

MRI-2: Integrated Simulation and Safety



Year 1 Final Report

Submitted by:

Dr. Essam Radwan, P.E. (PI), Ahmed.Radwan@ucf.edu

Dr. Hatem Abou-Senna, P.E. , habousenna@ucf.edu

Dr. Mohamed Abdel-Aty, P.E., M.Aty@ucf.edu

Jiawei Wu & Barry Darius



Center for Advanced Transportation Systems Simulation (CATSS)
Department of Civil, Environmental & Construction Engineering (CECE)

University of Central Florida

Orlando, FL 32816-2450

(407) 823-4738

December 15th, 2015

TABLE OF CONTENTS

Chapter 1: Introduction	6
1.1 Background.....	6
1.2 Objectives	6
1.3 Summary of Project Tasks	6
Chapter 2: Literature Search	8
2.1 VISSIM.....	8
2.2 Cellular Automata Micro simulation	9
2.3 Driving Simulator	9
Chapter 3: Model Development and Testing	10
3.1 VISSIM and SSAM Overview	10
3.2 Development of VISSIM simulation model.....	11
3.3 Data Collection	12
3.4 Results and Analysis	13
3.4.1 Travel Time and Delay	13
3.4.2 Conflict Analysis.....	15
3.4.3 TTC and PET	18
3.5 Conclusion	20
Chapter 4: Simulation Safety Needs and Data Collection	21
4.1 Experimental Sites.....	21
4.2 Field Data Collection Procedures	21
4.3 Field Data Description and Analysis	23
4.3.1 Pedestrian Crossing	23
4.3.2 Conflicts	24
4.4 Conclusions.....	25
Chapter 5: VISSIM and SSAM Calibration and Validation.....	26
5.1 Calibrated and Validated VISSIM model.....	26
5.2 Surrogate Safety Assessment Model.....	28

Chapter 6: Result Analysis	30
6.1 Determine the thresholds for TTC and PET	30
6.2 Relationship between simulated conflicts and observed conflicts	31
6.3 Analysis of TTC and PET	33
6.4 Multivariate Analysis for MaxS, DeltaS, DR and MaxD.....	35
Chapter 7: Conclusions.....	36
Reference	37
Appendix A: Pictures showing each experimental site	40

LIST OF FIGURES

Figure 1: VISSIM simulation model for the mid-block crossing	11
Figure 2: 3-D plot of the VISSIM model	12
Figure 3: Relationship among pedestrian volume, vehicle volume, and vehicle travel time and delay.....	14
Figure 4: Relationship among volume, travel time, and delay between different pedestrian volume and vehicular traffic volume.....	14
Figure 5: Crossing conflict count in different pedestrian volume level with different vehicular traffic volume	15
Figure 6: Relationship among pedestrian volume, vehicular traffic volume, and the number of crossing conflicts.....	16
Figure 7: Mean of rear-end conflicts under different vehicular traffic volume.....	18
Figure 8: Relationship among pedestrian volume, vehicular traffic volume, and the mean of PET and TTC for crossing conflict	19
Figure 9: TTC mean and PET mean on different pedestrian volume and vehicular traffic volume for rear-end conflicts	19
Figure 10: VISSIM simulation model for Sand Lake Rd & I-Drive	28
Figure 11: Contour plot for MAPE value with different TTC and PET threshold	31
Figure 12: Relationship between simulated conflict and observed conflicts.....	32
Figure 13: Time to collision (TTC) frequency distribution.....	33
Figure 14: Post-encroachment Time (PET) frequency distribution	34
Figure 15: PET versus TTC.....	34
Figure 16: scatterplot matrix for MaxS, DeltaS, DR, and MaxD.....	36

LIST OF TABLES

Table 1: Linear regression model results.....	15
Table 2: Final model for the crossing conflicts	16
Table 3: The descriptive statistics of number of rear-end conflicts and ANOVA results	17
Table 4: Analysis of variance (ANOVA) results for the mean of TTC and PET	18
Table 5: The Selected Mid-blocks and Intersections.....	21
Table 6: The Data Collection Schedule.....	22
Table 7: Summary of Pedestrian Crossings at Intersections	23
Table 8: Descriptive Statistical results of pedestrian crossing behavior at intersections	24
Table 9: Descriptive Statistical results of conflicts at intersections	24
Table 10: Compare observed and simulated number of pedestrian volume and vehicular traffic volume	27
Table 11: MAPE value with different TTC and PET threshold values	31
Table 12: The number of simulated conflicts and observed conflicts	32
Table 13: Correlation table for MaxS, DeltaS, DR, and MaxD	35

Chapter 1: Introduction

1.1 Background

Pedestrian safety has become more prevalent for governmental agencies to address the safety of the public. The number of pedestrian fatalities in the United States in 2006 was 4795, and declined to 4109 in 2009. However, there was an upward trend between 2010 and 2012 on pedestrian fatalities. The number of pedestrian deaths increased from 4302 in 2010 to 4743 in 2012 (*Williams, 2013*). Various studies on assessing pedestrian safety have developed in recent years. Traditionally, pedestrian safety assessment uses crash data as a measure of effectiveness to evaluate the pedestrian safety performance of traffic facilities (*Noland & Quddus, 2004; Qi & Yuan, 2012; Zegeer et al., 2002*). However in practice, it is an issue to collect sufficient pedestrian crash data since it requires long periods of time to secure the needed data. Moreover, crash data analyses may not be suitable or sufficient to analyse pedestrian behaviours during the crash period. A credible crash analysis necessitates securing pedestrian exposure measures at the sites under evaluation. This data may not be available unless special efforts are made to collect pedestrian counts at these sites. The use of simulation can serve as a supplemental source for information to support this analysis. Accordingly, traffic simulation can be an efficient alternative to overcome the shortcoming of crash data analysis approaches (*Alhajyaseen et al., 2012*).

1.2 Objectives

This study focuses on the use of both traffic simulation models and driving simulators to better understand causes of traffic crashes and test and assess selected countermeasures to enhance the safety of the public. Specifically, this part of the major research initiative #2 (MRI-2), sponsored by the Southeast Transportation Center at the University of Tennessee as part of the University Transportation Center, is aimed at exploring the use of simulation to evaluate vehicular/pedestrian safety surrogate measures (Tasks 1-5).

1.3 Summary of Project Tasks

The two-year project was designed around the following tasks:

- Task 1 Literature Search
- Task 2 Model Development and Testing
- Task 3 Simulation Safety Needs and Data Collection
- Task 4 VISSIM/SSAM Calibration and Validation
- Task 5 Year 1 Final Report
- Task 6 Year 2 Design of Simulator Experiment and Conduct the Experiment

- Task 7 Analysis Simulator Experiment Data
- Task 8 Year 2 Final Report

Task 1: Literature Search

A comprehensive search for published work related to the use of simulation in testing the safety and operations of vehicular traffic and pedestrians was conducted. The studies included the discrete event simulation models as well as driving simulators. Evaluation of safety issues that could be addressed by or benefit from a simulation-based approach was carried out. In addition, simulation tools related to conflict analysis need to be investigated. This simulation tool can identify and evaluate the potential conflicts between vehicles and pedestrians.

Task 2: Model Development and Testing

In this task, both VISSIM and SSAM software were utilized to evaluate their suitability for simulating conflicts between vehicles and pedestrian. Conflict analysis was investigated to how it can be applied as a surrogate safety measure and recommendations were made to the suitability of using this approach for further research.

Task 3: Simulation Safety Needs and Data Collection

A pilot study was conducted at selected sites for the purpose of calibrating and validating both software. Extensive field data collection secured the needed data.

Task 4: VISSIM/SSAM Calibration and Validation

Numerous simulation runs complemented with a design of statistical experiment resulted in a successful calibration and validation of VISSIM and SSAM.

Task 5: Year 1 Final Report

This first year report documents tasks 1, 2, 3, and 4, and the second year report will document the tasks 6 and 7.

Chapter 2: Literature Search

A comprehensive literature review was carried out to document previous published work related to the use of simulation in testing the safety and operations of vehicular traffic, pedestrians, and bicycles. There have been numerous studies that attempted to use simulations to analyze and assess pedestrian and bicycle safety. The main simulation tools include VISSIM, cellular automata micro simulation, and driving simulator.

2.1 VISSIM

Many researchers have attempted to use VISSIM to evaluate and analyze pedestrian safety in the road network. Muhammad and Robert (2005) used the vehicle following model to simulate pedestrian flow characteristics in urban traffic networks and demonstrated that VISSIM can be used for multimodal network analysis by coding pedestrians as a vehicle, which was very important to allow full consideration of pedestrians in traffic policies by using traffic simulation software. Besides, they also set up a complex network in VISSIM to analyze pedestrian exposure to vehicle emissions and the role played by signal timings (Muhammad & Robert, 2008). The results showed that longer signal cycles could result in less vehicle emission, but cause longer pedestrian delay.

Cornelia and Tobias (2009) simulated pedestrians crossing a street with a lane for each direction in VISSIM. They found that a vehicle demand of 700 to 800 vehicles per hour showed the maximum travel time for pedestrians. A study by Chen et al. (2010) attempted to develop a pedestrian delay estimation model for both signalized and unsignalized intersection considering vehicle-pedestrian conflicts. The pedestrian delay model was built by field data, but the effectiveness of the model was checked in VISSIM by simulating the two actual intersections.

In addition to the intersection, researchers recently started looking into pedestrian behavior for roundabout by using VISSIM. Astrid et al. (2011) investigated how well the Redegerdts and Blackwelder model can affect level of service when pedestrians and bicycles cross the exit of roundabout. Redegerdts and Blackwelder model calculate a percentage capacity loss for the approach situated closest to the exit being blocked, which was more suitable for analytical traffic model. By comparing the result from a microscopic simulation in VISSIM, it was found that the total travel time increased if the pedestrians and bicycles were included in the model. Besides, a high vehicle pedestrian flow seemed to be more affected by small changes in pedestrian flow according to the simulation results. Another study also used VISSIM to simulate roundabouts (Rouphail et al, 2005). First, they used observational data to validate the pedestrian gap parameter for blind and sighted pedestrians. And then, the pedestrian crossing treatment, which was the use of an upstream/downstream (midblock) pedestrian-activated signal and crosswalk, were proposed and tested in the simulation, indicating that it would guarantee a crossable gap and minimize any negative impact at roundabout.

2.2 Cellular Automata Micro simulation

A cellular automata model is a discrete model studied in compatibility theory, mathematics, physics, complexity science, theoretical biology and microstructure modelling (Cellular Automaton, 2014). As the cellular automata model could characterize traffic flow's discreteness feature and easy to simulate in computer, it has been used to simulate traffic by many researches (Rickert et al., 1996; Maerivoet & De Moor, 2005).

In recent years, the cellular automata model has been applied to investigate pedestrian movements and behaviors. Victor and Jeffrey used cellular automata model to simulate three modes of bi-directional pedestrian flow, including flows in directionally separated lanes, interspersed flow, and dynamic multilane flow (V.J. Blue & J. L. Adler, 2001). They found that the pedestrian emergent behavior from cellular automata model was consistent with the empirical data. Another study by Li et al. (2012) attempted to investigate pedestrian conflicts with vehicles at a crosswalk of a signalized intersection using cellular automata simulation. The simulation results showed the effects of different pedestrian signal timing and crosswalk widths on the crosswalk capacity, the number of traffic conflicts between pedestrians and vehicles, and pedestrian delay due to the conflicts. Besides, they also demonstrated that the cellular automata simulation could realistically capture the behaviors and characteristics of pedestrian-vehicle flows, which are similar to the findings of Zhang and Chang (2014), and Yue et al (2010).

2.3 Driving Simulator

The driving simulator is another important tool for researchers to analyze traffic events. It can provide a well-controlled experimental condition and can collect the data, which are difficult to achieve in the real world as well. Mostly, driving simulators are used to analyze driving behaviors under different conditions (Kolisetty et al., 2006; Lee and Abdel-Aty, 2008). However, some studies also involve pedestrians in the driving simulator experiments in order to find out the interaction effects between pedestrians and vehicles.

Yuan et al. (2013) combined driving simulator and computer simulation to reconstruct the process of pedestrian-vehicle crash. The purpose of this study was to find out the relation between drivers' various emergency measures and pedestrians' injury severity. The findings indicated that the most effective way to reduce injury severity was steering with braking. Boot et al. (2004) invited 63 participants to do the driving simulator experiment in order to test the new pedestrian marking, which was called special emphasis marking. All the participants were divided into three different age groups and a 3D model of an intersection was created in the driving simulator. The results showed that drivers could recognize the special emphasis marking much more quickly than the normal crosswalk marking. Moreover, when there was a pedestrian crossing the street, drivers were not affected by the special emphasis marking.

Chapter 3: Model Development and Testing

VISSIM and SSAM were the simulation tools utilized to simulate the conflicts between vehicles and pedestrian. The primary objective in this chapter is to determine whether VISSIM and SSAM models collectively provide reasonable results of the surrogate safety measures for pedestrians to vehicles conflicts. It is not the intention of this chapter to validate or calibrate these two models but rather substantiate the model ability to produce trends that are consistent with the increasing levels of vehicular and pedestrian traffic.

3.1 VISSIM and SSAM Overview

VISSIM is a microscopic, time-step, stochastic simulation model for traffic system operational analysis. VISSIM model consists of set cross-linked sub-models that depend on a number of parameters to describe traffic control operation, traffic flow characteristics, and drivers' behavior. Besides, VISSIM could simulate pedestrian flow as well. According to the literature, there are two different methods that could realize pedestrian simulation in VISSIM. The first method is to use the default method, which applies general rules in VISSIM for pedestrian behavior. In this method, all the pedestrian-related parameters are built-in. However, all the pedestrian movements are independent of the presence of other pedestrians in the vicinity, which means each pedestrian cannot affect other pedestrians' behaviors. The second method is to model pedestrians as vehicles. This method applies the vehicle-following model and assumes that the pedestrian behaves like a vehicle and set the related parameters in the model to replicate pedestrian behaviors. The advantage of this method is that pedestrians can react to the presence of other pedestrians. However, the disadvantage of this method is that all the parameters need to be validated using actual road network data which requires a large amount of data that shows pedestrian behavior (Ishaque and Noland, 2009).

The Surrogate Safety Assessment Model (SSAM) is a software application designed by the Federal Highway Administration (FHWA) to execute conflict analysis of vehicle trajectory data from microscopic traffic simulation models, such as VISSIM, AIMSUN, PARAMICS, and TEXAS. It can provide a summary of the total number of conflicts broken down by type of conflicts. In SSAM, there are three types of conflicts; crossing, rear-end and lane-changing. Classification of conflicts are based on the conflict angle, which these vehicles (or pedestrians) converge to a hypothetical collision point. The conflict angle is classified as follows:

- Crossing: $||\text{conflict angle}|| > 85^\circ$
- Rear-end: $||\text{conflict angle}|| < 30^\circ$
- Lane-changing: $30^\circ \leq ||\text{conflict angle}|| < 85^\circ$

SSAM is mainly used for vehicle-to-vehicle conflicts to assess the safety of traffic facilities and it cannot detect the pedestrian trajectory. However, if pedestrians are set as a vehicle while applying the vehicle-following model, SSAM can successfully import the vehicle trajectory file

and detect the pedestrian to vehicle conflicts. Therefore, this study applies the vehicle-following model and assumes that the pedestrian behaves like a vehicle in VISSIM.

3.2 Development of VISSIM simulation model

VISSIM, version 7.00, was used in this research to develop simulation model for pedestrians. A hypothetical mid-block crossing was established in VISSIM to substantiate the model ability for simulating the conflicts between pedestrians and vehicle. VISSIM uses the psychophysical driver behavior model developed by Wiedemann 74, which is recommended in urban traffic.

A hypothetical mid-block crossing was simulated in VISSIM, as shown in Figure 1. The model consisted of a four-lane divided roadway segment with 40 mph (64km/h) speed limit and the vehicle lanes stretched approximately 1650 feet (500 meters) long. A 3-foot (1 meter) wide pedestrian crosswalk was designed for both directions. The right-of-way for the unsignalized conflicting movements was modelled with conflict areas and priority rules. In this simulation model, vehicles must yield to pedestrians in the conflict area if vehicles and pedestrians entered the crosswalk at the same time. In addition, pedestrians also need to decide if they can cross the street safely according to the vehicle gaps. Two parameters related to priority rules included minimum gap time for the first lane and the second lane in each direction. The minimum gap time was set as 2 seconds for the first lane and 3 seconds for the second lane, respectively. The median acted as a refuge island between the two opposite directions so that pedestrians can wait if there was insufficient gap to cross opposite lanes.

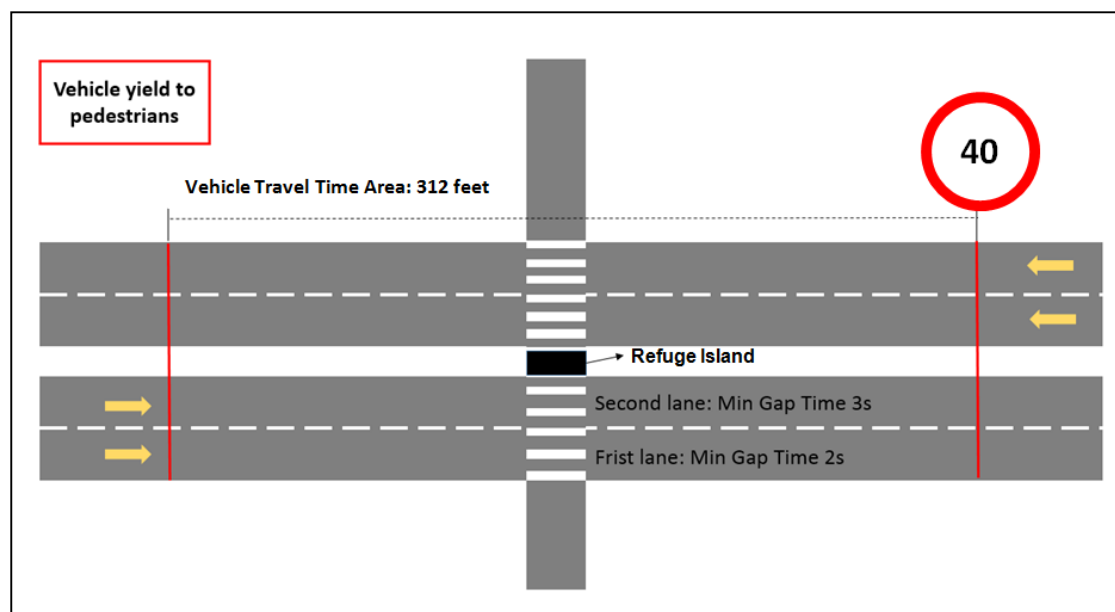


Figure 1: VISSIM simulation model for the mid-block crossing

Vehicles were composed of two types; 98% were light gasoline vehicles (LGV) and 2% were heavy gasoline trucks (HGTs). Pedestrians consisted of men and women, who have different speed distributions. The lower bound and upper bound for men's walking speeds were 3.49

km/h, and 5.83 km/h, respectively. While the lower bound and upper bound for the women's were 2.56 km/h, and 4.28 km/h.

Multiple runs in VISSIM with different vehicular traffic volumes and pedestrian volumes were executed. The pedestrian volume started at 0, and increased in increments of 400 pedestrians per hour, up to 2400 pedestrians per hour (7 levels). Additionally, the vehicular traffic volume started at 600 vehicles per hour, and increased in increments of 400 vehicles per hour, up to 3800 vehicles per hour (9 levels). The average of simulation runs with different random seeds was used to account for the vehicle and pedestrian random arrivals. Thus, the experiment consisted of 7x9 multilevel-factorial design. The simulation period was 3600 seconds for each run and there was no warm up period. Default values for the driver and pedestrian behavior parameters were used since the experiment consisted of hypothetical scenarios and there was no need for calibration or validation procedures. The 3-D plot of the VISSIM model is shown in Figure 2.

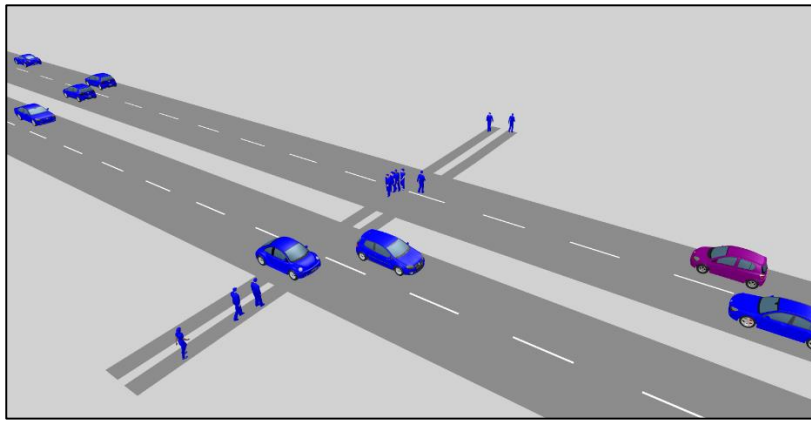


Figure 2: 3-D plot of the VISSIM model

3.3 Data Collection

The data collected from simulation runs was divided into two parts, which are from VISSIM and SSAM, respectively.

In VISSIM, the data collection included vehicle travel time, vehicle delay, pedestrian crossing time and pedestrian delay. Vehicle travel time and delay were picked to decide if these two measures significantly increase with the increase of the vehicular traffic and pedestrian volumes. Pedestrian crossing time was measured as the time between pedestrian arriving at stop line and leaving the opposite stop line. Therefore, the time that pedestrian spent on waiting to cross the street was already included and the same approach applied for the pedestrian delay time.

SSAM software can automate conflict analysis by directly processing vehicle trajectory data from VISSIM. It can provide a summary of the total number of conflicts broken down by type of conflicts. The analysis focused mainly on vehicle-to-pedestrian crossing conflicts and

vehicle-to-vehicle rear-end conflicts caused by sudden braking to yield to pedestrians at mid-block crossings. The vehicle-to-pedestrian crossing conflict and the vehicle-to-vehicle rear-end conflict can be selected from the SSAM output based on the length of the vehicle and the type of the conflict. The numbers of vehicle-to-pedestrian crossing conflicts and vehicle-to-vehicle rear-end conflicts were collected for each scenario. Furthermore, SSAM also calculates surrogate safety measures for each conflict. In this study, two measures were applied to evaluate the traffic safety; time-to-collision (TTC) and post-encroachment time (PET). TTC is defined as the time that remains for a potential collision of two road users if they keep their directions and velocities (17). The shorter the TTC is, the more dangerous the situation is. The PET is defined as the period of time from the moment when the first road user is leaving the conflict area until the second road user reaches it. Since the pedestrians are modelled as vehicles as mentioned earlier, the minimum conflict thresholds of the TTC and PET were assumed as the default values of 1.5 and 5 seconds, respectively.

3.4 Results and Analysis

Based on the output of VISSIM and SSAM, the analyses focused on exploring how safety performance measures were associated with different vehicular traffic volumes and different pedestrian volumes. The hypothesis testing in the following analyses were based on a 0.05 significance level.

3.4.1 Travel Time and Delay

The travel time and delay are basic parameters used to estimate traffic flow efficiency at intersections as well as roadway segments. Figure 3 shows the effects of vehicle travel time and delay on vehicle flow and pedestrian flow at the mid-block crossing. It was found that vehicle travel time and delay were monotonously increasing with the increase in pedestrian volume. This was attributed to the fact that pedestrians have the right of way at the conflict area. So, as pedestrian volume increases, the waiting time for vehicles increases. Another interesting phenomenon was that the vehicular traffic volume itself did not have a significant effect on vehicle travel time or delay. In other words, vehicle travel time and delay were almost the same with different vehicular traffic volume provided that the pedestrian volume was constant. This finding can be explained by the fact that pedestrian volume is the only external effect on the vehicular traffic flow, since the roadway segment is unsignalized with no traffic control device affecting the flow.

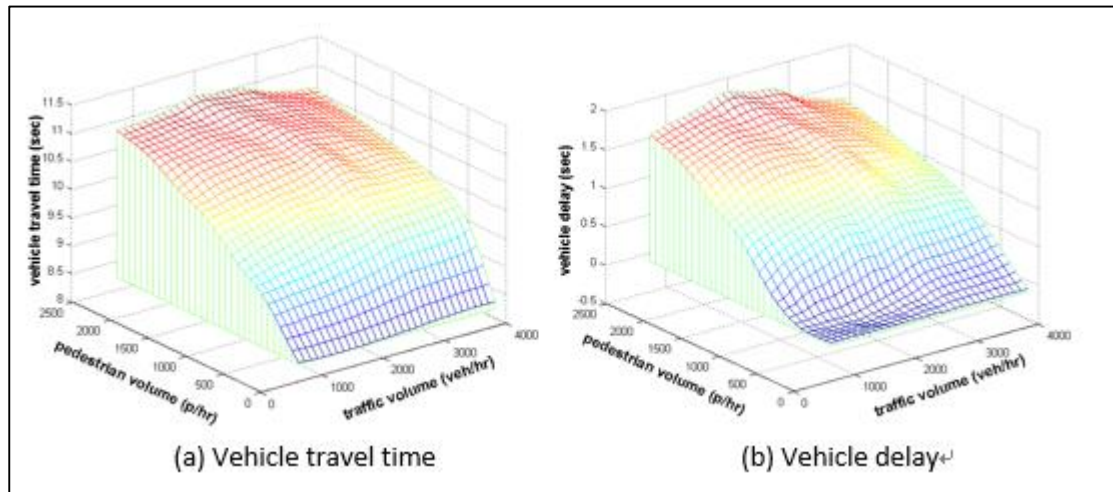


Figure 3: Relationship among pedestrian volume, vehicle volume, and vehicle travel time and delay

In addition, Figure 4 illustrates the relationship among pedestrian volume, vehicle volume, and pedestrian travel time and delay at the mid-block crossing. It indicated that the pedestrian travel time and delay were increasing with the increase in vehicular traffic volume; however, pedestrian volume did not have a significant effect on pedestrian travel time and delay. This finding can be explained that if the vehicular traffic volume is constant, pedestrians can cross the street in a group at the same time. Even though there is a large amount of pedestrians crossing the street, they seldom interfere with each other. However, when the vehicular traffic volume increases, the gap between vehicles starts to decrease. Since the decision that pedestrians take, whether to stop or go, is based on the minimum gap time, pedestrians need to wait for longer time to cross the street. That's why the pedestrian travel time and delay obviously increase as the vehicular traffic volume increases.

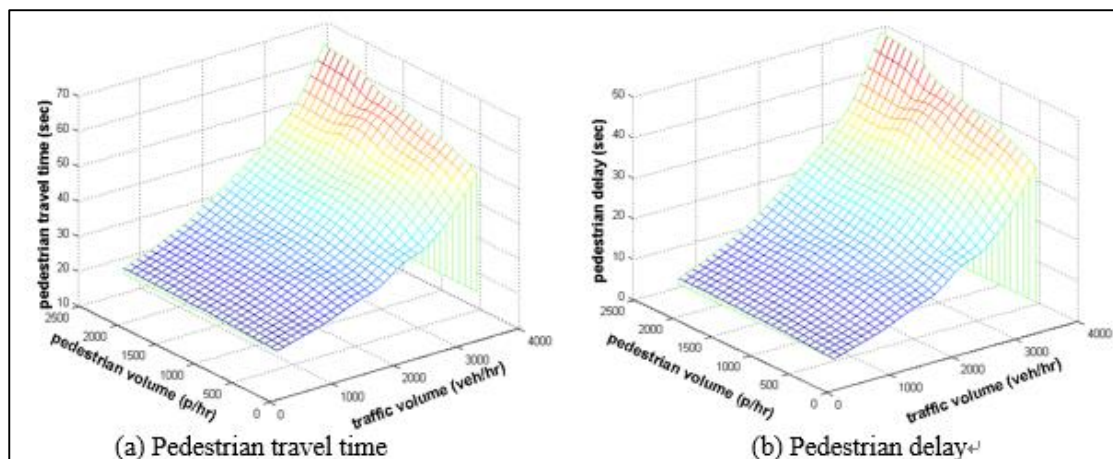


Figure 4: Relationship among volume, travel time, and delay between different pedestrian volume and vehicular traffic volume

3.4.2 Conflict Analysis

Traffic conflict technique is one of the effective methods used for evaluating traffic safety (Oh et al, 2006). “A conflict can be defined as an observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged” (Leur and Sayed, 2002). The number of conflicts between pedestrians and vehicles at the crosswalk is one of the most significant factors for pedestrian safety. The increasing conflicts between pedestrians and vehicles may lead to more traffic crashes, resulting in injuries and fatalities more likely for pedestrians (Lee and Abdel-Aty, 2005). Additionally, the rear-end conflict is another factor that needs to be taken into account due to the fact that vehicles might have to brake unexpectedly at the crosswalk.

Two types of conflicts were analysed based on SSAM output; crossing conflicts and rear-end conflicts. Figure 5 shows the effect of different pedestrian volumes and different vehicular traffic volumes on the number of crossing conflicts between pedestrians and vehicles. When the number of the pedestrian volume was constant, the number of the crossing conflicts increased with the increase of vehicular traffic volume. With the increment of pedestrian volume, the number of crossing conflicts raised as well. In order to explore the inner relationship among conflict counts, pedestrian volume and vehicular traffic volume, a linear regression model was applied for each given pedestrian volume. Table 1 shows the regression results of six models for each level of the pedestrian volume.

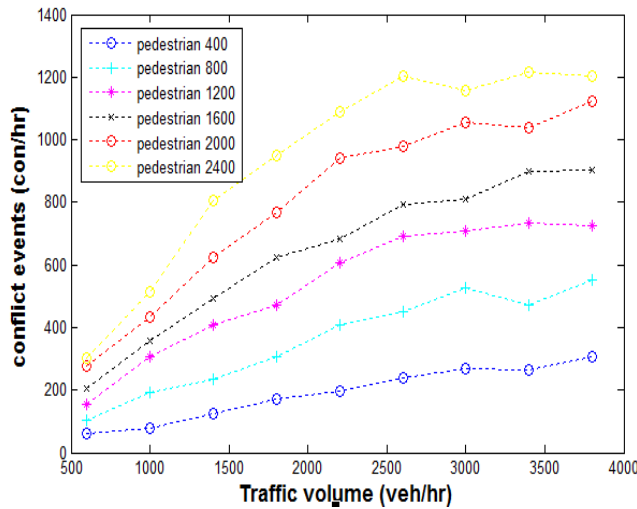


Figure 5: Crossing conflict count in different pedestrian volume level with different vehicular traffic volume

Table 1: Linear regression model results

Pedestrian volume	Model	R square
400	$y = 17.103 + 0.079x$	0.973
800	$y = 53.400 + 0.14x$	0.941

1200	$y = 132.028 + 0.183x$	0.911
1600	$y = 162.664 + 0.217x$	0.945
2000	$y = 229.844 + 0.261x$	0.913
2400	$y = 324.725 + 0.278x$	0.833

* y is the number crossing conflicts, x is the number of vehicular traffic volume

According to the regression results, it was found that the number of crossing conflicts was increasing linearly with the increase of the vehicular traffic volume if the pedestrian volume was constant. In addition, the trend of the β_1 coefficient in each linear regression model was increasing as the pedestrian volume increased: 0.079, 0.14, 0.183, 0.217, 0.261, and 0.278. Accordingly, the increased pedestrian volume increased the effect of vehicular traffic volume on crossing conflicts. Based on the analysis above, hypothesis test with a 0.05 significance level is used to decide on the significant factors for the crossing conflicts. As shown in Table 2, all the parameters' p-values are less than 0.05 and there is an interaction effect found between pedestrian volume and vehicular traffic volume. The relationship among pedestrian volume, vehicular traffic volume and the number of crossing conflicts is shown in Figure 6, illustrating that the number of the crossing conflict was increasing as either vehicular traffic volume or pedestrian volume increased. In addition, the pedestrian volume effect on the number of crossing conflicts was also correlated to the vehicular traffic volume according to the significance of the interaction term.

Table 2: Final model for the crossing conflicts

Independent Variable	Estimate	Std Error	t Ratio	Sig.
Intercept	-364.03	33.08	-11.00	0.000
Vehicular traffic volume	0.193	0.010	18.81	0.000
Pedestrian volume	0.369	0.015	23.81	0.000
(Vehicular traffic-2200) * (Pedestrian-1400)	9.98e-5	0.000	6.64	0.000

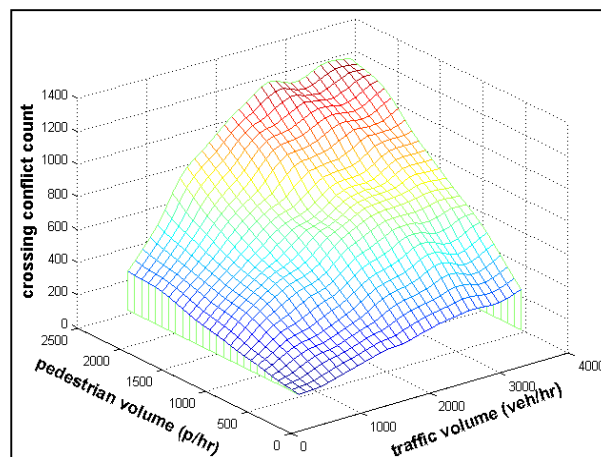


Figure 6: Relationship among pedestrian volume, vehicular traffic volume, and the number of crossing conflicts

In order to determine the impacts of the vehicular traffic volume and pedestrian volume on the number of rear-end conflicts at the mid-block crossing, the analysis of variance (ANOVA) model was conducted for the number of rear-end conflicts. The descriptive statistics of the number of rear-end conflicts are reported in Table 2 and the influence of vehicular traffic volume on the number of vehicular rear-end conflicts are shown in Figure 7. The ANOVA results showed the significant effect of pedestrians on the number of vehicular rear-end conflicts ($F=15.601$, $p\text{-value}=0.000$). Although it appeared that the number of rear-end conflicts increased with the increase in vehicular traffic volume, those conflicts were mainly due to the pedestrian effect. In other words, the increasing vehicular traffic volume along with the presence of pedestrians led to higher possibility of rear-end conflicts between vehicles braking for pedestrians. However, the increase in pedestrian volume did not have a significant impact on the vehicular rear-end conflicts ($F=1.533$, $p\text{-value}=0.197$).

Table 3: The descriptive statistics of number of rear-end conflicts and ANOVA results

Independent Variable	Classification	The Number of Rear-end Conflicts				F-Value	Sig.
		Mean	Min	Max	S.D.		
Vehicular traffic volume	600	0.17	0	1	0.41	15.601	0.000
	1000	1.67	1	3	0.82		
	1400	3.67	0	6	2.07		
	1800	6.5	3	13	3.45		
	2200	9.50	6	14	2.66		
	2600	15.00	8	23	5.62		
	3000	13.33	4	26	7.53		
	3400	18.50	11	29	6.32		
	3800	20.00	12	28	5.69		
Pedestrian Volume	400	5.44	0	12	4.19	1.533	0.197
	800	8.00	0	18	6.60		
	1200	8.67	0	18	6.32		
	1600	10.44	0	25	8.46		
	2000	11.33	1	23	8.67		
	2400	15.00	0	29	11.30		

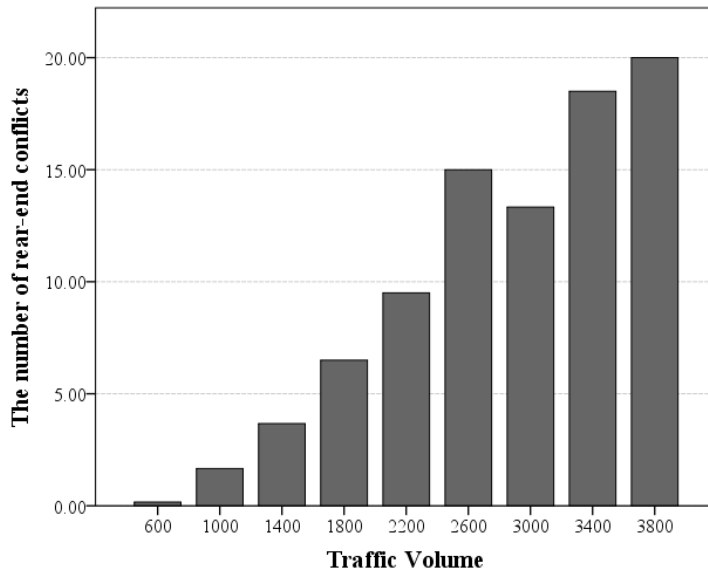


Figure 7: Mean of rear-end conflicts under different vehicular traffic volume

3.4.3 TTC and PET

TTC and PET are collected for each conflict in each scenario. The average of the TTC and PET of all conflicts for each scenario are also used for exploring how vehicular traffic volume and pedestrian volume affect traffic safety performance. The analysis of variance was conducted to analyze the effect of vehicular traffic volume and pedestrian volume on TTC and PET for crossing conflicts between vehicles and pedestrians, as shown in Table 3.

As for the crossing conflict, PET was significantly influenced by vehicular traffic volume and pedestrian volume (vehicular traffic volume: $F=5.274$, $p\text{-value}=0.000$; pedestrian volume: $F=8.013$, $p\text{-value}=0.000$). As shown in Figure 8(a), PET increased as either the pedestrian volume or the vehicle volume increased. The result indicated that if there were fewer pedestrians or vehicles at the mid-block crossing, vehicles or pedestrians could leave the conflict point more quickly. Instead, if there were more pedestrians or vehicles at the mid-block crossing, vehicles or pedestrians needed more time to leave the conflict point. However, there was no obvious evidence that either vehicular traffic volume or pedestrian volume affected the TTC, as shown in Figure 8(b). Even though the pedestrian volume and the vehicular traffic volume were increasing, the average of TTC was constant, which was around 1.35 seconds. The possible explanation for this phenomenon is that pedestrian behavior and driver behavior are the same no matter how many pedestrians cross the street or how many vehicles cross the crosswalk at the mid-block crossing.

Table 4: Analysis of variance (ANOVA) results for the mean of TTC and PET

Dependent Variable	Independent Variable	Df	Mean Square	F-value	Sig.
--------------------	----------------------	----	-------------	---------	------

TTC	Vehicular traffic volume	8	0.001	1.319	0.259
	Pedestrian Volume	5	0.001	1.067	0.391
PET	Vehicular traffic volume	8	0.103	5.274	0.000
	Pedestrian Volume	5	0.155	8.013	0.000

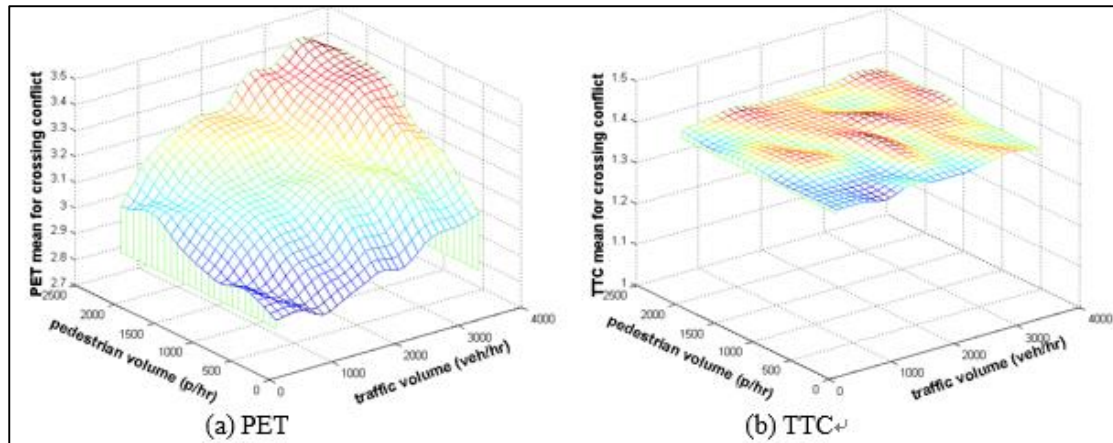


Figure 8: Relationship among pedestrian volume, vehicular traffic volume, and the mean of PET and TTC for crossing conflict

For the rear-end conflicts, Figure 9 shows the trends for pedestrian volume, vehicular traffic volume, the mean of TTC and PET for rear-end-conflicts. It indicated that when the pedestrian volume was 2000 ped/hr and vehicular traffic volume was 1000 veh/hr, the mean of PET and TTC were around 2.5 seconds and 1.3 seconds, respectively. However, as the vehicular traffic volume and pedestrian volume increased, the mean of PET and TTC for rear-end conflicts decreased, implying higher probability of rear-end crashes.

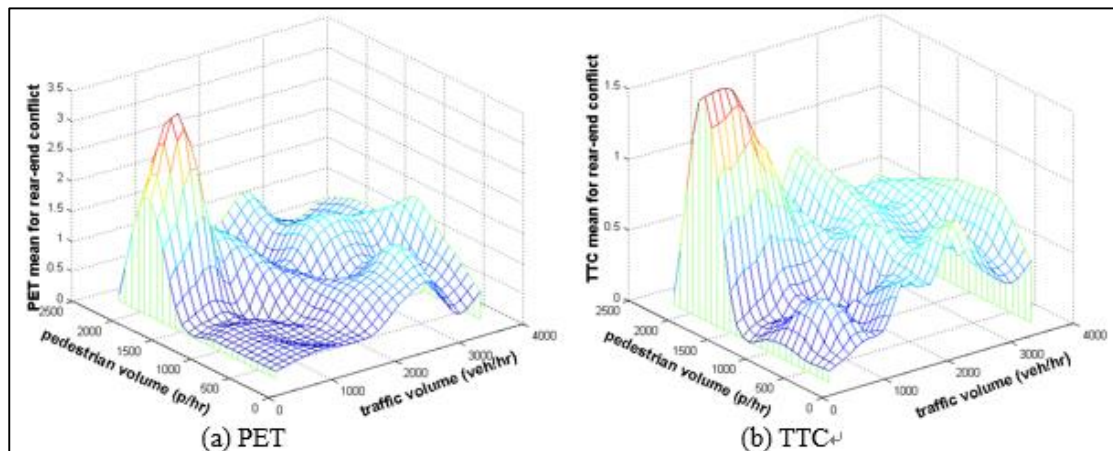


Figure 9: TTC mean and PET mean on different pedestrian volume and vehicular traffic volume for rear-end conflicts

3.5 Conclusion

The main purpose of this study was to verify whether VISSIM simulation model and SSAM software could be potential tools to simulate pedestrians and vehicles and provide reasonable estimates for pedestrian conflicts with vehicular traffic. A mid-block crossing was tested in VISSIM to simulate different levels of pedestrian volumes and vehicular traffic volumes. SSAM software was used to extract the surrogate safety measures for each conflict by directly processing vehicle trajectory data from VISSIM. Finally, using the results from both VISSIM and SSAM, the travel time/delay measures and the surrogate safety measures for both crossing conflicts and rear-end conflicts were analysed under different pedestrian volumes and vehicular traffic volumes.

According to the simulation results, only pedestrian volume has a significant effect on vehicle travel time and delay at the mid-block crossing. As pedestrian volume increases, the vehicle travel time and delay increase. In contrast, vehicular traffic volume is the only significant factor that affects pedestrian crossing time and delay. When vehicular traffic volume increases, pedestrian crossing time and delay significantly raise as well. Linear regression models and AVONA were developed to investigate the effects of pedestrian volume and vehicular traffic volume on both crossing conflicts and rear-end conflicts. The number of crossing conflicts between vehicles and pedestrians is increasing linearly with the increase of vehicular traffic volume when the pedestrian volume is constant. Likewise, pedestrian volume has a positive effect on the number of crossing conflicts. Another interesting finding is that the increase in pedestrian volume also increases the effect of vehicular traffic volume on the number of crossing conflicts. In addition, the pedestrian volume effect on the number of crossing conflicts was also correlated to the vehicular traffic volume according to the significance of the interaction term. ANOVA results indicate that the increase in vehicular traffic volume and the increase in pedestrian volume are the main factors that affect the number of rear-end conflicts. Additionally, two surrogate safety measures, including PET and TTC, are examined for exploring how vehicular traffic volume and pedestrian volume affect traffic safety performance. It is found that the value of PET for crossing conflicts increases as either vehicular traffic volume or pedestrian volume increases. However, the mean of TTC for crossing conflicts is not affected by the increasing vehicular traffic volume or pedestrian volume. On the other hand, the mean of PET and TTC for rear-end conflicts decreases as the vehicular traffic volume and pedestrian volume increases, implying higher probability of rear-end crashes. The findings provide abundant evidence that VISSIM and SSAM models can be used to estimate pedestrian conflicts with vehicular traffic. Although the results of VISSIM and SSAM model offer reasonable trends, it is still undecided how accurate the simulation results are compared to the real world. Therefore, a calibrated and validated network is necessary to evaluate crossing conflicts for pedestrian safety in the following chapters.

Chapter 4: Simulation Safety Needs and Data Collection

4.1 Experimental Sites

The data collected in the field was used to develop, calibrate, and validate the VISSIM and SSAM simulation models. Eight intersections were selected from urban areas in Orange County and Volusia County in Florida. All of the intersections are four-leg intersections with pedestrian signals and marked crosswalks. The selected intersections are listed in Table 4. These sites were prime candidates because they have high pedestrian volumes. Orange Ave & Central Blvd is located in a downtown area where a large number of pedestrian activity occur during lunch hour. Sand Lake Rd & I-Drive is located in a tourist area where a high volume of pedestrian activity exists. Martin Luther King & US 92 is located near the university campus in Daytona Beach in Volusia County. Furthermore, selections of the remaining intersections were done according to the severity of pedestrian crashes. Silver Star & Hiawasse Rd had one fatality out of 20 pedestrian crashes as well as Kirkman Rd & Conroy Rd with two fatalities out of 13 pedestrian crashes. Pictures showing each site location are presented in Appendix A.

Table 5: The Selected Mid-blocks and Intersections

Intersection Name	5-year Ped Crashes	Location	County
Orange Ave & Central Blvd	8	Orlando	Orange
Primrose Dr & Colonial Dr	9	Orlando	Orange
Silver Star & Hiawasse Rd	20	Pine Hills	Orange
Sand Lake Rd & I-Drive	6	Orlando	Orange
Kirkman Rd & Conroy Rd	13	Orlando	Orange
Martin Luther King & US 92	7	Daytona Beach	Volusia
Orange Ave & Kaley St	8	Orlando	Orange
Semorán Blvd & Pershing Ave	8	Orlando	Orange

a. 5-year Ped Crashes are from June 2009 to May 2014.

4.2 Field Data Collection Procedures

VISSIM has a complicated data input requirement to build a model for the local traffic conditions. Calibration and validation of the VISSIM model are very important procedures, thus sufficient data are needed for this process. Two types of data are required before setting up a VISSIM simulation model. The first type is the basic input data for VISSIM network coding such as network geometry, traffic volume data, turning movement data, vehicle characteristics, and pedestrian volume. The second type is the observation data for the calibration and validation, which includes processed traffic volume data, maximum queue length, and pedestrian crossing time.

In this study, field data collection was conducted on eight experimental sites in Florida. Several steps were implemented in order to extract the data from the field. In the first step, Google Maps were utilized to determine the intersection geometry, such as link lengths, number of lanes, and connectors between links to model turning movements. Second, cameras were set up at each intersection to record the traffic volume, pedestrian volume, pedestrian crossing behavior, maximum queue length, and pedestrian-vehicle conflicts. One camera was set up on top of the roadside to achieve adequate viewing height to cover the functional area of the intersections and mid-blocks. However, three intersections, Sand Lake Rd & I-Drive, Kirkman Rd & Conroy Rd, and Semoran Blvd & Pershing Ave were too large to cover the whole intersection with one camera. Therefore, two video cameras were utilized for each of these intersections, and each camera attached on the opposite corner of the intersection in order to cover the whole intersection. Furthermore, field data collection was conducted during the weekday peak hours under normal weather condition. The data collection schedule is given in Table 5. In total, 6 hours of data were recorded for each signalized intersection.

Table 6: The Data Collection Schedule

Intersection Name	Days of Data Collection	Hours	Hours of Filming
Orange Ave & Central Blvd	1	9am-12pm, 3pm-6pm	6
Primrose Dr & Colonial Dr	1	9am-12pm, 3pm-6pm	6
Silver Star & Hiawasse Rd	1	9am-12pm, 3pm-6pm	6
Sand Lake Rd & I-Drive	1	9am-12pm, 3pm-6pm	6
Kirkman Rd & Conroy Rd	1	9am-12pm, 3pm-6pm	6
Martin Luther King & US 92	1	9am-12pm, 3pm-6pm	6
Orange Ave & Kaley St	1	9am-12pm, 3pm-6pm	6
Semoran Blvd & Pershing Ave	1	9am-12pm, 3pm-6pm	6

The recorded videos were later reviewed for evaluation and analysis in the laboratory. For traffic volume and pedestrian volume, data was recorded in 15-min time intervals. Maximum queue length was recorded for further validation of driver behavior in VISSIM model. Furthermore, the camera angles allowed only one or two approaches to be recorded for the queue length of each intersection. Pedestrian behavior was collected to calibrate and validate VISSIM model for pedestrian behaviors. The parameters of pedestrian behavior observed included the directions, platoon number, waiting time, crossing time, and violation. Pedestrian conflicts between pedestrians and vehicles were recorded from the video by identifying pedestrian or vehicle evasion actions meaning the potential occurrence of a vehicle crashing into a pedestrian. Two trained observers were designated to review and analyze all the videotapes as well as recorded the information for each conflict.

The pedestrian-to-vehicle conflicts observed in the field are classified into two types, including (a) vehicle-yield-pedestrian and (b) pedestrian-yield-vehicle. If the vehicle decelerates in order to avoid the crossing pedestrian, (which means the pedestrian arrives at the conflict point first), this is the type (a) of conflict called vehicle-yield-pedestrian conflict. In contrast, if the vehicle arrives at the conflict point first and the immediate arrival of the pedestrian comes afterward, then this is the type (b) of conflict called pedestrian-yield-vehicle. In practice, the vehicle-yield-pedestrian conflict is more dangerous than the pedestrian-yield-vehicle conflict. This is due to the fact that when the pedestrian yields to the vehicle at the signalized intersection, the pedestrian stands still until the vehicle passes the potential conflict point. Under this condition, the TTC of pedestrian-yield-vehicle conflict is infinite. However, the TTC of vehicle-yield-pedestrian is always small so that it is a potential collision. Therefore, vehicle-yield-pedestrian conflict is more likely to lead to a traffic crash. Accordingly, this study only focuses on analyzing the vehicle-yield-pedestrian conflicts.

4.3 Field Data Description and Analysis

4.3.1 Pedestrian Crossing

Table 6 summarizes the pedestrian crossing number recorded during the data collection period. As there are some pedestrians who did not use the crosswalk to cross the street, those pedestrian counts were disregarded and eliminated from the analysis. Therefore, the number of pedestrian volume in this section may slightly differ in comparison to the total pedestrian volume count. There were a total of 4611 pedestrian crossings at eight intersections observed in the field. 40.8% (1882 out of 4611) at intersections of the pedestrian crossing behaviors are single pedestrian crossing behaviors. The following subsections explained the pedestrian crossing behaviors for intersections in further details.

Table 7: Summary of Pedestrian Crossings at Intersections

Intersection Name	Total Crossings	Single	Two or More
Orange Ave & Central Blvd	2001	815	418
Primrose Dr & Colonial Dr	214	152	28
Silver Star & Hiawasse Rd	305	148	65
Sand Lake Rd & I-Drive	1310	264	352
Kirkman Rd & Conroy Rd	299	192	46
Martin Luther King & US 92	140	107	16
Orange Ave & Kaley St	150	95	24
Semoran Blvd & Pershing Ave	192	109	32
Total	4611	1882	981

The basic statistical descriptions of pedestrian crossing behavior at intersections are shown in Table 7. A total of 2863 pedestrian crossings were recorded at the eight signalized intersections. The average speed of all pedestrians was 1.57m/s (5.15 ft/sec). In addition, 10% of pedestrians

have violation behaviors of which most of the violations were running the red light. 50% of pedestrians stopped on red and the average waiting time for all pedestrians were 47 seconds.

Table 8: Descriptive Statistical results of pedestrian crossing behavior at intersections

Intersection	Number of observations	Walking Speed (m/s)	Violation	Stop on Red	Waiting Time (Seconds)
Orange Ave & Central Blvd	1233	1.51	147	367	22
Primrose Dr & Colonial Dr	180	1.70	19	53	47
Silver Star & Hiawasse Rd	213	1.65	43	138	44
Sand Lake Rd & I-Drive	616	1.57	9	484	66
Kirkman Rd & Conroy Rd	238	1.66	15	146	62
Martin Luther King & US 92	123	1.87	32	48	38
Orange Ave & Kaley St	119	1.42	12	67	41
Semoran Blvd & Pershing Ave	141	1.49	13	106	59

4.3.2 Conflicts

The statistical results of conflicts at intersections are given in Table 8. A total of 912 conflicts were detected in the field. The average PET was 4.13 seconds with a standard deviation of 1.6. The conflicts between pedestrians and right-turn vehicles account for 74.3% of conflicts and 20.6% were accounted for conflicts between pedestrians and left-turn vehicles. There were only 5.1% of conflicts between pedestrians and through vehicles, which was mainly due to the pedestrian red light running.

Table 9: Descriptive Statistical results of conflicts at intersections

Intersection	Conflict Count	PET		Conflict with right-turn vehicle		Conflict with left-turn vehicle		Conflict with through vehicle	
		Mean	Std. D	Count	Mean PET	Count	Mean PET	Count	Mean PET
Orange Ave & Central Blvd	204	4.38	1.41	78	4.33	110	4.5	16	3.67

Primrose Dr & Colonial Dr	64	4.44	1.77	22	4.00	37	4.93	5	3.00
Silver Star & Hiawasse Rd	86	4.24	1.67	74	4.21	8	4.80	4	3.25
Sand Lake Rd & I- Drive	295	3.93	1.63	293	3.90	2	2.00	0	
Kirkman Rd & Conroy Rd	94	3.81	1.30	100	3.81	0		0	
Martin Luther King & US 92	34	3.59	1.33	17	3.59	6	4.7	14	3.2
Orange Ave & Kaley St	62	3.57	1.69	42	3.46	19	3.81	1	3.73
Semoran Blvd & Pershing Ave	73	5.0	1.60	61	5.0	6	5.2	6	4.50
Total	912	4.13	1.6	678	4.11	188	4.60	46	3.52

4.4 Conclusions

The main objective of this chapter was to collect the field data and summarize the data extraction process. The data collected in the field was to calibrate and validate the VISSIM and SSAM model, which is to be conducted in the next chapter. Eight signalized intersections were selected from urban areas in Orange County and Volusia County in Florida. Five various types of data input are required to build a VISSIM model and calibrate it in order to study the actual field conditions. These parameters include traffic volume, pedestrian volume, queue length, pedestrian crossing, and conflicts between pedestrians and vehicles.

Chapter 5: VISSIM and SSAM Calibration and Validation

5.1 Calibrated and Validated VISSIM model

In this study, VISSIM version 7 was used to develop the vehicle/pedestrian simulation model at intersections. Wiedemann 74 car-following model was used since it was recommended for urban traffic. The first step of developing the VISSIM model was to draw the network. Second, traffic volume and pedestrian volume for each direction were allocated to each lane group. In addition, the traffic volume included 2% heavy vehicles on all approaches. Third, the signal was set up in the VISSIM simulation model according to the field signal timing data. Finally, conflict areas and priority rules were coded in the simulation model in order to simulate the vehicle and pedestrian movements in a realistic manner.

The VISSIM model cannot provide accurate results until the model is properly calibrated and validated. A total of eight intersections were separated into two groups, including a calibration dataset with six intersections, and a validation dataset with two intersections. The six intersections were used to develop and calibrate the VISSIM models, while the other two intersections were used to validate the effectiveness of simulation model calibration.

First, the VISSIM simulation model was calibrated to reproduce the performance measures for both traffic and pedestrians, such as vehicular traffic volume and pedestrian volume. The difference between observed value and simulated value of vehicular traffic volume and pedestrian volume is shown in Table 10. The average percent difference for all scenarios of pedestrian volume and vehicular traffic volume are 3.6% and 1.3%, respectively. In addition, the queue length of the vehicle and the pedestrian crossing time are also calibrated. By applying the Chi-square tests, it was found that the difference in these measures between the field and the simulation model were not statistically significant, which shows that vehicular and pedestrian flows were calibrated. In addition, the driving behavior and pedestrian behavior parameters were also calibrated. The objective is to generate similar conflicts between pedestrians and vehicles so that the number of conflicts and average TTC generated by SSAM were calibrated. A sensitivity analysis was used to calibrate the car-following model; however, none of the parameters were sensitive to the results. Therefore, the default value of the car following model was used in this case. Last, animation of the VISSIM simulation models were checked to find out if some unusual events happen. It was found that few numbers of crashes took place in the simulation model. Based on the results, the two intersections were validated. Therefore, the VISSIM simulation model was calibrated and validated. The graphical representation of the Sand Lake Road and I Drive is shown in Figure 10.

Table 10: Compare observed and simulated number of pedestrian volume and vehicular traffic volume

Intersection		Pedestrian volume			Vehicular traffic volume		
		Observed	Simulated	%	Observed	Simulated	%
Orange Ave @ Central Blvd	9:00 am	200	208	3.8%	2354	2408	2.2%
	10:00 am	218	223	2.2%	2320	2354	1.4%
	11:00 am	412	393	4.8%	2584	2518	2.6%
	3:00 pm	377	361	4.4%	2872	2873	0.0%
	4:00 pm	350	360	2.8%	3202	3215	0.4%
	5:00 pm	336	321	4.7%	2978	2968	0.3%
Primrose Dr @ Colonial Dr	9:00 am	27	28	3.6%	6204	6235	0.5%
	10:00 am	29	30	3.3%	6396	6529	2.0%
	11:00 am	35	34	2.9%	7244	7229	0.2%
	3:00 pm	57	54	5.6%	8010	8052	0.5%
	4:00 pm	43	41	4.9%	8023	7892	1.7%
	5:00 pm	43	45	4.4%	8378	8408	0.4%
Silver Star @ Hiawasse Rd	9:00 am	59	58	1.7%	5798	5754	0.8%
	10:00 am	43	45	4.4%	5634	5753	2.1%
	11:00 am	60	61	1.6%	5582	5583	0.0%
	3:00 pm	52	51	2.0%	6921	6833	1.3%
	4:00 pm	90	89	1.1%	7520	7366	2.1%
	5:00 pm	59	57	3.5%	8323	8133	2.3%
Sand Lake Rd @ I-Drive	9:00 am	115	120	4.2%	6773	6937	2.4%
	10:00 am	92	95	3.2%	6719	6776	0.8%
	11:00 am	177	174	1.7%	7008	6914	1.4%
	3:00 pm	150	159	5.7%	7429	7485	0.7%
	4:00 pm	130	135	3.7%	7810	8000	2.4%
	5:00 pm	179	184	2.7%	8105	8145	0.5%
Kirkman Rd & Conroy Rd	9:00 am	11	11	0.0%	7451	7270	2.5%
	10:00 am	42	41	2.4%	6863	6669	2.9%
	11:00 am	25	26	3.8%	7611	7716	1.4%
	3:00 pm	31	32	3.1%	10257	10230	0.3%
	4:00 pm	38	37	2.7%	10490	10334	1.5%
	5:00 pm	82	86	4.7%	11446	11547	0.9%
Martin Luther King @ US 92	9:00 am	16	15	6.7%	3179	3177	0.1%
	10:00 am	13	14	7.1%	3983	3988	0.1%
	11:00 am	17	16	6.3%	4680	4701	0.4%
	3:00 pm	38	37	2.7%	5119	4999	2.4%
	4:00 pm	35	36	2.8%	4967	5096	2.5%
	5:00 pm	28	27	3.7%	4772	4651	2.6%
Orange Ave & Kaley St	9:00 am	39	40	2.5%	5126	5166	0.8%
	10:00 am	25	24	4.2%	4794	4720	1.6%
	11:00 am	36	37	2.7%	4997	5101	2.0%

	3:00 pm	30	31	3.2%	5627	5615	0.2%
	4:00 pm	22	23	4.3%	5785	5794	0.2%
	5:00 pm	33	34	2.9%	5780	5819	0.7%
Semoran Blvd & Pershing Ave	9:00 am	22	21	4.8%	6637	6664	0.4%
	10:00 am	20	19	5.3%	6462	6389	1.1%
	11:00 am	27	28	3.6%	6943	7122	2.5%
	3:00 pm	25	24	4.2%	8416	8229	2.3%
	4:00 pm	46	48	4.2%	9114	9076	0.4%
	5:00 pm	30	29	3.4%	9931	9806	1.3%



Figure 10: VISSIM simulation model for Sand Lake Rd & I-Drive

Furthermore, the simulation was run for 3600 seconds (1 hour) with additional warm up period of 15 minutes in each scenario. A total of 10 runs with different seeding values for each one-hour time interval per intersection were completed for each scenario. For example, six hours of simulated data were collected at the eight intersections, and then the VISSIM model was run for $10 \times 6 \times 8 = 480$ times.

5.2 Surrogate Safety Assessment Model

SSAM software can automate conflict analysis by directly processing vehicle trajectory data from VISSIM. It can provide a summary of the total number of conflicts broken down by type of conflict. In addition, SSAM could also calculate some surrogate safety measures for each event. Five measures were relevant to evaluate the traffic safety, which are TTC, PET, MaxS, DeltaS, DR and MaxD. Each surrogate safety measure is defined as follows:

- TTC (Time to collision): the time distance to a collision of two road users if they keep their directions and velocities. The shorter the TTC, the more dangerous the situation.
- PET (Post-encroachment time): the period of time from the moment when the first road user is leaving the conflict area until the second road user reaches it.
- MaxS: the maximum speed of either vehicle throughout the conflict measured in meter per second.
- DeltaS: is the difference in vehicle speeds as observed at the simulation time where the minimum TTC value for this conflict was observed measured in meter per second.
- DR: the initial deceleration of the second vehicle measured in meter per square second.
- MaxD: the maximum deceleration of the second vehicle measured in meter per square second.

After running the VISSIM model, SSAM software was used to analyze pedestrian-to-vehicle conflicts using vehicle trajectory files generated from VISSIM. However, SSAM was not explicitly designed for pedestrian conflict analysis, so there is no vehicle or entity type available in the trajectory file format by which to identify pedestrian conflicts. The only way to get the pedestrian-to-vehicle conflicts is to export the result as a csv file. From the csv file, the pedestrian-to-vehicle conflict can be filtered based on the “vehicle” length. The length of pedestrian is usually defined between 0.3 and 0.5 meter. In comparison, the length of vehicle is usually defined over 3.5 meters.

Chapter 6: Result Analysis

6.1 Determine the thresholds for TTC and PET

SSAM software uses two threshold values for surrogate measures of safety to detect the conflicts, which are maximum TTC and maximum PET. Also, SSAM utilizes a default maximum TTC value of 1.5 seconds and maximum PET value of 5 seconds to delineate the vehicle-to-vehicle conflicts. However, this study attempts to evaluate the pedestrian-to-vehicle conflict, which is totally different from the vehicle-to-vehicle conflicts. Therefore, the TTC and PET thresholds need to be adjusted for pedestrian-to-vehicle conflicts.

A number of trials were applied to arrive at the optimum TTC and PET thresholds. Finally, it is found that when the maximum TTC threshold ranges from 2 to 3 and the maximum PET ranges from 5 to 9, SSAM can provide a better estimate of number of conflicts that matches the field data. Therefore, further analysis is needed to determine the exact value of TTC and PET for pedestrian-to-vehicle conflicts. Then, the maximum TTC threshold is set as 2.0, 2.3, 2.5, 2.7, 3 for 5 levels, and the maximum PET threshold is set as 5, 6, 7, 8, and 9 for additional five levels. Therefore, 5*5=25 combinations of pedestrian-to-vehicles conflicts were generated by SSAM. The mean absolute percent error (MAPE) was used to measure the differences between the mean PET observed in the field and the mean PET simulated in VISSIM and SSAM. The MAPE value can be calculated by the following equation:

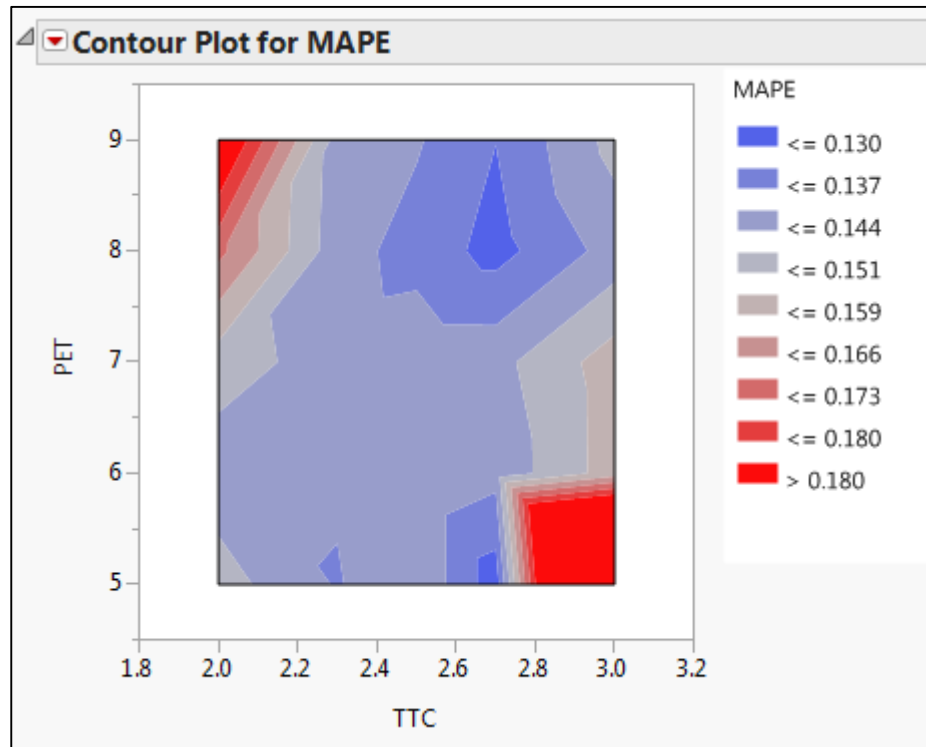
$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{c_s^i - c_o^i}{c_o^i} \right|$$

Where n represents the number of intersections, c_s^i represents the mean PET of the simulated conflicts for one intersection, and c_o^i represents the mean PET of the observed conflicts for one intersection.

MAPE value with different maximum TTC and PET threshold values is shown in Table 9. The MAPE value for the total conflicts varied from 12.7% to 73.2% for different TTC and PET threshold. In addition, the contour plot for MAPE is shown in Figure 11. It is found that when the TTC ranges from 2.6 to 2.8 seconds and PET threshold ranges from 8 to 9, the best goodness-of-fit between the observed and the simulated conflict of mean PET is achieved with the MAPE value under 13%. Therefore, the following analysis is based on the results when the TTC threshold is set as 2.7 and PET threshold is set as 8.

Table 11: MAPE value with different TTC and PET threshold values

Maximum PET threshold	Maximum TTC threshold				
	2	2.3	2.5	2.7	3
5	0.1473	0.1365	0.1438	0.1256	0.2885
6	0.1402	0.1382	0.1439	0.1394	0.1549
7	0.1475	0.1409	0.1421	0.1420	0.1551
8	0.1678	0.1399	0.1344	0.1273	0.1399
9	0.1922	0.1410	0.1378	0.1301	0.1467

**Figure 11: Contour plot for MAPE value with different TTC and PET threshold**

6.2 Relationship between simulated conflicts and observed conflicts

The number of average simulated conflicts for each three-hour interval (am hours or pm hours) is summarized and compared to the observed conflicts in the field. The data is shown in Table 10. From the field observation, it was found that Orange Ave & Central Blvd in the downtown area had large number of pedestrians and relatively low traffic volume compared to other intersections. This intersection was totally different from the other intersections. In addition, the simulated conflicts of this intersection were higher than the other intersections, which was abnormal. This was attributed to the fact that when a group of pedestrians cross the street in the field, they are only counted as one conflict. However, a group of pedestrians are counted as multiple conflicts in VISSIM. Since Orange Ave & Central Blvd has a large number of pedestrians and most of them cross the street as a group, the number of the simulated conflicts is much higher than that of observed conflicts. In comparison, other intersections have a relative

low pedestrian volume so that few people cross the street as a group. Therefore, the Orange Ave & Central Blvd is excluded in the following analysis. In this study, a linear regression model is applied to analyze the relationship between simulated and observed conflicts. The linear model is fitted to relate simulated conflicts to observed conflicts for each half-day time (three hours) interval. Figure 12 shows the regression analysis results of the linear regression model between observed conflicts and simulated conflicts.

Table 12: The number of simulated conflicts and observed conflicts

Intersection Name	Time	Simulated Conflicts	Observed Conflicts
Kirkman Rd & Conroy Rd	am	14	32
	pm	39	62
Martin Luther King & US 92	am	13	13
	pm	35	21
Orange Ave & Kaley St	am	33	33
	pm	50	29
Orange Ave & Central Blvd	am	404	90
	pm	432	114
Primrose Dr & Colonial Dr	am	7	23
	pm	12	41
Sand Lake Rd & I-Drive	am	116	139
	pm	174	156
Semoran Blvd & Pershing Ave	am	16	35
	pm	30	38
Silver Star & Hiawasse Rd	am	36	35
	pm	53	51

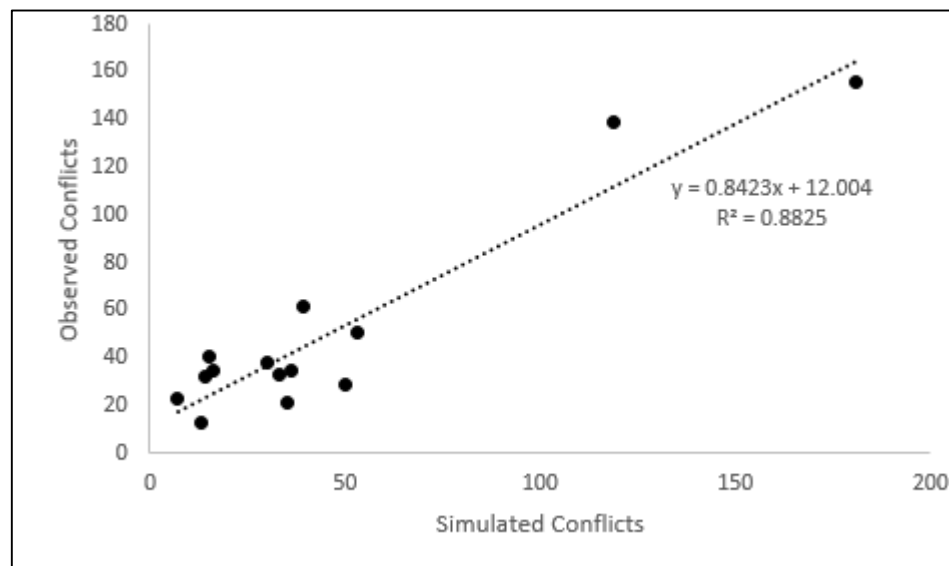


Figure 12: Relationship between simulated conflict and observed conflicts

According to the linear regression results, it is found that the p-value of independent variable is 0.00, indicating that number of simulated conflicts is significantly associated with the number of observed conflicts. In addition, the R^2 value for the model was 0.8825, which means that 88.25% of the variability in the observed conflicts can be explained by the variation in the simulated conflicts. For each one additional unit increase in the number of simulated conflicts, the mean of the observed conflicts is estimated to increase by 0.84. Although there is a significant statistical relationship between simulated conflicts and observed conflicts, the number of simulated conflicts estimated by VISSIM model and SSAM is less than the number of conflicts observed in the field. One possible explanation is that pedestrians may not adhere to the rules of the traffic signal 100% of the time in the field so that sometimes pedestrians could cross the street when the pedestrian signal is flashing or red. However, pedestrian could follow the pedestrian signal 100% in the VISSIM simulation model, thus resulting in the simulated conflicts being lower than the observed conflicts in the field.

6.3 Analysis of TTC and PET

The pedestrian-to-vehicle conflict data were from SSAM when the TTC threshold is set as 2.7 and PET threshold is set as 8. The statistical frequency distributions were developed for both TTC and PET, which are shown in Figure 13, and 14. The total conflicts for 7 intersections are 628 and the mean of TTC is 1.75 seconds with a standard deviation of 0.41 and the mean PET is 3.84 seconds with a standard deviation of 0.88.

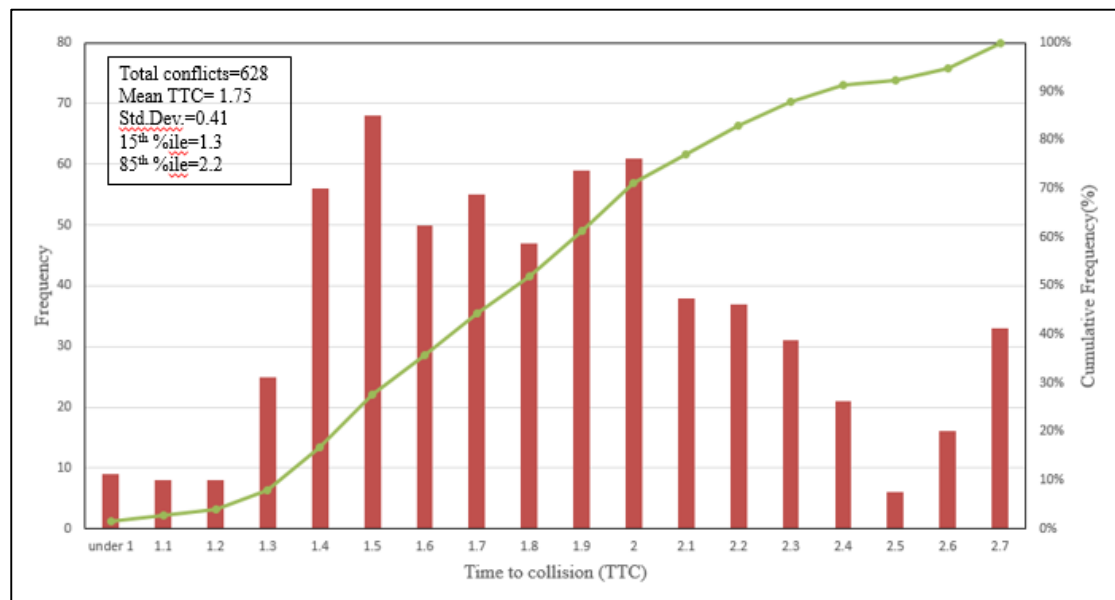


Figure 13: Time to collision (TTC) frequency distribution

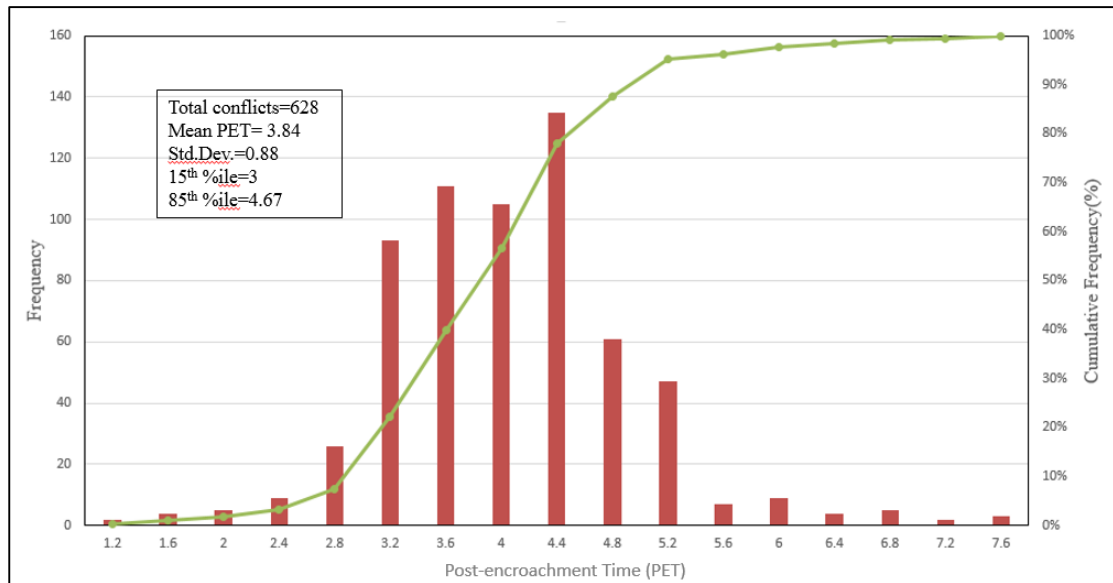


Figure 14: Post-encroachment Time (PET) frequency distribution

To investigate the relationship between TTC and PET, a simple linear regression is conducted. Figure 15 shows PET versus TTC with a linear regression model. According to the linear regression results, it is found that the p-value of independent variable is 0.00, indicating that TTC is significantly associated with PET. In addition, the R^2 value for the model is 0.62, which means that 62% of the variability in the PET can be explained by the variation in the TTC. It is believed that as the TTC increases, the PET increases.

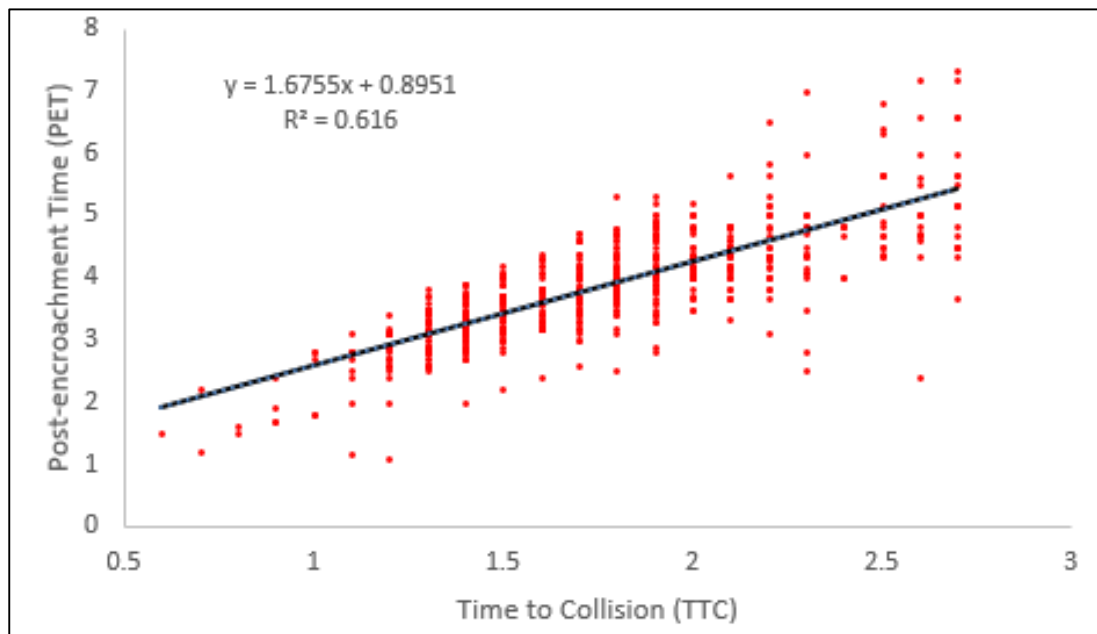


Figure 15: PET versus TTC

6.4 Multivariate Analysis for MaxS, DeltaS, DR and MaxD

In order to find out the relationship among the proposed countermeasures, the multivariate analysis was conducted among MaxS, DeltaS, DR and MaxD, which is shown in Table 11. According to the results, all of the correlation are over 0.05, indicating that each pair of response variables has the linear relationship. Figure 16 shows the scatterplot matrix for these variables. MaxS is correlated with DeltaS. The higher MaxS leads to the higher DeltaS. The DeltaS is the difference in vehicle speeds as observed at the simulation time where the minimum TTC value for this conflict was observed. However, MaxS is the maximum speed of vehicle during the conflict time period. MaxS is often very close to the DeltaS because the MaxS usually happens near the simulation time where the minimum TTC value is observed. In addition, MaxS is also correlated with DR and MaxD. As either DR or MaxD increases, MaxS decreases. This is because when the vehicles have a more deceleration rate, the speed during the vehicle throughout the conflict zone will decrease. DeltaS have the similar results on DR and MaxD. The larger DR and MaxD have the lower DeltaS.

Table 13: Correlation table for MaxS, DeltaS, DR, and MaxD

	MaxS	DeltaS	DR	MaxD
MaxS	1.000	0.953	-0.631	-0.379
DeltaS	0.953	1.000	-0.631	-0.415
DR	-0.631	-0.631	1.000	0.461
MaxD	-0.379	-0.415	0.461	1.000

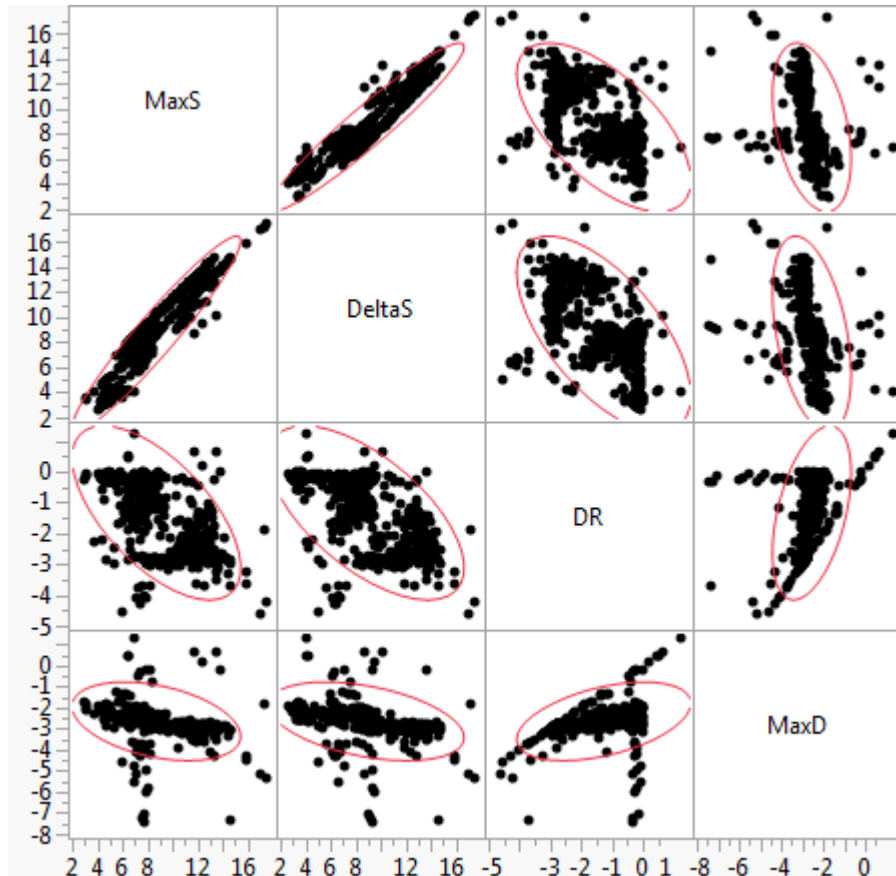


Figure 16: scatterplot matrix for MaxS, DeltaS, DR, and MaxD

Chapter 7: Conclusions

The main purpose of this study was to use traffic simulation models to better understand causes of pedestrian-related traffic crashes and assess selected countermeasures to enhance the safety of the public.

A comprehensive literature review was conducted to document previous published work related to the use of simulation in testing the safety and operations of vehicular traffic, and pedestrians. The literature included the simulation tools of VISSIM, cellular automata micro simulation, and driving simulator.

The appropriate simulation tool was needed to test the vehicle to pedestrian conflicts. The VISSIM and SSAM models were utilized to explore their abilities to provide reasonable results of surrogate safety measures. A virtual mid-block crossing was tested in VISSIM to simulate different levels of pedestrian volumes and vehicular traffic volumes and SSAM software was used to extract the surrogate safety measures for each conflict by directly processing vehicle trajectory data from VISSIM. Finally, it was concluded that the findings provide abundant evidence that VISSIM and SSAM models can be used to estimate pedestrian conflicts with vehicular traffic.

It was necessary to develop a calibrated and validated VISSIM model for the actual intersections. So eight intersections were selected from the field to collect the data and develop the VISSIM model. After that, SSAM was used to extract the pedestrian to vehicle conflicts by processing the vehicle trajectory data from the calibrated and validated model.

The mean absolute percent error (MAPE) was used to measure the differences between the mean PET observed in the field and the mean PET simulated in VISSIM and SSAM to get the suitable maximum TTC and PET threshold for pedestrian-to-vehicle conflicts. According to the results, it is found that when the maximum TTC and PET threshold are 2.7 and 8 seconds, respectively, the MAPE is the lowest, indicating the best goodness-of-fit between simulated conflicts and observed conflicts.

A linear regression model was used to identify whether the simulated conflicts are associated with the observed conflicts. According to the regression result, it was found that the number of simulated conflicts is significantly related to the number of observed conflicts. However, the number of simulated conflicts estimated by VISSIM model and SSAM were less than the number of conflicts observed in the field based on the regression result.

By analyzing the simulated conflict data, it was found that the mean of TTC is 1.75 seconds with a standard deviation of 0.41 and the mean PET is 3.84 seconds with a standard deviation of 0.88. In addition, six surrogate measures, including TTC, PET, MaxS, DeltaS, DR and MaxD, were analyzed to investigate the relationship between each other. It was found that TTC is significantly associated with PET and MaxS is correlated with DeltaS. Besides, MaxS is also correlated with DR and MaxD. As either DR or MaxD increases, MaxS decreases.

Acknowledgement

The authors extend their appreciation for the project sponsorship by the Southeast Transportation Center at University of Tennessee and for Mr. Charles Ramdatt at the city of Orlando for assisting with field data collection.

Reference

- Alhajyaseen, Wael K.M., Asano, M., and Nakamura, H. (2012) "Estimation of Left-turning Vehicle Maneuvers for the Assessment of Pedestrian Safety at Intersections", IATSS Research 36, pp. 66-74.
- Astrid, B., Johan, O., and Andreas, A. (2011). Analytical traffic models for roundabouts with pedestrian crossings. *Procedia Social and Behavioral Sciences*, Vol. 16, pp.697-708.
- Boot, W., Charness, N., Mitchum, A., Landbeck, R. and Stothart, C. (2014). Aging road user studies of intersection safety (No. BDV30 TWO 977-04). Retrieved from http://www.dot.state.fl.us/research-center/Completed_Proj/Summary_TE/FDOT-BDV30-977-04-rpt.pdf.

Cellular Automaton. (2014). In Wikipedia, the free encyclopedia. Modified on 13 November, 2014, from http://en.wikipedia.org/wiki/Cellular_automaton.

Chen Kuan-min, Luo Xiao-qiang, Ji Hai, and Zhao Yang-dong, (2010). Towards the pedestrian delay estimation at intersections under vehicular platoon caused conflicts. *Scientific Research and Essays* Vol. 5(9), pp.941-947.

Cornelia, B., and Tobias, K. Simulation of pedestrian crossing a street. (2009). *Traffic and Granular Flow* 09, 2009.

Ishaque, M. and Noland, R. Pedestrian and Vehicle Flow Calibration in Multimodal Traffic Microsimulation. *Journal of Transportation Engineering*, Vol. 135, No. 6, 2009, pp. 338-348.

Joon-Ki, K., Sungyop, K., Gudmundur, F. U., and Luis, A.P. (2007). Bicyclist injury severities in bicycle-motor vehicle accidents. *Accident Analysis & Prevention*, Vol 39, No. 2, pp.238-251.

Kolisetty, V.G.B., Iryo, T., Asakura, Y., and Kuroda, K. (2006). Effect of variable message signs on driver speed behavior on a section of expressway under adverse fog conditions- a driving simulator approach. *Journal of Advanced Transportation*, Vol. 40, no. 1, pp. 47-74.

Lee, C., and Abdel-Aty, M. (2008). Testing effects of warning messages and variable speed limits on driver behavior using driving simulator. *Transportation Research Record*, no. 1069, pp. 1743-1748.

Lee, C., and Abdel-Aty, M. Comprehensive Analysis of Vehicle-pedestrian Crashes at Intersections in Florida. *Accident Analysis and Prevention*, Vol. 37, 2005, pp. 775-786

Leur, D. P., Sayed, T. Development of a Road Safety Risk Index. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1784, Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 33-42.

Li, X., Yan, X., Li, X., and Wang, J. (2012). Using cellular automata to investigate pedestrian conflicts with vehicles in crosswalk at signalized intersection. *Discrete Dynamics in Nature and Society*, 2012.

Maerivoet, S., and De Moor, B. (2005). Cellular automata models of road traffic, *Physics Reports*, Vol 419, no.1, pp.1-64.

Muhammed, M.I., and Robert, B.Noland. (2005). Pedestrian modeling in urban road networks: Issues, limitations and opportunities offered by micro simulation. Paper presented in the 9th International Conference on Computers in Urban Planning and Urban Management, London.

Muhammed, M.I., and Robert, B.Noland. (2009). Pedestrian and vehicle flow calibration in multimodal traffic micro simulation. *Journal of Transportation Engineering*, Vol 135, pp.338-348.

Muhammed, M.I., and Robert, B.Noland. (2008). Simulated pedestrian travel and exposure to vehicle emissions. *Transportation Research Part D*, Vol.13, Bo.1, pp.27-46.

Noland, R. B., Quddus, M. A. (2004) "An Analyses of Pedestrian and Bicycle Casualties Using Regional Panel Data", Transportation Research Record: Journal of the Transportation Research Board, Vol.1897, pp. 28-33.

Oh, C., Park, S., and Ritchie, S. G. A Method for Identifying Rear-end Collision Risks Using Inductive Loop Detectors. Accident Analysis and Prevention, Vol. 38, 2006, pp. 295-301.

PTV, VISSIM 5.10 User Manual. (2008). PTV Planung Transport Verkehr AG, Junly, 2008.

Qi, Y., Yuan, P. (2012) "Pedestrian Safety at Intersections Under Control of Permissive Left-Turn Signal", Transportation Research Record: Journal of the Transportation Research Board, Vol.2299, pp. 91-99.

Robert, B.Noland, and Mohammed, A. (2004). Quddus. An analyses of pedestrian and bicycle casualties using regional panel data. Transportation Research Record: Journal of the Transportation Research Board, 1897, 28-33.

Rouphail, N., Hughes, R., and Chae, K. (2005). Exploratory simulation of pedestrian crossings at roundabouts. Journal of Transportation Engineering, 131(2), pp.211-218.

Rickert, M., Nagel, K., Schreckenberg, M., and Latour, A. (1996). Two-lane traffic simulation using cellular automata. Physica A, Vol. 231, pp.534-550.

Souleyrette, R., and Hochstein, J. Documentation of Development of a Conflict Analysis Methodology Using SSAM. Publication InTrans Project 10-376, Highway Administration, 2012.

V.J. Blue, J.L. Adler. (2001). Cellular automata micro simulation for modeling bi-directional pedestrian walkways. Transportation Research Part B, Vol. 35, pp.293-312.

Wael K.M., Alhajyaseen, Miho, A., and Hideki, N. (2012). Estimation of left-turning vehicle maneuvers for the assessment of pedestrian safety at intersections. IATSS Research 36, pp. 66-74.

Williams, A. (2013) "Pedestrian Traffic Fatalities by State".

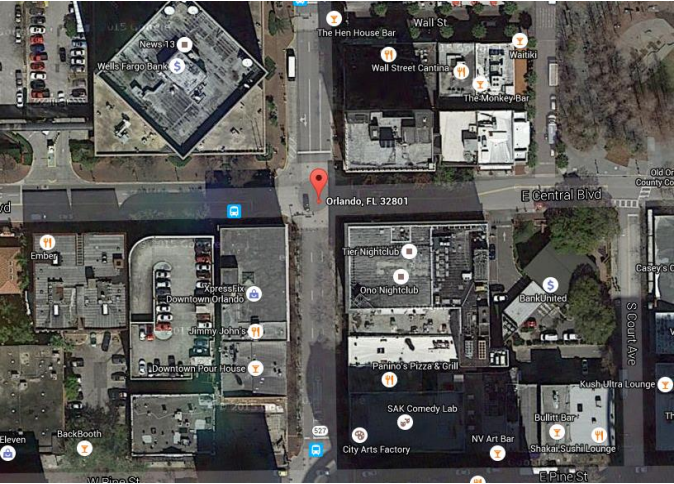


Yuan, Q., Li, Y., Liao, Y., and Tang, S. (2013) Study of correlation between driver emergency measures and pedestrian injury based on combined driving simulator and computer simulation. Advances in Mechanical Engineering, 2013.

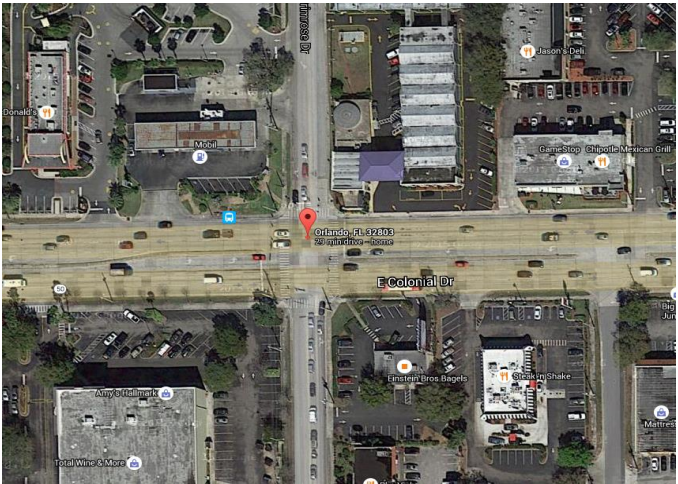
Yue, H., and Guan, H. (2010). Study on bi-direction pedestrian flow using cellular automata simulation. Physica A, Vol. 389, pp.527-539.

Zegeer, C. V., Stewart, R., Huang, H., and Lagerwey, P. (2002) "Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations: Executive Summary and Recommended Guidelines", FHWA-RD-01-075, McLean, Va., Federal Highway Administration.

Zhang, X., and Chang, G. (2014). A mixed-flow simulation model for congested intersections with high pedestrian-vehicle traffic flows. Simulation: Transactions of the Society for Modeling and Simulation International, Vol. 90(5), pp.570-590.

Appendix A: Pictures showing each experimental site

	<p>Orange Ave & Central Blvd</p> <p>Image from Google Maps</p>
	<p>Orange Ave & Central Blvd</p> <p>Eastbound of Central Blvd</p>
	<p>Orange Ave & Central Blvd</p> <p>Southbound of Orange Ave</p>



Primrose Dr & Colonial Dr

Image from Google Maps



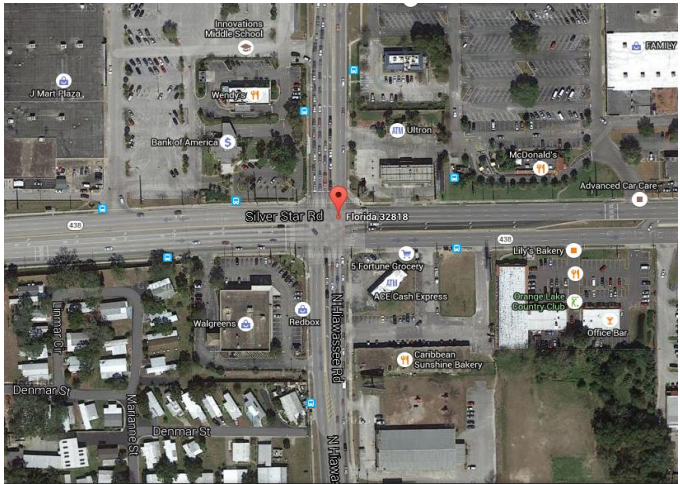
Primrose Dr & Colonial Dr

Eastbound of Colonial Dr



Primrose Dr & Colonial Dr

Northbound of Primrose Dr



Silver Star & Hiawasse
Rd

Image from Google Maps



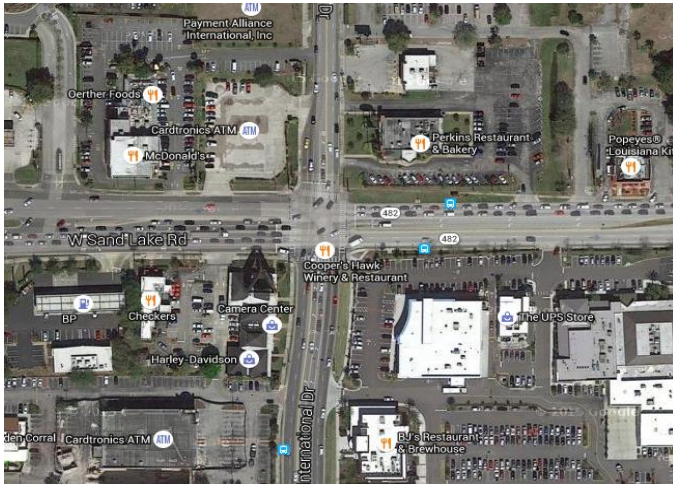
Silver Star & Hiawasse
Rd

Eastbound of Silver Star



Silver Star & Hiawasse
Rd

Northbound of Hiawasse
Rd



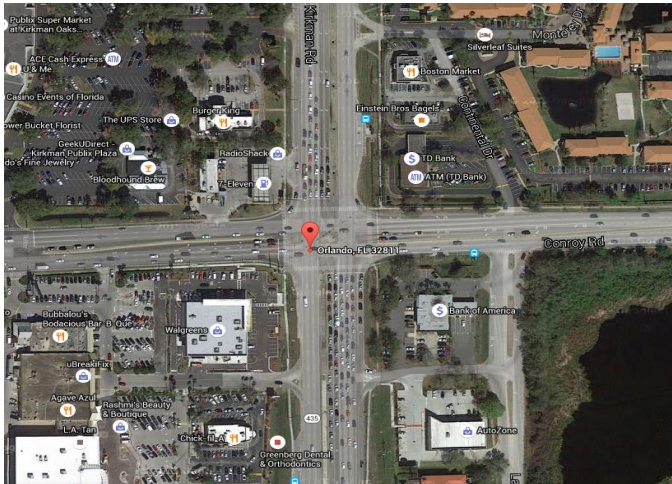
Sand Lake Rd & I-Drive
Image from Google Maps



Sand Lake Rd & I-Drive
Eastbound of Sand Lake Rd



Sand Lake Rd & I-Drive
Northbound of I-Drive



Kirkman Rd & Conroy Rd

Image from Google Maps



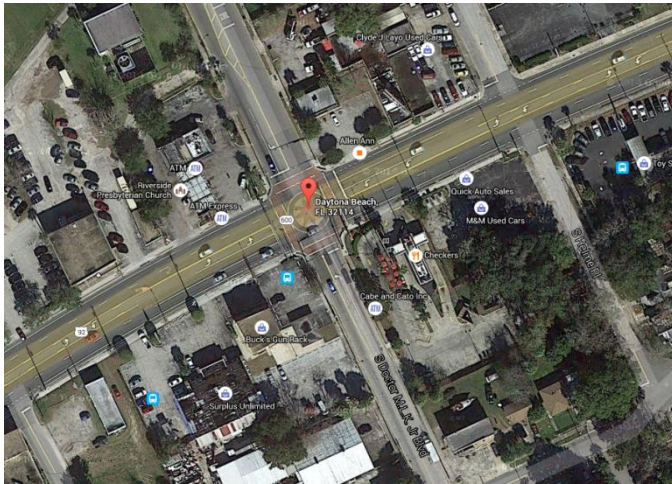
Kirkman Rd & Conroy Rd

Eastbound of Conroy Rd



Kirkman Rd & Conroy Rd

Northbound of Kirkman Rd



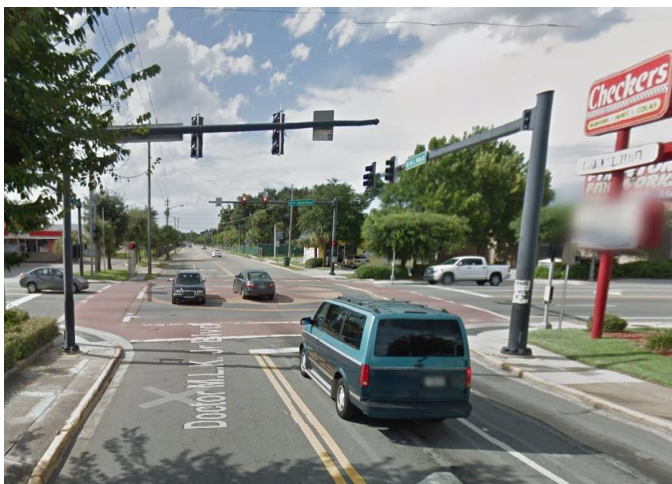
Martin Luther King & US
92

Image from Google Maps



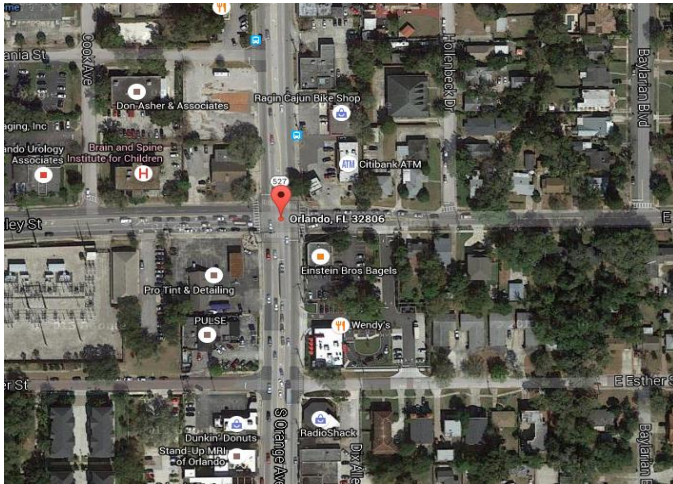
Martin Luther King & US
92

Eastbound of US 92



Martin Luther King & US
92

Northbound of Martin
Luther King



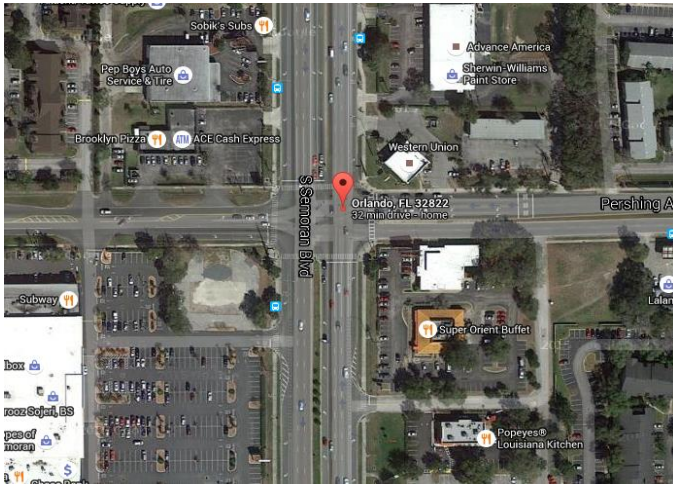
Orange Ave & Kaley St
Image from Google Maps



Orange Ave & Kaley St
Eastbound of Kaley St



Orange Ave & Kaley St
Northbound of Orange Ave



Semoran Blvd & Pershing Ave

Image from Google Maps



Semoran Blvd & Pershing Ave

Eastbound of Pershing Ave



Semoran Blvd & Pershing Ave

Northbound of Orange Ave