum_{i=1}^{n} \alpha_i [y_i(\sum_{j=1}^{n} \alpha_j y_j x_j.x_i + b) - 1] \\ &= \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i.x_j) - \sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i.x_j) - \sum_{i=1}^{n} \alpha_i y_i b + \sum_{i=1}^{n} \alpha_i \\ &= \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i.x_j) \end{aligned} \tag{4-15}$$

Subject to

$$\alpha_i \geq 0 \quad and \quad \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{4-16}$$

Eq. (4-15) shows the linear kernel $K(x_i.x_j) = (x_i.x_j)$, but when the points are not linearly classified, there is a need to conduct another kernel. In this study, the Gaussian radial basis kernel was used,

$$K(x_i.x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2), \quad for \ \gamma > 0 \tag{4-17}$$

where γ was set as 0.5. Compared to a linear kernel, the Gaussian radial basis kernel has been proven to be better in a real-time safety study by Yu and Abdel-Aty (2013b).

4.3 Data Preparation

One hundred and forty one ramps from three expressways (SR 408, SR 417, and SR 528) in Central Florida were chosen for this study. The study period was from July, 2013 to March, 2014. Five dataset were collected: crash, traffic, geometric, trip generation, and land-use data.

The crash data were from Signal Four Analytics (S4A). For each crash observation, crash report provided crash time, coordinate, type and severity, etc. The traffic data were supplied by MVDS detectors from Central Florida Expressway Authority (CFX). The MVDS detectors record aggregated vehicle counts, time mean speed, and lane occupancy every minute for each lane.

In addition to crash and traffic data, ramp geometric characteristics data were collected. The shoulder width information was obtained from the FDOT RCI database; ramp type, ramp configuration, and presence of a toll booth were gathered manually using ArcGIS. The studied ramps exist in 69 Statewide Traffic Analysis Zones (SWTAZs). Both trip generation and land-use data of these SWTAZs were from the Florida Statewide Model from the Florida Department of Transportation Central Office. The trip generation data were estimated using observed socio-demographic data.

There were 122 crashes documented and matched with traffic, geometry, land-use and trip generation information. Suppose that a crash is reported within 5 minutes after its occurrence, the traffic conditions 0-5 min before the crash reporting time may have already been impacted by the crash occurrence. Hence, the traffic conditions which were present 5-10 minutes before the reported traffic time were more appropriate to represent the disturbance condition that contributes to crash occurrence. For example, if a crash occurs at 8:00 A.M., traffic data extracted are from 7:50 to 7:55 A.M. of the same day. They were aggregated into 5-minute intervals to mitigate data noise. The non-crash dataset was made up of normal traffic conditions which did not result in a crash or were not impacted by a crash. In this study, they were the traffic conditions that were more than 2 hours before or after a crash observation at the same ramp.

The non-crash dataset consisted of more than 10 million observations. It was not practical to use the entire non-crash dataset. Hence, this study adopted an unmatched case-control design. A total of 1,220 controls (non-crash events) were randomly sampled from the non-crash dataset. Thus, the total number of observations was 122 crash and 1,220 non-crash events. The descriptive analysis of variables of the final dataset is shown in Table 4-1.

Table 4-1 Descriptive analysis for real-time ramp anaysis

Variables	Description	Mean	Std.	Min	Max
Traffic Parameters					
Vehcnt	Vehicle count in 5-min intervals (veh/5minutes)	18.1	20.7	1	170
Spd	Average speed in 5-min intervals (mph)	52.7	9.0	3.8	103.6
Std_spd	Standard deviation of speed in 5-min intervals (mph)	4.1	3.2	0	34.0
Occ	Average lane occupancy in 5-min intervals (%)	2.5	3.7	0	47.0
Geometric Parameters					
Sldwth_R	Right shoulder width (in ft)	1.9	1.9	1.0	6.0
Sldwth_L	Left shoulder width (in ft)	4.3	2.9	1.0	12.0
Type	1=if the ramp is an off-ramp; 0=otherwise	0.46	0.50	0	1
Configuration	1=if the ramp is a diamond-ramp; 0=otherwise	0.58	0.49	0	1
Toll	1=if there is a toll booth on the ramp; 0=otherwise	0.29	0.46	0	1
Trip Generation Parameters					
Production	Total productions (trips/day)	5,601	5,910	84	25,010
Attraction	Total attractions (trips/day)	5,666	7,663	20	33,742
P_HBWA	Home-based-work attractions divided by total attraction (%)	16.4	9.3	0	74.8
P_HBWP	Home-based-work productions divided by total production (%)	14.8	7.1	0	27.6
P_HBSRA	Home-based-social recreational attractions divided by total attraction (%)	8.4	3.2	3.2	19.1
P_HBSRP	Home-based-social recreational productions divided by total production (%)	7.1	4.2	1.4	31.0
P_HBSHA	Home-based-shopping attractions divided by total attraction (%)	9.3	7.4	0	27.2
P_HBSHP	Home-based- shopping productions divided by total production (%)	15.8	5.8	3.9	25.0
Land-use Parameters					
Area	In square mile	1.25	1.62	0.02	10.62
Pop_density	Population density (people/square mile)	2,215	2,038	0	10,312
Emp_density	Employment density (people/ square mile)	1,577	2,633	0	13,295
Enr_density	Enrollment density (people/ square mile)	902	2,607	0	14,945
P_agri	Agriculture employment divided by total employment (%)	1.3	0.3	0	2.2
P_service	Service employment divided by total employment (%)	50.0	9.5	25.0	66.7
P_constr	Construction employment divided by total employment (%)	3.0	2.2	0	10.0
P_manu	Manufacturing employment divided by total employment (%)	2.7	2.1	0	8.3
P_whole	Wholesale employment divided by total employment (%)	3.1	2.3	0	10.0
P_retail	Retail employment divided by total employment (%)	19.3	10.4	0	48.8
P_financ	Financial employment divided by total employment (%)	6.7	1.3	3.3	9.5
P_public	Public administration employment divided by total employment (%)	8.5	1.5	5.0	11.1
P_transp	Transportation employment divided by total employment (%)	5.3	1.0	2.5	7.0

4.4 Model Estimation

This section first estimates a logistic regression to identify the significant variables and then applies SVM in crash prediction. The whole dataset was randomly split into training and validation datasets with a ratio of 70:30, respectively.

For the logistic regression model, in order to prevent high correlation between variables, the Pearson correlation test was done before the modelling process. If the absolute of the correlation coefficient value of two parameters was higher than 0.3, only the variable which resulted in a lower Akaike information criterion (AIC) was kept in the model. The training and validation AUCs of the logistic regression model were 0.835 and 0.797, respectively. It indicated the model had a good ability to distinguish crash and non-crash events. The logistic regression model results are shown in Table 4-2.

Table 4-2 Logistic regression model result for ramp

Variables	Estimate	Std.	Z value	P value
Intercept	-3.25	1.31	-2.48	0.01
Log(Vehcnt)	0.80	0.16	5.10	0.00
Spd*	0.03	0.02	1.90	0.06
Type	0.66	0.28	2.36	0.02
Configuration	-1.12	0.27	-4.15	0.00
P_HBWP	0.05	0.02	2.60	0.01
P_Transp	-0.72	0.13	-5.41	0.00
Model Performance				
AIC		456.51		
Training AUC		0.835		
Validation AUC		0.797		

* Variable significant at a 90% confidence interval

The Logarithm of vehicle count in 5-minute intervals is positive, indicating that high traffic volume result in high crash risk on a ramp. Traffic volume is the most common exposure variables in previous traffic safety analysis, a significant positive relationship between traffic volume and crash count or crash ratio has been widely found by researchers (Yu and Abdel-Aty, 2013; Abdel-Aty et al., 2005). Speed was also found to be significant at a 90% confidence interval with a positive sign. Higher speed definitely increases both braking and reaction distance; hence a vehicle travelling at a higher speed would more likely have a collision with other objects.

Two geometric factors were found to be significant in the model. The results indicate that the crash ratio on off-ramps is about 1.94 times higher that of on-ramps. The reason for this is that vehicles on the off-ramps need to decelerate to adjust to lower speed limits on ramps; meanwhile, they have to decrease speed in order to prepare to brake or even stop at the cross-street intersection. If a following vehicle does not react and decelerate in time, it will collide with the vehicle ahead. Ramp configuration is significant and proven to be negatively related to crash likelihood. The odds of a crash on a diamond ramp are 0.33 times of that on non-diamond ramp. Non-diamond ramps have smaller turning radii, and can lead to a loss of vehicle control and result in crashes.

The percentage of Home-based-work production is positively related to crash risk. The Home-based-work production includes two trips, one is from home to work, and the other is from work to home. There may be two reasons for this result. First, drivers who travel from home to work have to arrive at destinations on time. They may want to avoid being late and may rush to get to work. Thus, they might drive at a higher speed than usual. Second, drivers may be tired after whole day of work, so the crash potential of work-to-home trip may be higher than other trips.

The most significant land-use parameter is the percentage of transportation employment. It is interpreted that a higher percentage of transportation employees will produce better traffic safety conditions. Transportation employees are those who work in the trucking, mass transit, delivery, etc. Compared to other drivers, transportation employees have to strictly follow regulations such as drug and alcohol testing, resulting in safer driving (U.S. DOT, 2010). Meanwhile, they are more experienced in driving.

In addition to the logistic regression, SVM models with Gaussian radial basis kernel were tested using the same training and validation datasets as the logistic regression model. The model results are in Table 4-3.

Table 4-3 Performance of SVM models

	SVM with the selected variables	SVM with all variables
Training AUC	0.895	0.949
Validation AUC	0.900	0.739

Taking the variables which were significant in the logistic regression model into consideration, the SVM model performed better than the logistic regression model by providing higher training and validation AUCs. It indicates that the SVM model was better in discriminating between crash and non-crash conditions. In addition, the training and validation AUCs of the SVM are almost the same and are more stable than that of the logistic regression. However, when all variables were used to estimate the crash occurrence via SVM, the validation AUC is as low as 0.739 though the training AUC is very high. It indicates that the SVM model using all variables has an overfitting issue. Too many independent variables may cause the SVM model to “memorize” training data instead of finding the underlying the relationship between dependent and independent variables. The similar phenomenon was also found by other researchers (Yu and Abdel-Aty, 2013b).

4.5 Summary and Conclusion

Previous studies have found that several real-time traffic and environmental factors are significant crash precursors. However, no study has been conducted to analyze the impact of land-use and trip generation parameters on crash risk. This study explored real-time crash risk for expressway ramps using traffic, geometric, land-use, and trip generation predictors.

A logistic regression model was utilized to find the variables which effected ramp crash risk. The model identified that volume and speed have a positive impact on crash risk. High traffic volume increases crash exposure and interactions between vehicles, and high speed increase braking and reaction distance. Thus, under higher volume or high speed conditions, ramp crash risk increases. The model also indicated that off-ramps and non-diamond ramps also significantly increase the crash risk, because drivers of vehicles on off-ramps need frequent braking and when on non-diamond ramps they may lose control. As for the trip generation parameters, the percentage of home-based-work production compared to other trip-generation parameters was found to have a positive impact on crash risk. If drivers are on the way to work or from work back home, they may be in a hurry or tired, so the possibility of involving in a crash is higher. The percentage of transportation employment was negatively related to crash risk. This may be due to the careful and experienced driving of transportation employees, and may also be because more regulations have been implemented to improve their safe driving.

Subsequently, two SVM models were applied to predict crash occurrence: one with all variables and the other only with significant variables identified by the logistic regression model. It was found that the SVM model with identified significant variables outperformed the logistic regression model by providing higher and more stable AUCs. However, the SVM model with all variables might have an overfitting issue as it provided high training AUC but lower validation AUC. Therefore, instead of using all collected variables, it would be better to build SVM models based on significant variables identified by other models such as the logistic regression models.

There are several limitations to this study. Since ramps from only three expressways in Central Florida were chosen for this study, the variations in zonal characteristics were limited. Hence, models ended with a limited number of significant land-use and trip generation predictors. The follow-up study should extend the study area in order to increase SWTAZs and improve the variation of the zonal characteristic. Thus, the effects of trip generation and land-use elements can be better interpreted.

CHAPTER 5: MICROSCOPIC SAFETY PREDICTION FOR FREEWAY-TO-FREEWAY INTERCHANGE RAMPS

5.1 Introduction

Freeway-to-freeway interchange ramps are critical components of the freeway network and the safety of interchange ramps is a major concern. In order to provide high speed and efficient traffic transfers between two separate freeways, interchange ramps are designed to have horizontal or vertical curvatures or both. These curvatures make interchange ramps much more complicated and also might be more dangerous than the freeway mainline segments. Previous research has indicated that the crash rates of interchange ramps were 43.7% higher than that of freeway mainlines (Zhang et al., 2012). Thus, the safety of interchange ramps needs to be addressed.

There have been a significant number of studies on roadway safety analyses. Among these research efforts, plenty of them have used highly aggregated traffic data, e.g., ADT, AADT. Nevertheless, ADT or AADT cannot represent traffic conditions at the time of a crash. Though two expressway segments may have the same ADT, a segment with high volume during peak hours might have a different crash potential than a segment whose flow is evenly spread out (Persaud and Dzbik, 1993; Mensah and Hauer, 1998). To solve this problem, this study proposes two types of microscopic safety analyses for interchange ramps: crash frequency prediction based on 3-hour intervals, and real-time crash risk estimation.

One important contributing factor of traffic safety is roadway surface conditions. Previous studies, which intended to explore the relationship between traffic safety and weather, were merely based on weather station recordings (Abdel-Aty and Pemmanaboina, 2006; Xu et al., 2013b). However, the majority of roadway segments cannot acquire weather information because they are far away from weather stations. On the other hand, crash reports record the roadway surface condition and weather condition at the time of a crash. Crashes share similar weather information with traffic on nearby roadway segments and during the same time period. Hence, crash reports may also be a valid weather source.

This study analyzed 22 months of traffic, weather, geometric, and crash data from 52 interchange segments, and 22 months' worth of reports on crashes which occurred close to the studied segments. The crashes were divided into two types: SV and MV, since crash mechanisms for each type differ (Yu and Abdel-Aty, 2013a; Wang et al., 2015b). The objectives are as follows: 1) to explore whether crash reports can provide valid roadway surface condition information for studied events; 2) to build multilevel Poisson-lognormal models to reveal contributing factors for SV and MV crashes based on 3-hour intervals; 3) to develop real-time crash risk evaluation models for SV and MV crashes using multilevel logistic regression models.

The following part of the chapter is organized into five sections. The second section discusses the collected data and presents preliminary analysis. The third section describes methodologies: Multilevel Poisson-lognormal and Multilevel logistic regression models. The fourth section shows model estimation results. Finally, the fifth section summarizes the findings of this chapter.

5.2 Experimental Design and Data Description

The studied 52 interchange segments were from 15 interchanges which connected two freeways in Florida. Each of the interchange has several segments, but only the segments whose traffic data were available were chosen for the safety analysis. The study period was from July, 2013 to April, 2015.

Previous traffic safety studies which focused on segment always divided a freeway into several homogeneous segments according to geometric characteristics such as vertical grades (Hauer et al., 2004). This study did not divide interchange ramps into homogeneous segments, but divided them by merge or diverge points. The homogeneous segments were very short because the geometry of interchange ramp changes frequently. The use of segments that are too short might create uncertainty in the location of crashes (Hauer et al., 2004). Meanwhile, utilizing short segments will probably result in excess zero observations and may have a low sample mean issue.

5.2.1 Crash Frequency Analysis

During the study period and on the studied interchange ramp segments, there were 359 crashes in total, of which 178 were SV and 181 were MV crashes. The crash characteristics are shown in Table 5-1.

Table 5-1 Crash characteristic for interchange ramp segments

Percentage (%)	SV	MV	Total
Crash Type			
Run-off-road	77.0	5.5	40.9
Rear-end	0	65.7	33.1
Sideswipe	0	18.2	9.2
Rollover	9.6	0.6	5.0
Other	13.5	9.9	11.7
Total	100	100	100
Crash Severity			
Fatality	1.1	0	0.6
Injury	19.1	27.6	23.4
PDO	79.8	72.4	76.0
Total	100	100	100

More than half (77.0%) of SV crashes were run-off-road crashes, and 65.7% of MV crashes were rear-end collisions. As for total crashes, the most common crash type was run-off-road (40.9%), which was followed by rear-end (33.1%). The results are consistent with a previous study by McCartt et al. (2004). Yet the percentage of sideswipe crashes (9.2%) is not as high as what McCartt et al. (2004) have found. The main reason is that 31 out of 52 (59.6%) ramp segments are one-lane segments, so the occurrences of sideswipe crashes are not frequent.

Roadway geometry has significant impact on traffic safety (Lord and Bonneson, 2005; Wang et al., 2015b; Yu et al., 2015). The most common geometric contributing factors of interchange ramp safety are shoulder width, horizontal alignment, and vertical alignment (Bonneson et al., 2012). There are three geometric data sources. One source is the RCI which is maintained by FDOT. RCI records 323 features of roadway systems. The features normally used are pavement condition, number of lanes, auxiliary lane type, shoulder type and width, median type and width, horizontal degree of curvature, and speed limit. In this study, after collecting RCI data, it was found that the horizontal and vertical alignment information of the majority of the studied segments were missing. Thus, AutoCAD was used to obtain horizontal variables, such as curve length and angle. In addition, Google Earth was used to obtain vertical alignment information, including the elevations of the beginning and end points of segments, the elevation of the highest points of crest curves, and the elevation of the lowest points of sag curves. Google Earth elevation measurement was not sensitive under some conditions, such as when the elevation of a roadway was much higher or lower than its surrounding geography. In order to solve this issue, the elevations of target points were measured several times, and the accuracies were checked by comparing several measuring attempts.

Traffic data were provided by the Regional Integrated Transportation Information System (RITIS). Compared to ADT or AADT, RITIS traffic data were more microscopic. In RITIS, each radar detector provided volume, average speed, and lane occupancy for each lane in short time intervals (less than one minute). When considering sample mean and sample size for crash frequency analyses, 3-hour intervals was chosen for the study, e.g., 0:00-3:00 A.M., 3:00-6:00 A.M., 6:00-9:00 A.M., etc. A study by Lord and Mannering (2010) has pointed out that excess zero observations may have a low sample mean issue, and may result in incorrect parameter estimations. Under a situation with low sample mean, Poisson-lognormal models have been proven to be better than Poisson-gamma models by providing better stability (Lord and Miranda-Moreno, 2008). For the non-vague prior and Poisson-lognormal model, Lord and Miranda-Moreno (2008) stated that the required sample size was 50 when the sample mean was below 1.0. Nevertheless, their study did not provide thresholds for sample mean and sample size for the vague prior and Poisson-lognormal models used in this study. It was assumed that a 3-hour interval dataset (whose sample size was 416 and mean was around 0.42) did not have a low sample mean issue because using the Poisson-lognormal model relaxed the requirements of minimum sample mean and minimum sample size.

After collecting crash, traffic, and geometric information, there were 416 observations each for both SV and MV models. Each observation had a crash count in a 3-hour interval as the dependent variable, and traffic, geometric features, and daytime as independent variables. The traffic parameters, i.e., volume, speed, and occupancy, were average values over 22 months. For example, the traffic volume during the 3:00-6:00 A.M. interval was collected over a period of 22 months, that is, around 669 days (365/12 x 22) and then the average was calculated. Table 5-2 provides descriptive statistics of the variables in crash frequency analysis.

Table 5-2 Variable descriptive statistics for the crash frequency analysis

Variables	Description	Mean	Std.	Min	Max
Dependent Variables					
SV crash counts	SV crash counts (per 3-hour interval during the entire study period)	0.43	1.36	0	14
MV crash counts	MV crash counts (per 3-hour interval during the entire study period)	0.44	1.53	0	21
Independent variables					
Length	Segment length (feet)	2933	1714	1060	8957
Angle	Angle of direction change from the beginning of a segment to the end (degree)	85.86	75.93	0	300
Curve length	Length of curve (feet)	1718	1481	0	4593
Average Turning Angle	Angle of direction change per meter (Angle/Curve Length) (degree/feet)	0.05	0.04	0.00	0.18
Curve length ratio	Percentage of curve length to total segment length (%)	0.59	0.25	0	1
Right shoulder width	Mean right shoulder width (feet)	7	3	2	17
Left shoulder width	Mean left shoulder width (feet)	6	3	2	13
Crest	1=if vertical alignment is crest; 0=otherwise	0.02	0.14	0	1
Sag	1=if vertical alignment is sag; 0=otherwise	0.29	0.45	0	1
Downgrade	1=if vertical alignment is downgrade; 0=otherwise	0.29	0.45	0	1
Upgrade	1=if vertical alignment is upgrade; 0=otherwise	0.33	0.47	0	1
Flat	1=if vertical alignment is flat; 0=otherwise	0.08	0.27	0	1
Grades	=absolute difference in grade for crest or sag curve =absolute grade for others (%)	1.84	2.43	0	9.33
Volume	Average 3-hour volume (1,000 vehicles)	1.17	1.09	0.01	5.68
Spd	Average Speed (mph)	57.4	8.7	14.6	78.3
Occ	Average Lane Occupancy (%)	3.70	4.57	0.01	39.24
Daytime	1=if time between 6:00 A.M.- 6:00 P.M.; 0=otherwise	0.5	0.50	0	1

5.2.2 Roadway Surface Condition

Roadway surface condition is a crash contributing factor, and wet roadway surfaces might significantly increase crash risk (Wang et al., 2015b). In this study roadway surface condition was collected from two data sources. One was airport weather station recordings, and the other was from the reports of crashes which happened close to the studied interchanges.

National Climate Data Center (NCDC) records the weather data from airport weather stations which monitor weather continuously. If weather parameters do not change, the weather status is recorded once an hour. When weather parameters change, the stations immediately record the new weather state. At a timestamp, if hourly precipitation is higher than zero, or the weather type contains TS, RA, or DZ, it is assumed that the roadway surface condition was wet during the following hour of that timestamp.

The crash reports were obtained from S4A. They provided roadway surface condition and weather type at the time of crashes. If a crash report showed that the roadway surface condition was “Wet” or weather type was “Rain”, it was assumed that the surface condition of the roadway within a 15-mile buffer of this crash was wet an hour before and after the crash. Figure 5-1 illustrates the process of obtaining roadway surface condition.

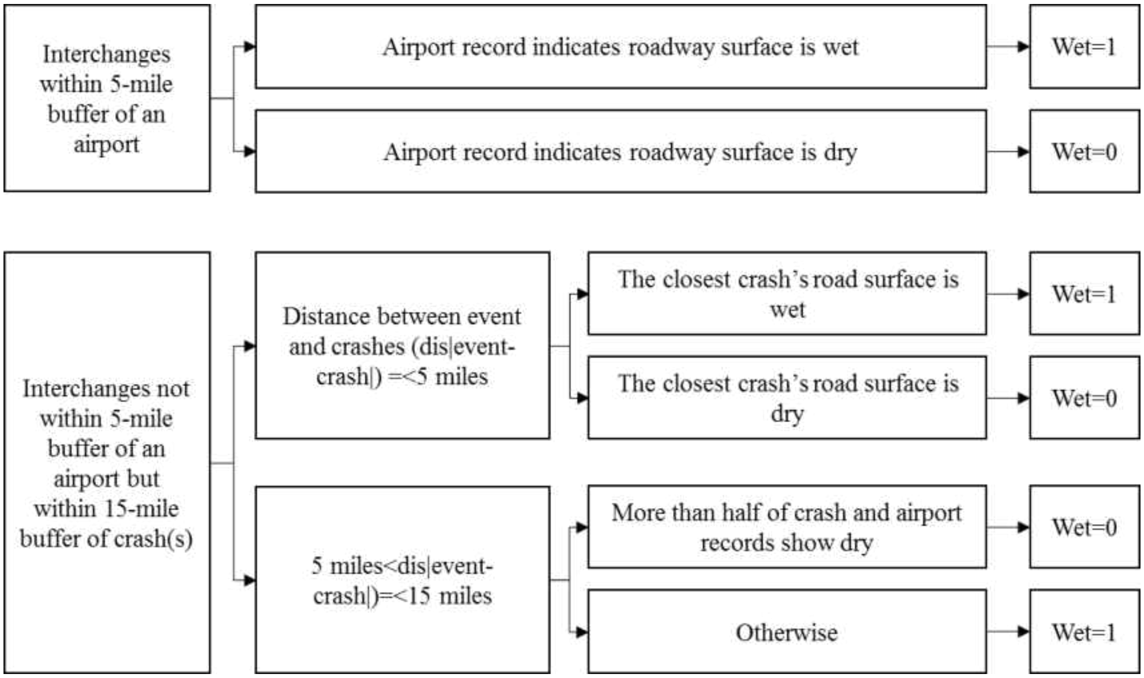


Figure 5-1 Data preparation for roadway surface condition

The result showed that the method in Figure 1 could provide roadway surface condition for 86.0% of studied events. For crash events, the predicted roadway surface conditions were compared with their true conditions as recorded in crash reports. It was found that 84.2% of crashes' predicted roadway surface conditions were accurate. If only the reports from airport weather stations had been used, a mere 49.2% of studied events could be matched with roadway surface conditions with a 76.8% accuracy. These results indicate that the method proposed in this study is able to provide more roadway surface condition information for study events with a higher accuracy.

5.2.3 Real-time Crash Analysis

By comparing crash events with non-crash events, real-time crash analysis intends to identify crash precursors that are relatively more 'crash prone' than others. Then, the analysis can further distinguish crash events from non-crash events by modeling crash risk based on those significant crash precursors in real-time.

In this study, crash events were the situations which occurred 5-10 minutes prior to crashes. It was assumed that traffic, weather, and other parameters in these 5-10 minutes contributed to crash occurrences (Abdel-Aty et al., 2004; Abdel-Aty and Pemmanaboina, 2006; Xu et al., 2013a). Non-crash events were also in 5-minute intervals. They did not cause crashes and also were not impacted by crashes. In order to ensure the purity of non-crash events, all non-crash events were those that occurred more than five hours before and more than five hours after crashes.

There were approximately 9 million non-crash events. It was impossible to put all these non-crash events in the real-time safety analysis model. Hence, this study used a case-control design, which could provide a valid estimation of variables' impact on crash odds ratios with regardless of crash and non-crash ratio (Andersen and Skovgaard, 2010; Vittinghoff et al., 2011). The controls (non-crash events) were randomly selected from the whole non-crash dataset by SAS, and the control to case (crash events) ratio was 5:1. A previous study has proven that this ratio could provide a stable result (Zheng et al., 2010).

In real-time crash analysis, five datasets were used, among which the crash, geometric, and traffic data sources were the same as those in the crash frequency analysis. Additionally, roadway surface condition and daytime have also been collected since they might contribute to crash occurrence (Yu and Abdel-Aty, 2014b; Wang et al., 2015b). Roadway surface condition information was achieved using the method in Figure 5-1. Daytime was from the United States

Naval Observatory (USNO), which provides sunrise and sunset times every day for many cities and towns in the United States. This study collected the sunrise and sunset times of Orlando, Tampa, Miami, and Jacksonville. Then, the time when an event occurred was compared with the same day's sunset and sunrise times of the city where the event occurred in. If the time of the event was between sunrise and sunset, then it was considered to have occurred during daytime; if the time of the event was before sunrise or after sunset, then it was considered to have occurred during nighttime. For example, the sunrise time and sunset time of Orlando on January 15, 2015 is 7:19 A.M. and 5:51 P.M. respectively; if an observations happens in Orlando at 7:00 A.M., then the observation is during nighttime.

Combining five datasets together produced 279 crash events and 1,395 non-crash events. All these events had complete information, i.e., traffic, weather, daytime, and geometry. For these 1,674 events, the descriptive statistics of traffic, roadway surface condition, and daytime variables are shown in Table 5-3.

Table 5-3 Variable descriptive statistics for the real-time crash analysis

Variables	Description*	Mean	Std.	Min	Max
Spd	Average speed (mph)	55.2	12.1	3.0	84.4
Std_spd	Standard Deviation of speed (mph)	3.2	2.3	0.0	20.4
Vehcnt	Vehicle count (veh/5min)	35.3	37.3	0.3	187.0
Occ	Average lane occupancy (%)	5.3	8.1	0.0	66.8
Daytime	1=if between sunrise and sunset; 0=otherwise	0.60	0.49	0	1
Wet	1=if roadway surface condition is wet; 0=otherwise	0.19	0.39	0	1

* All traffic variables were measured in 5-minute intervals

Then, non-crash events were randomly assigned to the SV or MV dataset by using SAS simple random sampling. In simple random sampling, each event has an equal probability of selection, and sampling is without replacement, which means that an observation can be only selected once. In the SV dataset, there were 140 crash and 700 non-crash events; in the MV dataset, there were 139 crash and 695 non-crash events.

5.3 Methodology

An interchange ramp segment had several correlated observations, which shared common information, such as geometric design. Multilevel models can handle the correlation among observations in the same group. It can properly estimate multilevel data and outperform classical regression by providing better model accuracy (Gelman, 2006). In this study, models had two levels: segment-level and individual-level. The segment-level model used segment geometric information; the individual-level model specified the variables which were unique to each observation, e.g., volume in 6:00 A.M. to 9:00 A.M. for a segment.

5.3.1 Multilevel Poisson-lognormal

Several previous crash frequency studies have utilized mixed-Poisson models to overcome possible over-dispersion in the data (Park and Lord, 2007). This study utilized Poisson-lognormal models since they outperform Poisson-gamma models when samples have low sample means (Lord and Miranda-Moreno, 2008). In the multilevel Poisson-lognormal models, the observed crash frequency at time t on segment i (y_{ti}) had a Poisson distribution. It was conditioned on its expected crash frequency ($\boldsymbol{\lambda}_{ti}$):

$$y_{ti} \sim Poisson(\lambda_{ti}) \tag{5-1}$$

The expected crash frequency was modeled as a function of traffic and time of day parameters in the individual-level model:

$$\log(\lambda_{ti}) = \beta_{0i} + \sum_{r=1}^{R} \beta_r x_{rij} + \mu_{ti} \tag{5-2}$$

where β_r is the regression coefficient of r^{th} individual-level independent parameter and was specified to be normal priors as $\beta_r \sim Normal(0, 10^6)$ (Xu et al., 2014; Wang et al., 2015b), R the total number of individual-level independent parameters, μ_{ti} the residual and was set to follow a normal distribution $\mu_{ti} \sim Normal\ (0, 1/\tau_1)$, where τ_1 was set to be a gamma prior $Gamma(0.001{,}0.001)$, β_{0i} the intercept at the individual-level model, it was assumed to vary across segments and was conditioned on the geometric factor g_i, which in turn was a function of geometric parameters. The segment-level model is as follows,

$$\beta_{0i} \sim Normal(g_i, 1/\tau_2) \tag{5-3}$$

$$\tau_2 \sim Gamma(0.001, 0.001) \tag{5-4}$$

$$g_i = \gamma_0 + \sum_{q=1}^{Q} \gamma_q w_{qi} + \mu_i \tag{5-5}$$

where γ_0 is the intercept of segment-level model, and γ_q the regression effect of the q^{th} segment-level variable w_q. Both γ_0 and γ_q were specified to be vague normal priors: $\gamma \sim Normal(0, 10^6)$. Q is the total number of segment-level explanatory variables, μ_j the unexplained segment-level errors, was normally distributed with a mean of 0 and a deviation of $1/\tau_3$, and τ_3 was specified to be gamma prior as $Gamma(0.001{,}0.001)$.

5.3.2 Multilevel Logistic Regression

Logistic regression models have been widely used in real-time crash studies (Abdel-Aty and Pande, 2005; Hourdos et al., 2006; Lee et al., 2006a). In addition, data mining methods have also been used, e.g., Multilayer perceptron neural network models (Pande et al., 2011) and Support Vector Machine (Qu et al., 2012). Though data mining methods might provide better crash prediction accuracy, they might not be able to provide the specific impact of significant variables on crash risks. This study aimed at identifying significant variables and finding their influence. Thus, logistic regression models were used.

Supposing an event (y_{ij}) has a binary outcome, crash (y_{ij}=1) and non-crash (y_{ij}=1). The outcome was conditioned on the expected crash probability for event j in segment i (p_{ij}):

$$y_{ij} \sim Bernoulli(p_{ij}) \tag{5-6}$$

In the individual-level model, the expected crash probability was modeled as a function of traffic, roadway surface condition, and daytime parameters:

$$\log it(p_{ij}) = \beta_{0i} + \sum_{r=1}^{R} \beta_r x_{rij} \tag{5-7}$$

where β_r is the regression coefficient of r^{th} individual-level parameter and was specified to be normal priors as $\beta_r \sim Normal(0, 10^6)$, R the total number of individual-level independent parameters, β_{0i} the intercept at the individual-level model and was conditioned on the geometric factor g_i, and g_i is decided by the following segment-level model,

$$\beta_{0i} \sim Normal(g_i, 1/\tau_1) \tag{5-8}$$

$$\tau_1 \sim Gamma(0.001, 0.001) \tag{5-9}$$

$$g_i = \gamma_0 + \sum_{q=1}^{Q} \gamma_q w_{qi} + \mu_i \tag{5-10}$$

where γ_0 is the intercept of segment-level model, γ_q the regression effect of q^{th} segment-level variable, and Q the total number of segment-level variables. Both γ_0 and γ_q were specified to be normal priors as $\gamma \sim Normal(0, 10^6)$. μ_j is the unexplained segment-level errors, was normally distributed with a mean of 0 and a deviation of $1/\tau$, and τ was specified to be gamma prior as $Gamma(0.001,0.001)$.

5.3.3 Bayesian Inference

All multilevel Poisson-lognormal and multilevel logistic regression models were estimated in Winbugs by implementing Bayesian inference. For each model, three chains of 10,000 iterations were set up, among which the first half of the iterations (burn-in step) were discarded, and the second half were used in the final analysis (Gelman et al., 2014). Parameter convergences were checked by examining their Markov chain Monte Carlo (MCMC) trace plots (Spiegelhalter et al., 2003). If all trace plots appear to have been stabilized and three chains are overlapping each other, the models are converged.

DIC was used as a Bayesian measurement of model complexity and fit. Smaller DIC indicates better model fitting. In addition to DIC, the performance of multilevel logistic regression models were also evaluated by AUC. Compared to sensitivity and specificity, AUC is a better measure of classification accuracy for logistic regression models (Hosmer Jr et al., 2013). It plots true positive rate against false positive rate for all possible thresholds. The range of AUC is 0.5 to 1.0, a higher value indicating a better ability in discriminating crash and non-crash events. When the AUC of a model is higher than 0.80, it indicates the model has a good discrimination (Hosmer Jr et al., 2013).

5.4 Model Estimation

5.4.1 Crash Frequency Model

The crash frequency models for SV and MV crashes per segment per 3-hour were built using Bayesian multilevel Poisson-lognormal models. Table 5-4 provides the estimated parameters, 95% CI and DIC for each model.

Table 5-4 Crash frequency models for interchange ramp segments

Variable	Mean	Std.	95% CI
Single-vehicle Crash			
Intercept	-3.84	0.82	(-5.43, -2.31)
Log(3-hour interval volume)	0.24	0.11	(0.03, 0.43)
Average Turning Angle	3.27	1.39	(0.57, 5.86)
s.d. of μ_j	0.58	0.42	(0.03, 1.30)
DIC		565.73	
Multi-vehicle Crash			
Intercept	-9.64	1.02	(-12.14, -7.48)
Log(3-hour interval Volume)	1.07	0.13	(0.77, 1.38)
Sag	0.95	0.38	(0.20, 1.64)
Downgrade	1.00	0.36	(0.29, 1.67)
s.d. of μ_j	0.44	0.26	(0.04, 0.90)
DIC		543.92	

For the SV crash frequency model, the average turning angle was found to be positively significant, which indicated that segments with sharp horizontal curves were more likely to have SV crashes. Similar results have also been found by previous research (Harwood et al., 2000; Banihashemi, 2015). When a vehicle travels on a roadway with a sharp horizontal curve, the roadway may not be able to provide enough centripetal force. Then, the vehicle may lose control and may have an SV crash. The logarithm of traffic volume was also found to be significant with a positive sign. This can be understood that higher volume means higher exposure and indicates a higher crash frequency.

The coefficient of the logarithm of volume in the MV model was much higher than that in the SV model. It referred that volume had more impact on MV crash frequency. This may be because a higher volume increases the exposure and possibility of MV crash, but decreases SV crash possibility. When volume increases, the possibility that a vehicle encounters another vehicles increases, and the possibility that it is involved in a crash with another vehicles also increases, so MV crash likelihood increases. But under high volume conditions, a vehicle is less likely to have an SV crash without involving other vehicles. So higher volume indicates low SV crash probability (Hauer, 2015). To sum up, when volume increases, the combination of increased exposure and decreased SV probability results in slightly increased SV crash frequency; but for MV crashes, the both increased exposure and MV crash probability largely increased MV crash frequency. Thus, volume has more impact on MV crash frequencies.

Sag and downgrade vertical alignment have been proven to significantly increase MV crash count. Vehicles traveling from mainlines to ramps are at high speeds. They need to decelerate in order to adjust to the lower speed limits on the ramps. Reducing speed on a downgrade or sag vertical curve is harder than on other vertical alignments (i.e., crest, upgrade or flat). Unlike the conclusion made in a previous study (Hauer et al., 2004), crest vertical curve was not found to have a significant impact on MV crash frequency in this study. The crest interchange ramps in this study were all one-lane, one-way roadways. Vehicles on these roadways were not impacted by oncoming vehicles and could not overtake the vehicles ahead. Hence, the presence of a crest vertical curve did not necessarily increase MV crash risks.

5.4.2 Real-time Crash Risk Estimation Model

Bayesian multilevel logistic regression models were used to model real-time crash risks. Both SV and MV crash model-building datasets were split into calibration and validation with a ratio of 70:30. During the process of model estimation, variables were checked for possible high correlations. If two variables were correlated with each other and their correlation coefficients higher than 0.4, only the variable which could provide the lower DIC was kept. Table 5-5 shows the final model results.

Table 5-5 Real-time crash risk estimation model for interchange ramp segments

Variable	Mean	Std.	95% CI
Single-vehicle Crash Risk Model			
Intercept	-2.87	0.34	(-3.60, -2.78)
Wet	2.34	0.31	(1.76, 2.92)
Upgrade*	-0.89	0.53	(-1.95, 0.10)
s.d. of μ_j	0.76	0.45	(0.05, 1.58)
DIC		373.13	
Calibration AUC		0.88	
Validation AUC		0.85	
Multi-vehicle Crash Risk Model			
Intercept	-4.23	0.39	(-4.99, -3.53)
Occ	0.15	0.02	(0.11, 0.19)
Wet	1.35	0.33	(0.70, 1.98)
Daytime	0.81	0.34	(0.16, 1.45)
Downgrade*	0.70	0.41	(-0.08, 1.45)
s.d. of μ_j	0.48	0.32	(0.04, 1.14)
DIC		356.06	
Calibration AUC		0.90	
Validation AUC		0.86	

* Significant at a 90% confidence interval

Upgrade vertical alignment were negatively significant in the SV model. It indicates that upgrade vertical alignment decreased SV crash risk. The odds of SV crash risk on wet roadway surfaces relative to that on dry roadway surfaces was 10.4. Wet roadway surface increases the possibility of losing control and skidding off the road. A sharp horizontal curve indicates the need for higher friction force and superelevation. If the need cannot be satisfied, an SV crash may happen.

Though the number of significant variables in the SV crash risk model is limited, the AUCs of calibration and validation are as high as 0.88 and 0.85. It means that the model's ability to discriminate crash events from non–crash events was good. Random forests, a frequent tool used in estimating variable importance (Breiman, 2001), were used to explore the reason why these two variables provided good predictions. It was found that the roadway surface condition was much more important than any other variables: its importance was about 2 times that of the second most important variable. The roadway surface condition alone can provide very important information for SV crash risk estimation. This conclusion is not consistent with the conclusion in the previous chapter; the main reason is that the geometric design of interchange ramps is different from that of regular ramps. On interchange ramps, the horizontal or vertical curvatures are sharper. This makes the vehicles on interchange ramps more sensitive to roadway surface conditions.

Four variables have been found to be significant in MV crash risk: occupancy, roadway surface condition, daytime, and downgrade vertical curve. A higher lane occupancy indicates more congested traffic, and the interactions between vehicles are also higher. Hence, under higher occupancy condition, MV crash risk is higher. A similar result has also been found by another research (Abdel-Aty et al., 2004). Wet roadway surface significantly increased MV crash risk. If a vehicle intends to avoid running into the vehicles ahead, it needs longer braking distance under wet pavement conditions. Hence, the possibility of avoiding an MV crash under wet pavement condition is lower than that on dry pavement. Additionally, the MV crash risk during daytime was significantly higher than the risk during nighttime. It may be understood as drivers being more cautious when driving during the night. In addition to increased driver cautiousness, there existed raised pavement markers on many of the studied interchange ramp segments. They enabled the roadway edges to be clearly visible at long distances during the night, further enhancing traffic safety during nighttime. Downgrade vertical curve is significant at a 90% confidence interval with a positive sign, indicating that it increases MV crash risk. The reason is similar as what has been stated in the results of the MV crash frequency model.

5.5 Summary and Conclusion

Freeway-to-freeway interchange ramps are critical components of freeway networks. The safety of interchange ramps is a concern because of their complicated horizontal and vertical alignment. While there is no safety study of interchange ramps from microscopic aspects, which are crash frequency estimations based on 3-hour intervals and real-time crash risk evaluation. In order to better understand the crash mechanism of interchange ramps, this work builds multilevel Poisson-lognormal models to estimate crash frequencies in 3-hour intervals, and multilevel logistic regression models to predict real-time crash risks. All models are separately applied to both SV and MV crashes. Furthermore, this study explores the feasibility of using crash reports to provide pavement conditions for study events.

The SV crash frequency model reveals that the logarithm of traffic volume and average turning angle are positive significant parameters in estimating crash frequency. The MV crash frequency model shows that traffic volume, sag, and downgrade vertical curve are positively significant. Comparing the SV to the MV model, it was found that volume has more impact on MV crashes.

The SV real-time crash risk model depicts that roadway surface condition and average turning angle have a significant impact on SV crash risk. Random Forests uncover that roadway surface condition is the most important and indispensable variable in estimating SV crash risk. On the other hand, MV crash risk is determined by lane occupancy, roadway surface condition, time of day, and the presence of a downgrade vertical alignment. High lane occupancy, wet roadway surface conditions, daytime driving, and downgrade vertical curve significantly increase MV crash risk.

The roadway surface condition has been found to be a significant contributing factor. Wet roadway surfaces can reduce pavement friction and result in skidding or hydroplaning. For interchange ramps, the sharp horizontal or vertical curves further enlarge the impact of wet pavement conditions. However, in spite of the significant impact of wet roadway surfaces on crash risk, it is challenging to obtain its value because the number of weather stations is limited. This study therefore proposed implementing weather information from crash reports in real-time risk studies. By adding the weather information from crash reports, 36.8% more studied events were matched with its corresponding roadway surface condition, and the accuracy of the prediction also was increased by 7.4%. Hence, crash reports can be a good complement to weather station records in providing weather information.

There are two potential applications of this study. First, the impact of horizontal curve and vertical alignment on crash frequency of interchange ramps might be added to the Highway Safety Manual (HSM). The AASHTO (2010) states that the effect of the interchange ramp roadway's vertical alignment is still unknown, and the impact magnitude of a horizontal curve on crashes is not certain. Second, since roadway surface conditions have been proven to be significant in real-time crash risk, practitioners could consider countermeasures such as applying high friction pavement at interchanges. Meanwhile, pavement moisture sensors along with DMS can also be used to advise drivers on interchange ramps under wet pavement conditions. Then the CMFs of these countermeasures can be studied in the future.

There are some limitations to this study. Though the number of interchange ramp segments was 52 and was sufficient for the study, the number of studied interchanges was only 15. If more interchange data were available, it would be possible to add another level in the model to identify the impact of interchange type and complexity on traffic safety.

CHAPTER 6: REAL-TIME CRASH PREDICTION FOR WEAVING SEGMENTS

6.1 Introduction

Weaving is generally defined as the crossing of two or more traffic streams traveling in a same direction along a significant length of highway without the aid of traffic devices (except for guide signs) (HCM, 2010). When a merging segment is closely followed by a diverging segment and the two are joined by auxiliary lane(s), a weaving segment is formed. Normally, there are three types of movement in weaving segments: mainline-to-mainline, mainline-to-ramp and ramp-to-mainline. The types of traffic movements are shown in Figure 6-1.

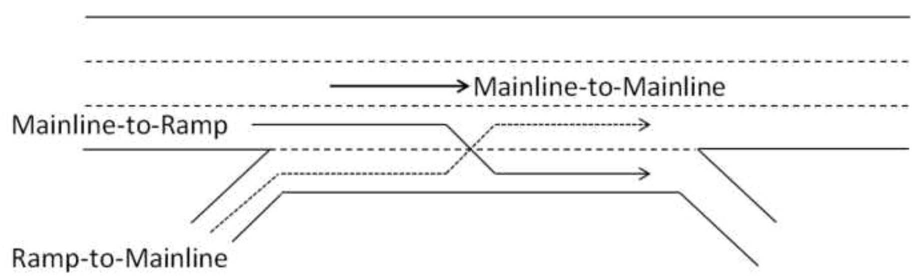


Figure 6-1 Weaving segment traffic movements

Weaving segments are also one of the most complicated segments since on- and off-ramp traffic merge, diverge, and weave in a limited space. When weaving segment lengths are limited, merging and diverging maneuvers cannot be operated independently. Vehicles entering and exiting expressways have to compete for lane-changing opportunities. This may easily lead to crashes. The occurrence of crashes in weaving segments can bring about serious results. On-ramp vehicles might not be able to get on expressways, and may queue up along ramps or have to change their routes. Off-ramp traffic may have difficulty to get off mainlines and would queue up on mainlines. Moreover, if the crash cannot be cleared in time, the queue may block all traffic, including non-weaving and weaving traffic. Then the capacity and level of service of weaving segments are reduced significantly. Hence, understanding the safety of weaving segments and further finding potential solutions to mitigate crash risks are important and need to be addressed.

This study conducted a real-time crash prediction study for weaving segments. Three types of parameters were considered in the model building. They were traffic, geometry, and weather explanatory variables. Of these, traffic explanatory variables are essential and the traffic turbulence is one of the most important contributing factors crashes. The geometric characteristics, e.g., segment length and number of lanes involved in weaving, are more site-specified for weaving segments. Exploring the connection between geometric characteristics and crash risks would be helpful in finding hazardous weaving segments. Meanwhile, in addition to traffic and geometric factors, weather factors are also important. Severe weather, e.g., rain or snow, makes traffic in weaving segments be vulnerable to frequent lane-changing, deceleration, and acceleration maneuvers.

This chapter is organized into five sections. The second section describes the research methodology which has been used in building the model. The third section describes the data, defines the variables and presents the crash characteristics. The fourth section shows the model results and also discusses the findings of the model. The fifth section summarizes the findings and conclusions.

6.2 Methodology

The real-time safety analysis assumes that the occurrence of an event (crash or non-crash event) is due to traffic, weather, or other conditions which happened just before the event. By analyzing and comparing conditions before crash and non-crash events, crash contributing factors can be identified. Then, a logistic regression model is built to quantify the impact of contributing factors on crash occurrence.

Supposing an event, which is the i^{th} observation, has binary outcome: crash (y_i=1) or non-crash (y_i=0). The possibilities for these two outcomes are p_i (y_i=1) and 1-p_i (y_i =0), respectively. The models are as follows:

$$y_i \sim Bernoulli(p_i) \tag{6-1}$$

$$\log it(p_i) = \beta_0 + \sum_{r=1}^{R} \beta_r x_{ri} \tag{6-2}$$

where y_i follows a Bernoulli distribution whose success probability is p_i, β_o the intercept, β_r the regression coefficient of predictor x_{ri}, x_{ri} is the r^{th} explanatory variable for i^{th} observation, e.g., volume.

This study implemented the k-fold cross-validation method to evaluate the prediction accuracy of the real-time crash risk model. The k-fold cross-validation method is able to minimize the bias caused by the random sampling of the training and validation data samples (Olson and Delen, 2008). In k-fold cross-validation, the complete dataset is randomly divided into k mutually exclusive subsamples, each subsample having proximately equal sample size. The model is trained and tested k times. For each attempt, a subsample acts as the validation data for testing the model, and the remaining k-1 subsamples are training data. Each of the k subsamples is used exactly once as the validation data, so the cross-validation process is repeated k times in total. Then the k results from the k validation folds are combined to provide a single estimation of model performance. In this study, a 10-folder cross validation was adopted.

6.3 Experimental Design and Data Description

6.3.1 Study Area and Data

The 22-mile SR 408 in Central Florida was chosen. Four datasets were collected: crash, traffic, weather, and geometry data. The study period was from July 2013 to April 2015. However, due to the absence of traffic data in April, 2014, only the other 21 months data were utilized.

The crash data were from S4A. It is an interactive, web-based system designed to support the crash mapping and analysis needs of law enforcement, traffic engineering, transportation planning agencies, and research institutions in the state of Florida (University of Florida, 2015). It provides information for all reported crashes, e.g., crash time, location, type, and severity. One hundred and sixty five crashes were identified in the studied weaving segments during the study period. The traffic data were from MVDS detectors of CFX. They included traffic count, lane occupancy, and speed for each lane at one-minute intervals.

As for the weather data, they were collected from the NCDC which records the weather for ORL. The airport is about 0.5 miles north of the middle of SR 408. Its weather data are continuously monitored. If the weather condition does not change, the data are recorded every one hour. Once the weather parameters change, the weather station records the new weather state at once. The weather dataset included weather type, wind direction and speed, temperature, visibility, hourly precipitation, etc.

The geometric data were collected manually by using ArcGIS map. There were 17 segments in which off-ramp is closely followed by on-ramp on the studied expressway. Among these 17 segments, the configuration of one segment is different from others. The number of lanes for on-ramp is 2 for this segment, but all the others are 1. This special case was excluded from the study.

6.3.2 Experimental Design

The two segment lengths which are relevant to this study are illustrated in Figure 6-2. The short length (*Ls*) is the distance between the end points of solid white lines that prohibit of discourage lane changing. However, this does not mean lane changing maneuvers only happen within this length (*Ls*). Some lane changing actions take place over the solid white lane and is within base length (*Lb*) (HCM, 2010). Hence, the study area was within *Lb*, and crashes happened in this area were collected.

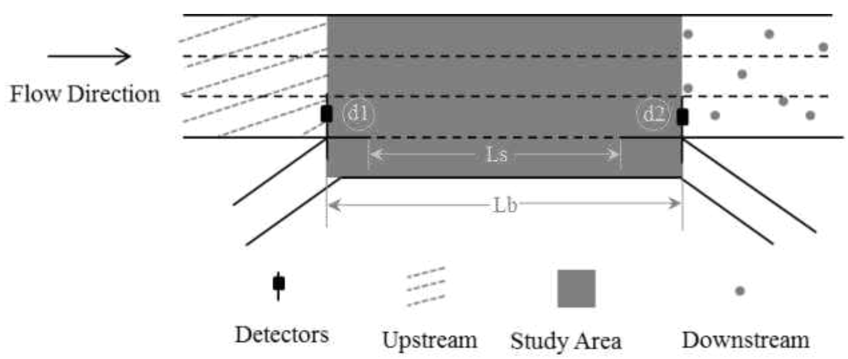


Figure 6-2 Segment length and experimental design

The location of traffic detectors is illustrated by Figure 6-2. The d1 detector can detect traffic of all lanes which are at the beginning of the segments, including mainline and on-ramp. The d2 can also detect all lanes at the end of segments, including mainline and off-ramp. Because of the high coverage of the MVDS system on SR 408, all studied segments had two detectors, which were d1 and d2. Hence, the traffic data of all weaving segments were available.

The traffic data were divided into two datasets depending on whether traffic contributed to crash occurrence. The traffic data which existed 5-10 minutes prior to crash occurrence were extracted as crash traffic. In previous studies (Hossain and Muromachi, 2013b; Xu et al., 2013a; Yu and Abdel-Aty, 2013a), the researchers also assumed that the traffic 5-10 minutes prior to crashes contributed to crash occurrence. The reason why the 5-10 minute data were used is as follows. First, compared to the traffic data which are 10-15 minutes prior to crashes, it can provide traffic information more relevant to crashes. Second, compared to the traffic data which are 0-5 minute prior to cases, it can provide sufficient time for the traffic management center to analyze, react, and announce warning information to the drivers. What is more important, the recorded crash time is normally the time when drivers call the policeman. This means that the recorded crash time is actually the time after crash. If the 0-5 minute data had been used, some traffic conditions had already been impacted by crashes and were not crash-precursor conditions any more.

For the weather data, three parameters were selected, i.e., weather type, hourly precipitation, and visibility. The former two parameters were combined into a binary predictor named road surface condition. Combining these two parameters can provide more accurate and complete rain information. If, for a given time point, weather type includes TS, RA, or DZ, or hourly precipitation is higher than 0, they indicate that it has rained at that point. Then it was assumed that the roadway surface condition of an event was wet in the following one hour.

Not all segments which is formed by merging closely followed by diverging can be regarded as weaving segments. HCM (2010) proposed a parameter named the maximum weaving segment length, simply referred to as maximum length in the rest of this chapter. It is the length at which weaving turbulence no longer has impact on the operation within the segment or on the capacity of the weaving segment. The maximum length represents the weaving influence length. The value of this parameter is not fixed, but changeable according to geometric and traffic conditions. The HCM (2010) also expressed that when the short length (*Ls*) of a segment is larger than the maximum length, the segment is not a weaving segment but a regular merging area followed by a diverging area. The calculation of this parameter is given in the next section. The study's objective is weaving segments, only those cases which happened within weaving segments were chosen. In order to achieve it, the maximum lengths of all cases were dynamically calculated and were compared with their short length (*Ls*) in a 5-minute interval. If an observation's maximum length was larger than its short length, the case was kept; if an observation's maximum length was less than its short length, the case was discarded.

After the processes above, all datasets were combined together. Since the number of non-crash cases are millions, it was hard to put all non-crash cases into analysis. A case control design was used to handle this issue. Non-crash cases were randomly selected from the population of non-crash cases. For each crash case, 20 non-crash cases were selected. One hundred and twenty five crashes and 2,500 non-crash cases were filtered out in the study. The non-crash cases were randomly chosen from the non-crash datasets by SAS. All selected observations happened in weaving segments and had complete traffic, geometric, and weather information. Meanwhile, in order to ensure the purity of the non-crash observations, no crashes happened within 5 hours before and after the selected non-crash events.

6.3.3 Variable Definition

The definitions and acronyms of variables which can be obtained from the traffic, geometric and weather data are shown in

Table 6-1.The speed standard deviation in the table is the speed changes over time. In order to obtain this value, the average speed of a mainline section for every one minute was obtained, then standard deviation of speed was calculated based on a 5-minute interval.

Table 6-1 List of variables in real-time safety analysis for weaving segments

Variables*	Description
Bm_spd	Average speed at the beginning of weaving segments (mph)
Bm_vol	Vehicle count per lane at the beginning of weaving segments (vehicles)
Bm_occ	Average lane occupancy at the beginning of weaving segments (%)
Bm_std_spd	speed standard deviation at the beginning of weaving segments (mph)
Onr_spd	Average speed for on-ramp (mph)
Onr_vol	Total vehicle count for on-ramp (vehicles)
Onr_occ	Average lane occupancy for on-ramp (%)
Em_spd	Average speed at the end of weaving segments (mph)
Em_vol	Vehicle count per lane at the end of weaving segments (vehicles)
Em_occ	Average lane occupancy at the end of weaving segments (%)
Em_std_spd	speed standard deviation at the end of weaving segments (mph)
Offr_spd	Average speed for off-ramp (mph)
Offr_vol,	Total vehicle count for off-ramp (vehicles)
Offr_occ	Average lane occupancy for off-ramp (%)
V_{FF}	Mainline-to- mainline vehicle count (vehicles)
Vehcnt	Total traffic count in the weaving segment (vehicles)
VR	Weaving volume ratio, weaving volume over total traffic count (%)
Spd_dif	Speed difference. Spddif =0 if Bm_spd is lower than Em_spd; otherwise Spddif = Bm_spd- Em_spd
Ls	Short length, distance between the end points of any barrier markings (solid white lines) that prohibit or discourage lane changing (feet)
Lb	Base length, distance between points in the respective gore areas where the left edge of the ramp-traveled way and the right edge of the freeway-traveled way meet (feet)
N_{WL}	Number of lanes from which a weaving maneuver may be made with one or no lane changes (lane)
N	Number of lanes within the weaving segment (lane)
LC_{RF}	Minimum number of lane changes that must be made by a single weaving vehicle moving from the on-ramp to the expressway (lane)
LC_{FR}	Minimum number of lane changes that must be made by a single weaving vehicle moving from expressway to off-ramp (lane)
LC	Weaving configuration
LC_{min}	Minimum rate of lane change that must exist for all weaving vehicles to complete their weaving maneuvers successfully (lane/hour)
L_{max}	Maximum weaving segment length (1000 feet)
Visibility	The distance at which an object or light can be clearly discerned (miles)
Wet	1=if roadway surface condition is wet; 0=otherwise

* All traffic data are measured in a 5-minute interval and in the weaving segment

The definition of LC, LC_{min}, and L_{max} are in Eq. (6-3) to (6-5). Among these three variables, the calculations of LC_{min} and L_{max} are based on the HCM (2010).

$$LC = \begin{cases} 0 & if \ \ LC_{RF} = 1 \ and \ LC_{FR} = 1 \\ 1 & if \ \ LC_{RF} = 0 \ \ or \ \ LC_{FR} = 0 \end{cases} \tag{6-3}$$

$$LC_{\min} = \left(LC_{RF} \times Onr\_vol\right) + \left(LC_{FR} \times Offr\_vol\right) \tag{6-4}$$

$$L_{\max} = [5728\left(1+VR\right)^{1.6} - 1566 N_{WL}]/1000 \tag{6-5}$$

Eq. (6-3) integrates LC_{RF} and LC_{FR}, and generates a new binary variable LC named Configuration. In this study, both LC_{RF} and LC_{FR} for all weaving segments only have two values which are 0 and 1. Meanwhile, their values are not equal to 0 simultaneously. By integrating, one variable (LC) is able to represent two important parameters: LC_{RF} and LC_{FR}. Figure 6-3 shows the weaving segment configuration types based on the newly defined LC. In the studied area, 10 weaving segments' LC were 0, and 6 weaving segments' LC were 1.

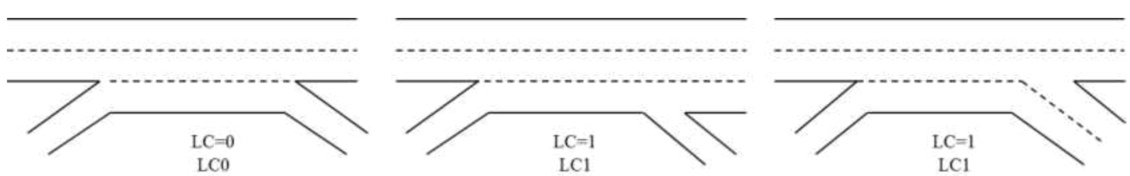


Figure 6-3 Configuration of weaving segments

LC_{min} stands for the minimum rates of lane changing that must exist for all weaving vehicles to complete their weaving maneuvers in a 5-minute interval. Segments with higher LC_{min} have higher crash risks when controlling for the configurations. However, when the configurations are different, it's not comparable because the crash mechanisms for different configurations may vary.

L_{max} is the maximum length and can be also called weaving influence length. L_{max} is decided by weaving volume ratio (VR) and number of lanes from which weaving maneuvers may be made (N_{WL}). The higher VR, the higher interaction between weaving vehicles and other vehicles, and higher maximum length.

6.3.4 Crash Characteristics

There were 85 crashes on *LC0* weaving segments, and 80 in *LC1* weaving segments. The number of crashes per segment was 8.5 for *LC0* and 13.3 for *LC1*. In the study period, the average ADT of *LC1* weaving segments was 1.186 times of that of *LC0*, the million vehicle-miles traveled (VMT) of *LC1* was 1.108 times of that of *LC0*. Meanwhile, the average segment lengths of these two type of weaving segments were almost the same. However, the average crash number of *LC1* weaving segment was 1.564 times of that of *LC0*, which was significantly higher than the segment's traffic and VMT ratio. This indicates that *LC1* may have a higher risk than *LC0*. The result is similar to a previous study by (Liu et al., 2009).

There are one possible reason for this phenomenon. For *LC0*, the auxiliary lane is almost fully occupied by weaving vehicles, and the lane which is close to the auxiliary lane is shared by weaving and non-weaving vehicles. But for *LC1* weaving segment, in which the minimum lane change for off-ramp vehicle is 0, there is one through lane for off-ramp weaving vehicles. In addition, the two lanes which are adjacent to the through lane are also used by weaving vehicles. Hence, more lanes are involved in weaving movements, and then more non-weaving vehicles are affected by weaving vehicles.

The crash severity, number of vehicles involved in crash, and crash type information of each weaving configuration are shown in Table 6-2. The Chi-square test indicates that weaving configuration did not have a significant impact on crash severity and number of vehicles involved in the crash. However, it clearly demonstrates that weaving configuration had significant impact on crash type at a 95% confidence interval.

Table 6-2 Crash characteristics for weaving segments

	LC0	LC1	Chi-square	p-value
Crash Severity				
Injury	25	23	0.0087	0.9255
PDO	60	57		
Number of Vehicle Involved				
1	22	13	2.2879	0.1304
More than 1	63	67		
Crash Type				
Rear End	28	48	12.2520	0.0066
Sideswipe	22	13		
Off Road	18	9		
Other	17	10		

Table 6-2 shows that 76 out of 165 (46.1%) crashes are rear-end crashes, and a rear-end crash has the highest likelihood of occurrence in weaving segments. A previous paper by (Golob et al., 2004) also discovered the similar result. *LC1* weaving segments tend to have more rear-end crashes as shown. For *LC0*, the weaving vehicles change lane as soon as they get the opportunity, and they tend to use the beginning portion of the auxiliary lane (Kwon et al., 2000). At the beginning portion, the speed difference between merging and diverging vehicles does not vary significantly. The merging vehicles are in low speed due to the speed limitation of the on-ramps, and the diverging vehicles also are at low speed since they have to adjust to off-ramps' speed limit.

However, for *LC1*, in addition to the weaving interactions at the beginning portion, a significant number of entering vehicles might meet exiting vehicles at the end of the weaving segments. For the weaving segment, in which the minimum lane change for on-ramp traffic is 0, a large number of entering vehicles do not change their lane and keep on the through lane where all exiting vehicles have to pass in a low speed. For the weaving segment, in which the minimum lane change for off-ramp traffic is 0, plenty of exiting vehicles may take the through lane which all entering vehicles have to use. There exists a big speed difference between these entering and exiting vehicles for *LC1*. Entering vehicles are in high speed to follow speed limits on mainlines, but exiting vehicles are in low speed to follow the speed limits on ramps separately. Under this situation, a rear-end crash may happen.

6.4 Model Estimation

A logistic regression model was used to estimate the relationship between crash odds and contributing factors for weaving segments. One hundred and sixty five crashes were identified in the weaving segments on SR 408 during the study period, among which 125 crashes had complete traffic and weather information. For each crash event, 20 non-crash events were randomly selected from the non-crash event dataset. The PROC LOGISTIC procedure in SAS was used to obtain the real-time crash estimation model, and the 10 folder cross validation method was used to validate model performance.

Beginning with all variables considered, each variable was tested whether it was statistically significant to the target variable. The insignificant variables were eliminated from the next model building step. Later, in order to select the most significant and not highly correlated variables, Random Forests were used to rank the variable's importance and the Pearson correlation test was done. Random Forests are a combination of tree predictors and are robust with respect to noise. One important implementation of Random Forests is estimating the variable importance (Breiman, 2001). If two variables were found to be highly correlated (coefficient>0.4), the variable which was more important was chosen for further analysis.

Then, the variables selected above were put in the model estimation. The result shows that only speed difference between the beginning and the end of a weaving segment, volume, weaving configuration, maximum length, and pavement surface condition are significant in the presence of other variables.

Table 6-3 Real-time crash prediction model for weaving segment

Variables	Mean	Std.	p-value
Intercept	-7.86	0.79	0.00
Spd_dif	0.11	0.03	0.00
Log(Vehcnt)	0.65	0.12	0.00
Configuration	0.57	0.20	0.01
Maximum length	0.21	0.07	0.00
Wet	1.22	0.24	0.00
Training ROC		0.716	
Validation ROC		0.704	

The speed difference between the beginning and the end of the weaving segment has a positive impact on crash odds. The higher speed difference the higher crash odds. When the speed at the beginning of weaving segment is higher than that at the end, vehicles have to decelerate. If drivers are distracted or cannot react in time, it is easy to have a rear-end crash. Previous research by Hossain and Muromachi (2013b) shows that the speed difference can best explain the crash risk and type for a basic freeway segment. The studied weaving segment includes lanes which do not involve in weaving. These lanes are similar to lanes at freeway basic segment, and the crashes on these lanes may have similar indicators as a freeway basic segment.

The logarithm of vehicle count in 5-minute intervals is with a positive coefficient, indicating the high volume might increase the crash odds on a weaving segment. It is easy to be understood why this would be the case. High volume means high exposure to a single-vehicle crashes. Meanwhile, high volume also indicates that the interactions between vehicles are high, and then resulting in a higher exposure to a multi-vehicle crash.

As for the weaving configuration (*LC*), the model result confirms what has been discussed in the crash characteristics section. Weaving segments (*LC1*), in which there is no need for on- or off-ramp traffic to change lane, have an increased crash odds, since the interactions between weaving and non-weaving vehicles are likely to increase and more rear-end crashes would occur due to high speed difference at the end of the weaving segments.

Maximum length (L_{max}) is an estimated factor which measures the distance at which weaving turbulence no longer has an impact on operation and capacity (HCM, 2010). This study finds that maximum length also has significant impact on crash odds. This variable is associated with two factors, i.e., weaving ratio (*VR*), number of lanes from which a weaving maneuver may be made (N_{WL}). The increase of maximum length is mainly contributed by the increase of weaving ratio. When the weaving ratio increases and the whole volume at weaving segment does not change, there are more on-ramp and/or off-ramp vehicles. These vehicles would lead to more turbulence comparing to mainline-to-mainline vehicles, and further result in high crash risk.

Wet roadway surface conditions increase crash odds in weaving segments. It leads to less friction and results in longer braking distances compared to dry surfaces. Meanwhile, vehicles are more likely to lose control. The impact of wet pavement surfaces on weaving segments is even more severe than on basic segments. The on- and off-ramp vehicles have to execute lane changing maneuvers along with deceleration and acceleration. The complicated traffic condition enlarges the wet pavement surface's impact.

Previous real-time crash studies have mainly focused on mainline and ramp vicinity. The weaving segment belongs to mainline and also is at ramp vicinity. Hence, the result found in this study is similar to the previous studies, e.g., the impact of speed difference on crash odds. However, due to the special traffic condition at the weaving segment, more factors which are related to weaving are found, e.g., maximum length and configuration.

6.5 Summary and Conclusion

Weaving segments are potential recurrent bottlenecks which affect the efficiency and safety of expressways during peak hours. Meanwhile, they are one of the most complicated segments, since on- and off-ramp traffic merges, diverges, and weaves in the limited space. One effective way to improve the safety of weaving segments is to study crash likelihood using real-time crash data with the objective of identifying hazardous conditions and reducing the risk of crashes by ITS traffic control. In order to provide effective predictors for real-time weaving segment crash risk, this study collected almost two years' MVDS traffic, geometry, and weather data of 16 weaving segments.

The logistic regression model shows that weaving segment configuration is an important factor. For *LC1* weaving segments, in which there is no need for on- or off-ramp traffic to change lanes, the minimum lane change rate is low and lane changing maneuver is much less. However, *LC1* weaving segments have with high crash odds because there exists high speed differences between on- and off-ramp traffic.

In addition to geometric factors, several traffic related parameters are found to have significant impact on crash odds. Speed difference plays an important role in estimating crash. If the speed difference increases 1 mph, the crash ratio increases by 11.6%. The low speed at the end of weaving segment may be due to congestion at downstream to the segment, or because of the disturbance generated by merging and diverging. Under high speed difference conditions, if VSL is used to reduce the speed limit at the beginning of a weaving segment, both the speed difference and crash odds may be decreased.

The maximum length, which measures the distance at which weaving turbulence no longer has impact, is found to be positively related to the crash odds at a 95% confidence interval. Decreasing maximum length is also an option to decrease crash likelihood. Weaving ratio has the most important impact on maximum length. If *VR* changes from 0.2 to 0.1, the maximum length decrease by 758 feet and crash ratio decrease by 14.7%. RM could be implemented in decreasing on-ramp traffic and weaving ratio, thus improving the safety of weaving segment in real-time.

Previous weaving segment safety studies did not explore the impact of maximum length on crashes. However, as a new proposed parameter in HCM (2010), it is very important. First, it is a dynamic threshold which changes according to weaving ratio and the number of lanes from which a weaving may be made. When the short length (*Ls*) of a weaving segment is more than maximum length, the segment is not weaving segment. Previous weaving segment safety papers did not compare maximum length with short length. It may have one disadvantage. When a segment is 2500 feet and the maximum length is only 2000 feet, this segment is not weaving segment but merging followed by diverging. And weaving maneuvers actually seldom happens in this segment. Second, this parameter is more important in real-time crash studies than short length (*Ls*) and base length (*Lb*). The segment length (short and base length) cannot determine whether weaving segments are prone to have a crash or not. A short weaving segment may be safer than a long weaving segment when the weaving influences length of this short segment is much shorter than that of a long segment.

Besides traffic and geometric factors, wet roadway surface condition significantly increases crash ratios. In weaving segments, frequent lane changing along with deceleration and acceleration makes the safety condition is sensitive to roadway surface condition. Wet road surface can reduce pavement friction and result in skidding or hydroplaning, and then result in a crash. High friction surface might be a good treatment to relieve this impact.

Based on the proposed model, the crash hazard for weaving segments can be identified. ITS, e.g., RM, and high friction surface treatment can be used to enhance the safety of weaving segments in real-time. There are limitations to this study. The weaving segment sample size was only 16 though the crash sample size was enough for real-time safety study. All the studied weaving segments were from one expressway, their geometric designs did not vary too much, for example, the speed limits of these weaving segments were only with two values: 55 and 65 mph. More geometric parameters can be explored by identifying more weaving segments with different geometric design in the future.

CHAPTER 7: IMPLEMENTATION OF ATM ON A CONGESTED WEAVING SEGMENT

7.1 Introduction

Traffic conditions in weaving segments are complicated because on-ramp and off-ramp vehicles have to compete for lane-changing opportunities. Meanwhile, low-speed entering vehicles need to accelerate in order to join mainline traffic, and exiting vehicles have to decelerate in order to adjust to the lower speed limits of off-ramps. These frequent lane changing, acceleration, and deceleration maneuvers might result in an increased crash risk in weaving segments. As for a congested weaving segment, these maneuvers might be more intense, and the safety of the congested weaving segment is perhaps severer than other segments.

One of the methods to improve the safety of weaving segments is ATM, which is able to dynamically manage roadway facilities based on prevailing and predicted traffic conditions. Plenty of practitioners and researchers have proven that ATM has the capability of providing safer and smoother traffic (Abdel-Aty et al., 2006; Bhouri and Kauppila, 2011). Among ATM strategies, RM and VSL are widely used approaches.

The basic concept of the RM algorithm, ALINEA, is adjusting on-ramp entering volume based on mainline traffic operational conditions (Papageorgiou and Kotsialos, 2000). For example, if an on-ramp's downstream freeway is congested, its ramp metering rate will be decreased and then the congestion might be alleviated since less on-ramp traffic is allowed to enter the freeway. Nevertheless, a congested traffic situation is not equivalent to a high crash risk condition. Hence, the traditional ALINEA, which only considers downstream occupancy in the algorithm, may not be able to improve safety. In order to enhance both safety and operational efficiency, this study developed a modified ALINEA, which took both traffic operation and safety conditions into account.

Another useful ATM strategy is VSL, the adjustment of speed limits based on different traffic and weather conditions. It can possibly improve traffic safety and mitigate traffic congestion by adjusting vehicles' speed and decreasing speed variation among vehicles (Li et al., 2014). However, the success of VSL is dependent on the level of compliance (Yu and Abdel-Aty, 2014a). If drivers do not follow the new speed limit, the VSL would fail to improve traffic safety.

The coordination of RM and VSL might be an approach to avoid the failure of ATM. Even if the VSL strategy does not work, the RM is still able to improve traffic safety. Meanwhile, RM is able to regulate on-ramp traffic, and VSL can change mainline traffic conditions. Hence, the coordination of RM and VSL is able to change the traffic conditions of the on-ramp and mainline simultaneously, and might further improve the safety of a weaving segment network.

Based on the crash mechanism of weaving segment from last chapter, the safety impact of RM and VSL on a congested weaving segment was analyzed through micro-simulation. Additionally, the influence of an integrated RM-VSL was tested. This chapter is organized into five sections. The second section discusses the methodologies of crash odds calculation, RM, and VSL. The third section describes experimental design, including building a simulation network and the design of the ATM scenarios. The fourth section shows the results of ATM scenarios' effects on safety and average travel time. Finally, the fifth section summarizes the findings and conclusions.

7.2 Methodology

7.2.1 Odds Ratio Calculation

By utilizing the crash estimation model for weaving segments from the last chapter, the real-time crash odds of the studied weaving segment can be obtained given the values of explanatory variables. But what needs to be kept in mind is that the crash estimation model for weaving segment (Table 6-3) was based on a case control design. The true crash risk cannot be obtained from Table 6-3, but rather the crash odds ratio (OR) between two conditions can be obtained using the following function,

$$OR = \frac{Crash\ Odds_2}{Crash\ Odd_1} = \exp\{0.11(Spd_{dif\,2} - Spd_{dif\,1}) + 0.65[\log(vehcnt_2) - \log(vehcnt_1)] + 0.57(LC_2 - LC_1) \\ +0.21(L_{\max 2} - L_{\max 1}) + 1.22(Wet_2 - Wet_1)\} \tag{7-1}$$

The condition 1 is the crash condition under non-ATM control, and condition 2 is the crash condition under ATM control. If OR is higher than 1, it means condition 2 is more dangerous than condition 1; if OR is 1, it means the safety of condition 2 is the same as the safety of condition 1; if OR is less than 1, it means condition 2 is safer than condition 1.

7.2.2 Ramp Metering Algorithm

The concept behind the traditional ALINEA is to determine an on-ramp metering rate by two parameters: the road occupancy observed at the downstream of a merge area, and a pre-specified critical occupancy (Papageorgiou et al., 1991). This study adopted a modified ALINEA which additionally considered safety conditions. The ramp metering rate was updated every 5 minutes based on four parameters: traffic and safety conditions. The metering rate at time step k is calculated in Eq. (7-2):

$$r(k) = r(k-1) + K_R(\hat{o} - o_{k-1}) + K_s(\hat{p} - p_{k-1}) \tag{7-2}$$

where $r(k)$ is the metering rate (veh/h) at time interval k, $r(k-1)$ the metering rate at the previous time interval k-1, K_R the occupancy regulator parameter (veh/h), $\hat{o}$ the critical occupancy (%), o_{k-1} the occupancy (%) at time interval k-1, K_S the safety regulator parameter (veh/h), p_{k-1} the conditional crash risk (calculated from Table 6-3) based on case control design at the time interval k-1, and $\hat{p}$ the critical crash risk.

The ramp metering was achieved by adjusting the timing of the ramp signal, which was set at the end of the on-ramp. The metering signal permitted on-ramp vehicles to enter the weaving segment only when the signal turned to green. Otherwise, vehicles were required to stop at the signal and waited for a green phase. The green-phase duration at time interval k, $g(k)$, is calculated as follows,

$$g(k) = \left(\frac{r(k)}{r_{sat}}\right).C \tag{7-3}$$

$$g_{\min} \leq g(k) \leq g_{\max} \tag{7-4}$$

where C is the fixed cycle time (10 seconds), r_{sat} the ramp saturation flow (1800 veh/(h.lane)) (Bhouri et al., 2013), g_{min} is 3 seconds, and g_{max} the maximum green-phase duration (10 seconds). Meanwhile, in order to prevent the ramp metering rate from increasing greatly and resulting in a large amount of vehicles entering the mainline at time interval k, the maximum increment of $\mathrm{r(k)}$ for each time interval was set to be 60 veh/h.

7.2.3 Variable Speed Limit Strategy

Previous studies have proven that the speed difference between the upstream and downstream of a segment is positively related to the crash risk of this segment (Hossain and Muromachi, 2010;

Xu et al., 2013b). Meanwhile, several studies have found that VSL is capable of reducing speed variation (Rämä, 1999; Kwon et al., 2007). Hence, the implementation of VSL might reduce crash risk. In this study, when crash risk was higher than the critical crash risk ($\hat{p}$), VSL at the upstream and the downstream of the congested weaving segment were activated to reduce the speed difference between the beginning and the end of the weaving segment.

The application of VSL in microsimulation was carried out by changing the desired speed distributions. The field desired speed data were obtained from the MVDS detectors on the studied weaving segment. As for other desired speed distributions under different speed limits, it was supposed that if the original speed limit changed (by decreasing or increasing) by n mph, all vehicles' speed would accordingly change by n mph. Hence, based on this assumption and the field desired speed distribution, the desired speed distributions of different speed limits could be obtained.

7.3 Experiment Design

7.3.1 VISSIM Simulation Network

Simulations were conducted in PTV VISSIM, version 7.0. VISSIM is a microscopic traffic simulation software. It has been widely used by researchers and practitioners to obtain roadway operation and safety performance. It is capable to simulate a large number of vehicles in a wide road network. Meanwhile, VISSIM allows users to program and regulate vehicle movement through the Component Object Model (COM) interface, which was achieved by implementing Visual Basic for Applications (VBA) from Excel in this study.

The ATM strategies were tested on a weaving segment whose milepost (MP) is from 12.6 to 13.0 on the westbound side of SR 408. The field speed limit of this weaving segment is 55 mph. Its morning peak hours are from 7:00 A.M. to 9:00 A.M. The simulation time was from 6:30 A.M. to 10:30 A.M. The geometric characteristics of the simulation network, such as lane width, were the same as the field. Meanwhile, the traffic information of the simulation network, including input volume and desired speed distribution, was obtained from the MVDS data from four Thursdays in August, 2015.

The simulation network was well calibrated and validated by evaluating Geoffrey E. Havers (GEH) and absolute speed difference. GEH is a valid volume calibration parameter. The definition of GEH is as follows,

$$GEH = \sqrt{\frac{(E-V)^2}{(E+V)/2}} \tag{7-5}$$

where E is modeled volume (vehicle/hour), and V field volume (vehicle/hour).

If more than 85% of the measurement locations' GEH values are less than 5, then the simulated volume would accurately reflect the field volume (Yu and Abdel-Aty, 2014a). The absolute speed difference between simulated speeds and field speeds should be within 5 mph for more than 85% of the checkpoints (Nezamuddin et al., 2011b).

The simulated traffic volumes and speeds were aggregated to 15-minute intervals, and then compared with the corresponding field traffic data. Ten simulation runs' worth of results showed that 96.4% of observed GEHs were less than 5, and 86.46% of the aggregated speeds in simulation were within 5 mph of field speeds. This proved that the traffic conditions of the VISSIM network were consistent with that of the field.

7.3.2 ATM Scenarios

There were four parameters, in the modified ALINEA algorithm, which needed to be calibrated: the critical occupancy ($\hat{o}$), the occupancy regulator parameter(K_R), the critical crash risk ($\hat{p}$), and the safety regulator parameter(K_S). These parameters were set as follows:

1. In previous studies, the critical occupancy ($\hat{o}$) was set between 17% and 23%, and it has been found that a higher value of the critical occupancy ensures better safety benefits (Abdel-Aty et al., 2007a) . For this study, the critical occupancy was set to be 23%.
2. The range of the occupancy regulator parameter (K_R) in previous studies varied from 70 to 120 vehicle/h. But the value did not have significant effects on metering rate (Papamichail et al., 2010). This study used 70 vehicle/h.
3. In order to reduce the false alarm percentage, the threshold of identifying a crash was set to be 0.15 for p. When the threshold is 0.15, the specificity was 0.973 and the false positive rate was 0.027. That meant only 2.7% of non-crash events were falsely identified as crash events.
4. The safety regulator parameter (K_S) was set to be 0 and then to be 2.5×10^3. When K_S was 0, the ALINEA algorithm was the same as the traditional ALINEA algorithm. Setting the value of K_S is very important. If the value K_S is too small, the safety factor would not have a significant impact on ramp metering rate; if the value is too large, the ramp metering rate might substantially change because of a small variation of crash risk. This study supposed that when the conditional crash risk reached the highest value, the ramp metering rate was

decreased by 180 vehicle/h, that is 1 second green phase time. The maximum conditional crash risk for the weaving segment without ATM control is around 0.22. Then,

$$K_s\left(\hat{p} - p_{\max}\right) = -180 \tag{7-6}$$

$$K_s = \frac{-180}{\hat{p} - p_{\max}} = \frac{-180}{0.15 - 0.22} \tag{7-7}$$

The field speed limit of the studied weaving segment is 55 mph. In VSL scenarios, the speed limit at the upstream, which was about 2,000 feet upstream of the beginning of weaving segment, was set to be 45, 50, or 55 mph. The speed limit at the downstream, which was about 1,300 feet downstream to the end of weaving segment, was set to be 55, 60, or 65 mph. The locations of RM and VSLs are shown in Figure 7-1. The detectors were used to measure the downstream occupancy (o), and data collection points collected other traffic information, i.e., traffic count, speed.

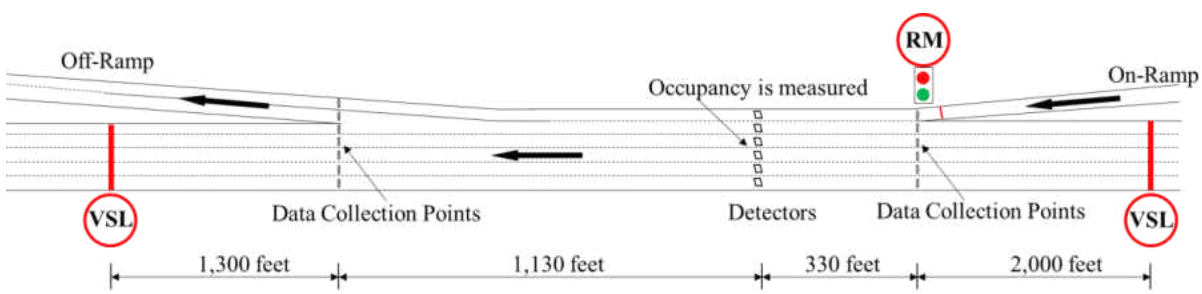


Figure 7-1 Studied weaving segment microsimulation network

RM might result in long travel times for on-ramp vehicles (Kotsialos and Papageorgiou, 2004). Hence, there was a need to increase the green phase time when there were plenty of vehicles piling up on ramps. The increased green phase time (g') was set as,

$$g' = \begin{cases} g & Queue \le 10 \\ g+1 & 10 < Queue \le 20 \\ g+2 & 20 < Queue \le 30 \\ g+3 & Queue > 30 \end{cases} \tag{7-8}$$

where g was calculated based on Eq. (7-3), Queue the number of vehicles in the queue of the on-ramp and was updated every 5 minutes, the maximum of g' is 10 seconds.

On the other hand, merely increasing the green phase time might not be enough, as entering vehicles needed sufficient gaps in order to merge into the mainline. Hence, it might be better to simultaneously set the upstream speed limit as 45 mph in order to provide a bigger gap for entering vehicles.

To sum up, there was 13 cases in total, the detailed information is listed in Table 7-1. Case 1 is non-control case, Case 2-4 are RM strategies, Case 5-12 are VSL strategies, and Case 13 is the integrated RM-VSL strategy.

Table 7-1 ATM scenarios

Case	VSL	RM
1	N/A*	N/A
2	N/A	Ks=0
3	N/A	Ks=2.5×10^6 (without controlling queue)
4	N/A	Ks=2.5×10^6 (Control Queue)
5	Upstream 50 mph, Downstream 55 mph	N/A
6	Upstream 45 mph, Downstream 55 mph	N/A
7	Upstream 55 mph, Downstream 60 mph	N/A
8	Upstream 55 mph, Downstream 65 mph	N/A
9	Upstream 50 mph, Downstream 60 mph	N/A
10	Upstream 45 mph, Downstream 60 mph	N/A
11	Upstream 50 mph, Downstream 65 mph	N/A
12	Upstream 45 mph, Downstream 65 mph	N/A
13	Upstream 45 mph, Downstream 55 mph	Ks=2.5×10^6 (Control Queue)

*N/A: Not Applicable

7.4 Results and Discussion

7.4.1 Real-time Crash Prediction Estimation

Using Eq. (7-1), the crash odds ratio weaving segments can be calculated using the values of parameters from VISSIM at 5-minute intervals. All traffic parameters' values can be obtained from VISSIM by data collection points, and the weaving configuration was from geometric characteristics of the studied weaving segment. The *Wet* condition of the simulated weaving segment was assumed to be 0. Then, the cumulative odds ratio can be obtained for each simulation run,

$$\overline{OR}_j = \frac{\sum_i (OR)_{ij}}{N} \tag{7-9}$$

where OR_{ij} is the crash odds ratio during i^{th} time slice in j^{th} simulation run, N the number of observations.

7.4.2 Evaluation of ATM Strategies

Ten simulation runs were conducted to eliminate random effects. After excluding 30 minutes of VISSIM warm up time and 30 minutes of cool down time, 180 minutes' VISSIM data was put into use. The average cumulative odds ratio over 10 simulation runs for each case was computed. Additionally, in the simulation, the study adopted the SSAM to provide conflict count, which has proven to be highly correlated with field crash frequency (Shahdah et al., 2014). In each simulation, there existed "virtual" crashes whose TTC was 0. These cases were the result of inaccurate and incomplete logic in the simulation models. Hence, the same as what Gettman et al. (2008) have done in their study, these "TTC=0" cases were excluded from further analysis. Meanwhile, average travel time was obtained to check the network's efficiency. The average results over 10 simulation runs are shown in Table 7-2.

Table 7-2 ATM Simulation results

Case	Weaving			Non-weaving		Whole	
	Conflict	Conflict reduced %	$\overline{OR}$	Conflict	Conflict reduced %	ATT#	ATT reduced %
1	705	N/A*	1.00	59	N/A	98.3	N/A
2	653	-7.3	1.01	38	-35.6	97.9	-0.4
3	555	-21.2	0.95	41	-30.5	113.7	15.7
4	621	-11.9	0.92	40	-31.7	101.4	3.2
5	639	-9.3	0.88	62	5.8	100.1	1.9
6	575	-18.4	0.82	43	-26.9	101.3	3.1
7	705	0.1	1.00	59	-0.3	97.7	-0.5
8	705	0.0	1.00	60	1.4	97.4	-0.8
9	639	-9.3	0.88	63	7.7	99.8	1.5
10	575	-18.4	0.82	44	-25.2	101.1	2.9
11	639	-9.3	0.88	63	7.8	99.6	1.4
12	575	-18.4	0.82	43	-26.1	101.0	2.8
13	586	-16.8	0.94	43	-27.6	105.0	6.9

* N/A: Not Applicable

Average Travel Time in seconds

Overall, compared to the non-control case (Case 1), the safety of the congested weaving segment was improved by the ATM strategies. For 9 out of 12 cases, their conflict numbers were reduced and the average odds ratios were less than 1. In addition to improving the safety at the weaving segment, the safety of the non-weaving segments, which were located upstream and downstream of the weaving segment, was also improved significantly (more than 10%) in 7 out of 12 cases. Except for three cases (i.e., 2, 7, and 8), the average travel time of most cases increased, because on-ramp vehicles were delayed or the average speed was reduced or both.

In the traditional ALINEA case (Case 2), the average conflict count was decreased by 7.3% but the average odds ratio was 1.01, which means the crash odds increased by 1%. On the other hand, the modified ALINEA without controlling queue length (Case 3) decreased conflict by 21.2% and decreased odds by 5%. And for the modified ALINEA whose queue length was controlled (Case 4), it decreased conflict by 11.9% and decreased odds 8%. Since the modified ALINEA cases (i.e., 3 and 4) adjusted the ramp metering rate based on traffic operation and safety conditions simultaneously, they were able to better improve safety than the traditional ALINEA (Case 2). Though the safety benefit of modified ALINEA without controlling queue length (Case 3) performed good among ALINEAs, the good performance was at the cost of travel time. It increased the average travel time by 15.7%.

Examination of the results in Table 7-2 clearly shows that setting VSL at the downstream of the weaving segment did not improve the safety of the weaving segment. The main reason was that the high speed limit at the downstream of weaving segment does not necessarily increase the speed at the end of the weaving segment, which is mainly impacted by traffic conditions in the weaving segment. Hence, even though the speed limit at the downstream of the weaving segment was increased, the speed at the end of weaving segment was still low, the difference between the beginning and the end of the weaving segment remained the same, and the crash risk was almost constant. On the contrary, setting the VSL at the upstream of the weaving segment reduced both conflict number and crash odds. Furthermore, compared to setting the upstream weaving segment VSL to 50 mph, the 45 mph VSL improved the safety more. It is not hard to understand: the lower the speed limit of the upstream segment, the lower the speed at the beginning of the weaving segment, and the lower the speed difference. And the lower speed difference produced lower crash risk.

Though the 45 mph VSL strategy was capable of improving safety without significantly increasing the average travel time, the effectiveness of VSL can be impacted by the compliance level. The VSL system might fail to enhance traffic safety under low compliance condition (Yu and Abdel-Aty, 2014a). In contrast, the modified ALINEA without controlling queue length (Case 3) improved safety at the expense of increased average travel time, but there is no compliance issue for RM. Meanwhile, only controlling queue length of modified ALINEA worsened the impact of modified ALINEA on the weaving segment's safety. Therefore, the RM-VSL was needed to enhance and combine the advantages of VSL and RM. The simulation results demonstrated that the RM-VSL (Case 13) significantly decreased the average travel time by 8.7 seconds than the modified ALINEA without controlling queue length (Case 3). Meanwhile, the RM-VSL (Case 13) was as good as the modified RM without controlling queue length (Case 3) in enhancing the safety of the weaving segment.

Additionally, to test the level of agreement between the conflict count and average odds ratio value, the Spearman's rank correlation test, a non-parametric correlation, was used since there were only 13 cases in total. The higher the Spearman's rank correlation coefficient indicates that there is a high dependence between two variables. A coefficient of 1.0 represents a perfect agreement and that of 0 indicates no correlation (Gettman et al., 2008). The result suggested that the relationship between conflict count and average odds ratio value (Spearman's rank coefficient=0.670, p=0.01) was statistically significant. This confirms that the safety of the simulation is consistent with the crash risk, whose model was built based on field data. But there still existed small inconsistencies between conflicts and $\overline{OR}$. The 45 mph VSL (Case 6) was better than the modified ALINEA without controlling queue (Case 3) since Case 6's crash odds compared to the crash odds under base condition is lower than the odds ratio of Case 3. On the other hand, the conflict count of the modified ALINEA without controlling queue (Case 3) was slightly less than that of the 45 mph VSL. Meanwhile, in the modified ALINEA without controlling queue case (Case 3), the percentage of conflict count reduced was higher than the percentage of odds reduced.

Table 7-2 gives cumulative results and does not show detailed information for each step. In order to better understand the effects of ATM strategies on crash risk for each time slice, Figure 7-2 shows the average crash odds ratio of 10 runs for the non-control case (Case 1), the traditional ALINEA (Case 2), the modified ALINEA without controlling queue length (Case 3), 45 mph upstream VSL (Case 6), and RM-VSL (Case 13).

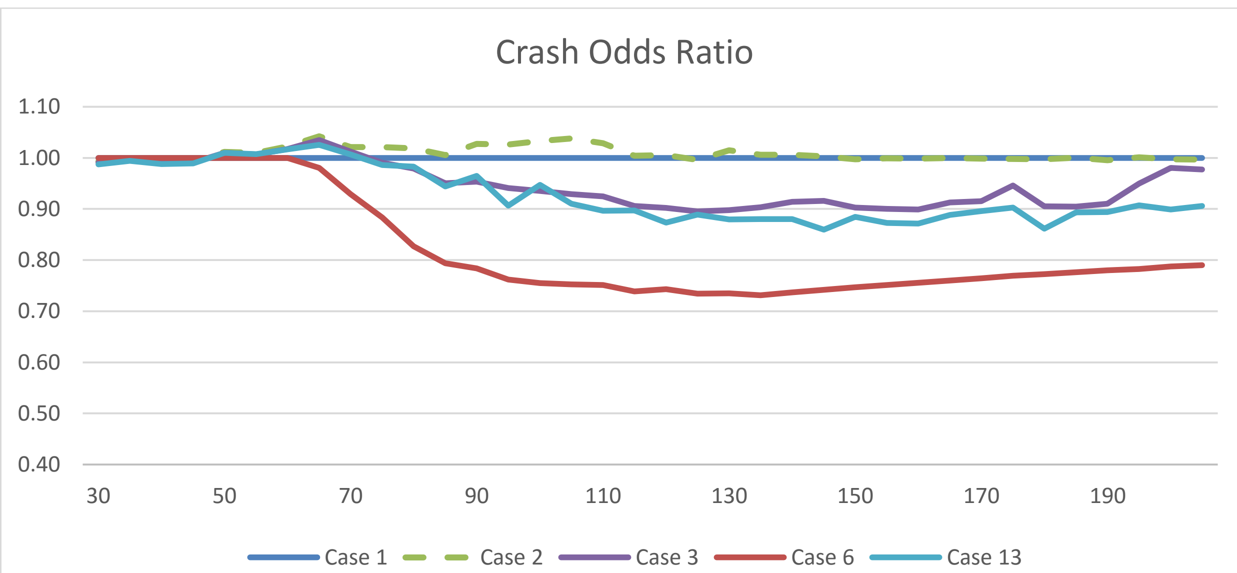


Figure 7-2 Crash risk for different cases

In Figure 7-2, the crash risk curve of the traditional ALINEA (Case 2) almost overlaps with that of the non-control case (Case 1). This indicates that the traditional ALINEA (Case 2) did not have a significant impact on the safety of the studied weaving segment in each step. The result is not coherent with the previous studies by Lee et al. (2006b) and Abdel-Aty and Gayah (2008), which have found that the traditional ALINEA significantly improved real-time safety. This might be because of the difference in study subjects. Their studies focused on freeway segments without distinguishing the segment type, but this study only concentrated on weaving segments. On weaving segments, the traffic behavior and crash mechanisms are not the same with other non-weaving segments.

The crash risk curve of 45 mph VSL (Case 6) is always lower than that of modified RM without controlling queue length (Case 3). It means that the 45 mph VSL outperformed the RM by providing lower crash risks. The reasons might be as follows. 1. When a crash risk is higher than the critical crash risk, the VSL strategy reacts more quickly and effectively than the RM: the speed limit was able to change immediately using VSL; however, the RM adjusted the ramp metering rate gradually. 2. Though RM had the capability of reducing speed variances, the VSL can decrease variance of speed more: in the simulation run with the random seed of 17, the average speed difference of the non-control case (Case 1) was 6.8 mph, and the average speed difference of the 45 mph VSL (Case 6) and the RM without controlling queue length (Case 3) was 4.6 and 5.7 mph, respectively. Other simulation runs with different random seeds also had similar results.

Another finding from Figure 7-2 is this: when the crash risk was lower than the critical crash risk and the speed limit was returned to 55 mph, the 45 mph VSL at the upstream segment (Case 6) consistently improved the safety of the studied weaving segment. Vehicles did not accelerate significantly and rapidly when the speed limit has changed from 45 mph to 55 mph. The vehicles were impacted by vehicles ahead which were still at low speeds. Meanwhile, when the crash risk was reduced below the critical crash risk, the modified ALINEA without controlling queue length (Case 3) also improved the real-time safety because the metering rate increased gradually and the ramp metering signal broke up platoons of entering vehicles. The same finding also applies to RM-VSL case (Case 13).

7.5 Summary and Conclusion

Traffic conditions in weaving segments are complicated since traffic merges, diverges, and weaves in limited spaces. The complication might result in a low capacity and a high crash risk in weaving segments. In order to improve the safety of a congested weaving segment, ATM strategies were applied to it in microsimulation. The simulation results show that several ATM strategies were able to improve the safety of the studied weaving segment by providing lower conflict numbers and lower crash risks, but higher average travel times.

From the perspective of safety, the modified ALINEA cases, which take both traffic operation and safety into consideration, outperformed the traditional ALINEA algorithm. However, the average travel time of the modified ALINEA without controlling queue was significantly higher than the non-control case and the traditional ALINEA case. The modified ALINEA which controlled the queue length shortened the average travel time, but impaired the safety impact of modified ALINEA algorithm.

Both the location and speed limit value of VSL are important. The VSL downstream at the studied weaving segment did not mitigate crash risks, but the upstream VSL significantly enhanced the safety of the weaving segment. Meanwhile, the 45 mph VSL better improved safety than the 50 mph VSL without a significant increase of average travel times. Though VSL more effectively improved the safety compared to RMs, the VSLs have a potential problem of compliance whereas the compliance is not a big concern of the RM strategy.

In order to reduce the average travel time and mitigate the compliance issue, an RM-VSL was proposed. In RM strategy, when the queue of an on-ramp was long, the ramp signal green phase time was increased in order to reduce the queue, and the speed limit at the upstream of the weaving segment was reduced to 45 mph in order to provide enough gaps for entering vehicles. The results indicate that the RM-VSL produced lower conflict number than the RM with queue control and traditional RM, and substantially reduced the average travel time comparing to RM without queue control. The impact of RM-VSL in this study was ideal and could be changed according to the level of compliance. Studying the impact of RM-VSL strategy on safety using different VSL compliance levels might be a future study topic.

The relationship between the simulated conflict number and the crash risk was found to be statistically significant. The same relationship has also been found by other researchers (Gettman et al., 2008; Huang et al., 2013). However, there were small inconsistencies between the conflict count and the total crash risk. The variance might owe to the difference between crash mechanisms and conflict mechanisms. This finding might inspire further research about studying the relationship between crash and conflict mechanisms in the real-time perspective.

There are some limitations to this study. It was assumed that all drivers followed the new speed limit, but previous studies have found that the compliance rate of drivers might not be 100%, and have concluded that the success of VSL was dependent on the level of compliance (Yu and

Abdel-Aty, 2014a). Meanwhile, the ATM strategies were only applied to a congested weaving segment in this study. The safety impact of ATM strategies on more highway segments under different traffic conditions may also be tested in follow-up studies.

CHAPTER 8: REAL-TIME CONFLICT PREDICTION FOR WEAVING SEGMENTS IN SIMULATION

8.1 Introduction

Traditional traffic safety studies are mainly based on historic traffic crash data, which are one of good roadway safety measurements. But the usage of crash data is sometimes limited because of the unreliability of crash records and the long time needed to collect adequate crash samples (Glennon and Thorson, 1975; Essa and Sayed, 2015). Therefore, there has been plenty of traffic safety research which relies on surrogate safety measures.

One of the most commonly used surrogate measures is traffic conflicts. A traffic conflict was defined as a traffic event involving two or more road users, in which one user performs some unusual actions, such as a change in direction or speed, these unusual actions place another user in danger of a collision unless an evasive maneuver is undertaken (Migletz et al., 1985). Previous studies have proven that conflict counts are positively related to crash counts, and the relationship is statistically significant (Meng and Qu, 2012; Sacchi and Sayed, 2016). Furthermore, researchers collected field conflict counts on roadway facilities to uncover potential safety hazard (Van Der Horst et al., 2014), and to verify the safety impacts of countermeasures, such as raised crosswalks (Cafiso et al., 2011; Autey et al., 2012). However, the majority of previous studies only focused on conflict count, but were not interested in each conflict and did not analyze conflicts from a microscopic aspect.

One of the studies which explore traffic safety from a microscopic aspect is real-time safety analysis. The real-time safety analysis intends to identify precursors that are relatively more “hazard prone” that other parameters. It is accomplished by comparing and analyzing traffic, weather, and other conditions right before the occurrence of hazard and non-hazard events, and furthermore by estimating the likelihood of hazard events. The hazard events include crash and conflict events. The real-time crash analysis research has been successfully done (Zheng et al., 2010; Yu and Abdel-Aty, 2013). However, there is not enough real-time conflict analyses work that has been carried out.

This study implements microscopic simulation and SSAM to conduct real-time conflict study. Microscopic simulation networks are built based on a two level calibration and validation method. The method is able to enhance the consistency between simulated safety and filed safety, and between simulated traffic and field traffic. In simulation, conflicts are identified by SSAM, a software developed by FHWA. The SSAM automatically conducts conflict analysis by directly processing vehicle trajectory data from simulation output. The conflict analysis contains conflict location, time, type, etc. After obtaining time and location of a conflict or non-conflict event, the event is matched with the traffic data just before it. Then a logistic regression models are employed to distinguish conflict events from non-conflict events using traffic parameters.

This chapter is organized into five sections. The second section describes the experiment design. The third section shows the network calibration and validation results. The fourth section describes real-time conflict prediction model. The fifth section summarizes the findings and conclusions.

8.2 Experiment Design

8.2.1 VISSIM Network Building

One of the most important parts of this chapter is building a validated VISSIM network. Previous studies on weaving segments' microscopic simulation only compared simulated traffic with field traffic (Wu et al., 2005; Jolovic and Stevanovic, 2013). The results showed that the simulated traffic was consistent with field traffic if driver behavior parameters in the simulation were adjusted. However, this study focuses on real-time conflict analysis in microscopic simulation. Hence, not only traffic condition in simulation needs to be calibrated and validated, but also safety condition of the simulation network requires validation.

In order to ensure both traffic and safety of the simulation network are consistent with those of the field, a two level calibration and validation method was used. At the first level, the traffic condition of weaving segments, including volume and speed, was calibrated and validated using field MVDS data. At the second level, the simulated conflict count of each weaving segment was compared to its crash frequency. If the simulated speed or conflict is not consistent with its corresponding field value, driver behavior parameters need to be adjusted. The calibration and validation procedure is shown in Figure 8-1.

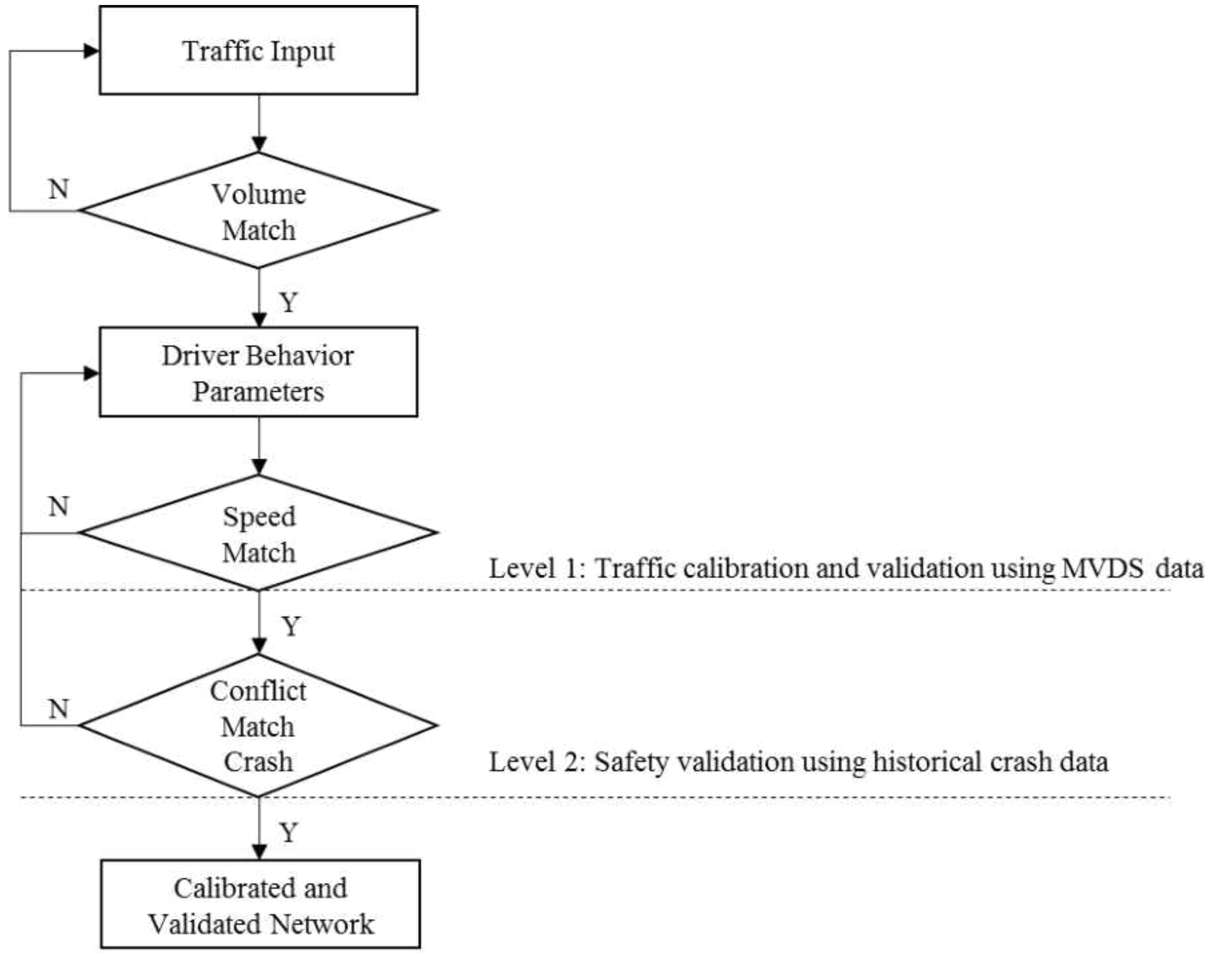


Figure 8-1 Two level calibration and validation procedure

8.2.2 Simulation Network Data Preparation

The study chose 16 weaving segments located on SR 408 in Central Florida. Two datasets were collected for these 16 weaving segments: crash and traffic. Crash data were from S4A. Eighty three crashes were identified on the 16 studied weaving segments from July, 2013 to July, 2014. The traffic data were obtained from MVDS. MVDS records volume, speed, and lane occupancy for each lane at 1-minute interval, and also categorizes vehicles into four types according to their length:

- Type 1: vehicles 0 to 10 feet in length
- Type 2: vehicles 10 to 24 feet in length
- Type 3: vehicles 24 to 54 feet in length
- Type 4: vehicles over 54 feet in length

The traffic data from 1:00 P.M. to 3:00 P.M. on Thursday in August, 2014, were aggregated into 15 minutes to provide the VISSIM traffic input, including volume and Heavy Goods Vehicles (HGV) percentage. The Type 3 and Type 4 vehicles in MVDS data are considered to be HGV in VISSIM. It is assumed that the weekday daytime moderate traffic (from 1:00 P.M. to 3:00 P.M), which is neither the peak hour traffic nor the lowest traffic, can represent the average traffic condition. The peak hour of SR 408 for weekday is 6:00 A.M. to 9:00 A.M. in the morning and 4:00 P.M. to 7:00 P.M. in the afternoon.

Desired speed distribution is also an important input for the VISSIM network. If not hindered by other vehicles or network objects, e.g. signal controls, a driver will travel at his/her desired speed (PTV, 2013). The speed data during 11:00 A.M. to 1:00 P.M. on Thursday in August, 2014, were chosen. During this time period, the traffic volume is the lowest in the daytime. Thus, the possibility of a vehicle constrained by other vehicles is low and vehicles are more likely to travel at their desired speed. Generally, the desired speed distribution is decided by the speed limit and also by geometric design, e.g., degree of curvature. The desired speed distribution for each location might not be the same. Hence, this study divided the locations of SR 408 into seven groups according to the similarity of speed limit and field speed distribution of each location. The group information is in Table 8-1. In the table, for each location, the beginning two letters stand for direction, i.e., WB is westbound and EB is eastbound; the numbers stand for milepost.

Table 8-1 Speed distribution for each location

Speed Limit	Group	Locations
55	1	WB 22.7, EB 21.8, WB 10.3, EB 22.7, EB 9.2
	2	EB 9.4, EB 9.6, WB 9.9,WB 20.8, EB 10.8,WB 10.6, WB 8.1, WB 14.5, WB 8.4, WB 9.7, WB 12.1, WB 20.7, EB 10.3
	3	WB 7.4, WB 9.2, WB 11.3, EB 11.5, EB 8, EB 12.5, WB 10.9, EB 8.4 WB 8.9, WB 15.2, EB 22.3, EB 7.6, WB 13, EB 10.6, EB 7, WB 11.6, WB 14.4
	4	EB 12.9, EB 8.9, WB 7.3, WB 14.2, EB 11.2, EB 7.4, EB 12.1, EB 14.5 WB 22.3, EB 6.8, EB 14.7, WB 12.6, EB 16.1, WB 6.8, WB 15.7, WB 21.8, WB 7.6, EB 15.7
65	5	EB 20.8, WB 19.7, WB 1.4, WB 1.6,WB 5.3, EB 5.3, WB 2.4, EB 20.3
	6	WB 15.9, EB 18.4, EB 16.5, WB 18.4, WB 4.6, EB 2.4, WB 19.9, EB 1.4 EB 4.6, WB 16.5, WB 3.6, WB 18.8, EB 3.6, EB 4.3, EB 18, EB 18.8 EB 20.1, WB 17, WB 2, WB 4.9, WB 17.8, WB 18, EB 19.5, EB 2.2 EB 17.7, WB 16.1, EB 17.3, EB 1.7, WB 4.3
	7	EB 4.9

Figure 8-2 shows the cumulative percentage of desired speed distribution for each group. The desired speed distribution in the figure is the average speed of all vehicles, including passenger cars and HGV. However, passenger cars and HGV are at different speeds. Johnson and Murray (2009) concluded that the average speed difference between cars and trucks was 8.1 miles per hour. The HGVs might be considered as trucks. The HGV percentage of these 16 weaving sections is about 13%. Suppose x is the speed of passenger cars, then the speed for HGV is equal to (x-8.1), the average speed is y, then,

$$87\%x + 13\%(x - 0.81) = y \tag{8-1}$$

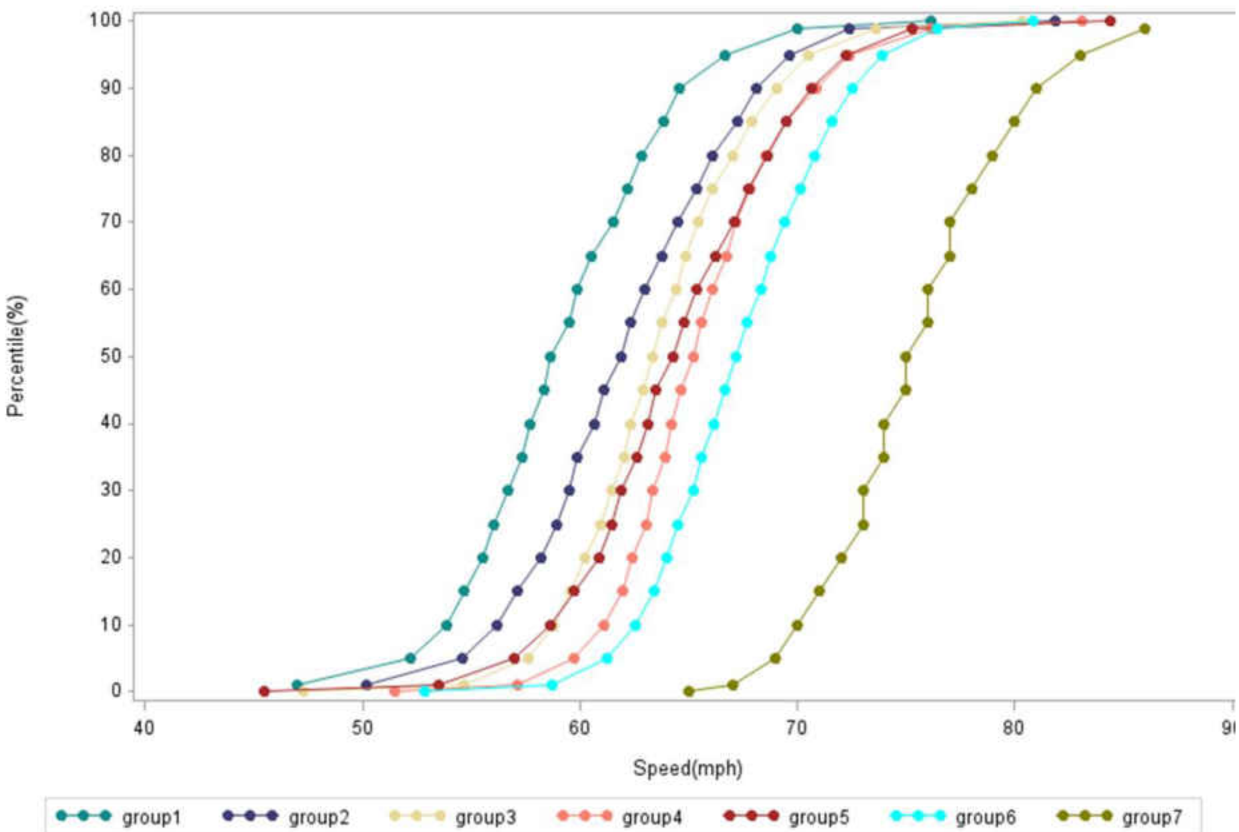


Figure 8-2 Speed distribution for each group

From Equation (8-1), passenger car speed is about y+1, and the truck speed is about y-7. By shifting the curve in Figure 8-2 to the right by 1 mph, passenger car speed distributions for each group can be obtained. Similarly, by shifting the curve by 7 mph to the left, HGV speed distributions can be gained. Finally, there are 14 desired speed distributions, among which seven are for passenger cars and seven for HGVs.

8.2.3 Data Extraction

Once driver behavior parameters were obtained after the calibration and validation procedure, they were put into the VISSIM network. Then 15 simulation runs were carried out. The simulation output trajectory files were analyzed in SSAM to provide conflict information. For each conflict, its corresponding traffic data were from data collection points in VISSIM. The layout of data collection points in VISSIM is illustrated by Figure 8-3. When vehicles pass the data collection points, the points collected every vehicle's data, including entry time, exit time, vehicle classification, speed, occupancy, etc.

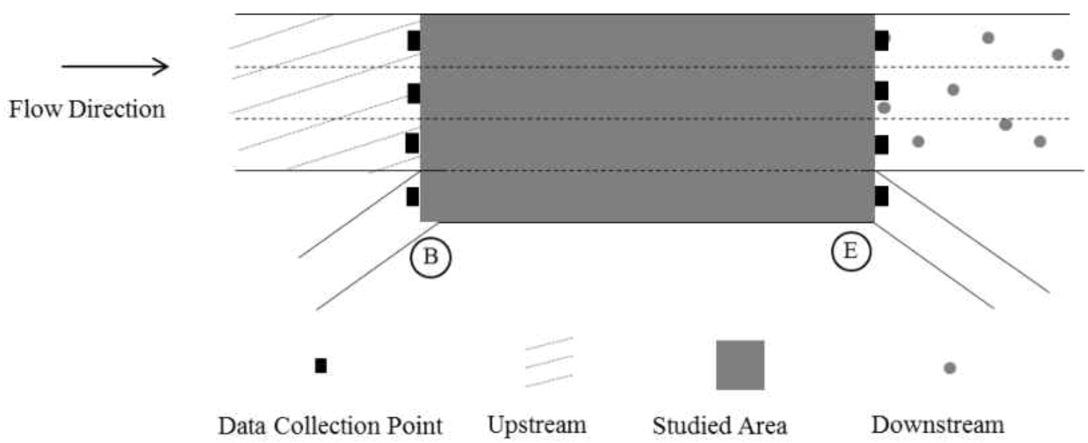


Figure 8-3 Traffic data extraction

The data extraction of the real-time conflict study is different from that of a crash precursor study. First, crash disruptive condition is usually 5-10 minutes before a crash (Abdel-Aty and Pemmanaboina, 2006; Xu et al., 2013a). The crash time of crash dataset is actually the crash reporting time which is after crash occurrence. Thus, the traffic data which are 0-5 minutes before crash reporting time might already been impacted by a crash, so the trafific data 5-10 minutes before crash reporting time are usually chosen. However, for the conflict precursor study, the accurate conflict time can be obtained from SSAM, hence, the traffic data which are 0-5 minutes before a conflict were chosen as conflict disruptive events. As for the non-disruptive events, they were 5-minute interval traffic data and were defined as the conditions which did not result in a conflict and also were not influenced by conflicts. In this study, the traffic conditions were considered to be no longer impacted by conflicts if traffic condition were more than 60 seconds after conflicts because conflicts are cleared quickly in simulation and the influence of conflicts on traffic vanish soon. Furthermore, in order to explore conflict mechanisms more closely, the study also adopted the traffic data which are 0-1 minutes before conflicts as disruptive condition, and the definition of non-disruptive traffic data was 1-minute interval traffic data which did not result in and were impacted by conflicts. Hence, two datasets were prepared: one was based on 5-minute interval; the other one was based on 1-minute interval.

Second, in crash prediction studies, the number of non-disruptive conditions is much more than that of disruptive conditions. In order to balance the sample size of disruptive and non-disruptive conditions, non-disruptive condition observations are randomly selected from the full samples (Abdel-Aty et al., 2004; Xu et al., 2013a; Hossain and Muromachi, 2010). Nevertheless, conflict number is much more than crash number. Gettman et al. (2008) found that the probability of being involved in a crash given a traffic conflict is 0.005% at intersections. This indicates that the conflict number is 20,000 times of the crash number in their study. In real-time conflict study, the sample size of disruptive conflict condition is largely enriched, and the sample size of non-disruptive conflict condition is significantly decreased. There was no need to randomly select the non-disruptive conflict condition samples.

The variables obtained from data collection points of VISSIM network and from the geometric design of weaving segments are shown in Table 8-2.

Table 8-2 Variable definition

Variables*	Description
Bm_spd	Average speed at the beginning of weaving segments (mph)
Bm_vol	Vehicle count per lane at the beginning of weaving segments (vehicles)
Bm_occ	Average lane occupancy at the beginning of weaving segments (%)
Bm_std_spd	speed standard deviation at the beginning of weaving segments (mph)
Onr_spd	Average speed for on-ramp (mph)
Onr_vol	Total vehicle count for on-ramp (vehicles)
Onr_occ	Average lane occupancy for on-ramp (%)
Em_spd	Average speed at the end of weaving segments (mph)
Em_vol	Vehicle count per lane at the end of weaving segments (vehicles)
Em_occ	Average lane occupancy at the end of weaving segments (%)
Em_std_spd	speed standard deviation at the end of weaving segments (mph)
Offr_spd	Average speed for off-ramp (mph)
Offr_vol,	Total vehicle count for off-ramp (vehicles)
Offr_occ	Average lane occupancy for off-ramp (%)
V_{FF}	Mainline-to- mainline vehicle count (vehicles)
Vehcnt	Total traffic count in the weaving segment (vehicles)
VR	Weaving volume ratio, weaving volume over total traffic count (%)
Spd_dif	Speed difference. Spddif =0 if Bm_spd is lower than Em_spd; otherwise Spddif = Bm_spd- Em_spd
Bm_acc	Average acceleration at the beginning of weaving segments (fts)
Em_acc	Average acceleration at the end of weaving segments (fts)
Bm_headway	Average headway at the beginning of weaving segments (s)
Em_ headway	Average headway at the end of weaving segments (s)
L_S	Short length, distance between the end points of any barrier markings (solid white lines) that prohibit or discourage lane changing (feet)
Lb	Base length, distance between points in the respective gore areas where the left edge of the ramp-traveled way and the right edge of the freeway-traveled way meet (feet)
N_{WL}	Number of lanes from which a weaving maneuver may be made with one or no lane changes (lane)
N	Number of lanes within the weaving segment (lane)
LC_{RF}	Minimum number of lane changes that must be made by a single weaving vehicle moving from the on-ramp to the expressway (lane)
LC_{FR}	Minimum number of lane changes that must be made by a single weaving vehicle moving from expressway to off-ramp (lane)
LC	Weaving configuration, 0 when LC_{RF} =LC_{FR}=1, 1 otherwise
LC_{min}	Minimum rate of lane change that must exist for all weaving vehicles to complete their weaving maneuvers successfully (lane/hour)
L_{max}#	Maximum weaving segment length (1000 feet)

* All traffic data are separately measured in 5-minute interval and 1-minute interval

$L_{\max} = [5728(1+VR)^{1.6} - 1566N_{WL}]/1000$

8.3 VISSIM Network Calibration and Validation

Based on the literature review, four parameters were chosen for VISSIM calibration and validation. They were DLCD, CC0, CC1, and CC2: DLCD defines the distance at which vehicles begin to attempt to change lanes in order to arrive at their desinations; CC0 is desired distance between stopped vehicles; CC1 is following headway time, it means the time (in seconds) a driver wants to keep, the higher the value, the more cautious the driver is; and CC2 is following variation, it restricts the longitudinal oscillation or how much more distance than the desired safety distance a driver allows before he/she intentionally moves closer to the car in front (PTV, 2013) .

The study first used the recommended parameters' value from previous studies to validate the VISSIM network (Koppula, 2002; Wu et al., 2005; Woody, 2006; Jolovic and Stevanovic, 2013). The results showed the previous studies' conclusions were valid only when simulated volume and speed were compared with field volume and speed. However, when comparing the simulated conflict counts with the field crash frequencies, the correlation coefficients were not significant. This is because the parameters' values were gained without taking the safety into consideration in previous studies.

There was a need to revalidate the weaving segment VISSIM network with respect to both traffic and safety. Twenty three sets of parameters were tried and each set was run three times with different random seeds. Excluding 30 minutes VISSIM warm up time and cool down time, 60 minutes VISSIM data were put into use. For the 16 weaving segments network, the results showed that VISSIM can provide good traffic and safety results when the DLCD was 300 meters, CC0 was 1.5 meters, CC2 was 4 meters, and CC1 was 1.5 seconds.

In order to further confirm the driver behavior parameters, a total of 15 more runs were carried out. For the 15 simulation runs, the average GEH value of the validated VISSIM network was 1.82, and 96.0% of GEH were less than 5 for a 15 minutes interval. As for the speed, the average absolute of speed difference was 2.00 mph, and 92.2% of speed differences were less than 5 mph for a 5 minutes interval. The results above approved that the traffic calibration and validation satisfy the requirements, and indicate the traffic on the weaving segment network was consistent with that of the field (Nezamuddin et al., 2011b; Yu and Abdel-Aty, 2014a).

After the traffic calibration and validation, the trajectory files of the ten simulation runs of the 16 weaving segments were processed in SSAM. A number of conflict measurements can be obtained from SSAM, such as TTC and PET. TTC is defined as the expected time for two vehicles to collide if they remain at their present speed and continue on their respective trajectories; PET is time difference between the arrivals of two vehicles at the potential point of collision (Gettman and Head, 2003). In this study, a conflict was found when TTC was less than 1.5 seconds and PET was less than 5.0 seconds. The same thresholds were also widely adopted by other studies (Saleem et al., 2014; Saulino et al., 2015; Stevanovic et al., 2013). Meanwhile, when TTC was 0, the observation was deleted because it was the result of inaccurate and incomplete logic in the simulation models (Gettman et al., 2008)

The average simulated conflict count for each weaving segment was then compared with the corresponding crash frequency. The information can be found in Table 8-3. Then, SAS procedure ‘Corr’ was used to conduct a Spearman rank correlation test. The range of Spearman’s rank correlation coefficient is 0 to 1; a coefficient of 0 indicates no correlation and 1.0 represents a perfect agreement (Gettman et al., 2008). The result showed that the correlation coefficient between simulated conflict counts and field crash frequencies was 0.506 (p-value= 0.0457), which indicates that there was a significant positive relationship between field crash count and conflicts.

Table 8-3 Simulated conflict count and field crash count

ID	Run															Avg*	Crash
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15		
1	2	3	2	3	1	0	3	3	1	0	2	0	0	3	0	1.5	4
2	6	4	2	5	6	3	3	7	10	6	7	4	6	5	8	5.5	3
3	0	1	0	1	1	1	2	0	0	0	1	1	0	3	2	0.9	4
4	1	1	3	2	1	1	2	1	1	0	1	2	2	0	2	1.3	1
5	16	5	5	15	12	15	14	4	7	5	8	10	13	16	13	10.5	8
6	17	17	13	20	12	24	16	22	20	11	24	27	14	17	34	19.2	8
7	2	1	2	2	0	0	0	0	0	0	1	1	1	4	3	1.1	4
8	0	1	0	0	0	1	0	0	1	0	0	0	0	0	1	0.3	6
9	4	6	5	1	8	4	9	7	1	1	10	11	4	6	9	5.7	4
10	7	12	8	9	6	16	9	10	3	7	7	18	8	7	8	9.0	9
11	19	13	4	11	8	5	12	13	9	11	6	16	6	11	10	10.3	15
12	1	6	3	1	1	0	2	1	1	4	3	0	0	1	2	1.7	4
13	5	2	4	1	5	5	3	1	1	5	3	4	5	0	3	3.1	1
14	0	0	0	0	1	2	0	0	1	1	0	1	0	6	0	0.8	3
15	4	1	2	0	1	0	0	0	0	1	0	2	1	2	1	1.0	3
16	1	1	0	2	3	2	3	4	2	2	1	3	3	3	2	2.1	6

* Average conflict number

8.4 Model Estimation

In order to find significant conflict precursors and to quantify their impacts on conflict risk, two logistic regression models were built: one was based on 5-minute interval; the other one based on 1-minute interval. Ten-folder cross validation method was used to validate models' performance. The methodologies about logistic regression model and ten-folder cross validation can be found in Section 6.2. The model results are shown in Table 8-4.

Table 8-4 Real-time conflict prediction model for weaving segment

Variables	Mean	Std.	p-value
Based on 5-minute interval			
Intercept	-17.99	1.42	<0.01
Log(Vehcnt)	2.40	0.21	<0.01
L_{max}	0.36	0.09	<0.01
Bm_acc	-2.85	0.54	<0.01
Training ROC		0.727	
Validation ROC		0.721	
Based on 1-minute interval			
Intercept	-19.24	0.69	<0.01
Log(Vehcnt)	3.82	0.16	<0.01
L_{max}	0.21	0.03	<0.01
Bm_acc	-1.73	0.22	<0.01
Training ROC		0.827	
Validation ROC		0.827	

Both the 5-minute interval and 1-minute interval models showed that the Logarithm of vehicle count, maximum length, and average acceleration at the beginning of weaving segments were conflict precursors which were significant at a 95% confidence interval. The 1-minute interval model performed better than the 5-minute interval model by providing higher training and validation ROCs. The reason might be as follows, compared to the model using traffic aggregated at a 5-minute interval, the model using 1-minute interval traffic was able to capture more detailed information.

The coefficients of significant variables in the two models vary. The main reason might be the way traffic was aggregated. From the standard deviations of the coefficients, it could be found that the 1-minute interval model provided lower standard deviations than the 5-minute interval model, which indicates that the 1-minute interval model is more reliable than the 5-minute interval model. It is not hard to understand, the disruptive traffic 0-1 minutes before a conflict can better present the traffic condition contributing to the conflict than the disruptive traffic 0-5 minutes before the conflict.

The Logarithm of vehicle count was found to be positively related to conflict risk. When vehicle count increases, the exposure increases and then the conflict likelihood increases. The maximum length is with a positive sign. A longer maximum distance is because of a higher percentage of weaving volume. Weaving volume is the combination of on- and off-ramp volumes. For on-ramp vehicles, they need to accelerate to merge into mainline traffic; for off-ramp vehicles, they have to diverge from mainline and decelerate to adjust to low speed limits on off-ramps; meanwhile, high on- and off-ramp traffic volume also rises weaving opportunity. The acceleration, deceleration, weaving, merging, and diverging actions definitely worsen traffic safety. Additionally, the average acceleration at the beginning of weaving segment was proven to have a significantly negative impact on conflict risk, which means an increase of average acceleration decreases conflict risks. Acceleration indicates the speeds of heading vehicles are higher than speeds of following vehicles and the distance between heading and following vehicles increases in weaving segments. The increased distance between vehicles would substantially enhance safety.

Comparing to the crash risk estimation model in Table 6-3, the conflict prediction models have less significant variables but the model performances are better. The common variables in crash and conflict prediction models are Logarithm of vehicle count and maximum length. The impacts of Logarithm of vehicle count on conflict risk, both in the 5-minute and 1-minute interval models, are more than that on crash risk. On the other hand, the coefficient of maximum length in the 1-minute interval conflict model is the same as that in the crash model in Table 6-3. The different significant variables and different coefficient in conflict and crash prediction models indicate that there are differences in conflict and crash mechanisms; on the other side, the two common significant variables and same coefficient of maximum length in both models imply there exists similarity in conflict and crash mechanisms.

8.5 Summary and Conclusion

There has been plenty of traffic safety research that relies on surrogate safety measures. One of the most commonly used surrogate safety measures is traffic conflicts. The majority of previous conflict studies focused on conflict frequencies but did not explore conflict mechanisms from a microscopic aspect. This chapter built a real-time conflict prediction model based on the traffic and conflict information captured from a calibrated and validated weaving segments network.

Driving behavior parameters in simulation were adjusted to validate the simulation network. When DLCD was 300 meters, CC0 was 1.5 meters, CC2 was 4 meters, and CC1 was 1.5s, not only the traffic condition but also the safety condition of simulated network were consistent with the field weaving segment network. The validated VISSIM network had an overall average GEH value of 1.82 and the average speed difference was 2.00 mph. The Spearman rank correlation test was carried out to compare the simulated and filed safety, the coefficient was 0.506 and was significant at a 95% confidence interval.

Two conflict prediction models were estimated, one was based on a 5-minute interval and the other was based on a 1-minute interval. In both models, Logarithm of vehicle count, maximum length, and average acceleration at the beginning of weaving segment were significant variables. The increase of Logarithm of vehicle count and maximum length might increase conflict risk; but the increase of average acceleration enhanced safety. The model performance of the 1-minute interval model was better than that of the 5-minute interval model by providing higher ROCs and lower standard deviation of variable coefficients.

Comparing conflict to crash model for weaving segments, there were two common variables (Logarithm of vehicle count and maximum length), and among which the coefficient of maximum length in the 1-minute interval conflict model is the same as that in the crash model. The similarity between conflict and crash model indicates the crash and conflict mechanisms are similar. On the other hand, the different significant variables in conflict and crash prediction models implies that there are differences in crash and conflict mechanisms.

This study is the first one which use the simulated conflict to study the traffic parameters' impact on safety in real-time. Before this study, if researchers intended to build the real-time safety prediction model, several months' crash and traffic data for several locations should be prepared to obtain enough sample size. The traffic data had to be collected continuously and be with high resolution. If the funding is limited, it's hard to equip road facilities with enough traffic detectors. Hence, implementing simulation to study the real-time safety analysis might be an economic, time saving and validate method.

There are some limitations to this study. Only 16 weaving segments were studied, more weaving segments should be added. Meanwhile, if the simulated conflict could be validated using field conflict data, the simulation network could be further validated. As for the future work, more detailed traffic information from the VISSIM can be taken into consideration. For example, non-aggregated traffic data for every vehicle and at other locations which are not limited to the beginning and end of weaving segments, hence more parameters can be obtained and used in the real-time safety analysis study.

CHAPTER 9: CONCLUSIONS

9.1 Summary

This dissertation concentrates on microscopic safety evaluation and prediction for special expressway facilities, and utilizing ATM to improve safety in real-time. The crash mechanisms of two special facilities (ramps and weaving segments) were explored by utilizing two types of microscopic safety analyses: hourly crash prediction and real-time safety analysis. The crash mechanisms were discovered through adopting statistical models and data mining methods, and the quantitative impact of crash contributing factors–traffic, geometry, weather, land-use, and trip generation–were presented. Meanwhile, the importance of statistically significant variables was ranked. Then, based on the discovered weaving segment crash mechanisms, ATM strategies were successfully applied in microscopic simulation to reduce crash risk and conflict count. Furthermore, real-time conflict prediction was carried out employing the data from well calibrated and validated simulation networks.

In Chapter 3, real-time crash analysis was carried out for SV and MV crashes on expressway ramps. The analysis was based on Bayesian logistic regression models using real-time MVDS traffic data, real-time weather data, and ramp geometric information. The results found that the Logarithm of vehicle count, average speed in a 5-minute interval, and visibility were significant factors for the occurrence of SV and MV crashes. The Bayesian logistic regression models showed that non-diamond ramp and wet road surfaces would increase the possibility of an SV crash, and off-ramps would result in high MV crash risk. The high standard deviation of speed in a 5-minute interval would significantly increase MV crash likelihood. Meanwhile, a random forest was applied in variable importance analysis, and the result reveals that the most important factors influencing crashes on ramps are traffic variables, the second most important factors are weather variables, and the least important but still significant factors are ramp geometries.

In Chapter 4, the real-time crash risk for expressway ramps was explored using real-time traffic, geometric, land-use, and trip generation predictors. A logistic regression model was utilized to identify significant variables and the impact of these variables on ramp crash risks. The results showed that volume, speed, and percentage of home-based-work production have positive impact on crash risk, also off-ramp and non-diamond ramp significantly increased crash risk; while the percentage of transportation employment was negatively related to crash risk. Subsequently, two SVM models were applied to predict crash occurrence, one with all variables and the other with significant variables identified by the logistic regression model. It was found that the SVM model with significant variables outperformed the logistic regression model by providing higher and more stable AUC. However, the SVM model with all variables might have an overfitting issue.

In Chapter 5, the crash mechanisms of interchange ramps were investigated using multilevel Poisson-lognormal models to estimate 3-hour interval crash frequencies and using multilevel logistic regression models to predict real-time crash risks. All models were applied to both SV and MV crashes. In addition, it explored the feasibility of using crash reports to identify roadway surface conditions at study sites. The crash frequency models revealed that the logarithm of 3-hour traffic volume and average turning angle were positive significant parameters in estimating SV crash frequency; and high traffic volume, sag, or downgrade vertical curve increased MV crash frequency. Meanwhile, the crash risk models presented that the average turning angle had a positive impact on SV crash risk. MV crash risk increased if lane occupancy increased or interchange ramp vertical alignment was a downgrade. Furthermore, the crash risk estimation models also indicated that roadway surface condition was one of the most important parameters: wet roadway surfaces increased SV crash ratio by 8.87 and MV crash ratio by 2.82. This Chapter also has proved that implementing crash reports is an effective method of providing a study event's weather information. After adding the weather information from crash reports, 36.8% more studied events obtained roadway surface condition information, and the predicted weather accuracy also increased by 7.4%.

In Chapter 6, the real-time crash analysis was applied to weaving segments using a logistic regression model and a 10-folder cross validation method. The results showed that the speed difference between the beginning and the end of a weaving segment and the logarithm of volume have significant impacts on crash risk for the next 5-10 minutes of weaving segment traffic. The configuration of a weaving segment was also an important factor. Weaving segments in which there is no need for on- or off-ramp traffic to change lane were with high crash risk because it had more traffic interactions and higher speed differences between weaving and non-weaving traffic. Meanwhile, maximum length, which measures the distance at which weaving turbulence no longer has impact, was found to be positively related to the crash risk at a 95% confidence interval. In addition to traffic and geometric factors, wet pavement surface conditions significantly increase the crash likelihood.

In Chapter 7, in order to improve the safety of a congested weaving segment, various ATM strategies were tested in microsimulation along with a real-time safety evaluation. The strategies included RM strategies, VSL strategies, and an integrated RM-VSL strategy. Overall, the results showed that the ATM strategies were able to improve the safety of the studied weaving segment.

The modified ALINEA RM algorithms, which took both lane occupancy and safety into consideration, outperformed the traditional ALINEA algorithm from a safety point of view but at the expense of average travel time. The 45 mph VSLs, which were located at the upstream of the studied weaving segment, significantly enhanced the safety without notably increasing the average travel time. In order to reduce the average travel time of the modified ALINEA RM and maintain its impact on safety, the modified ALINEA RM was adjusted to control queue length and was integrated with the 45 mph VSL strategy. The results proved that the consolidated RM-VSL approach yielded slightly better safety, but provided much lower average travel times than the modified ALINEA without queue control.

In Chapter 8, a two level microscopic simulation network calibration and validation procedure was developed. It aimed at enhance the consistency between simulated traffic and field traffic, and also the consistency between the simulated safety and field safety. A calibrated and validated simulation network with 16 weaving segments was built. Then conflict data were obtained by processing vehicle trajectory files in SSAM, and traffic data were captured from simulation output. Two logistic regression models were used to connect traffic and conflict: one was based on 5-minute interval and the other one was based on 1-minute interval. Both models showed that the Logarithm of vehicle count, maximum length, and acceleration at the beginning of weaving segment were significant conflict precursors. Meanwhile, the 1-minute interval model had better model performance since the 1-minute interval traffic data were able to provide more detailed and accurate conflict disruptive conditions.

9.2 Implications

Chapter 3 and Chapter 5 estimated crash risk and crash frequency for SV and MV crashes separately. In the estimation models, the significant variables and their quantitative impact on safety were not the same for SV and MV crashes. Meanwhile, the primary analyses also found that SV and MV crashes are prone to happen on different traffic, geometric, and weather conditions; for example, MV crashes are more likely to happen on off-ramps than SV crashes, and SV crashes are more likely to happen on on-ramps than MV crashes. These findings implies that the crash mechanisms of SV and MV vehicles vary. It is recommended that the crash mechanisms for SV and MV crashes should be separately estimated in future safety studies if the number of observations is adequate. Furthermore, different crash severity levels (fatal, injury, etc.) and crash types (rear-end, sideswipe, etc.) might also have different crash mechanisms and could be individually studied.

Finding significant variables might not be enough, ranking the importance of significant variables is of great importance for providing engineers suggestions on how to effectively improve the safety of special facilities. If several countermeasures can be applied to a segment, the countermeasure related to a variable with higher importance level should be given higher priority. In safety analysis for freeway-to-freeway interchange ramps in Chapter 5, the most important SV crash contributing factor is roadway surface conditions. Hence, if engineers intend to decrease SV crash number on interchange ramps, the most effective way would be improving safety under wet roadway surface conditions with strategies such as applying high friction pavement.

Chapter 5 has already proved that the usage of crash reports is able to provide valuable and valid weather information for studied observations. In addition to weather, crash reports also provide several other environmental information, such as lighting and glare condition. Meanwhile, driver information from not-at-fault drivers can act as quasi information for all drivers (e.g., quasi induced exposure), and the driver information from at-fault drivers might be significant contributing factors of crash likelihood. Therefore, it is suggested that more information from crash reports are used in microscopic safety analysis.

Chapter 6 provides two important implications for practitioners: First, for *LC1* weaving segments, in which there is no need for on- or off-ramp traffic to change lanes, the minimum lane change rate is lower, lane changing maneuver is much less, and capacity is higher than *LC0* weaving segments, in which both on- and off-ramp traffic have to change one lane. However, *LC1* weaving segments have high crash risks because there exist high speed differences between on- and off-ramp traffic. Hence, when deciding the weaving segment configuration, the capacity and safety need to be simultaneously considered. Second, compared to using the physical weaving segment length, the maximum weaving length, which is the weaving influence length, can give better model performance. The physical length of the weaving segment cannot decide whether or not it is easy for crashes to occur there. A short weaving segment may be safer than a long weaving segment when the influence length of this short segment is much shorter than that of the long segment. Hence, before constructing a new weaving segment, estimating the influence length is needed. For existing weaving segments, estimating their influence based on the current traffic condition and then identifying hazardous weaving segments would be helpful for reducing crash risk for the expressway system.

Chapter 7 found that the conflict number was significantly related to crash risk in simulation. However, there were still small inconsistencies between conflict number and total crash risk. This variance might owe to the difference between crash mechanisms and conflict mechanisms. This finding implies that studying conflict mechanisms might be a worthwhile endeavor. Additionally, compared to the RM-VSL strategy, only applying RM increased conflict number and crash risk because on-ramp vehicles could not find enough gaps and also because the speed difference between the beginning and the end of the studied weaving segment was not reduced. Meanwhile, the ATM strategy might fail if only VSL was applied because the success of VSL is largely depended on driver compliance. Integrating RM and VSL is a good way to guarantee the effect of ATM, because the RM still works even if the VSL fails.

Chapter 8 conducted a real-time conflict prediction study in simulation, and proved there are differences and similarity between conflict and crash mechanisms form a microscopic aspect. This finding might inspire further researchers to find different contributing factors for conflict and crash frequency analysis. Meanwhile, the simulation is able to provide disaggregate traffic data, for example, the traffic information for each vehicle at locations researchers interested. The availability of the disaggregate traffic data could deepen the safety study to a more microscopic aspect than the current real-time safety study. The current real-time safety study focuses on safety of a segment in a short time interval; the safety study using data from each vehicle might be able to predict safety condition for each vehicle and further provide different guidance for each vehicle to enhance its traffic safety.

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