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A Microscopic Simulation Study of Applications of Signal Phasing and Timing Information in a Connected Vehicle Environment

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A MICROSCOPIC SIMULATION STUDY OF APPLICATIONS OF SIGNAL PHASING AND TIMING INFORMATION IN A CONNECTED VEHICLE ENVIRONMENT

By

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DEDICATION

I would like to dedicate this thesis to my late father Lt. Col. Lameck Njobelo; may his soul rest in peace.

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I would like to express my sincere gratitude to every person who in one way or another contributed in developing the idea for this thesis work. I would like to thank my supervisor, Dr. Thobias Sando for his extensive support, guidance, encouragement and corrective work. His help has been a great support towards the execution of this thesis work.

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AASHTO	American Association of State Highway and Transportation Officials
AGLOSA	Adaptive Green Light Optimized Speed Advisory
API	Application Programming Interface
ASAS	Advance Stop Assist System
AV	Autonomous Vehicle
BSM	Basic Safety Message
C2X	Car-to-Devices
CAV	Connected and Autonomous Vehicles
CICAS	Cooperative Intersection Collision Avoidance System
CICAS-LTA	Cooperative Intersection Collision Avoidance System (Signalized Left-Turn Assist)
CICAS-TSA	Cooperative Intersection Collision Avoidance System (Traffic Signal Adaptation)
CICAS-V	Cooperative Intersection Collision Avoidance System (Traffic Signal Violation)
COM	Component Object Model
CORSIM	Corridor Simulation
CV	Connected Vehicles
dBm	Decibel-Milliwatts
DOT	Department of Transportation
DSRC	Dedicated Short Range Communications

EBL	East-Bound Left
EBR	East-Bound Right
EBT	East-Bound Through
Eco-CACC	Eco-Cooperative Adaptive Cruise Control
EPA	Environmental Protection Agency
FCC	Federal Communications Commission
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GA	Genetic Algorithm
GEV	Generalized Extreme Value
GHG	Greenhouse Gases
GHz	Giga Hertz
GIS	Geographic Information System
GLOSA	Green Light Optimized Speed Advisory
GPS	Global Positioning System
I2V	Infrastructure-to-Vehicle
ID	Identification
ITS	Intelligent Transportation System
K-S	Kolmogorov-Smirnov
LHD	Latin Hypercube Design
MaxD	Maximum Deceleration
MHz	Mega Hertz
MOEs	Measures of Effectiveness

NB	North Bound
NBL	North-Bound Left
NBT	North-Bound Through
NBR	North-Bound Right
NDS	Naturalistic Driving Study
OBU	On-Board Unit
OD	Origin-Destination
PET	Post Encroachment Time
PHEM	Passenger Car and Heavy Duty Emission Model
RMSE	Root Mean Square Error
RSU	Roadside Unit
SBL	South-Bound Left
SBR	South-Bound Right
SBT	South-Bound Through
SHRP2	Strategic Highway Research Program 2
SPaT	Signal Phasing and Timing
SSAM	Surrogate Safety Assessment Model
THEA	Tampa-Hillsborough Expressway Authority
TTC	Time to Collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VB	Visual Basic
VII	Vehicle-Infrastructure-Integration

VISSIM	Verkehr In Städten – SIMulationsmodell
WBL	West-Bound Left
WBR	West-Bound Right
WBT	West-Bound Through

ABSTRACT

The connected vehicle technology presents an innovative way of sharing information between vehicles and the transportation infrastructure through wireless communications. The technology can potentially solve safety, mobility, and environmental challenges that face the transportation sector. Signal phasing and timing information is one category of information that can be broadcasted through connected vehicle technology. This thesis presents an in-depth study of possible ways signal phasing and timing information can be beneficial as far as safety and mobility are concerned. In total, three studies describing this research are outlined.

The first study presented herein focuses on data collection and calibration efforts of the simulation model that was used for the next two studies. The study demonstrated a genetic algorithm procedure for calibrating VISSIM discharge headways based on queue discharge headways measured in the field. Video data was used to first compute intersection discharge headways for individual vehicle queue position and then to develop statistical distributions of discharge headways for each vehicle position. Except for the 4th vehicle position, which was best fitted by the generalized extreme value (GEV) distribution, the Log-logistic distribution was observed to be the best fit distribution for the rest of vehicle positions. Starting with the default values, the VISSIM parameters responsible for determining discharge headways were heuristically adjusted to produce optimal values. The optimal solutions were achieved by minimizing the Root Mean Square Error (RMSE) between the simulated and observed data. Through calibration, for each vehicle position, it was possible to obtain the simulated headways that reflect the means of the observed field headways. However, calibration was unable to replicate the dispersion of the headways observed in the field mainly due to VISSIM limitations. Based on the findings of this

study, future work on calibration in VISSIM that would account for the dispersion of mixed traffic flow characteristics is warranted.

The second study addresses the potential of connected vehicles in improving safety at the vicinity of signalized intersections. Although traffic signals are installed to reduce the overall number of collisions at intersections, rear-end collisions are increased due to signalization. One dominant factor associated with rear-end crashes is the indecisiveness of the driver, especially in the dilemma zone. An advisory system to help the driver make the stop-or-pass decision would greatly improve intersection safety. This study proposed and evaluated an Advanced Stop Assist System (ASAS) at signalized intersections by using Infrastructure-to-Vehicle (I2V) and Vehicle-to-Vehicle (V2V) communication. The proposed system utilizes communication data, received from Roadside Unit (RSU), to provide drivers in approaching vehicles with vehicle-specific advisory speed messages to prevent vehicle hard-braking upon a yellow and red signal indication. A simulation test bed was modeled using VISSIM to evaluate the effectiveness of the proposed system. The results demonstrate that at full market penetration (100% saturation of vehicles equipped with on-board communication equipment), the proposed system reduces the number of hard-braking vehicles by nearly 50%. Sensitivity analyses of market penetration rates also show a degradation in safety conditions at penetration rates lower than 40%. The results suggest that at least 60% penetration rate is required for the proposed system to minimize rear-end collisions and improve safety at the signalized intersections.

The last study addresses the fact that achieving smooth urban traffic flow requires reduction of excessive stop-and-go driving on urban arterials. Smooth traffic flow comes with several benefits including reduction of fuel consumption and emissions. Recently, more research efforts have been directed towards reduction of vehicle emissions. One such effort is the use of Green

Light Optimal Speed Advisory (GLOSA) systems which use wireless communications to provide individual drivers with information on the approaching traffic signal phase and advisory speeds to arrive at the intersection on a green phase. Previously developed GLOSA algorithms do not address the impact of time to discharge queues formed at the intersection. Thus, this study investigated the influence of formed intersection queues on the performance of GLOSA systems. A simulation test-bed was modeled inside VISSIM to evaluate the algorithm's effectiveness. Three simulation scenarios were designed; the baseline with no GLOSA in place, scenario 2 with GLOSA activated and queue discharge time not considered, and scenario 3 with GLOSA activated and where queue dissipation time was used to compute advisory speeds. At 95% confidence level the results show a significant reduction in the time spent in queue when GLOSA is activated (scenarios 2 and 3). The change in the average number of stops along the corridor was found not to be significant when the base scenario was compared against scenario 2. However, a comparison between scenarios 2 and 3 demonstrates a significant reduction in the average number of stops along the corridor, and also in the time spent waiting in queues.

Keywords: Discharge Headway, VISSIM, Genetic Algorithm, Connected vehicles, Vehicle-to-Infrastructure, Advanced Stop Assist System, Microsimulation, GLOSA, Advisory Speed, Advanced Signal Controls.

CHAPTER 1 INTRODUCTION

Background

The history of Connected Vehicles (CV) can be traced back to 2003 when the U.S. Department of Transportation first launched the Vehicle-Infrastructure-Integration (VII) program (Songchitruksa & Zha, 2014). The initial objective of VII was to address the traffic safety problems through high-speed wireless communications among Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I). Information about vehicles, infrastructure, and the environment can be relayed to individual entities such as drivers, vehicles, or transportation agencies through wireless communication. CV technology consists of different ways of sharing data and innovative ways to use these data to improve safety, mobility, and the environment. Due to CV technology's immense potential for solving various transportation problems, the U.S. Department of Transportation (DOT) has significantly invested in research in this area. There has been development of prototypes and test bed facilities in Arizona, Michigan, California, Florida, New York, Tennessee, and Virginia (Songchitruksa, Bibeka, Lin, & Zhang, 2016).

When fully implemented, it is expected that connected vehicles will yield unprecedented levels of anonymous data that will be the basis for a multitude of innovative applications that will lead to smart vehicles, smart infrastructure, and ultimately smart cities. Research has found that the technology could reduce unimpaired vehicle crashes by 80 percent, while also reducing the 4.8 billion hours that Americans spend in traffic annually (FHWA, n.d.).

One of the applications of connected vehicles is the communication of Signal Phasing and Timing (SPaT) information to vehicles which are approaching an intersection. Information like signal status, running time and signal switching times can be relayed to vehicles in the intersection approach to help drivers in making early and informed decisions. This technology has a potential of reducing vehicular conflicts, fuel consumption and emissions resulting from stop-and-go movements along corridors with signalized intersections.

CV test beds include prototype test beds and simulation test beds. Prototype test beds are limited by high cost and small scale. Most CV application algorithms are first tested and evaluated in simulation test beds. Only when the CV application development is in the real-world implementation phase, prototype test beds are used to test their functionality and feasibility (Songchitruksa et al., 2016).

Study Objectives

CV technology has an immense potential for solving various transportation problems. This thesis provides an in-depth simulation evaluation of different safety and mobility applications of SPaT information in a CV environment. The main goals are:

1. To calibrate a VISSIM simulation model using queue discharge headway data observed in the field.
2. To propose and demonstrate the implementation of an Advance Stop Assist System (ASAS) in a microscopic simulator.
3. To evaluate potential safety benefits of ASAS.
4. To develop a modified Green Light Optimized Speed Advisory (GLOSA) algorithm that considers the formed intersection queues and queue discharge headways for each vehicle position in helping drivers to arrive on green signal indication in a series of signalized intersections.

Potential Study Benefits

In 2013, a total of 4,700 fatal crashes, 826,000 injury crashes, and 1.76 million property-damage-only crashes occurred in relation to signalized intersections in the United States (U.S.); nearly 30% of these were rear-end collisions (NHTSA, 2013). Additionally, the transportation sector is the second largest source of Greenhouse Gas (GHG) emissions in the United States (U.S.), according to the Environmental Protection Agency (EPA) (U.S. Environmental Protection Agency, 2010). More than 60 percent of the energy used in the U.S. transportation sector is due to light-duty vehicles (EIA, 2010), a higher proportion being attributed to the stop-and-go vehicular movement. This study explores the potential of the CV technology for solving these problems by relaying SPaT information to vehicles approaching the intersection. Drivers are expected to make better and informed decisions that will reduce stop-and-go movements and vehicular conflicts at the vicinity of signalized intersections.

Thesis organization

This thesis is comprised of five chapters. Chapter 1 provides the general overview of the research problem, the description of the research objectives, and possible contributions of the study to research and industrial realm at large. The next three chapters of the thesis are comprised of three research articles. Chapter 2 is a stand-alone journal paper that addresses the efforts of calibrating vehicle discharge headways in a simulation model. It has been submitted for publication consideration. Chapter 3 focuses on the second and third objectives. It is another journal article that has already been accepted for publication. Chapter 4 focuses on the third objective. It is a stand-alone journal paper that was presented at the 97th annual meeting of the Transportation Research Board (TRB). Chapters 5 provides the overall conclusions of the study.

CHAPTER 2

Calibration of VISSIM Discharge Headways Based on Field Measured Values and Naturalistic Driving Study Data

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Introduction

Microscopic simulation is widely used in transportation engineering for evaluating facility performance during operation and for planning phase as well. When done correctly, simulation models also have the ability to capture most of the stochastic variability of real-world traffic conditions geometries (Park & Qi, 2005). For accurate and reliable results, simulation models have to be well calibrated and validated to account for site conditions. There are some agencies that have developed guidelines to use for calibration (Florida Department of Transportation, 2014; Hadi, Sinha, & Wang, 2007; Jin et al., 2009). These guidelines have focused on ensuring that a certain tolerance level is maintained for selected Measures of Effectiveness (MOEs). Most calibration efforts reported in the literature have focused on macroscopic parameters like volume, travel time, capacity, and delay (Hadi et al., 2007). With the increasing research efforts in the field of transportation, microscopic parameters like discharge headways can no longer be overlooked in the calibration and validation procedures. A need for calibrating microscopic variables such as discharge headway has been heightened by an increased interest in the use of microscopic simulation to evaluate the benefits of connected and autonomous vehicles (CVs and AVs). The current traffic flow – with mixed traffic flow characteristics, has highly stochastic discharge headways, with widely dispersed distributions (Jin et al., 2009). Also, the current car following behavior causes varied vehicle spacing when stopped and different headways when being discharged from the queue. On the other hand, the extreme end of automation (100% AVs) is expected to have relatively uniform headway distributions and possibly shorter headways due to platooning effect. If discharge headways are not calibrated, the simulation results would potentially underrepresent the benefits of CVs and AVs because the default values do not capture heterogeneity of discharge headways. This study aimed at calibrating discharge headways based on field measurements and naturalistic driving study (NDS) data. VISSIM, one of the widely used microscopic simulator, is employed for this study.

Literature Review

Calibration

Traffic conditions are location-specific. As a result, calibration and validation of a simulation model requires collection of local traffic data. Traffic volume, speed distributions, delays, travel time and queuing data are among the data required for calibration and validation. A report by Park and Won (Park & Won, 2006) discusses in detail the data requirements for calibration and validation of microscopic simulation models. For successful calibration and validation of simulation models, it is important to have accurate and detailed traffic data which include link traffic volumes, turning movement counts and travel times (Hollander & Liu, 2008). While a number of studies have suggested calibration of microsimulation models by only adjusting driving behavior parameters (Jayakrishnan, Oh, & Sahraoui, 2001; Kim & Rilett, 2003), other studies consider calibration as a wider problem and they also try to simultaneously incorporate calibration of route choice models (Toledo et al., 2003; Toledo, Ben-Akiva, Darda, Jha, & Koutsopoulos, 2004). The latter procedure is considered stronger because solving individual sub-problems separately might lead to biased estimates (Hollander & Liu, 2008).

Geographical scale also presents an interesting difference between different calibration studies. The differences arise from the size of the network being modeled and the number of observation points during the collection of actual field data (Hollander & Liu, 2008). While some studies focus on a single intersection (Tao Ma & Abdulhai, 2002; Buck, Mallig, & Vortisch, 2017), the network size may be as large as the whole metropolitan area (Park & Qi, 2005). There is also a substantial variation in the number of parameters being calibrated in different studies, generally in the range of 3 to 19 parameters (Hollander & Liu, 2008). With a smaller number of parameters, it is easy to observe the overall effect of a single parameter when it is modified. Bigger parameter sets are normally calibrated using automated algorithms. This improves the efficiency in getting closer to an optimum solution although the procedure may get very intensive computationally. Another important difference that is observed across different calibration studies is the choice and number of traffic measures used in comparing simulation outputs to observed data. While some studies propose procedures that use only a single measure (Tao Ma & Abdulhai, 2002; Kim & Rilett, 2003), a number of other notable studies perceive calibration as a multi-stage procedure that uses a different measure for each calibration stage. In a study by Dowling et al. (Dowling, Skabardonis, Halkias, McHale, & Zammit, 2004), calibration starts by adjusting driving behavior parameters to match simulated and observed capacities. In the second stage, calibration of route choice parameters is done by using flow data. Finally, all parameters are fine-tuned by using travel time and queue length data. A similar procedure was used in a study by Hourdakis et al. (Hourdakis, Michalopoulos, & Kottommannil, 2003).

Calibration by using a number of measures simultaneously reduces the risk of obtaining an optimum fit by adjusting the wrong parameters (Hollander & Liu, 2008). However, there are circumstances in which different traffic measures are more appropriate for calibrating different parameters. In such a case, it is important to decompose the calibration problem into sub-problems. A study by Hollander and Liu (Hollander & Liu, 2008) suggests that decomposition of the calibration problem should only be done when the sub-problems are independent from each other.

Calibration of VISSIM Intersection Models

Although there are different guidelines on the calibration and validation of simulation models, most of them do not cover specific aspects of individual traffic flow simulation software. Calibration of VISSIM models for different facilities has been discussed in a number of studies (Gomes, May, & Horowitz, 2004; Menneni, Sun, & Vortisch, 2008; Manjunatha, Vortisch, & Mathew, 2013; Geistefeldt et al., 2014). Most of the available literature is on different procedures for calibrating freeway facilities and arterial corridors. Only a few notable studies exist that discuss the calibration of VISSIM intersection models. Calibration of roundabouts in VISSIM is discussed in a study by Cicu et al. (Cicu, Illotta, Bared, & Isebrands, 2011). The use of intersection maximum queue length data for validation is demonstrated in studies by Park et al. (Park & Qi, 2005; Park & Won, 2006). A study by Cunto and Saccomanno (Cunto & Saccomanno, 2008) provided an alternative approach to calibration of signalized intersections in VISSIM through the use of safety performance measures. Most of the VISSIM intersection calibration studies use delay or travel time data. The use of discharge headway data for calibration has not been deeply investigated. A study by Buck et al. (Buck et al., 2017) used discharge headway data as part of the calibration procedure. The performance of the calibrated model was measured by using average values of discharge headways for each queue position. The study did not provide an extensive analysis in the distribution of simulated discharge headway data and how the calibration process affected it. Therefore, the present study aims at calibrating the simulated VISSIM headways based to reflect the ones observed in the field by adjusting car following parameters that influence discharge headways. To extend the research that was conducted by Buck et al. (Buck et al., 2017), this study will not only base calibration on mean headways but would explore calibration of simulated headway distributions to resemble those of the observed field data.

Vehicle Discharge Headway

The discharge headway at signalized intersections is a microscopic traffic flow characteristic used for estimating intersection capacity and as a safety surrogate measure. The use of inaccurate discharge headways may lead to wrong estimations of traffic flow characteristics influenced by this parameter.

The headway of the first vehicle consists of three parts; start-up of the first vehicle, elapsed time for the first vehicle to pass the stop line, and elapsed time before the front of the second vehicle touches the stop line; while the headways of other vehicle positions do not have the first component (Jin et al., 2009). The characteristics of the first discharge headway is often studied independently from other vehicle positions (Jin et al., 2009). For similar reasons, the present study focused on the second through the tenth vehicle position in the queue.

Several studies have been carried out in the last five decades to investigate how discharge headways are influenced by external factors such as number of lanes, vehicle type and vehicle maneuver (Greenshields, Schapiro, & Ericksen, 1947; Carstens, 1971; Zegeer, 1986; Luttinen, 1992; Jin et al., 2009; Panichpapiboon, 2015; Badhrudeen, Ramesh, & Vanajakshi, 2016). One of the facts addressed by previous studies is that discharge headway tends to decrease sequentially with respect to the queue position. The first discharge headway is usually larger because it requires a longer reaction time. Normally, a steady headway is achieved starting at the fourth or the fifth vehicle. Nevertheless, while most previous studies focused on estimating the mean discharge headways, few studies have focused on the detailed distribution of the discharge headways (Jin et al., 2009; Yin, Li, Zhang, Yao, & Li Li, 2009; Wu, Hu, & Sun, 2010; Panichpapiboon, 2015).

Findings in studies that explored discharge headways using distributions identified different distributions to fit the observed discharge headway data. While Zhang et al. (Zhang, Wang, Wei, & Chen, 2007) determined that log-normal distributions fit observed headways better, other studies found the generalized extreme value (GEV) model to provide the best fit (Yin et al., 2009; Panichpapiboon, 2015) for field headway data. On the other hand, log-normal distribution was observed to be the best fit for headway data collected during off peak-hours while log-logistic distribution was observed to be better for discharge headways collected under the congested traffic environment (Yin et al., 2009; Wu et al., 2010; Jang, Park, Kim, & Choi, 2011). In general, these models provide a convenient way to characterize stochastic features of the vehicles discharge process.

Methodology

Study Site

A simulation model was developed for a signalized intersection located in the city of Tampa, Florida (Figure 2.1). It is an intersection between Bruce B Downs Boulevard and University Square Drive, adjacent to the University of South Florida. The intersection is one of the four major signalized intersections located in the Bruce B Downs corridor. The site was chosen because of the availability of naturalistic driving data for different age groups collected by the Strategic Highway Research Program 2 (SHRP2). The naturalistic driving data was used for simulation input data, specifically, speed profiles, deceleration and acceleration rates.

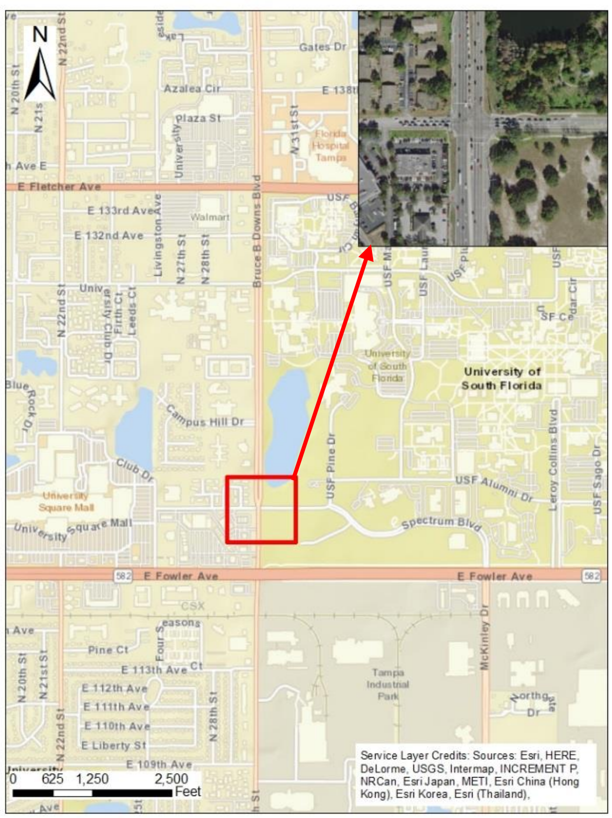


Figure 2.1 Study site.

Data Collection

Data were collected during the morning peak hour between 8:00 and 10:00 a.m. on three consecutive days, March 20 to March 22, 2017. This helped to capture the day to day variability. The morning peak was chosen because longer queues were observed to form during this time along the direction of the corridor that was used for data collection. Video recorders were used to record discharging queues at the intersection. The field set up included two video cameras as shown in Figure 2.2. The upper camera was strategically placed to capture vehicles as they cleared the intersection. The lower camera was used to record the signal switching times. In order to obtain a clear view of the vehicles and to capture the entire queue length, the upper camera was mounted at a height of at least 15 feet above the existing grade. Utility poles and sign posts were used for mounting the cameras as shown in Figure 2.2. Travel time data were obtained by using the floating car technique with a Global Positioning System (GPS) receiver that logged in data at every second. A total of 40 runs in 3 different days were done between two established points along the corridor.

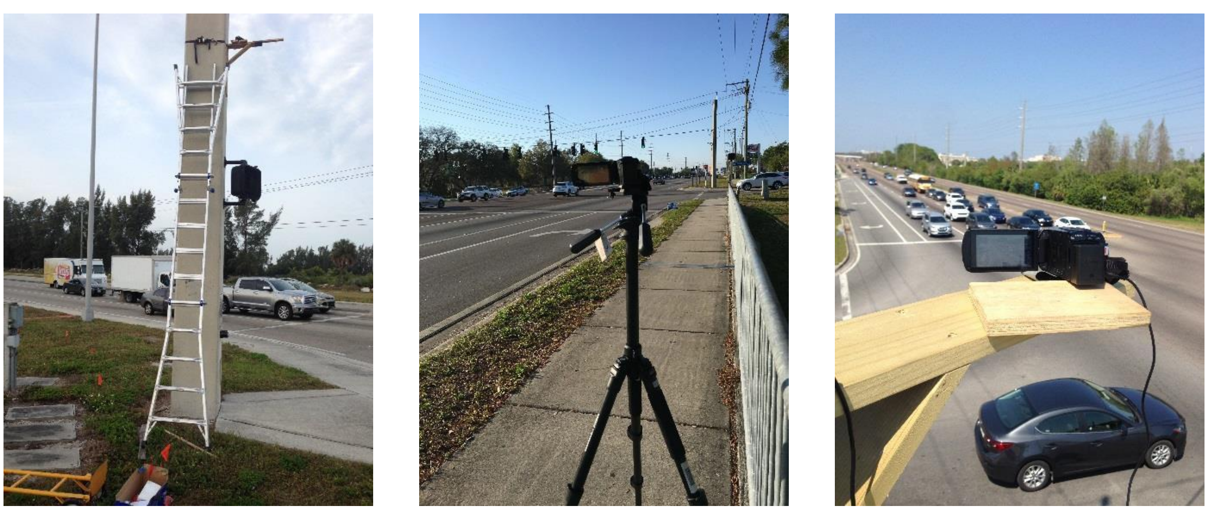


Figure 2.2 Video recording setup.

Data Reduction Process

The videos recorded by the lower and upper camera were synchronized in order to keep track of the start of green phase. Discharge headway data was then extracted from the videos by tracking the time at which the rear bumper of queued up vehicles crossed the stop line. The site chosen had an exclusive right turn lane. Only the discharge headways for the through movement was used in this study. The summary of the observed discharge headways is shown in Table 2.1. Travel time data was processed in Geographic Information System (GIS). To compute travel time, a shapefile for each trip was created from the GPS data that contained coordinates and time stamps at 1 second resolution. The travel time data was obtained by taking a difference between the time stamps at the first and the last point of the established measurement section. Queue lengths were extracted from the recorded videos by counting the number of queued up vehicles before the start of a green phase.

Table 2.1 Summary of Observed Discharge Headways

Position	Sample size	Maximum	Minimum	Range	Mean	Median	Variation
2	135	9.09	0.72	8.37	3.74	3.61	1.21
3	133	7.25	0.81	6.44	2.61	2.45	0.83
4	127	6.80	1.28	5.51	2.47	2.19	0.81
5	127	6.44	1.13	5.31	2.41	2.31	0.83
6	122	5.66	1.00	4.66	2.28	2.12	0.54
7	116	6.07	0.89	5.19	2.33	2.26	0.71
8	107	5.58	0.97	4.61	2.09	1.99	0.61
9	96	4.18	0.71	3.47	2.09	1.94	0.52
10	86	4.65	1.00	3.65	2.14	1.96	0.61

Fitting of Headway Distributions

MATLAB software was used to fit different parametric probability distributions to the field headway data for each of the vehicle queue position. The following parametric distribution models were tested: normal distribution, t-location scale distribution, log-normal distribution, log-logistic distribution, logistic distribution, generalized extreme value (GEV), Weibull distribution, inverse Gaussian distribution, Gamma distribution, exponential distribution, extreme value, and beta distribution. The Kolmogorov-Smirnov (K-S) test was used to determine the best fit distribution for each of the vehicle position. This test measures how well the data follow a particular distribution. The K-S test has also been used by previous studies (Jin et al., 2009; Yin et al., 2009; Wu et al., 2010; Panichpapiboon, 2015). The best-fit distribution is determined by checking the P-value of the K-S test. The best distribution is defined to be the one with highest P-value, above the alpha value (0.01 for this case). Table 2.2 presents the results of the best fit distribution for actual headway data collected from field with the K-S test P-values. Log-logistic distribution is observed to be the best fit distribution for 8 out of 9 vehicle positions used in this study. Literature indicates that log-logistic distribution is suitable during peak-hours (Yin et al., 2009; Wu et al., 2010). The log-logistic distribution model is presented in Equation (2.1) where h refers to the discharge headway value. The generalized extreme value (GEV) distribution was found to be the best fit for the 4th position. It has been found to be effective in modeling time headways by some previous studies (Wu et al., 2010; Panichpapiboon, 2015).

$$f(h) = \frac{exp\left(\frac{lnh - \mu}{\sigma}\right)}{\sigma\left[1 + exp\left(\frac{lnh - \mu}{\sigma}\right)\right]^2} \tag{2.1}$$

Table 2.2 The K-S Hypothesis Testing Results of Actual Discharge Headways Data

Position	**Best fit distribution**	**K-S test (default level 0.01)**	**k**	**Mu** (μ)	**Sigma** (σ)
2	Log-logistic	0.7053		3.5609	1.1972
3	Log-logistic	0.3829		2.4843	1.1853
4	GEV	0.9407	0.19	2.0500	0.5300
5	Log-logistic	0.9424		2.2479	1.2214
6	Log-logistic	0.8516		2.1383	1.1735
7	Log-logistic	0.2976		2.2255	1.2214
8	Log-logistic	0.8589		1.9542	1.1972
9	Log-logistic	0.7784		1.9739	1.2214
10	Log-logistic	0.8531		1.9937	1.1972

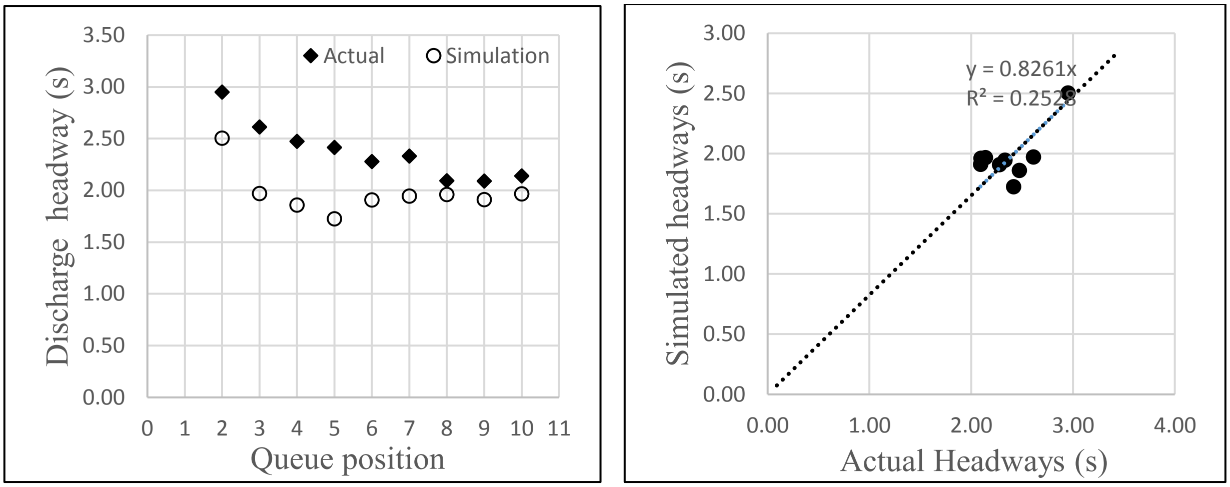
Simulation Input Data

Simulation input included NDS data, traffic volumes, signal timings and geometric data. This section provides a short discussion of the simulation data inputs.

- *Naturalistic Driving Study Data:* Part of the data employed for this study was obtained from the Strategic Highway Research Program 2 (SHRP2) insight website for Bruce B Downs corridor, in Tampa, Florida (Virginia Tech Transportation Institute, 2016). The data consist of speeds and vehicle acceleration/deceleration rates, collected on a Naturalistic Driving Study (NDS), and summarized based on the age groups. The Bruce B Downs corridor had the highest number of NDS participants, about 400-600 people.
- *Traffic Data:* Traffic volume data was provided by the city of Tampa traffic office in the form of intersection turning movement counts. Network balancing was done to develop the Origin-Destination (OD) matrix.
- *Signal Timings & Geometric Information:* Signal timing data was provided by the city of Tampa traffic office. Modeling was based on the AM peak. Geometric information such as number of lanes, lane widths and turning radius was extracted from Google Earth Pro.
- *Calibration and Validation Data:* Travel time and queue lengths data were used for general calibration and validation of the model following the Florida Department of Transportation (FDOT) simulation guidelines (Florida Department of Transportation, 2014). Discharge headway data were used in the second calibration stage.

Initial Evaluation

Once the simulation model was set up, multiple runs with default VISSIM parameters were conducted and the results are presented in Figure 2.3. The default parameters in VISSIM could not replicate the values of discharge headways very well and produced results which are rather low (Figure 2.3(a)). Therefore, calibration was necessary and the procedure recommended in a study by Park et al. (Park & Qi, 2005) was used.



(a) (b)

Figure 2.3 Average discharge headways before calibration.

Initial Calibration

Identification of Calibration Parameters

VISSIM uses a stochastic, time step based, microscopic traffic flow model that treats driver-vehicle units as basic entities. It provides two Wiedemann's traffic flow models which are based on the assumption that there are basically four different driving states for a driver: free driving, approaching, following, and braking (PTV AG., 2015). Out of the two Wiedemann's models, the VISSIM manual recommends Wiedemann 74 car-following model to be used for arterials (PTV AG., 2015). The Wiedemann 74 car following model is shown in Equation (2.2).

$$d = a_x + b_x \tag{2.2}$$

Where:

d = Desired safety distance

a_x = Standstill distance

$b_x = (b_{x_{add}} + b_{x_{mult}} \times z)\sqrt{v}$

v = Vehicle speed

$0 \le z \le 1, z \sim N(0.5,\ 0.15^2)$

The term $b_{x_{add}}$ allows adjustment of the time requirement values and $b_{x_{mult}}$ allows adjustment of the standard deviation of the safety distance values. In VISSIM, the discharge headways at the intersection are highly influenced by parameters of the car-following model. Vehicle accelerations are also known to affect the queue dissipation time. In this study, VISSIM acceleration functions were calibrated in the initial calibration stage. Therefore, discharge headway calibration was done by adjusting driving behavior parameters.

In addition to this, VISSIM provides a reaction time distribution parameter which causes a time delay between the time step when the signal switches to green and the time when the first vehicle upstream of the corresponding stop line starts to move (PTV AG., 2015). Calibration of the first discharge headway was done through selecting an established time distribution for this parameter. User-adjustable parameters selected for calibration and their acceptable ranges suggested by literature (Park & Won, 2006; Miller, 2009; PTV AG. VISSIM 8 User Manual., 2015; Lidbe, Hainen, & Jones, 2017) are as shown in Table 2.3.

Table 2.3 Driving Behavior Parameters

	Parameter	Units	Min. Value	Max. Value
Car-following model parameters	Standstill Distance (a_x)	ft.	2	8
	Additive part (bx_{add})	-	0	3
	Multiplicative part (bx_{mult})	-	0	3
Signal control parameters	Safety distance reduction factor	-	0	1
	Reaction time distribution	-	-	-

Experimental Design for Calibration

The number of possible combinations of the adjustable parameters is very large. In order to reduce the number of samples to a reasonable level while still covering the entire parameter surface, Latin Hypercube Design (LHD) was used for sampling. LHD is useful for limiting the experiment to a fixed user-defined number of combinations (Park & Qi, 2005). A total of 20 parameter sets that constituted the parent generation were generated by using LHD in MATLAB.

Parameter Calibration by Use of Genetic Algorithm (GA)

The use of heuristic algorithms like GA for simplifying the tedious task of calibration has been investigated in a number of studies (T. Ma & Abdulhai, 2001; Park & Qi, 2005; Manjunatha et al., 2013; Lidbe et al., 2017). The process starts by generating a number of parameter sets, each of which represents a possible solution. Multiple simulation runs are then performed for a selected number of sets and the simulation results are compared with the actual field data by using a defined fitness function. A fitness value is then assigned to each of the candidate solutions. If the stopping criterion is not met, a new set of parameters is generated through the process of selection, crossover and mutation. The chances of a candidate solution appearing in the next generation depends on the fitness value assigned to it. A summary of the algorithm used in this study is shown in Figure 2.4.

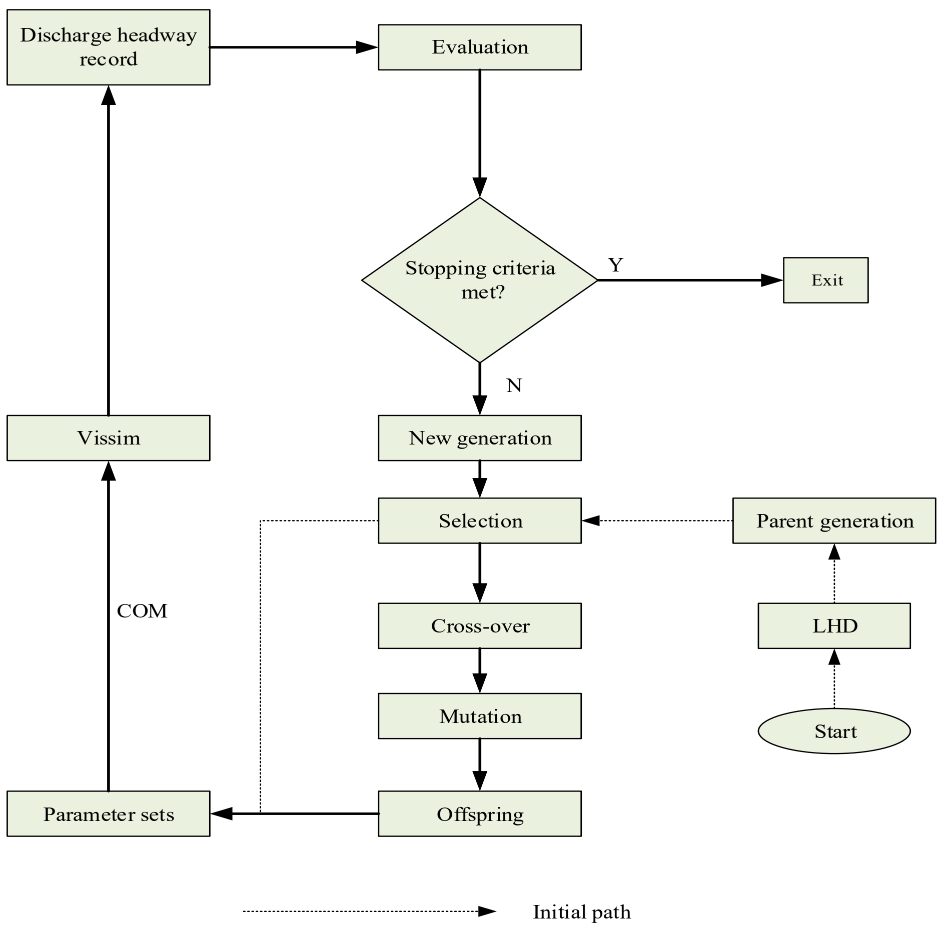


Figure 2.4 Calibration flow chart.

Calibration by using heuristic algorithms in VISSIM is normally automated through the Component Object Model (COM) environment. Parameters are fed in VISSIM by using scripts and multiple runs are performed. The results are then fed back to the heuristic algorithm for assessing the fitness of the solutions and the process is repeated until the stopping criterion is met.

In VISSIM, discharge headway is not available as one of the result attributes. It can only be obtained through direct output files, which require farther processing before average discharge headway values can be obtained. As a result, the calibration process in this study was semi-automated. The processing of discharge headway output files was done manually after which assigning of the fitness values and the remaining part of the heuristic algorithm was automated through a Visual Basic (VB) script. The COM interface allowed the task of performing multiple runs in VISSIM with different parameter sets to be automated. For each parameter set, five simulations with a different random seed were run. The output files were then processed manually to obtain the average discharge headways from the second queue position to the tenth queue position.

The Root Mean Squared Error (RMSE) of the discharge headway values from the second position in the queue to the tenth position between the simulation output and the field data was used as the fitness value for the GA. The fitness function is as shown in Equation (2.3).

$$FV = \sqrt{\frac{1}{9}\sum_{i=2}^{10}\left(H_{i_{field}} - H_{i_{sim}}\right)^2} \qquad (2.3)$$

Where:

FV = Fitness value

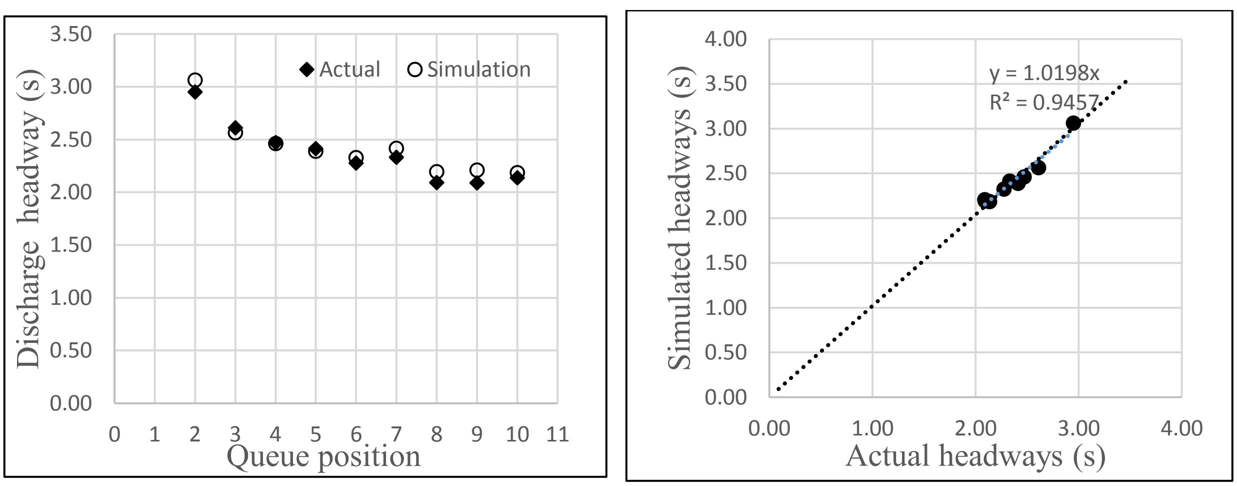
$H_{i_{field}}$ = Average discharge headway for position i from the field

$H_{i_{sim}}$ = Average discharge headway for position i from the simulation 18

The values of discharge headways are relatively low. Therefore, RMSE was used for computing the fitness values because it penalizes large errors heavily (Hollander & Liu, 2008). A total of 23 generations with a population size of 20 were produced as the algorithm converged. Proportionate selection, single point cross-over, and point mutation was used for this study. A mutation rate of 5 percent was used in the algorithm.

Calibration Results

This section discusses the results obtained after calibration and fitting the statistical distributions. Results in Figure 2.5(a) show that the simulated mean discharge headway values, after calibration, closely matched the actual mean discharge headways compared to the default simulated headways. In order to test the performance of the calibrated VISSIM model, Figure 2.5(b) is plotted to show the relationship between the simulated average headways, after calibration, and the observed headways. After calibration, the simulated mean discharge headways are close to the field observed average headways with an R-squared value of 0.95. This value is much higher than the R-squared value obtained using the default simulated values (0.25, see Figure 2.3). Thus, a conclusion can be drawn that after calibration, the averages of the simulated discharge headways are closer to the field observed headways, for each vehicle position.



(a) (b)

Figure 2.5 Average discharge headways after calibration.

Plots shown in Figure 2.6 provide a visual comparison of the simulated headways for the initial model (using default parameters), the final model (after calibration), and the field observations. The means of the calibrated headway distributions (green curves) are closer to the mean of the field observed headways (red curves) compared to those of the initial models. On the other hand, the calibration process was not able to replicate the dispersion of the field data. As shown in Figure 2.6, although the central tendency of both the calibrated and field headways appear to be relatively similar, the simulated probability distributions of simulated headways have higher picks and less dispersion compared to the field headways. In VISSIM, bx_{mult} allows adjustment of the standard deviation of the safety distance values. However, the variability that is inherent in the observed field data could not be captured even by using the highest reasonable values of bx_{mult} as suggested by literature (Park & Won, 2006; Miller, 2009; PTV AG. VISSIM 8 User Manual., 2015; Lidbe et al., 2017).

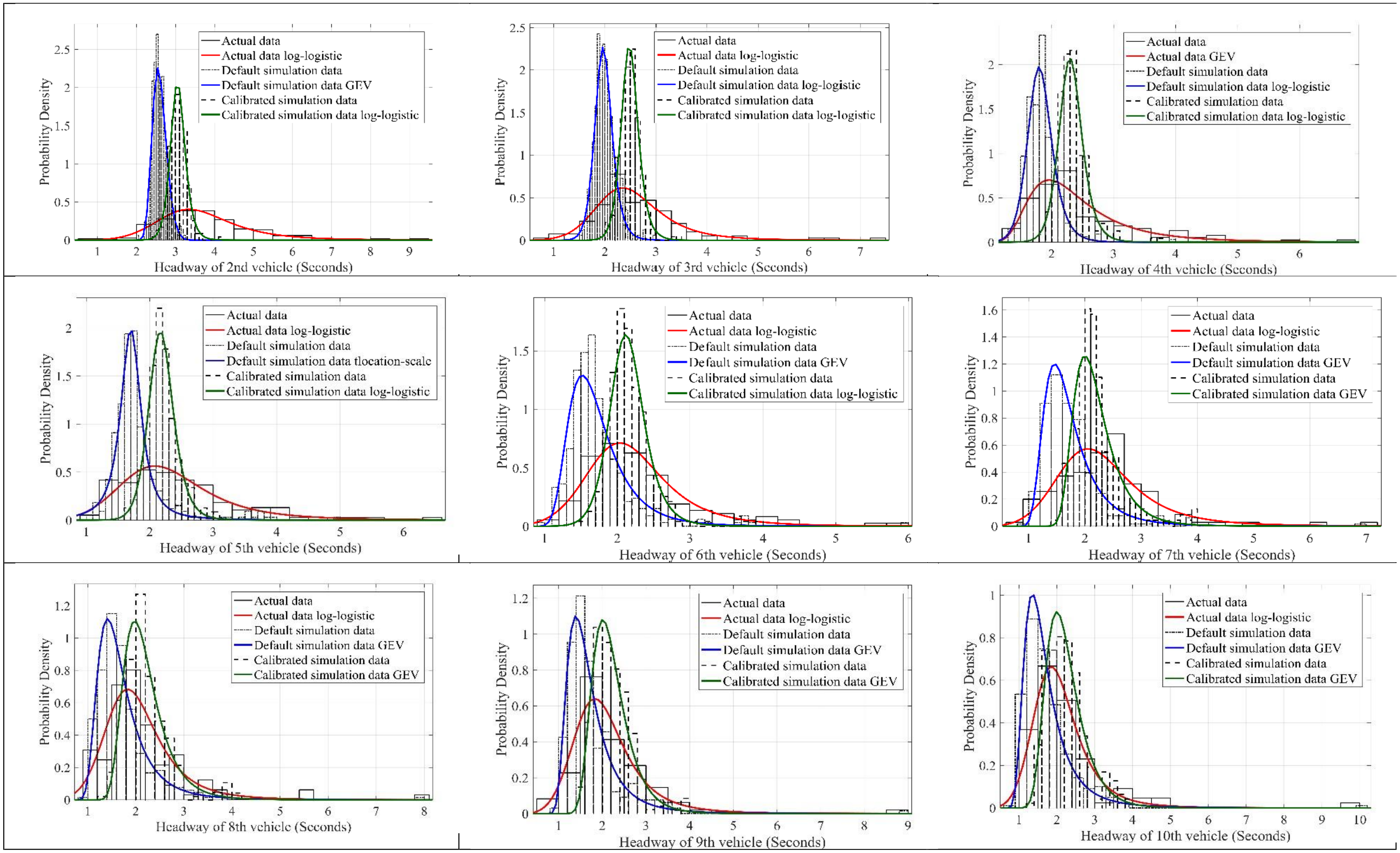


Figure 2.6 Fitted distribution for discharge headways data from the field, default simulation and calibrated simulation output.

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Conclusions and Recommendations

Calibration is an important process in microscopic traffic simulation. Most of the previous research efforts have used macroscopic measures including delay and travel time for calibrating traffic models and have ignored calibrating microscopic elements such as discharge headways. Rightfully so, in practice, typical transportation projects use microscopic models to evaluate measures of effectiveness (MOEs) such as delays and travel time hence a reason to ensure that the base model outputs for those MOEs are within a certain tolerance level. The advent of autonomous and connected vehicle (AV and CV) technologies have led to an increased use of simulation models to investigate the benefits of these technologies in improving traffic flow characteristics. Some of the benefits could include reducing stop-and-go conditions, reducing loss time due to reaction time caused by human limitations, and improved capacity. If discharge headways are not calibrated to reflect the characteristics of the mixed traffic flow, the simulation evaluation would not be accurate. This study presented the efforts in calibrating the intersection discharge headways by measuring discharge headways in the field, fitting the headways using a statistical distribution and adjusting VISSIM parameters that control discharge headways.

Four VISSIM parameters; average standstill distance (a_x), additive part ($b_{x_{add}}$), multiplicative part ($b_{x_{mult}}$) and safety distance reduction factor were used to adjust the distribution of discharge headways. This study was successful in shifting the distribution of the simulated discharge headways to replicate the mean of the field observed values. One of the significant revelations of this study was the inability of the calibration process to replicate the dispersion of the discharge headways obtained by the field measurements. Even by using high values of $b_{x_{mult}}$, the

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parameter that controls dispersion of the headways, the dispersion of the distributions of the simulated headways could not come closer to those of the field observations.

The inability of the calibration process to account for the dispersion of headway data requires special attention. On the simulator side, microscopic simulation software developers could modify the way discharge headways are modeled. In VISSIM, for example, allowing discharge headway data to be entered as a distribution similar to how it is done for speeds, reaction time, and stopping distance before the stop bar, would enable analysts to define discharge headways in terms of the distributions observed in the field.

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CHAPTER 3

Safety Evaluation of the Advanced Stop Assist System in Connected Vehicle Environment

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Introduction

The American Association of State Highway and Transportation Officials (AASHTO) offered a nationwide challenge to deploy Dedicated Short Range Communications (DSRC) infrastructure with Signal Phase and Timing (SPaT) broadcast on at least one corridor (approximately 20 signalized intersections) in each of the 50 states by January 2020 (AASHTO, 2016). These corridors are expected to play a significant role as test beds for implementing innovative initiatives in the connected and autonomous vehicle technology. One of the potential uses of such deployment would be an implementation of a Vehicle-to-Infrastructure (V2I)-based intersection crash avoidance system. Signalized intersections are associated with different types of conflicts due to various opposing movements and differential speeds. Although traffic signals are installed to reduce certain types of collisions (e.g., head-on and angle crashes), they are known to increase rear-end collisions (Roess, Prassas, & McShane, 2011; Nuyttens, Carpentier, Declerq, & Hermans, 2014) . In 2013, a total of 4,700 fatal crashes, 826,000 injury crashes, and 1.76 million property-damage-only crashes occurred in relation to signalized intersections in the United States (U.S.);, nearly 30% of these were rear-end collisions (NHTSA, 2013). Rear-end crashes at intersections are caused in part by differential speeds as vehicles approach the intersection, followed by abrupt decelerations at the onset of yellow and red indication. The indecision of drivers in these situations is likely to result in harder braking, thus increasing the likelihood of a rear-end crash.

Currently, there are several in-vehicle systems that use I2V communication to provide information of the signal states to drivers. For example, in the Tampa, Florida, there are two I2V systems that are currently being beta-tested. The first system, *EnLighten*, developed by Connected Signals (Marshall, 2016), is a cloud based I2V system that uses a smartphone application to show the amount of remaining green time and if the driver is stopped on a red signal the system advises the driver of the remaining amount of red time before the next green phase. In the second system, a U.S. Department of Transportation (DOT) pilot project, Siemens partnered with the Tampa-Hillsborough Expressway Authority (THEA) to install an I2V system in downtown Tampa to provide an advisory speed to drivers who wish to travel without stopping before the next green phase (Satow, 2016). While *EnLighten* is based on analytics of the signal grid master data, the second system uses DSRC and requires a Road Side Unit (RSU) to be installed at the intersection and an On-Board Unit (OBU) in the vehicle to enable short range communication. The I2V and V2V technology has a potential of reducing rear-end conflicts at signalized intersections.

There is a need to devise a system referred herein as the Advanced Stop Assist System (ASAS), which takes advantage of I2V and V2V communication technology to notify drivers to prepare to stop when the remaining green time is insufficient to clear the intersection under prevailing traffic conditions. Since the connected vehicle technology allows vehicles to communicate with each other and with the infrastructure, the broadcast information can be used to provide an advisory speed message in advance. It is worth pointing out that messages are sent not only to vehicles in the dilemma zone, but also to any qualifying vehicle that is within the communication range. Each driver will receive an advisory message when the signal is still green. Earlier stopping maneuvers would allow for smooth deceleration and potentially reduce the number of vehicles trapped in the dilemma zone, hence improving safety by reducing rear-end collisions and red-light running, a leading cause of angle crashes.

Objectives

The objectives of this study are to (1) propose and demonstrate the implementation of ASAS in a microscopic simulator, and (2) evaluate potential safety benefits of ASAS. In particular,

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reduction of rear-end collisions under the connected vehicle environment with I2V and V2V communications. Thus, this manuscript presents an algorithm used to develop the ASAS under the connected vehicle environment in the microscopic traffic simulator. The effectiveness of the proposed ASAS algorithm is assessed using two performance measures: speed profiles as vehicles approach the intersection to examine speed smoothness, and maximum deceleration rates to determine the effectiveness of the system in reducing hard-braking. The proposed system was implemented and evaluated using the Car-to-Devices (C2X) simulation module available in the VISSIM microscopic simulation software.

Literature Review

There are numerous research efforts that have documented the CV technology and its potential in improving mobility, safety, and environmental sustainability of transportation systems. The following sections provide a summary of the CV literature pertinent to this study.

Connected Vehicle Technology

The history of connected vehicles can be traced back to 2003 when the U.S. DOT first launched the Vehicle-Infrastructure-Integration (VII) program (Songchitruksa & Zha, 2014). The initial objective of VII was to address the traffic safety problems through high-speed wireless communications among Vehicle-to-Vehicle (V2V) and V2I. The connected vehicle framework is made up of three critical elements; On-Board Unit (OBU), Roadside Unit (RSU), and Back-Office Servers (SAE, 2013). OBU consists of devices embedded in the vehicle that support DSRC with nearby vehicles and RSU. RSU consists of roadside devices that support DSRC with nearby OBU-equipped vehicles within the communication distance, other RSUs, and the control centers. Back-office server represents the control center that connects RSUs and monitors the traffic network.

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The Federal Communications Commission (FCC) has allocated the spectrum from 5.850 Giga Hertz (GHz) to 5.925 GHz, i.e. the “5.9 GHz band”, for DSRC operations in the United States. This spectrum is divided into seven 10 Mega Hertz (MHz) channels with a 5 MHz guard (reserve) at the low end. Pairs of 10 MHz channels can also be combined into a 20 MHz channel (Kenney, 2011). Most of the wireless devices participating in safety applications have a maximum output power of 20 Decibel-Milliwatts (dBm) and a communication zone of nearly 400 m (Kenney, 2011). Due to hidden terminal problems and multipath interference, the effective range of communication may be lower than the nominal value. Although now vehicles collect and convey a lot of information, just a few years ago vehicles relied completely on low technology methods to communicate with each other and the environment by using turn signals, brake lights, and static signs. In recent years, technology that provides wireless communication between vehicles and transportation infrastructure has increased. This technology is a combination of number of technological advancements including advanced wireless communications, on-board computer processing, advanced sensors, Global Positioning System (GPS) navigation and smart infrastructure to provide a networked environment (Federal Highway Administration, 2012). A connected vehicle environment allows high speed broadcast of information from vehicles and infrastructure. Signal systems can use data from in-vehicle sensors transmitted wirelessly from equipped vehicles to the signal controller. A number of measures can be accessible such as vehicle speeds, positions, arrival rates, acceleration or deceleration rates, stopped time, and queue lengths. (Goodall, Smith, & Park, 2013).

Connected Vehicles at Intersections

Several studies have examined the use of connected vehicles for intersection control. Many of these studies focused on the optimization of signal phases by taking advantage of the

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information sent from the equipped vehicles. Guler et al. (Ilgin Guler, Menendez, & Meier, 2014) developed a traffic control algorithm to minimize delay using information from connected vehicles to mitigate urban congestion. V2I safety applications were proposed to address problems that V2V communications would not address (NHTSA, 2010). Safety applications that use V2I only require RSU at targeted facilities, normally at intersections. There are V2I safety applications that have been developed at intersections and tested for their effectiveness through simulation studies and field test beds. Some of these applications include Cooperative Intersection Collision Avoidance System (CICAS) framework and its related applications such as CICAS-V (traffic signal violation), CICAS-LTA (signalized left-turn assist) and CICAS-TSA (traffic signal adaptation) (Misener, 2010). Songchitruksa et al. (Songchitruksa & Zha, 2014) proposed safety performance monitoring using V2I data. However, the study proposed a framework for monitoring safety performance at signalized intersections by means of connected vehicle technology. The study only focused on through-vehicle movements because of their relatively well-defined paths and conflict regions. Types of messages commonly used for signalized intersection operations include the Basic Safety Message (BSM) which describe the vehicle kinematics, Map data describing the intersection geometry and Signal Phasing and Timing (SPaT) for sending signal status data (Zha, Zhang, Songchitruksa, & Middleton, 2016).

Connected Vehicles and Speed Advisory at Intersections

Katsaros et al. (Katsaros, Kernchen, Dianati, & Rieck, 2011) proposed a Green Light Optimized Speed Advisory (GLOSA) application implementation in a typical reference area and presented the performance analysis results using an integrated cooperative ITS simulation platform. The study focused on the improvement of fuel consumption and reduction of traffic congestion at intersections using wireless communication between intersection signals and vehicle

(I2V communication). Drivers of vehicles which were GLOSA equipped were provided with advisory speeds intended to reduce the number of stops at intersections. Stevanovic et al. (Stevanovic, Stevanovic, & Kergaye, 2013) and Tielert et al. (Tielert et al., 2010) employed GLOSA in an attempt to minimize delay, fuel consumption, and emissions at intersections by providing advisory speed messages to drivers to guide them in moving through the green phase. However, even with GLOSA in place, vehicles must come to a stop at the intersection at some point. With the upper and lower limits of speeds at which vehicles can drive, it is impractical for all the vehicles to arrive during the green phase. The present study focuses on vehicles that would come to a stop at the intersection due to the end of the green phase.

Methodology

Microscopic Simulation

Researchers and practitioners have widely used simulation applications for various purposes such as comparison of alternatives, analyzing the impact of developments, and cost estimation (Lownes & Machemehl, 2006). In this study, VISSIM software was used. Through the Component Object Model (COM) interface, the I2V and V2V wireless communications were modeled using an algorithm implemented through the C2X Application Programming Interface (API).

Study Site

The signalized intersection of Bruce B Downs Boulevard and East Fletcher Avenue (Figure 3.1), located in Tampa, Florida, and adjacent to the University of South Florida, was selected for the simulation model. The intersection is one four major signalized intersections located along the Bruce B Downs corridor. The site was chosen because of the availability of naturalistic driving

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data for different age groups collected by the Strategic Highway Research Program 2 (SHRP2). The naturalistic driving data was used for simulation data input, specifically, speed profiles, and deceleration and acceleration rates.

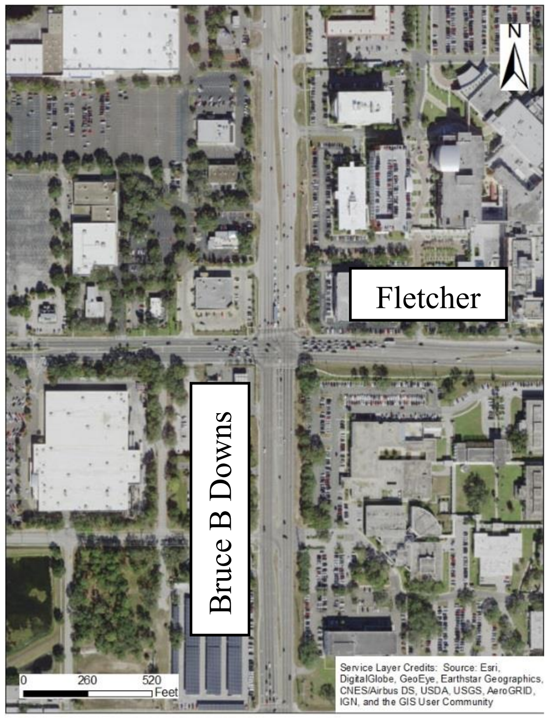

Figure 3.1 Study site.

Data Input

Data employed for this study was obtained from the SHRP2 Naturalistic Driving Study (NDS), through Virginia Polytechnic Institute, for the Bruce B Downs corridor, in Tampa, Florida (Virginia Tech Transportation Institute, 2016). Bruce B Downs corridor is a one mile stretch containing four major signalized intersections and the highest traversal density of NDS participants, about 400-600 people. This corridor is also one of the several corridors located in Hillsborough County, Florida with a high severe injury crash rate ("Tindale-Oliver and Associates Inc.," 2013).

Traffic and signal timing data were provided by the city of Tampa Traffic Office. Geometric information such as number of lanes, lane widths, and turning radii were extracted from Google Earth Pro software. PM peak traffic data were also used for this study. The model was calibrated based on the Florida Department of Transportation (FDOT) simulation guidelines to reflect real conditions (Florida Department of Transportation, 2014). The volume levels and signal timings are depicted in Table 3.1.

Table 3.1 Traffic Volumes & Signal Timing Settings

Traffic Volume												
Phase Number	1	2		3	4		5	6		7	8	
Lane Type	SBL	NBT	NBR	WBL	EBT	EBR	NBL	SBT	SBR	EBL	WBT	WBR
Volume (*veh/hr*)	275	1148	243	144	637	204	382	612	320	371	625	254
Signal Timing Setting												
Min Green (sec)	5	5		5	5		5	5		5	5	
Veh Extension (sec)	3	3		3	3		3	3		3	3	
Max 1 (sec)	7	19		7	20		7	19		9	18	
Yellow (sec)	3.5	3.5		3.5	3.5		3.5	3.5		3.5	3.5	
Red Clearance (sec)	1	1		1	1		1	1		1	1	

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Where;

SBL	=	South-Bound Left
NBT	=	North-Bound Left
NBR	=	North-Bound Right
WBL	=	West-Bound Right
EBT	=	East-Bound Through
EBR	=	East-Bound Right
NBL	=	North-Bound Left
SBT	=	South-Bound Through
SBR	=	South-Bound Right
EBL	=	East-Bound Left
WBT	=	West-Bound Through
WBR	=	West-Bound Right

Simulation Test Bed

The intersection simulation model was developed in VISSIM. I2V and V2V communication was modeled using the C2X module available in the software through the COM API. This module enables the modeling of the wireless communication involving high speed exchange of data plus other wireless communication characteristics such as the wireless transmission success rate. Scripting was done using Visual Basic (VB). The simulation resolution was set to 10 time steps/sim.sec, which is equivalent to the transmission frequency of 10 Hz for the Basic Safety Message (BSM).

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The intersection was modeled with pre-timed signal control to simplify the SPaT information tracking. The naturalistic driving data from the SHRP2-NDS was used for calibrating vehicle speeds at the intersection approach.

A number of operational assumptions were made in order to model I2V and V2V communications in this study. Some of these assumptions were derived from a study by Songchitruksa (Songchitruksa & Zha, 2014). These assumptions are listed below:

- Although the effective range of DSRC communications is over 2000 ft., communication was maintained for only those vehicles which were in the range of 765 ft. from the intersection stop bar. This range was established by considering the speed limit of the approach (45 mph) and the Green length + Amber time. A five mph allowance was made for vehicles driving at a speed slightly higher than the speed limit.
- At every time step, the RSU broadcasts SPaT and Map information to the OBUs where advisory messages to each "qualified" C2X equipped vehicle speed is calculated utilizing an algorithm described in more detail in the next section.
- The study assumed a 100% compliance rate to the speed advisory messages provided.

Vehicle-To-Infrastructure Communication Algorithm

The objective of the algorithm is to provide a smooth deceleration of vehicles that are coming to a stop at the intersection. This is achieved by providing speed advisory messages as soon as the algorithm detects that a vehicle will arrive at the intersection while the signal is red. Thus, the algorithm seeks to resolve the potential for hard-braking as the vehicle approaches the intersection stop bar.

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The algorithm was developed only for North-Bound Through (NBT) movements at the study intersection (see Figure 3.1). Dynamic arrays, populated after every time step, were used for storing the relevant connected vehicle data. The algorithm starts by checking if there are vehicles in NB approach within the range of communication. If there are vehicles approaching the intersection, three types of datasets, shown in Table 3.2 are produced.

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Table 3.2 Datasets Produced by the Algorithm

Type of information	**Variables collected**
SPaT information	• Signal state • Signal state running time • Remaining green time
Map data	• Stop bar location • RSU location
BSM	• Vehicle speed • Vehicle acceleration/deceleration • Vehicle location

The vehicle position and location of the stop bar were used to establish the vehicle distance to the stop bar. Given *d* as the distance to the intersection stop bar, *u* as the current speed of the vehicle, and *a* as the acceleration of the vehicle, the time to reach the intersection stop bar (T_{TL}) can be calculated using Equation (3.1).

$$T_{TL} = \begin{cases} \frac{d}{u} & when\ a = 0 \\ \frac{-u}{a} + \sqrt{\frac{u^2}{a} + \frac{2d}{a}} & when\ a \neq 0 \end{cases} \quad (3.1)$$

The value of T_{TL} was used to check the signal status by the time the vehicle arrives at the intersection.

`

If a queue exists at the intersection, drivers would start slowing down if the signal is still green. Therefore, no speed advisory messages would be required. As shown in Figure 3.2 with accompanying notation, a series of conditions had to be fulfilled before speed advisory messages were given to the driver of a "qualified" C2X vehicle. It is important to note that the advisory messages are provided when the signal is still green. The conditions imposed ensured that speed advisory messages were given to drivers of vehicles that will arrive at the intersection when the signal is red. The definitions of notations used in Figure 3.2 are shown below.

D	Distance to intersection stop bar
t_{clr}	Time to clear intersection
t_g	Green time
t_{gr}	Remaining green time
t_a	Amber time
V	Current vehicle speed

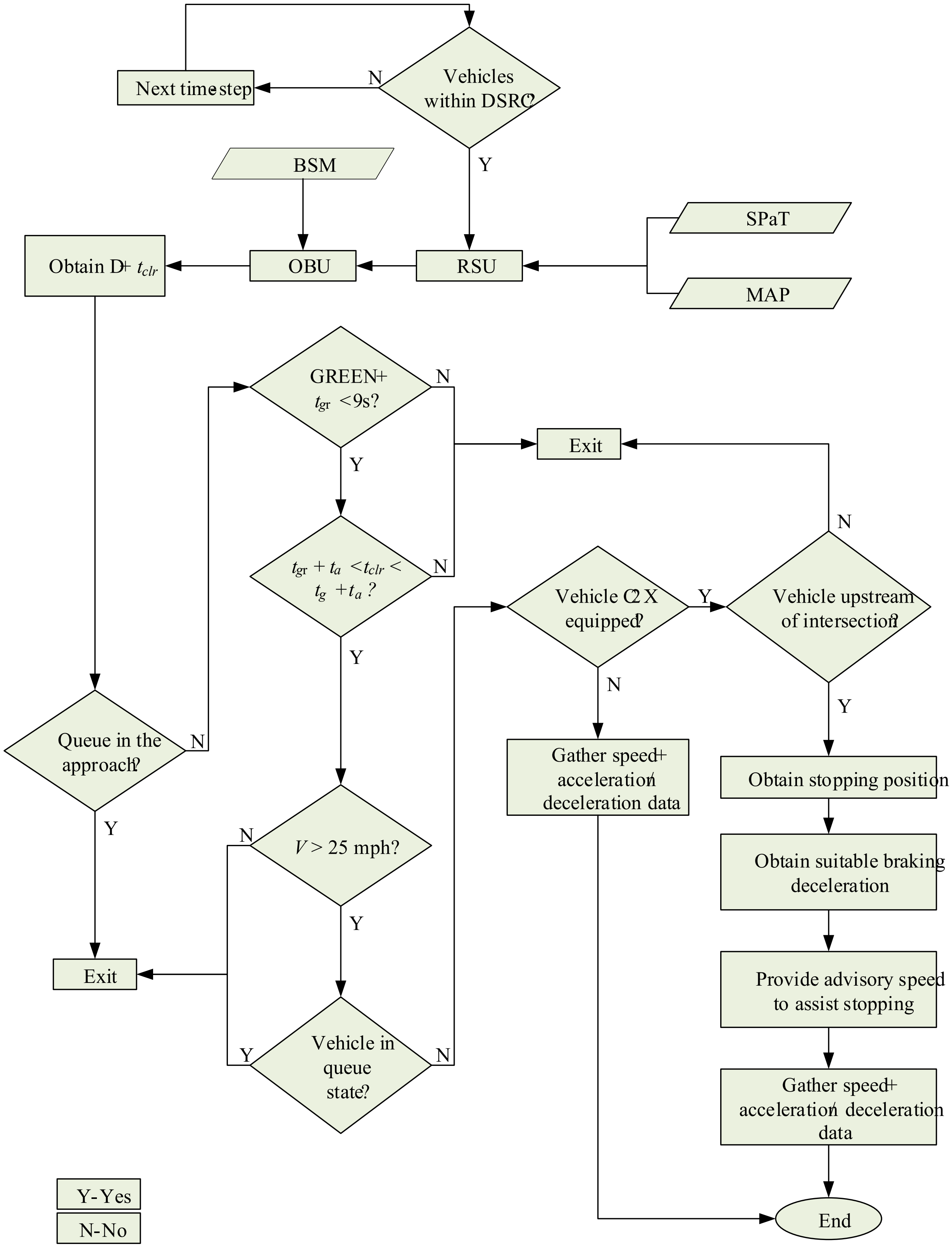

Figure 3.2 Algorithm for V2I communication.

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Stop Distance Estimation

Before the speed advisory messages were provided, the position where a vehicle would come to stop had to be estimated as shown in Figure 3.3. This location was then used as a reference for obtaining a suitable deceleration rate to stop the vehicle.

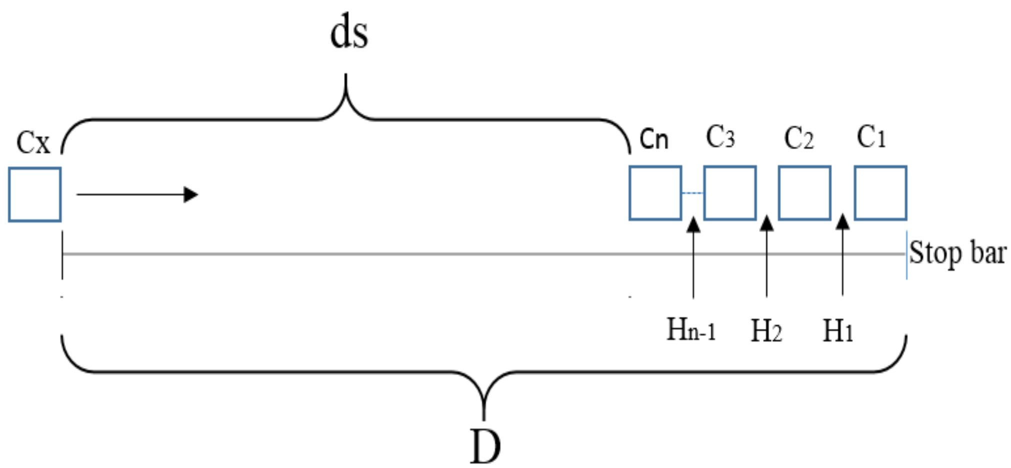

Figure 3.3 Stopping distance illustration.

Where: C_i = Vehicle length

H_i = Average standstill distance

D = Vehicle distance to stop bar

d_s = Stopping distance

If there are n vehicles ahead of the current vehicle, the stopping distance is computed as:

$$d_s = D - \sum_{i=1}^{n} C_i - \sum_{i=1}^{n-1} H_i \tag{3.2}$$

`

The value of d_s is obtained before the preceding vehicles come to a stop at the stop bar. The values of H were assumed to be fixed at 7.4 ft which is the average standstill distance of the Wiedemann 74 car following model after calibration.

Braking Deceleration Estimation

When a C2X equipped vehicle is "qualified" for computing advisory speed messages, a suitable uniform deceleration rate was calculated using the information extracted from the vehicle, plus additional Map data using Equation (3.3).

$$d_{br} = \frac{V^2}{2 \times d_s} \tag{3.3}$$

Where:

d_{br} = Uniform deceleration required to bring a vehicle to stop

V = Current speed of the vehicle

d_s = Stopping distance as obtained using Equation (3.2)

The calculated value of d_{br} was then used to calculate the values of speed as the vehicle moves along using Equation (3.4). These speed values were provided to the driver as speed advisory messages.

$$V_{adv} = \sqrt{2 \times d_{br} \times d_s} \tag{3.4}$$

Where:

V_{adv} = Advisory speed at the current position

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The values of d_s and V_{adv} decrease as the vehicle approaches the intersection. As a result, the speed advisory messages would prompt drivers to slow down before the signal turns red because the algorithm had already projected that these vehicles would arrive on a red signal indication.

Evaluation

Vehicle Approach-Speed Profiles

The main objective of an ASAS is to enable vehicles that come to a stop at the intersection to smoothly decelerate as a result of receiving advisory messages in advance. Therefore, a record of vehicle speeds as they approach the intersection would be a good measure of how well the objective is met.

Vehicle approach speeds were recorded using detectors modeled in VISSIM. The first detector was positioned at a distance of 750 ft. from the intersection stop bar. This is within the range of I2V communication used in this study (765 ft.). A total of 23 detectors were used to obtain a smooth speed profile at 32.8 ft. (10 m) intervals. Since the study focused on vehicles coming to a stop at the intersection, speeds were recorded only for such vehicles. Speed data for stopping vehicles that were not C2X equipped were also taken into consideration to provide a means for comparison.

Within the communication range, based on vehicle speed and acceleration, different C2X vehicles qualify to compute advisory messages at different locations. Detectors close to the stop bar recorded a higher number of vehicles. In order to obtain a complete speed profile for decelerating vehicles, a record was kept only for stopping vehicles that were detected from the first detector.

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Safety Evaluation

Surrogate safety evaluation is a widely-accepted alternative to historical crash data analysis (Bonneson & Ivan, 2013). Given the randomness and rareness of crash occurrence, statistics can be applied to relate surrogate safety measures with crash frequency and severity even before crashes occur. Traffic conflicts, a commonly used surrogate safety measure, are defined as situations where two or more vehicles will collide if their movements remain unchanged (Amundsen & Hyden, 1977). Thus, the number, type, and severity of collisions that occur can be used as an indicator of traffic safety (Wang & Stamatiadis, 2013). This study focused only on rear-end collisions since they are the most prevalent collision type at signalized intersections and can result from hard-braking, a condition addressed herein.

Specific thresholds are applied to measurable traffic indicators, such as time to collision (TTC) and post encroachment time (PET), to obtain quantitative data of traffic conflicts. The Surrogate Safety Assessment Model (SSAM), a software application provided by the Federal Highway Administration (FHWA), enables the identification of traffic conflicts by using a statistical analysis of vehicle trajectory files generated from microscopic simulations. Several conflict indicators are provided by the SSAM software based on the trajectory files developed from each scenario run.

For this study, the results from the SSAM did not prove to be useful for several reasons. First, this study specifically focused on the safety evaluation of vehicles that are coming to a stop at the intersection, of which SSAM provided a vast amount of conflict data that was difficult to filter to obtain the required data. Traffic conflicts also occur at different locations, and due to the very specific objective of this study, some attributes were not available in SSAM output to pin

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point conflicts resulting from stopping vehicles. As a result, a separate algorithm which uses a maximum deceleration (MaxD)-based event as a surrogate safety measure had to be developed.

A study by Songchitruksa (Songchitruksa & Zha, 2014) proposed a methodological framework designed to extract and compute safety indicators from vehicle movement, intersection description, and signal data available within the RSU at an isolated signalized intersection. The study classified the safety indicators as either single-OBU or dual-OBU, depending on the number of OBU equipped vehicles that needed to be monitored. One potential measure of the single-OBU, listed by the study, was the MaxD-based event – the maximum deceleration of a vehicle during an event of continuous braking (Allen, Shin, & Cooper, 1978). The frequency of these events on a particular roadway section can be related to disturbances in traffic flow, and can indicate the risk of rear-end crash occurrence. According to Songchitruksa (Songchitruksa & Zha, 2014), MaxD-based events are not always a precursor for rear-end crashes. Mixed results of potential indicators can occur with unsafe scenarios. MaxD-based events are triggered by a number of factors and require careful examination to avoid mixed results. This research work adopted this safety indicator, the MaxD-based event, and refined it to suit the objectives of this study.

VISSIM uses a stochastic, time-step based, microscopic traffic flow model that treats driver-vehicle units as basic entities. It uses the Wiedemann's traffic flow model which is based on the assumption that there are basically four different driving states for a driver: free driving, approaching, following, and braking (PTV AG., 2015). The braking state occurs when a driver applies medium to high deceleration rates if the distance to the preceding vehicle falls below the desired safety distance. This happens if the driver of the preceding vehicle abruptly changes speed or the driver of a third vehicle changes lanes to squeeze between two vehicles in the adjacent lane. Additionally, the built-in driver behavior component in VISSIM has four main states that can be

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used to determine the driving states of the vehicles in the network. The closeup state describes vehicles closing the distance to a stationary vehicle infront or a hindrance, such as signal heads, stop signs, priority rule, and conflict areas. Since this study focused on a signalized intersection approach, the closeup state could only result due to a preceding stationary vehicle or a signal head hindrance.

A threshold for recording a MaxD-based event was set to 14.8 ft/s^2, the emergency deceleration rate in accordance with the AASHTO Green Book (AASHTO, 2001). Vehicles braking harder than 14.8 ft/s^2 were tracked to the maximum value of deceleration reached, and the value was recorded along with vehicle speed, position, and driving state. The data of hard-braking vehicles, closing up at the intersection approach, were obtained together with the driving state of the vehicles. In the next step, the data were normalized by the total number of vehicles stopped at the intersection.

Results and Discussion

Speed Profiles

Speed profiles, illustrated in Figure 3.4, were developed using the average speed from each speed detector at a 95% confidence interval. The speed profiles show a clear difference between the base condition (0% penetration or 0% of vehicles with OBU) and when ASAS is implemented at 100% saturation of OBUs. When advisory speed messages were provided to drivers, deceleration started at about 740 ft. (225 m) from the stop bar, nearly 328 ft. (125 m) earlier when compared to the base condition. All of these vehicles will stop at the intersection, but having advance information would help the drivers in smoothening their brake action as they approach the stop bar.

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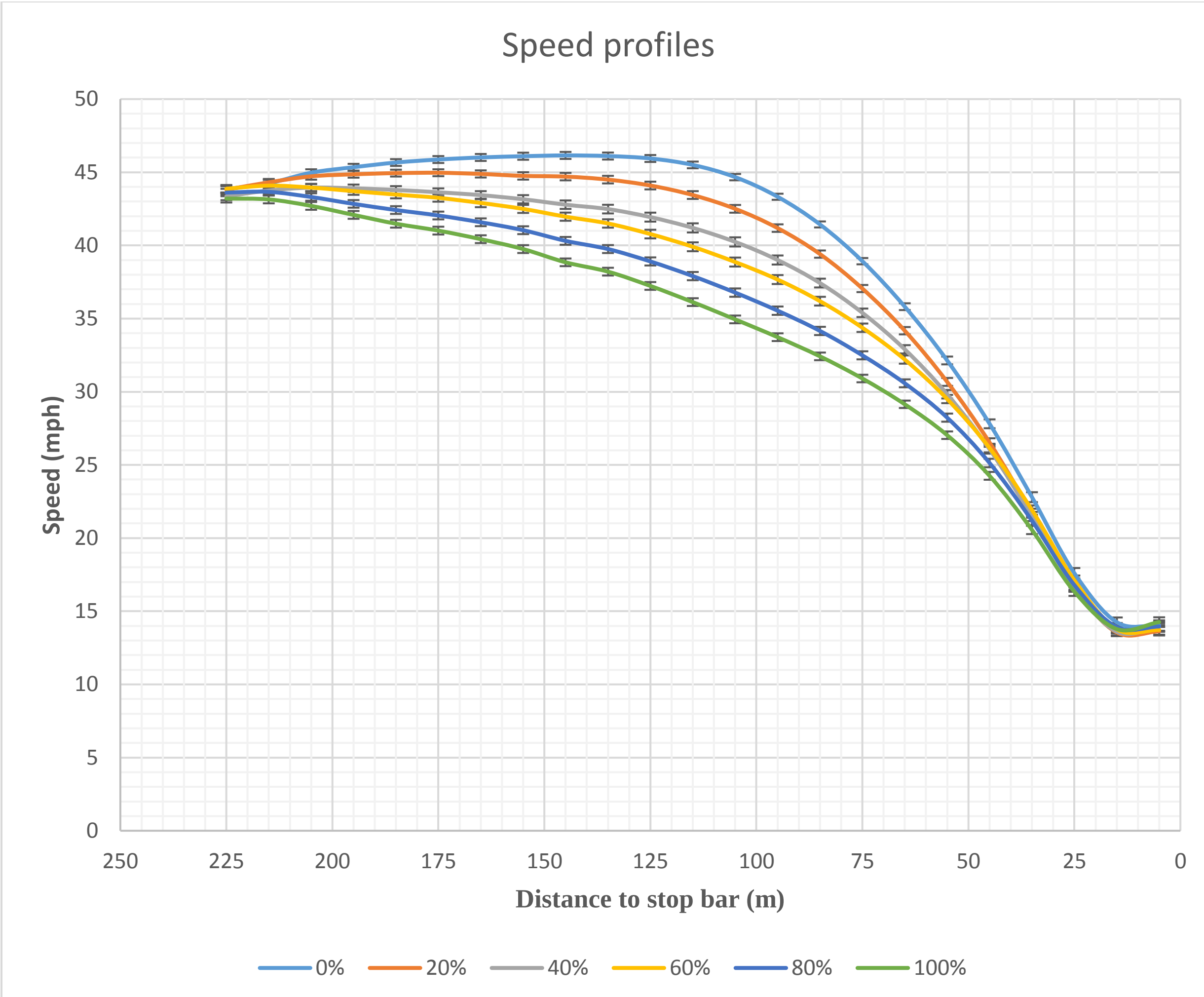

Figure 3.4 Speed profiles at different penetration rates.

The speed profiles shown in Figure 3.4 do not include speed at 0 mph as the detectors placed near the stop bar, also recorded speeds of accelerating vehicles during the discharge of the formed queue at the intersection.

Statistical Comparison of Safety Measures

The safety indicator used for statistical comparison was the number of vehicles experiencing hard-braking towards the end of the intersection approach, termed a MaxD-based event. To obtain a valid comparison between the baseline (0% saturation of OBUs) and the 100%

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saturation of OBUs scenarios, normalization was done by using a selected exposure variable. The exposure variable selected was the number of vehicles within 765 ft. (communication range of C2X vehicles) of the intersection stop bar during a green signal with no queue formed, but came to a stop upon arrival at the intersection due to a red signal indication. The statistical test procedure suggested by Griffin et al. (Griffin & Flowers, 1997) was performed to determine if significant differences between the recorded safety indicators were present. Simulation results and statistical comparison results are summarized in Table 3.3.

Table 3.3 Summary of Simulation Results

Measure	**Baseline**	**Scenario 1**
Number of MaxD-based conflicts	74	39
Number of stopped vehicles[a]	4460	4450

Statistical Comparison of Safety Indicator

Measure	**Baseline**	**Scenario 1**	**Z[1]**	**p-value**	**Change (%)**	**Statistically Significant**
MaxD-based conflict rate[2]	16.59	8.76	-3.19	<.01	-47.2	Yes

NOTE:

[a] Number of vehicles within 765 ft. (communication range of C2X vehicles) of the intersection stop bar during a green signal with no queue formed, but came to a stop upon arrival at the intersection due to a red signal indication.

[1]Computed as: $Z = \frac{\left(\frac{A+0.5}{EA} - \frac{B-0.5}{EB}\right)}{\sqrt{\frac{A+B}{(E_A+E_B)E_A} + \frac{A+B}{(E_A+E_B)E_B}}}$

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Where A = Total count in after period; B = Total count in before period; E_A = Exposure in after period; E_B = Exposure in before period.

[2]Computed as: $\frac{\sum Count}{\frac{\sum veh}{1000}}$, in count per 1,000 vehicles. The denominator represents exposure.

The difference in the number of observed MaxD-based conflicts was found to be statistically significant at 95% confidence level. The number of vehicles experiencing hard braking was reduced by about 50% as a result of the advisory speed messages. This shows that a connected-vehicle application is a viable solution for reducing the number of rear-end conflicts and possible crashes resulting from the change of signal indication as vehicles come to a stop at the intersection.

Sensitivity Analysis of Market Penetration Rates

Speed Profiles

The effectiveness of the connected vehicles' deployment depends on the market penetration rate (the overall percentage of vehicles equipped with OBU). Application of ASAS requires vehicles to be equipped with OBU so that they can be receive messages through I2V and V2V communications. Since 100% saturation of OBUs installation is not expected in the near future, a sensitivity analysis on the effectiveness and reliability of the proposed application was done at different penetration rates in increments of 20% ranging from 0% to 100%. Figure 3.4 demonstrates how the speed profiles vary with market penetration rates. The profiles indicate that as the number of vehicles that respond to speed advisory messaging increases, the average approach speed of the vehicles decreases.

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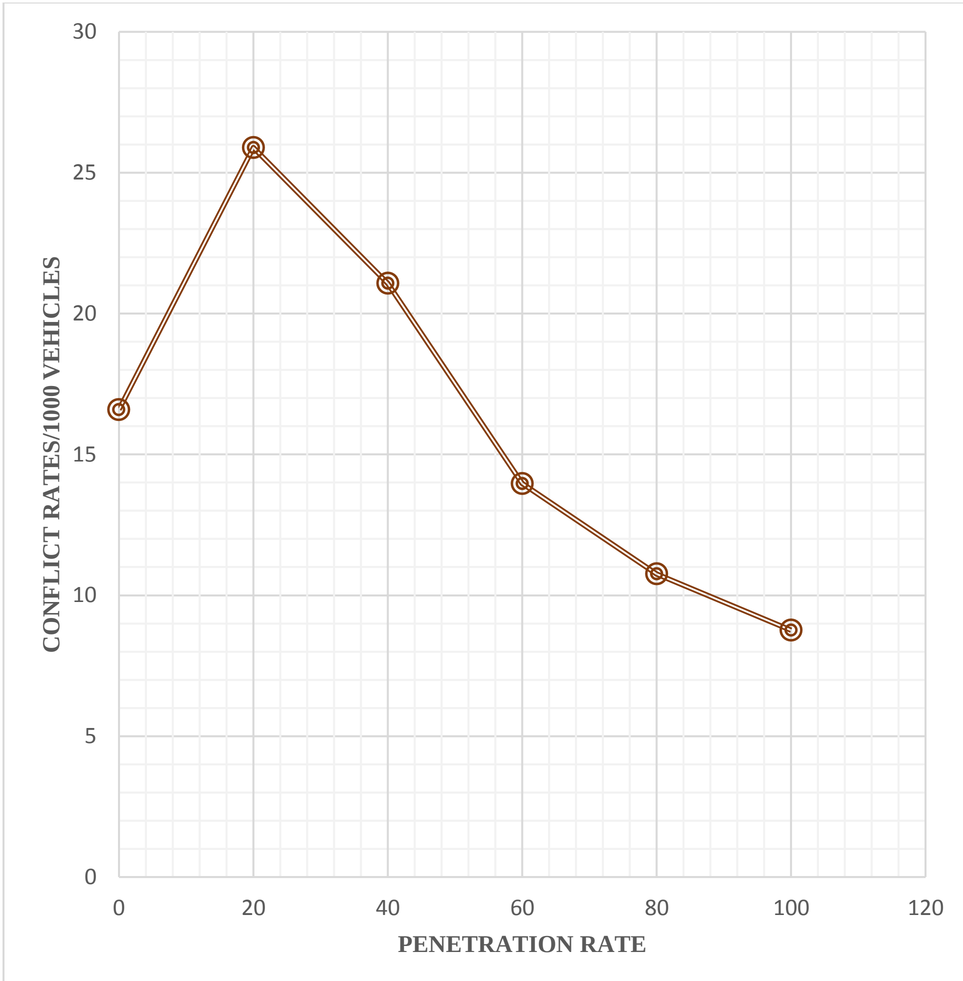

Figure 3.5 Variation of MaxD-based conflicts with market penetration rate**.**

Safety Measures

The proposed application was also examined at different saturation rates of the OBUs to obtain a general trend on how the adopted safety indicator varied with varying penetration rates. The results and statistical comparison are shown in Table 3.4.

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Table 3.4 Summary of Simulation Results at Different Penetration Rates

Penetration Rate	Number of MaxD-Based Conflicts	Number of Stopped Vehicles
Baseline	74	4460
20%	115	4441
40%	94	4462
60%	62	4438
80%	48	4459
100%	39	4450

Statistical Comparison of Safety Indicator at Different Penetration Rates

Penetration Rate	MaxD-Based Conflict Rate[a]	Z[b]	p-Value	Change (%)[c]	Statistically Significant @ 95% CL
0%	16.59				
20%	25.89	3.08	<.01	56.1	Yes
40%	21.07	1.62	0.105	27.0	No
60%	13.97	-0.91	0.362	-15.8	No
80%	10.76	-2.26	0.024	-35.1	Yes
100%	8.76	-3.19	<.01	-47.2	Yes

NOTE:

[a]Computed as in Table 3.3

[b]Computed as in Table 3.3 with reference to the base condition

[c]Computed with reference to the base condition.

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The results, as shown in Figure 3.5, indicate that there is a degradation in the level of safety up to 40% penetration rate when ASAS is implemented at the intersection. The mixture of normal vehicles and C2X-equipped vehicles following the speed advisory messages, which produced more variations in the approach speed of vehicles, is most likely the cause of this degradation. Results indicate that at least 60% saturation of OBUs is required to observe tangible improvements.

Conclusions and Recommendations

This study proposed a connected vehicle application which utilizes I2V and V2V communications at signalized intersections. The application aims at reducing the risk of rear-end crashes at signalized intersections caused by the indecision of drivers when a signal indication changes. The proposed application makes use of the information received at the OBU from other vehicles' OBUs through V2V communications in the form of BSM, as well as Map and SPaT information from the RSU. An algorithm was developed to provide advance speed advisory messages to drivers in C2X equipped vehicles projected to arrive at the intersection on a red signal indication.

A microscopic simulation approach was used for evaluating the effectiveness of the proposed system. VISSIM, a microscopic simulation software and the built-in C2X module was used in the analysis. The script was written in VB to implement I2V and V2V communications. First, two simulation scenarios were designed, one without the application of ASAS, and one with the application of ASAS at 100% market penetration rate (saturation of OBUs). Speeds of vehicles approaching the intersection, as well as the number of vehicles closing in that experienced hard-braking towards the end of the intersection approach, were recorded. This provided data used to evaluate the effectiveness of the proposed application. The evaluation results indicate that ASAS has a potential of reducing the number of MaxD-Based conflicts considerably. The results also revealed a reduction of about 50% in number of MaxD-Based conflicts resulting from drivers receiving advance speed advisory messages.

Since full market penetration of OBUs is not expected soon, a sensitivity analysis of market penetration rates was performed and showed a degradation in safety conditions at low penetration rates. The results demonstrated that at least 60% saturation of OBUs installation is required to observe a reduction in the number of MaxD-Based conflicts.

In future work, more research is needed to investigate the response of drivers to the speed advisory messages received. This study assumed 100% compliance rate of the received messages. The algorithm could also be modified to work with actuated signal control as this study only dealt with pre-timed signals. A mechanism of communicating messages from C2X equipped vehicles to non-equipped vehicles visually at lower market penetration rates respectively can be researched to potentially observe safety improvements.

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CHAPTER 4

Enhancing the Green Light Optimized Speed Advisory System to Incorporate Queue Formation

Included in the compendium of papers of the Transportation Research Board Annual Meeting, Washington D.C., 8th January, 2018

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Introduction

Achieving smooth urban traffic flow requires the reduction of excessive stop-and-go driving on urban arterials. Smooth traffic flow provides several benefits including improved safety, less fuel consumption, and improved intersection throughput by reducing lost times generated by stopped queues (Erdmann, 2013). The transportation sector is the second largest source of Greenhouse Gas (GHG) emissions in the United States (U.S.), according to the Environmental Protection Agency (EPA) (U.S. Environmental Protection Agency, 2010). More than 60 percent of the energy used in the U.S. transportation sector, an equivalent of 7.97 million barrels of oil per day, is due to light-duty vehicles (EIA, 2010). As a result, improving fuel economy and reducing emissions have drawn more attention of transportation researchers in recent years. Some of these research efforts are directed towards advanced traffic signal control.

Early developments in traffic control devices involved the use of conventional traffic signal systems that operate with pre-programmed timing schedules (Koone et al., 2008). Further improvements include signal coordination and signal actuation. More sophisticated forms of control have been developed in areas with unpredictable or rapidly changing traffic volumes. In these areas, adaptive traffic signals which rely on real-time traffic measurements to accommodate changing traffic patterns are suitable (FHWA, n.d.). All of these efforts share a common goal of reducing intersection delays and creating smoother traffic flows.

A recent development in intersection control, referred to as Green Light Optimal Speed Advisory (GLOSA), attempts to coordinate vehicles with a known and usually fixed signal plan, instead of adapting the signal plan to incoming vehicles (FHWA, n.d.; Koone et al., 2008). Through Connected Vehicle (CV) technology, which provides Infrastructure-to-Vehicle (V2I) and Vehicle-to-Vehicle (V2V) wireless communications, individual drivers are provided with

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information on the traffic signal phase and given advisory speeds to arrive at the intersection when the signal is green. Several previous studies have proposed different GLOSA algorithms (Tielert et al., 2010; Asadi & Vahidi, 2011; Katsaros et al., 2011; Erdmann, 2013; Seredynski, Dorronsoro, & Khadraoui, 2013; Xu, Zhang, Wang, & Li, 2015). However, only a few have investigated the impacts of formed vehicle queues at intersections.

The primary objective of GLOSA systems is to reduce stop-and-go driving on urban arterials by providing advisory speed messages to the driver to obtain an optimum speed trajectory. In addition to signal timing, the presence of vehicle queues introduces another temporal constraint, time required to dissipate formed queues. Failure to consider this variable may limit the efficiency of GLOSA systems. An algorithm that accounts for queue length and discharge headways for each position in the queue is needed to effectively compute advisory speeds.

Objective

The objective of this study was to develop a modified GLOSA algorithm that considers the formed intersection queues and queue discharge headways for each vehicle position. Therefore, this study used calibrated values of discharge headways in a simulation to better estimate queue dissipation time. A comparison was performed to evaluate the impact of disregarding the queue dissipation time. The proposed GLOSA algorithm was implemented and evaluated using VISSIM microscopic simulation software with the Car-to-Devices (C2X) simulation module.

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Literature Review

V2I and I2V applications have been developed for intersections and their effectiveness tested through simulation studies and prototype field test-beds. One such application is the GLOSA system, which utilizes broadcasted signal scheduling information over a wireless medium to the equipped vehicles in the vicinity, and subsequently computes the required speed to arrive on a green phase (Tielert et al., 2010). The system provides information to the drivers who can then adapt their speed accordingly. The effectiveness of GLOSA in reducing intersection delay, travel time, and emissions has been investigated in several previous studies. A study by Katsaros et al. (Katsaros et al., 2011) examined the impacts of GLOSA on fuel and traffic efficiency, average fuel consumption, and average stopped time at traffic signals. From this study, it was observed that lower penetration rates produced lower benefits; however, more improvement was obtained at higher penetration rates. The study also established an optimal activation distance of 300 m from the traffic lights, with slight variation depending on the road network. Rakha and Kamalanathsharma (Rakha & Kamalanathsharma, 2011) used VT-Micro to develop an eco-driving model to identify the optimal speed trajectory for approaching vehicles with the signal timing information available through I2V communications. The eco-driving model was integrated into a network wide simulator by Kamalanathsharma et al. (Kamalanathsharma, Rakha, & Yang, 2015). Similar studies have been conducted by Widodo et al. (Widodo, Hasegawa, & Tsugawa, 2000), Sanchez et al. (Sanchez, Cano, & Kim, 2006) and Wegener et al. (Wegener, Hellbruck, & Wewetzer, 2008). In addition to using signal timing information, a study by Dobre (Dobre, 2012) developed an algorithm that predicts the amount of emissions from a vehicle before an advisory speed is given to the driver. The driver is presented with an optional advisory speed that would result in less emissions. Tielert et al. (Tielert et al., 2010) coupled the Passenger car and Heavy

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duty Emission Model (PHEM) with VISSIM to investigate how gear choice and GLOSA activation distance from the traffic lights affected fuel consumption and emissions. Results indicated that sub-optimal gear choice can void the benefits of speed adaptation. In a more recent study, Jiang et al. (Jiang, Hu, An, Wang, & Park, 2017) proposed an eco-driving system for an isolated intersection under partially Connected and Autonomous Vehicles (CAV) environment to prioritize mobility and optimize traffic flow by optimizing speed profiles of the CAVs. All of the aforementioned studies have investigated different ways in which GLOSA can be activated in an arterial network, and the savings, in terms of fuel consumption, that may be realized from the use of GLOSA systems.

The majority of the GLOSA approaches developed provide speed advisory messages to drivers approaching the intersection by treating different segments independently. A study by Seredynski et al. (Seredynski, Mazurczyk, & Khadraoui, 2013) introduced the multi-segment GLOSA approach that considers several signals along a route. The study employed a genetic algorithm to obtain the advisory speeds for each segment. In a similar study, Seredynski et al. (Seredynski, Dorronsoro, et al., 2013) showed that in free flow conditions, multi-segment GLOSA performed better than the single-segment approach.

Unfortunately, GLOSA systems require advanced knowledge of signal switching times in order to work (Erdmann, 2013). The effectiveness of GLOSA is thus limited to the pre-timed signals. A study by Stevanovic et al. (Stevanovic et al., 2013) attempted to address this issue by implementing GLOSA in actuated-coordinated signal timings using average values of green, red, and amber times. Effects of the GLOSA, in the actuated-coordinated traffic control, were found to be negligible and even negative due to lack of accurate information for green intervals. The system is more complicated when the GLOSA is applied along with adaptive traffic control, which adjusts

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signal splits depending on real-time traffic demand. In an effort to solve this problem, a study by Erdmann (Erdmann, 2013) proposed the (AGLOSA) algorithm by combining Adaptive Junction Control simultaneously with GLOSA. With AGLOSA, vehicles announce their presence in advance to the traffic signals via V2I wireless communication, allowing optimization of an adaptive signal plan that is sufficiently stable for the GLOSA application. At 100% penetration, the study showed that the algorithm performed up to 72% better than other algorithms in similar situations.

Most GLOSA algorithms that use Dedicated Short Range Communication (DSRC) are constrained to the maximum range of wireless communication, the maximum and minimum speeds which can be provided as an advisory message to the driver. It will also take some time before all vehicles on the road are equipped with devices that allow V2I and V2V wireless communication. As a result, not all vehicles in the intersection approach, including equipped and non-equipped, will be able to arrive on a green phase. Queues will therefore be formed at the intersection. From the review of available literature, only a few GLOSA algorithms have incorporated the discharge headways of queues formed at the intersection approach when advisory speeds are computed. The algorithm proposed by Stevanovic et al. (Stevanovic et al., 2013) incorporated values of the discharge headways proposed by Greenshields (Greenshields et al., 1947); however, values of discharge headways vary from intersection to intersection. Moreover, the authors did not identify whether the simulation model used was calibrated to give discharge headways similar to the values used in the present study. A study by He et al. (He, Liu, & Liu, 2015) developed a more advanced multi-stage optimal control formulation that considers vehicle queue and traffic light status in obtaining the optimal vehicle trajectory. The study used numerical examples to demonstrate the effectiveness of the proposed control model. A recent study by Yang et al. (Yang, Rakha, & Ala,

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2017) tried to incorporate queue effects in an Eco-Cooperative Adaptive Cruise Control (Eco-CACC) through computation of the fuel-optimum vehicle trajectories. The study assumed a flow and density relationship as the basis for queue estimation. The present study investigates the impact of better discharge headway prediction on the performance of GLOSA systems using a micro-simulator. Actual discharge headway, retrieved from field data, of each position in the queue is used to calibrate the simulation model on which the GLOSA system is then applied. Additionally, the effects of using an algorithm that does not incorporate discharge headways is investigated.

Methodology

The methodological detail of the research study is presented in this section. Microscopic simulation modeling, the study site, and data input are discussed. Information on discharge headway calibration, simulation test-bed model, and estimation of queue dissipation time also are provided, as well as a detailed explanation of the proposed GLOSA algorithm.

Microscopic Simulation

Researchers and practitioners have widely used simulation applications for several purposes such as comparison of alternatives, analyzing the impact of developments, and estimating costs. Simulation offers an economic and efficient way of conducting these types of studies (Lownes & Machemehl, 2006). In this study, VISSIM microscopic simulation software was used, and the GLOSA algorithm was developed through Component Object Model (COM) interface available in the software. The I2V and V2V wireless communication between vehicles and signals were modeled using Car2X (C2X) Application Programming Interface (API) following an algorithm developed through COM interface.

Study Site

After researching available data on the driving behavior of different age groups, the Bruce B Downs corridor, located in Tampa, Florida was selected for study. The segment selected is a one mile stretch with four major signalized intersections (Figure 4.1). Additionally, naturalistic driving data, needed for microscopic simulation, was available for the corridor.

Figure 4.1 Bruce B Downs Corridor**.**

Data Input

Data used for simulations was collected from the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS), through the Virginia Polytechnic Institute website, for the Bruce B Downs corridor, in Tampa, Florida (Virginia Tech Transportation Institute, 2016). This corridor had the highest traversal density of NDS participants, about 400-600 people. The

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acquired data consisted of vehicle speeds and acceleration/deceleration rates, summarized by age group.

Additional traffic data were obtained from the City of Tampa. For the purpose of analysis, traffic data were categorized in three categories: traffic data, signal timing and geometric information, and calibration and validation data.

Traffic Data

Traffic volume data were provided by the City of Tampa traffic office in the form of intersection turning movement counts. Network balancing was performed, and the Origin-Destination (OD) matrix covering the morning peak hour was developed as shown in Table 4.1.

Signal Timings & Geometric Information

Signal timing data also were provided by the City of Tampa traffic office. Modeling was based on the AM peak hour. Geometric information, such as number of lanes, lane widths, and turning radii were extracted from Google Maps ("bruce B Downs - Google Maps," n.d.).

Calibration and Validation Data

Travel time and queue length data were used to calibrate and validate the model following the Florida Department of Transportation (FDOT) simulation guidelines (Florida Department of Transportation, 2014). Travel time data were determined by using the floating car technique with a Global Positioning System (GPS) receiver that logged data at one second intervals. Queue length data were obtained from video data of the intersections along the corridor. To account for day-to-day variability, video data were collected during the morning peak hours between 8:00 and 10:00

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AM for three consecutive days, March 20 to March 22, 2017. Discharge headway data were extracted using the same procedure, and later calibrated.

Table 4.1 Origin-Destination Matrix

Origins	Destinations: East 131st Ave	East Fletcher	East Fowler	East Pine	North Bruce B	South Bruce B	West 131st Ave	West Fletcher	West Fowler	West Pine	
East 131st Ave	0	4	9	3	19	12	91	8	4	1	151
East Fletcher	34	0	74	21	102	94	11	358	30	10	734
East Fowler	232	61	0	127	274	126	60	116	1032	46	2074
East Pine	13	4	11	0	16	14	3	7	4	16	88
North Bruce B	173	201	381	107	0	485	58	218	156	49	1828
South Bruce B	201	53	159	110	237	0	52	100	62	40	1014
West 131st	482	11	49	14	48	63	0	20	20	6	713
West Fletcher	33	355	72	20	141	92	11	0	30	9	763
West Fowler	182	48	1568	100	215	176	47	91	0	36	2463
West Pine	65	17	34	164	76	43	17	32	14	0	462
	1415	754	2357	666	1128	1105	350	950	1352	213	10290

Discharge Headway Calibration

Discharge headway data were first calibrated using the extracted video data to obtain the parameters used in VISSIM (see Table 4.2). Figure 4.2 shows an example of the calibration results for one of the four intersections along the study segment.

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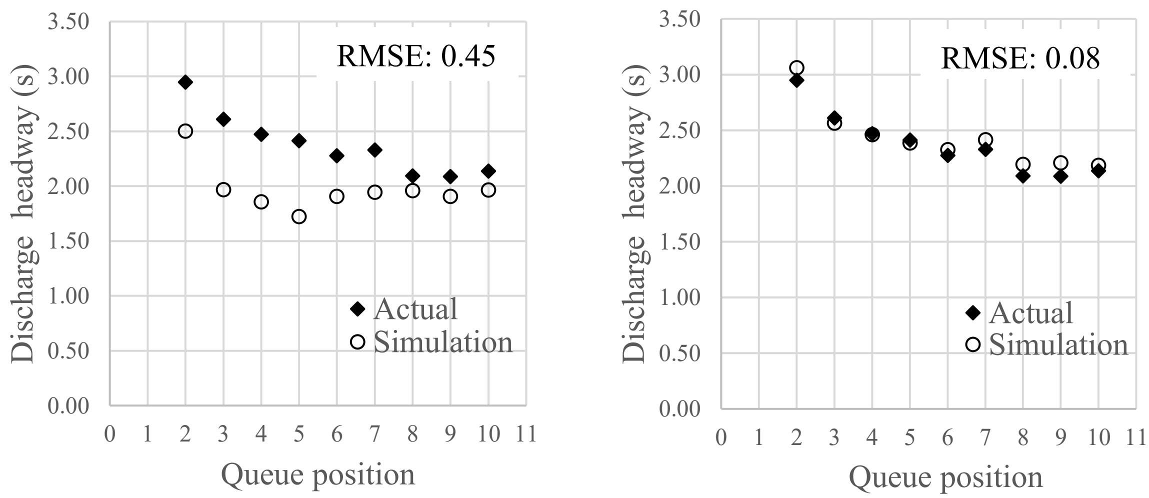
Table 4.2 VISSIM Parameter Sets

Parameter	Default	Calibrated
Average standstill distance (ft.)	6.56	7.4
Additive part of desired safety distance	2	2.95
Multiplicative part of desired safety distance	3	3
Safety distance reduction factor[a]	0.6	0.9

NOTE:

[a]Reduces the safety distance of vehicles close to the stop line.



(a) Before calibration (b) After calibration

Figure 4.2 Discharge headway calibration results.

Simulation Test-Bed

A simulation model for the corridor was developed in VISSIM. For demonstration purposes, the proposed GLOSA algorithm was implemented only for the North-Bound direction of the study segment. Wireless communications between the traffic signal system and the equipped vehicles were modeled using the C2X module available in the VISSIM through the COM API.

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Scripting was done using Visual Basic programming language (VBScript). The resolution was set to 10 time steps/Sim.sec, which is equivalent to a transmission frequency of 10 *Hz* for the Basic Safety Message (BSM).

The four intersections along the study corridor were modeled with coordinated signal control using the weekday AM signal plan. This facilitated the tracking of Signal Phasing and Timing (SPaT) information. To model the V2I communications, the following operational assumptions were made:

- The GLOSA activation frequency was set at 10 *Hz*. That is, every $\frac{1}{10}th$ of a second, the algorithm checks for vehicles which are in the communication range and have not yet received SPaT data and computed an advisory speed message. The algorithm then runs for these vehicles to provide their drivers with advisory speed messages.
- DSRC was used as the communication mode. Although the effective range of V2I communications is over 2000 ft. (Songchitruksa & Zha, 2014), the range of effective communication in this study was fixed depending on the segment length between intersections along the corridor.
- Communication was maintained between vehicles and the closest traffic signal ahead of the vehicle. Once the vehicle crossed an intersection, the communication between the vehicle and that intersection was terminated. Therefore, a traffic signal could not influence vehicles which are ahead of it or more than one intersection before it, a concept referred to as single-segment GLOSA.
- The method used for queue length estimation is different from that proposed by Stevanovic et al. (Stevanovic et al., 2013). Instead of only counting vehicles which are already in the queue, the algorithm derives the queue length from vehicles that are predicted to arrive on

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a red signal indication when required advisory speed messages are lower than the minimum or higher than the maximum allowable speed. The advantage of using this method is that vehicles that are predicted to come to a stop at the intersection, but have not yet joined the queue, are considered in establishing the queue length ahead of the vehicle.

- The study assumed 100% compliance rate to the speed advisory messages sent by the traffic signal system.
- A market penetration rate of 100% was assumed.

Estimation of Queue Dissipation Time

Speed thresholds used to determine if vehicles are in a queue state vary considerably for arterial roadways. In a study by Stevanovic et al. (Stevanovic et al., 2013) a vehicle was considered to be part of the queue when the speed drops lower than 3.6 km/h (2.2 mph*)*. Different definitions can be extracted from the default parameters of commercial simulation software. For example, in CORSIM, a vehicle is considered to be in the queue when its speed falls below 1 m/s (2 mph) (Mystkowski & Khan, 1999). Default parameters in VISSIM consider the queue state to start when the vehicle speed drops below 3.1 mph (5 km/h), with a maximum headway of 65.6 ft. The queue state ends when the speed of the vehicle goes above 6.2 mph (PTV AG., 2015). In this study, the default VISSIM parameters were adopted for defining the queue state of the vehicles.

The dynamics of queues can be complex as a result of shockwaves that propagate upstream, making it difficult to estimate the queue discharge time. The stochastic nature of discharge headways provides an additional challenge in obtaining accurate estimates of queue dissipation time. To simplify the evaluation of queue impact on the efficiency of GLOSA systems, two stages were considered:

1. Estimation of Queue length (number of vehicles).

Queue length was derived from vehicles that are predicted to arrive on a red signal indication when required advisory speed messages are lower than the minimum or higher than the maximum allowable speed.

2. Estimation of queue dissipation time.

   After multiple simulation runs, the discharge headway distribution for each queue position was obtained. Average discharge headway values for each queue position were used in estimating the queue discharge time.

GLOSA Algorithm

The objective of the algorithm was to provide speed advisory messages to assist drivers to arrive at the intersection during a green phase. The proposed algorithm differs from previous GLOSA algorithms by considering the time required to dissipate a formed queue at the intersection, ahead of the driver receiving the advisory message.

The algorithm first determines if vehicles are present in the DSRC area that have not computed advisory messages. If this condition is true, the algorithm performs computations for these vehicles. Data required for computations related to signal phasing and timing include: cycle length, cycle running time, and cycle time at both the start and end of the green phase. Vehicle data required for computations include: vehicle type, speed, acceleration/ deceleration status, position at the intersection, lane movement, as well as the C2X status of C2X equipped vehicles. Additionally, the stop bar location and the origin location of the wireless communication signals in the traffic signal system are required for the algorithm. The focus of this study was on vehicles that were required to slow down to arrive on a green signal indication, as indicated by the rectangle in Figure 4.3.

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Although similar, previous studies have not suggested a suitable value for the minimum allowable advisory speed (V_{min}). Therefore, a value of 10 mph was adopted for this study. Since the posted speed limit for the study corridor is 45 mph, the maximum allowable advisory speed (V_{max}) that can be provided was set at 45 mph.

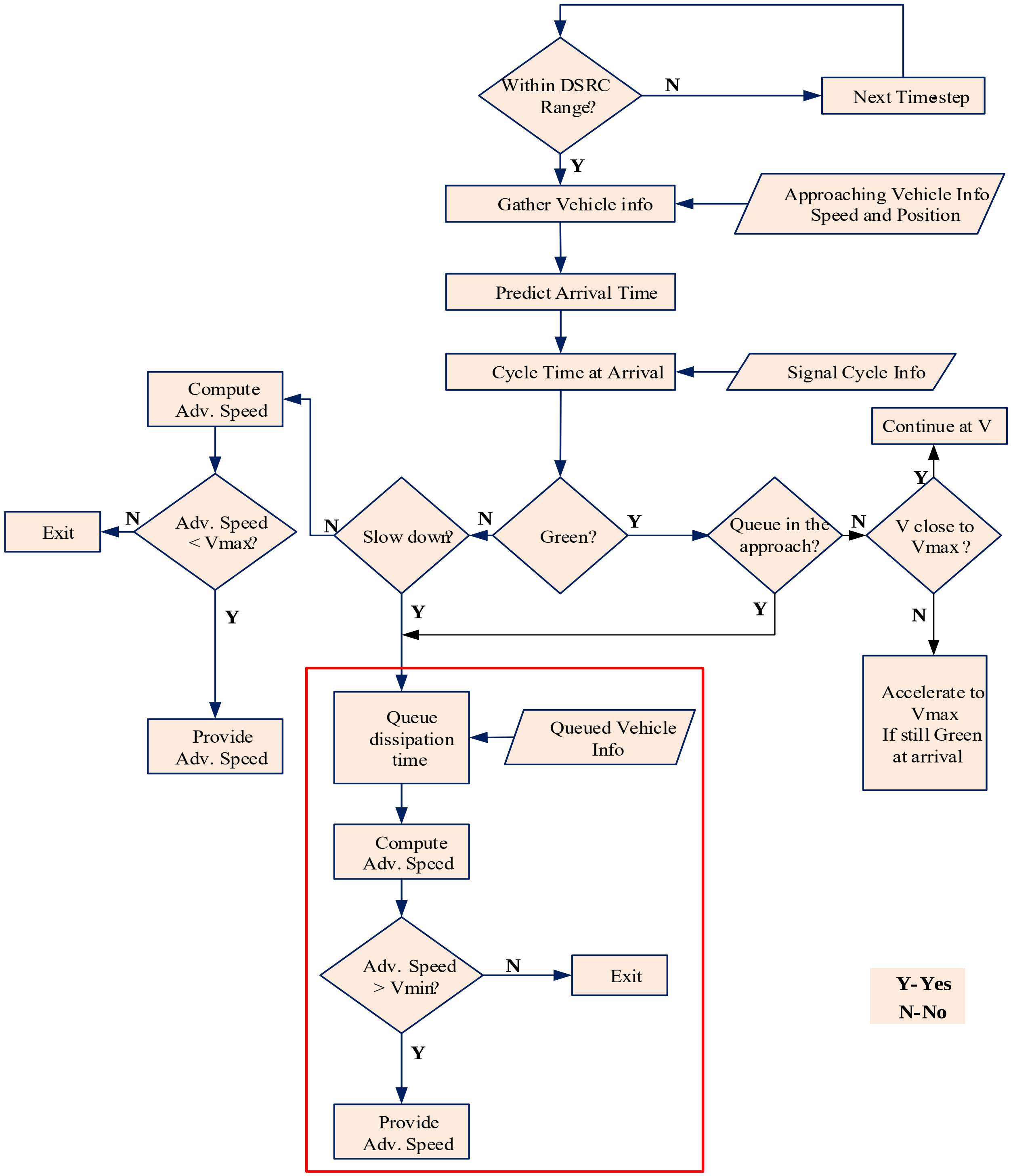

Figure 4.3 GLOSA Algorithm.

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For slowing vehicles approaching the intersection, the advisory speed was computed as follows:

Following the instability of acceleration/deceleration values in simulation, the acceleration/deceleration rate was not considered in the computation of the predicted time to arrive (t_{arr}), as shown by Equation (4.1).

$$t_{arr} = \frac{d}{V} \tag{4.1}$$

If $t_{arr} + C_{rt} < C_L$ **then**

$C_M = \boldsymbol{t_{arr}} + \boldsymbol{C_{rt}}$ (Arrival in the same signal cycle)

Else

$C_M = t_{arr} + C_{rt} - C_L$ (Arrival in the next signal cycle)

End if

The value of C_M is used to check the signal state at the predicted arrival time. If the signal state is red, and the vehicle qualifies to compute an advisory speed message to slow down, as shown in Figure 4.3, the advisory speed is computed using Equations (4.2) and (4.3), depending on whether the targeted arrival is in the current or next signal cycle, respectively.

$$Adv.Speed = \frac{d}{C_g - C_r + t_q} \tag{4.2}$$

$$Adv.Speed = \frac{d}{C_L + C_g - C_r + t_q} \tag{4.3}$$

`

Where:

C_L= Cycle length

C_{rt}= Cycle running time

C_g= Cycle time at start of green

t_q= Queue dissipation time

C_M = Predicted cycle time at arrival

d = Distance to intersection stop bar

t_{arr} = Predicted time to arrival

$Adv.\ Speed$ = Computed advisory speed

V = Current vehicle speed

Results and Discussion

The primary objective of GLOSA systems is to reduce stop-and-go driving on urban arterials using advisory speed messages to drivers as they approach the intersection. Therefore, a time-space diagram provides a good illustration of how well this objective is met.

To better evaluate how formed intersection queues affect the performance of GLOSA systems, three scenarios were created. The first scenario served as the base scenario using normal operations, with GLOSA not activated, and no advisory speed messages provided to the approaching vehicles. For the second scenario, GLOSA was activated, but the time to dissipate formed queues was not considered in the calculation of advisory speeds for slowing vehicles. In the third scenario, the time taken to discharge formed queues at the intersection was considered in computing the advisory speeds.

The time-space diagrams for selected cycles are depicted in Figure 4.4. Each scenario diagram consists of four independent segments because single-segment GLOSA was used. The

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advisory speed messages were computed independently for each segment. Only vehicles that computed advisory speeds to slow down to arrive on green are plotted. It is worth mentioning that the vehicles that appear in the diagrams are not the same for each segment. With single-segment GLOSA, a vehicle computes different kinds of advisory messages in each segment.

A general decreasing trend in stop delay is observed when scenarios 2 and 3 are compared with the base scenario. In scenario 2, most of the vehicles that computed an advisory speed to slow down still had to come to a full stop at the intersection. This effect is more pronounced in the shorter segments, shown in Figure 4.4(b), and illustrates how formed queues at the intersection can have a significant impact on GLOSA system efficiency.

Results from scenario 3 (Figure 4.4(c)) indicate a significant reduction in the number of stopping vehicles and amount of stopping time for vehicles that computed an advisory speed to slow down. Additionally, a significant reduction in the number of vehicles that qualified to compute a slowing down advisory speed was noted in the E Fowler Avenue-Uni. Square Drive segment. After the queue dissipation time was considered, the majority of computed advisory speeds fell below the allowable minimum speed for this segment.

Some vehicles were still observed to stop in scenario 3 because the advisory speeds were provided in the form of desired speeds during simulation. Reaction to the provided messages was not immediate, and the speeds of the vehicles in which drivers received the message oscillated around the provided advisory speed. Additionally, some simplifying assumptions were made in the queue dissipation time estimation which resulted in an underestimation of time to discharge the formed queue during some signal cycles.

More insight into the effect of queue discharge time is provided by the speed-time diagrams shown in Figure 4.5. Speeds of stopping vehicles were recorded as they approach the intersection

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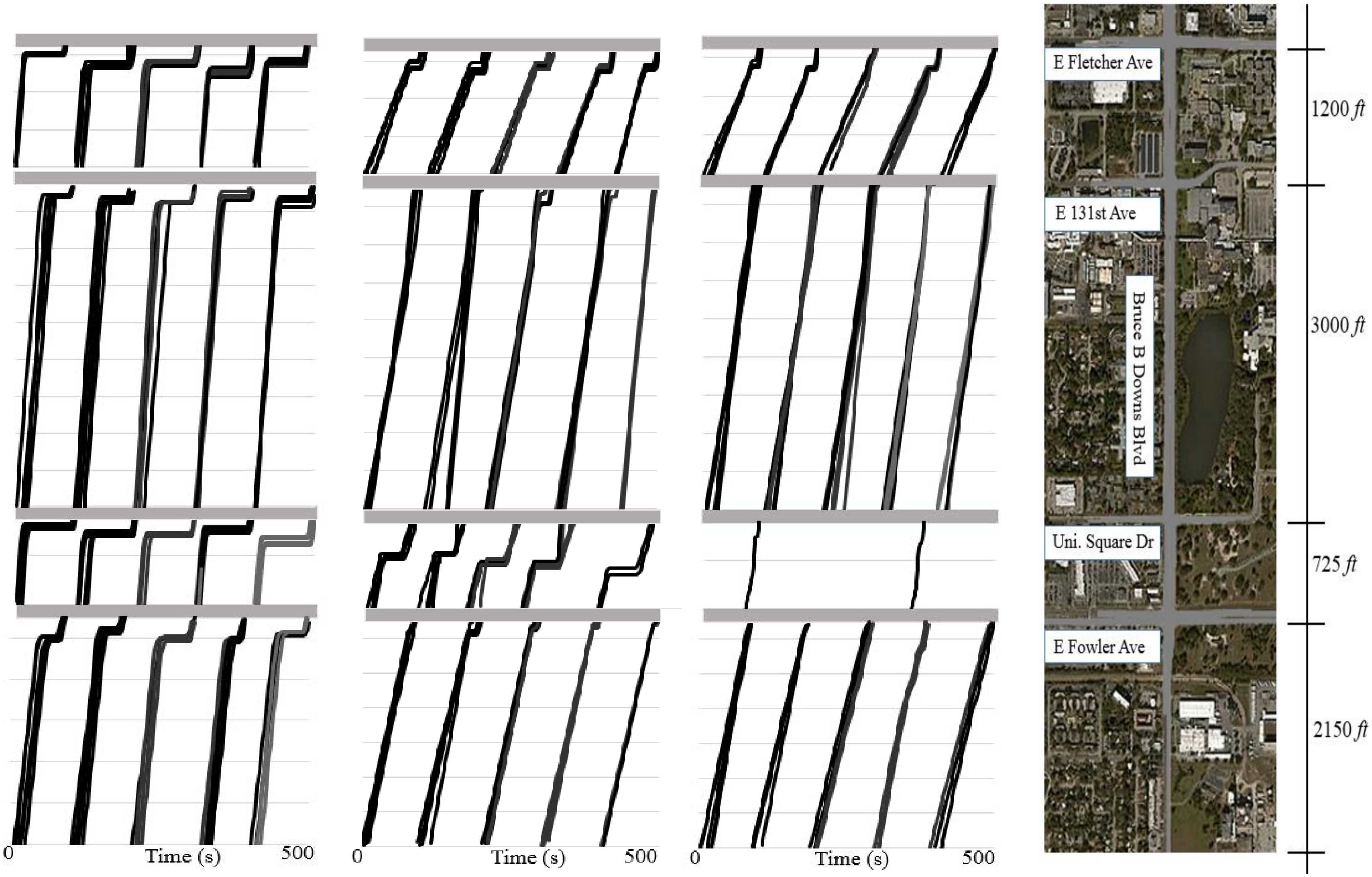
starting at 2000 ft. from the stop bar, south of E Fowler Ave. Drivers with no advisory messages were observed to approach the intersection at high speeds and spend more time stopped in the queue (Figure 4.5(a)), and some drivers appeared to accelerate before slowing. Scenario 2 (Figure 4.5(b)), where drivers are provided with advisory speeds, shows a reduction in time spent in the queue; however, many of the speeds still drop to zero. For this case, vehicles in which drivers are given advisory messages arrived when the queue had not cleared because queue discharge time was not considered. It is worth mentioning that the recording of vehicle speeds began after drivers had adjusted the speeds of the vehicles to the provided advisory speeds. In scenario 3 (Figure 4.5(c)), queue discharge time was considered in the computation of advisory speeds. Following the simplifying assumptions made in obtaining the queue dissipation time, vehicles still slowed down as they approached the intersections; however, few vehicles came to a complete stop.



(a) (b) (c)

Figure 4.4 Time-space diagrams: (a) base scenario (b) scenario 2 (c) scenario 3.

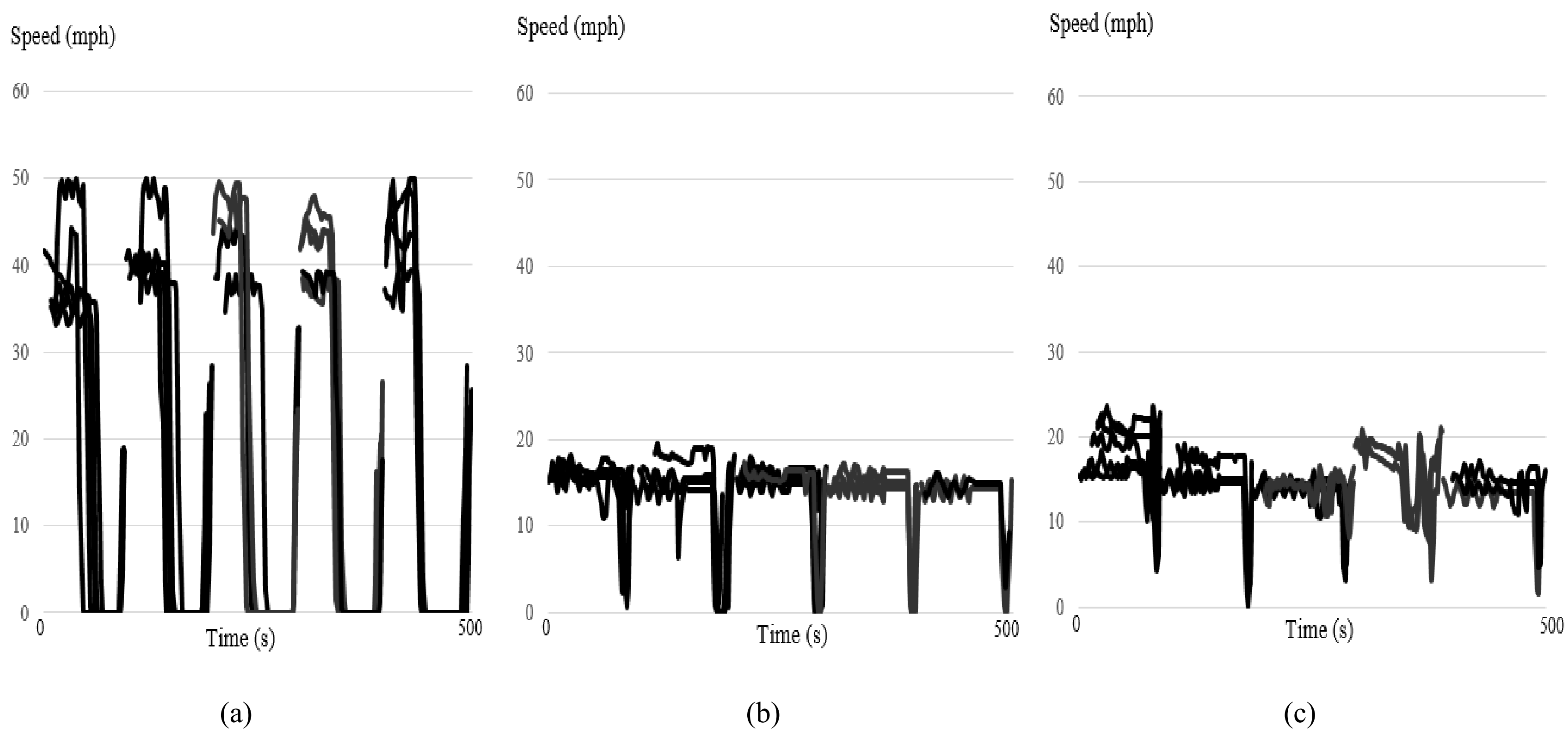


Figure 4.5 Intersection approach speeds: (a) base scenario (b) scenario 2 (c) scenario 3.

A record was kept for at least one segment of the time spent in the queue and the number of stops along the corridor for vehicles that computed an advisory message to slow down. For the base scenario, data for the same vehicle type were recorded, although no advisory speed was given to the drivers. Simulation results, summarized in Table 4.3, show the number of vehicles that qualified to compute advisory speeds decreased progressively through the scenarios. This is due to the minimum allowable advisory speed of 10 mph. A summary for all vehicles is also provided in Table 4.3.

Table 4.3 A Summary of Simulation Results

Scenario	**Total Number of Vehicles**	**Average time spent in queue (s)**	**Average number of stops**	**Average time spent in queue (s) (All Vehicles)**	**Average number of stops (All Vehicles)**
Baseline	658	203.33	2.31	212.16	3.22
Scenario 2	580	155.38	2.24	210.36	2.9
Scenario 3	365	99.65	1.42	182.84	2.27

A statistical comparison was performed across the scenarios to determine if the difference in the measured parameters was statistically significant. A one tailed t-test with $\alpha = 0.05$ was performed for the base scenario against scenario 2, and scenario 2 against scenario 3. The results are presented in Table 4.4.

Table 4.4 Comparison 1: Baseline against Scenario 2

Scenario	Baseline	Scenario 2	T-stat	P-Value	Statistically Significant
Average time spent in queue (s)	203.33	155.38	5.46	< 0.05	Yes
Average number of stops	2.31	2.24	0.92	0.18	No

Comparison 2: Scenario 2 against Scenario 3

Scenario	Scenario 2	Scenario 3	T-stat	P-Value	Statistically Significant
Average time spent in queue (s)	155.38	99.65	6.91	< 0.05	Yes
Average number of stops	2.24	1.42	10.03	< 0.05	Yes

Table 4.5 Comparison 1: Baseline against Scenario 2 (All Vehicles)

Scenario	Baseline	Scenario 2	T-stat	P-Value	Statistically Significant
Average time spent in queue (s)	212.16	210.36	3.699	< 0.05	Yes
Average number of stops	3.22	2.9	9.404	< 0.05	Yes

Comparison 2: Scenario 2 against Scenario 3 (All Vehicles)

Scenario	Scenario 2	Scenario 3	T-stat	P-Value	Statistically Significant
Average time spent in queue (s)	210.36	182.84	56.561	< 0.05	Yes
Average number of stops	2.9	2.27	18.504	< 0.05	Yes

Statistical tests indicate that the reduction in the time spent in the queue is significant even when GLOSA is activated without considering the queue discharge time (scenario 2). The change in the average number of stops along the corridor was found not to be significant when the base scenario was compared against scenario 2. This suggests that formed queues can significantly impact the efficiency of GLOSA systems. Comparison between scenarios 2 and 3 shows a significant change in the average number of stops along the corridor and the time spent waiting in queues. The overall impact on all vehicles is shown in Table 4.5 which shows significant improvements in both the average number of stops and average time spent in queue.

Conclusions and Recommendations

This study investigated the influence of formed intersection queues on the performance of GLOSA systems. A GLOSA algorithm was developed to address an issue not considered by existing algorithms. Actual discharge headway, retrieved from field data, for each position in the queue was used to calibrate the simulation model, on which the GLOSA system was applied. The algorithm was developed for coordinated signal control using the weekday AM signal plan.

A microscopic simulation approach was used for evaluating the effectiveness of the proposed algorithm. VISSIM microscopic simulation software and accompanying C2X module was used in the study. The corridor was modeled, and VBScript was used to implement the proposed GLOSA algorithm. Three simulation scenarios were designed; the baseline with no GLOSA in place, scenario 2 with GLOSA activated and queue discharge time not considered, and scenario 3 where queue dissipation time was used to compute advisory speeds. The time-space diagrams, time spent in queue state and number of stops were used as measures of performance of the proposed algorithm.

Findings reveal that the reduction in the time spent in the queue is significant even when GLOSA is activated without considering the queue discharge time. The change in the average number of stops along the corridor was found not to be significant when the base scenario was compared against scenario 2. This shows that formed intersection queues can impair the performance of GLOSA systems. Comparison between scenarios 2 and 3 shows a significant change in the average number of stops along the corridor and the time spent waiting in queues.

This study applied a single-segment GLOSA approach. In future work, similar investigations can be conducted on the performance of multi-segment GLOSA. Further studies can examine how fuel consumption and emissions are affected by queues in areas where GLOSA is activated. This study was also limited to only passenger cars. The study can be extended to mixed traffic in future studies. The present study assumed a 100% compliance rate of the received advisory speed messages. More research is needed to investigate the response of drivers to the speed advisory messages received.

CHAPTER 5 OVERALL CONCLUSIONS AND RECOMMENDATIONS

There has been increased research in the use of CV technology to address safety, mobility and environmental challenges that face the transportation sector. Most of the research efforts use simulation test beds as a way to test the functionality and feasibility of different applications of connected vehicles before actual field tests are conducted. This study used the VISSIM simulation software to assess the safety and mobility applications of SPaT information in a connected vehicle environment. This chapter lists the main findings of this study, mentions limitations of the study, and provides recommendations for future work.

Calibration of VISSIM Discharge Headways

Calibration in VISSIM produced mean discharge headways close to the values observed in the field but was not able to replicate the dispersion of the discharge headways obtained by the field measurements. Even by using high values of bx_{mult}, the parameter that controls dispersion of the headways, the dispersion of the distributions of the simulated headways could not come closer to those of the field observations.

Safety Evaluation of the ASAS in a Connected Vehicle Environment

A reduction of about 50% in number of MaxD-Based conflicts resulting from drivers receiving advance speed advisory messages. The results demonstrated that at least 60% saturation of OBUs is required to observe a reduction in the number of MaxD-Based conflicts.

Enhancing the GLOSA System to Incorporate Queue Formation

Findings reveal that the reduction in the time spent in the queue is significant even when GLOSA is activated without considering the queue discharge time. The change in the average number of stops along the corridor was found not to be significant when the base scenario was compared against scenario 2. This shows that formed intersection queues can impair the performance of GLOSA systems. Comparison between scenarios 2 and 3 shows a significant change in the average number of stops along the corridor and the time spent waiting in queues.

Limitations of the Study and Recommendations for Future Work

This study was limited to only passenger cars. The study can be extended to mixed traffic in future studies. In future work, more research is needed to investigate the response of drivers to the speed advisory messages provided. This study assumed 100% compliance rate of the received messages. The algorithms could also be modified to work with actuated signal control as this study only dealt with pre-timed signals. A mechanism of communicating messages received by C2X equipped vehicles to non-equipped vehicles visually at lower market penetration rates respectively can be researched to potentially observe safety improvements. Also, the inability of the calibration process to account for the dispersion of headway data requires special attention. VISSIM developers could modify the way discharge headways are modeled. Allowing discharge headway data to be entered as a distribution similar to how it is done for speeds, reaction time, and stopping distance before the stop bar, would enable analysts to define discharge headways in terms of the distributions observed in the field.

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<u>Relative Work Experience</u>

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Junior Transportation Engineer

1. Traffic Study and Traffic Operation Analysis
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University of North Florida, Jacksonville, Florida. August 2016-Present

Graduate Research Assistant

1. Collecting, processing, interpreting, analyzing, and compiling traffic data obtained for research projects.
2. Microscopic modeling of safety applications of connected vehicles.

Graduate Teaching/Tutorial Assistant

1. Preparing and carrying out lab tutorials for Microstation (SS4) with GeoPAK, spring 2018.

Publications

Published Papers

1. Safety Evaluation of the Advanced Stop Assist System in Connected Vehicle Environment – Transportation Research Record, Journal of the Transportation Research Board

Peer-reviewed papers conference proceedings

1. Calibration of VISSIM Discharge Headways Based on Field Measured Values and Naturalistic Driving Study Data. Transportation Research Board, Paper No. 18-06646, Washington D.C., January 2018.
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