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Quantifying the Mobility and Safety Benefits of Transit Signal Priority

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QUANTIFYING THE MOBILITY AND SAFETY BENEFITS OF

TRANSIT SIGNAL PRIORITY

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MD Sultan Ali

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To: Dean John L. Volakis
College of Engineering and Computing

This dissertation, written by MD Sultan Ali, and entitled Quantifying the Mobility and Safety Benefits of Transit Signal Priority, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Date of Defense: June 29, 2021

The dissertation of MD Sultan Ali is approved.

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Florida International University, 2021

DEDICATION

To my parents, Nargish Begum and Liakat Ali, and my siblings Najma and Jishan, for always being there for me and motivating me to dream big.

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ABSTRACT OF THE DISSERTATION

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Professor Priyanka Alluri, Major Professor

The continuous growth of automobile traffic on urban and suburban arterials in recent years has created a substantial problem for transit, especially when it operates in mixed traffic conditions. As a result, there has been a growing interest in deploying Transit Signal Priority (TSP) to improve the operational performance of arterial corridors. TSP is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections that helps transit service be more reliable, faster, and more cost-effective. The goal of this research was to quantify the mobility and safety benefits of TSP. A microscopic simulation approach was used to estimate the mobility benefits of TSP. Microscopic simulation models were developed in VISSIM and calibrated to represent field conditions. Implementing TSP provided significant savings in travel time and average vehicle delay. Under the TSP scenario, the study corridor also experienced significant reduction in travel time and average vehicle delay for buses and all other vehicles. The importance and benefits of calibration of VISSIM model with TSP integration were also

studied as a part of the mobility benefits. Besides quantifying the mobility benefits, the potential safety benefits of the TSP strategy were also quantified.

An observational before-after full Bayes (FB) approach with a comparison-group was adopted to estimate the crash modification factors (CMFs) for total crashes, fatal/injury (FI) crashes, property damage only (PDO) crashes, rear-end crashes, sideswipe crashes, and angle crashes. The analysis was based on 12 corridors equipped with the TSP system and their corresponding 29 comparison corridors without the TSP system. Overall, the results indicated that the deployment of TSP improved safety. Specifically, TSP was found to reduce total crashes by 7.2% (CMF = 0.928), FI crashes by 14% (CMF = 0.860), PDO crashes by 8% (CMF = 0.920), rear-end crashes by 5.2% (CMF = 0.948), and angle crashes by 21.9% (CMF = 0.781). Alternatively, sideswipe crashes increased by 6% (CMF = 1.060), although the increase was not significant at a 95% Bayesian credible interval (BCI). These results may present key considerations for transportation agencies and practitioners when planning future TSP deployments.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
ABM	Activity Based Model
API	Application Programming Interface
ASCT	Adaptive Signal Control Technology
ATMS	Advanced Traffic Management System
BCI	Bayesian Credible Interval
BRMS	Bayesian Regression Models using Stan
BRT	Bus Rapid Transit
CMF	Crash Modification Factor
CNOB	Cumulative Number of Buses
COM	Component Object Model
CV	Connected Vehicle
DMS	Dynamic Message Sign
EB	Empirical Bayes
FB	Full Bayes
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FI	Fatal & Injury
FV	Fitness Value
GA	Genetic Algorithm
GEH	Geoffrey E. Havers
GIS	Geographic Information System

GPS	Global Positioning System
HCM	Highway Capacity Manual
HMC	Hamiltonian Markov Chain
HSM	Highway Safety Manual
ID	Identification
ITS	Intelligent Transportation System
ITSA	Interrupted Time Series Analysis
KWT	Kinematic Wave Theory
LHS	Latin Hypercube Sampling
MAC	Media Access Control
MCMC	Markov Chain Monte Carlo
MEF	Mobility Enhancement Factor
NB	Negative Binomial
NUTS	No U-Turn Sampling
OR	Odds Ratio
PDO	Property Damage Only
PRG	Priority Request Generator
PRS	Priority Request Server
RBC	Ring Barrier Controller
RCI	Roadway Characteristics Inventory
RMSNE	Root Mean Squared Normalized Error
SG	Signal Group
SPF	Safety Performance Function

TIM	Traffic Incident Management
TMC	Transportation Management Center
TRB	Transportation Research Board
TSM&O	Transportation Systems Management and Operations
TSP	Transit Signal Priority
USDOT	United States Department of Transportation
WAIC	Widely Applicable Information Criterion

CHAPTER 1
INTRODUCTION

Continuous population growth has caused traffic congestion to become one of the primary concerns of economic development. Traffic congestion results in greater energy and fuel consumption, increased travel cost and travel duration, and increased environmental pollution (Treiber et al., 2008). In 2019, the cost of traffic congestion in the United States was $88 billion, an average of $1,377 per driver (INRIX, 2019). While transportation agencies strive to develop transportation systems that provide both mobility and safety benefits, with the ever-increasing demand for people and goods, traffic congestion continues to rise on the nation's transportation network. As a result, agencies have begun to explore traffic management strategies that provide more capacity without expanding the roadways' physical infrastructure. A number of agencies have adopted Transportation Systems Management and Operations (TSM&O) strategies and deployed Intelligent Transportation Systems (ITS) to maximize the efficiency, safety, and utility of the existing transportation infrastructure (Haule et al., 2021; Kadeha et al., 2021; Ali et al., 2021; Kodi et al., 2021). For example, Transit Signal Priority (TSP), Adaptive Signal Control Technology (ASCT), etc., are a few strategies that improve the safety and operational performance of arterial networks.

In recent years, the constant growth of vehicle traffic on urban and suburban roadways has created a substantial problem for transit, especially when operating in mixed traffic conditions. Even small variations in traffic patterns and station dwell times could potentially throw transit systems off schedule or disrupt their headways. TSP, a TSM&O strategy that could help transit services maintain their schedule, is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections (Smith et al., 2009). It is a tool that not only helps transit service be more reliable, faster, and more cost-effective (Smith et al., 2009), but also is relatively inexpensive and easy to implement to improve transit reliability and bus travel speed (Feng et al., 2015). Specifically, TSP is an operational improvement that adjusts signal timing to reduce public transit delays (Mishra et al., 2020).

TSP improves transit operations and addresses capacity constraints by prioritizing the movement of buses over passenger vehicles (Ali et al., 2017; Consoli et al., 2015; Hu et al., 2015; Skabardonis and Christofa, 2011; Smith et al., 2005; Zhou et al., 2006; Zlatkovic et al., 2013). Using detectors, TSP systems detect approaching transit vehicles and alter signal timings, when necessary, to prioritize transit vehicle passage and improve their performance. For example, during peak hours when queuing is more, TSP can allocate more green time for transit vehicles to traverse through an intersection and adhere to the schedule. TSP reduces waiting times of transit vehicles at signalized intersections, thereby increasing reliability (i.e., schedule adherence) and quality of service by reducing transit delay and travel time.

To improve the quality of transit service and increase bus ridership, there are several TSM&O strategies on transit priority with respect to time and space (Consoli et al., 2015; Hu et al., 2015; Skabardonis & Christofa, 2011; Smith et al., 2005; Zhou et al., 2006; Zlatkovic et al., 2013). Space-based TSP is, for example, dedicated bus lanes. In contrast, time-based TSP mainly refers to adjusting the traffic signal plan according to real-time bus arrivals to reduce the delay for transit buses at signalized intersections.

As shown in Figure 1-1, a TSP system consists of four main components: (1) a detection system which provides information on the location, arrival time approach, etc., of a transit vehicle requesting priority; (2) a priority request generator (PRG) which alerts the traffic control system that a transit vehicle would like to receive priority; (3) a priority request server (PRS) to process the priority request and decide whether and how to grant priority to the requested transit vehicle based on the programmed priority control strategy; and (4) software to manage the system, collect data, and generate a report of TSP operations after a priority decision is made (Smith, Hemily, & Inc, 2009).

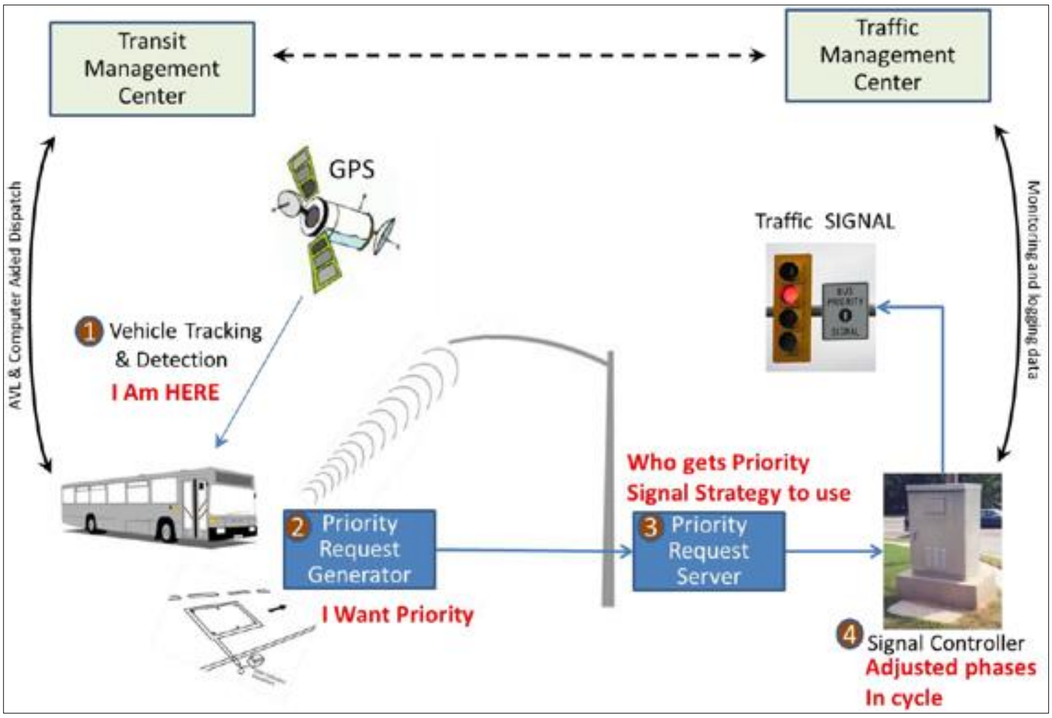


Figure 1-1: Conceptual Elements of Transit Signal Priority (Adapted: Wang & Associates, 2014)

In the stochastic setting of a transportation network, TSP prioritizes the movement of transit vehicles over other vehicles at a signalized intersection to assist transit vehicles in adhering to the schedule. Signal control and prioritization scenarios for TSP follow either a centralized TSP architecture or a distributed TSP architecture (Li et al., 2008). A centralized priority system utilizes the Transportation Management Center (TMC) in the decision-making process. In contrast, a distributed priority system does not involve the TMC in the decision-making process. The advantage of a centralized TSP architecture is that a local agency can have its signal controllers connected to a centralized system and managed by a TMC operator in real-time. However, this system always requires an operator, unlike a distributed priority system.

The advantage of a distributed TSP architecture is when there is no communication to a TMC or where the communication to a center does not occur in real-time. However, in a distributed TSP architecture, when a detector has a problem, it fails to detect transit buses and hence, fails to give them a priority.

The success of a TSP system depends on the bus frequency, bus speed, bus schedule adherence (travel time reliability), bus travel time and delay, and its ability to cause least disruption of all other vehicles along the main road and side roads. Not all corridors and signalized intersections are suitable for TSP deployment, as it could deteriorate traffic operations. Also, studies have found mixed results about the mobility and safety performance of TSP. Some studies concluded that the TSP deployment improved road safety (Naznin et al., 2016; Song and Noyce, 2019, 2018), while others associated it with deteriorating safety (Li et al., 2017; Shahla et al., 2009). Nevertheless, agencies have been deploying TSP across the nation. Therefore, this research aims to evaluate the mobility and safety performance of transit signal priority.

1.1 Problem Statement

Transit is continuing to be a priority, as more agencies are looking for strategies to increase transit ridership. Transit ridership is affected by several factors, including travel time reliability (i.e., schedule adherence), delay, dwell times, etc. These factors are directly impacted by the growing level of traffic congestion on urban arterial networks. Due to the shared dynamics of the transportation system, traffic congestion affects transit service more than other modes (Geneidy et al., 2015). Transportation agencies have been exploring strategies to optimize the performance of the existing multimodal infrastructure. TSP is one strategy that agencies can implement to minimize transit delay and improve travel time reliability by prioritizing transit vehicle movement at signalized intersections. However, there are several challenges associated with the

TSP strategy. TSP is often deployed at complex signalized intersections, with many conflicting movements, and these locations are also vital to the safety and efficiency of the arterial network. Therefore, the following fundamental questions need to be addressed when evaluating the operational and safety performance of a TSP deployment:

- Will prioritizing transit vehicles at a signalized intersection have any adverse effects on the traffic operations along the corridor?
- Can the TSP be implemented without creating unacceptable congestion on cross-streets?
- What are the benefits of proper calibration of microscopic simulation model for the evaluation of the mobility benefits of TSP?
- Does TSP improve traffic safety along the corridor?
- Will the crash frequency increase or decrease after TSP deployment?
- What type of crashes may be more likely to occur after TSP deployment?
- What type of crashes may be less likely to occur after TSP deployment?

1.1.1 Mobility Performance Evaluation of TSP

TSP affects the operational performance of not only transit vehicles, but also all other vehicles along both the corridor mainline and the cross-streets. Transit vehicles on the main road, in mixed traffic conditions, request priority to clear the intersection and avoid delay. This also allows other vehicle types to clear the intersection with the transit vehicles. However, studies that quantify the performance of TSP along a corridor with mixed traffic, consisting of both transit and other vehicles along the main road and cross-streets, are rare. The majority of existing studies have primarily focused on quantifying the impact of TSP only on transit vehicles, and very few have focused on estimating the impact of TSP on all other vehicles. For example, researchers have commonly used transit travel time, reliability of transit vehicles, and transit delay as performance measures in evaluating TSP. Note that these measures are all related to transit and are not related to all other vehicles on the network.

This study fills this gap in research by analyzing the impact of TSP on both the transit buses and all other vehicles on the corridor, using real-world traffic data to calibrate microscopic simulation models. The impact of TSP is analyzed for the main road, as well as the cross-streets.

1.1.2 Safety Performance Evaluation of TSP

Every traffic management strategy that focuses on improving mobility has a safety impact aspect. Regardless of the significant improvements in operational performance realized by the TSP deployment, the safety benefits are usually disregarded, especially during the project development process (Song and Noyce, 2019, 2018). The few studies that focused on measuring the safety implications of TSP have shown mixed results. Some studies indicated that TSP deployment improves road safety (Naznin et al., 2016; Song and Noyce, 2019, 2018), while others concluded that TSP worsens road safety (Li et al., 2017; Shahla et al., 2009). Therefore, there is a need to perform a comprehensive study to quantify the safety impacts of TSP. Additionally, if TSP benefits traffic safety, an assessment could help to further quantify and justify the wider deployment of the TSP strategy.

This study provides a comprehensive corridor-level assessment considering crash frequency for total traffic crashes, fatal/injury (FI) crashes, and property damage only (PDO) crashes, as well as crash types (i.e., rear-end, sideswipe, and angle crashes). CMFs were also developed for total crashes, specific crash levels (i.e., FI and PDO crashes), and crash types (i.e., rear-end, sideswipe, and angle crashes).

1.2 Research Goal and Objectives

The goal of this research was to evaluate the mobility and safety performance of transit signal priority. The specific objectives of this research include:

1. Assess the operational impacts of transit signal priority on buses and all other vehicles along a corridor in mixed traffic condition using a microscopic simulation approach.
2. Evaluate the safety effects of transit signal priority on total crashes, crash severity levels (i.e., FI and PDO crashes), and specific crash types (i.e., rear-end, sideswipe, and angle crashes) using a full Bayes before-after method.

1.3 Dissertation Organization

This dissertation includes six chapters. The remaining chapters are organized as follows:

- Chapter 2 presents a comprehensive synthesis of the literature on existing studies on the mobility and safety benefits of TSP. For mobility benefits, studies conducted using simulation and analytical modeling are discussed; whereas for safety benefits, studies conducted using different statistical approaches are discussed.
- Chapter 3 describes the data used to achieve the research goal.
- Chapter 4 discusses the methodologies used to achieve the research objectives.
- Chapter 5 presents the analyses and discusses the results. The results of the mobility performance of TSP are first discussed, followed by the discussion on the safety performance of TSP.
- Finally, the last chapter 6 concludes this dissertation by providing a summary of this research, contributions, and recommendations for future research.

CHAPTER 2
LITERATURE SYNTHESIS

This chapter provides a synthesis of previous studies on two broad topics: (a) mobility performance of TSP; and (b) safety performance of TSP. Section 2.1 discusses the existing studies on the TSP operations, simulation modeling methods, and analytical modeling methods. Section 2.2 presents the previous studies that evaluated the safety effectiveness of TSP. Section 2.3 discusses the challenges in quantifying the mobility and safety benefits of TSP.

2.1 Mobility Performance of TSP

2.1.1 Existing Studies on TSP Operations

The transit signal priority was introduced to improve the transit travel duration (Alluri et al., 2020; Cesme et al., 2015; Consoli et al., 2015; Shaaban and Ghanim, 2018; Skabardonis and Christofa, 2011; Zlatkovic and Stevanovic, 2013). To improve the operational performance of the transit systems, transportation researchers and transit agencies have devoted great efforts to the development of advanced transit systems during the past decades (Lin et al., 2015). Some of these treatments include but are not limited to the TSP, the queue jumpers, the bypass lanes, the bus-only lanes, etc. (Federal Transit Administration, 2010). Predominantly, the TSP, developed since the late 1960s (Smith et al., 2005), has been recognized as one of the most promising methods in reducing bus travel duration on arterials. Researchers have been evaluating the operational benefits of the TSP using several methods including simulation and analytical modeling. For simulation modeling mostly microscopic simulation modeling was used.

2.1.2 Simulation Modeling

Some studies have used a simulation modeling approach to optimize signal synchronization with TSP (Ali et al., 2018; Cesme et al., 2015; Consoli et al., 2015; Shaaban and Ghanim, 2018; Zlatkovic et al., 2013), while others have focused on resolving the concern of a system-wide traffic signal operation disrupted by the use of the TSP (Consoli et al., 2015; Dennis and Spulber, 2016). Microscopic simulation modeling using VISSIM has been commonly used to quantify the benefits of TSP (Lee et al., 2017). VISSIM is a microscopic multi-modal traffic flow simulation software package developed by PTV Planung Transport Verkehr AG in Karlsruhe, Germany (PTV, 2020). VISSIM was first developed in 1992. VISSIM is a time-step and behavior-based model developed to simulate traffic and depends on a psycho-physical car-following model based on the Wiedemann model which assumes that the driver can have one of four driving modes: free driving, approaching, following, and braking (PTV, 2010). VISSIM is an innovative microscopic simulation tool capable of modeling transportation networks. It can also evaluate performance for use in planning and operational analysis. The microscopic simulation includes each entity, i.e., car, transit, person, etc. that is simulated individually, i.e., it is represented by a corresponding entity in the simulation. The same holds for the interactions between entities.

VISSIM modeling was used to evaluate the TSP's effectiveness in a study conducted along International Drive in Orlando, FL (Consoli et al., 2015). The study compared the unconditional TSP and the conditional TSP (with bus 3 and 5 minutes behind schedule) with no TSP scenario. The authors concluded that the conditional TSP scenario considering a bus with 3 minutes behind schedule was the most effective scenario. The conditional TSP was found to result in a 2% to 12% reduction in travel time for transit vehicles.

Another study analyzed the optimal TSP strategy using VISSIM in combination with ASC/3 (advanced system controller) software-in-the-loop simulation (Zlatkovic et al., 2013). Four different models were used in the analysis: no TSP, TSP, TSP with phase rotation, and custom TSP. The custom-TSP scenario used custom-developed priority strategies created through the ASC/3 logic processor. The study findings indicated that TSP with phase rotation provided significant benefits for bus rapid transit, with some negative impacts on all other vehicles. Custom TSP provided major benefits for bus rapid transit in terms of travel time, delay and stops. However, this strategy had a negative impact when considering the overall traffic operations. It is also worth noting that in this study, the performance of cross-streets was not evaluated.

Cesme et al. (2015) conducted extensive simulation runs in VISSIM at an isolated intersection to evaluate the benefits of transit preferential treatments. The authors concluded that the greatest benefit was observed when the bus stop was relocated from a near-side stop to a far-side stop (Cesme et al., 2015). Moreover, with the TSP, the delay was reduced up to 19 seconds and benefits became more pronounced when the volume-to-capacity (v/c) ratio of the corridor is high. However, Ali et al. (2017) suggested that with a high v/c ratio, the benefits of the TSP at an intersection could be minimal.

Shaaban et al. (2018) used VISSIM to model, assess, and evaluate the potential benefits of implementing the TSP for transit buses. The authors used a *with* and *without* the TSP study to test the network performance of three transit routes. Different peak hours were considered in the performance assessment. The results indicated that the TSP lowered the transit delay and reduced the transit travel time by 40% (Shaaban and

Ghanim, 2018). A study by Pessaro and Van Nostrand (2012) discussed the performance of the TSP before and after its implementation for the I-95 express bus service in South Florida. The TSP deployment resulted in a 4% reduction in intersection delay and a 12.1% reduction in average bus travel time savings during morning peak hours.

Another study on the evaluation of Global Positioning System (GPS) technology-based TSP for mixed traffic bus rapid transit (BRT) for a 3-mile bus corridor was studied in Salt Lake County, Utah (Song et al., 2016). Although the study corridor was short, this study created eight microscopic simulation scenarios to cover current field conditions, the regular bus with the traditional TSP, the regular bus with GPS-based TSP, BRT with no TSP, BRT with traditional TSP, BRT with GPS-based TSP, BRT with conditional TSP, and BRT with multi conditional TSP implementation. The results indicated that GPS-based TSP performed as effectively as the traditional TSP. The conditional and multi-conditional TSP strategies showed benefits in providing the transit system considerable delay reduction (13% and 3%, respectively) and travel time savings (7% and 3%, respectively).

System-wide impacts of the green extension TSP was implemented on the U.S. Route 1 in the Northern Virginia area (Ahn and Rakha, 2006). The microscopic simulation results indicated the TSP generally benefitted transit vehicles, however, it did not guarantee system-wide benefits. A maximum of 3.40% of travel time savings was observed with the provision of green extension. This study further concluded that the green extension of the TSP did not increase side-street queue length. Lian et al. (2019) evaluated a TSP strategy that could consider the number of bus arrivals for real-world signal controllers. In order to achieve the objective, the authors presented the cumulative number of buses (CNOB) TSP strategy based on Siemens 2070 signal controllers. Here the TSP strategy extended the max call time according to the number of buses in the arrival section when priority phases are active (Lian et al., 2019). Also, the TSP strategy truncated the green time according to the number of buses in the storage section when non-priority phases are active. The results indicated that the CNOB TSP strategy not only significantly reduced the average delay per person without using the TSP optimization but also reduced the adverse effects on the general vehicles of non-bus priority approaches for the intersections with a lot of bus arrivals.

2.1.3 Analytical Modeling

In addition to simulation modeling, researchers have used analytical modeling to estimate the potential benefits of TSP. A study estimated the impacts of the TSP on intersection operations by using a moving bottleneck analytical approach (Wu and Guler, 2019). The study modeled buses as moving bottlenecks, incorporating it into a kinematic wave theory (KWT) model. A dynamic programming algorithm was developed to evaluate the changes in delays to buses and cars caused by the TSP using KWT and queuing theories considering bus is a moving bottleneck. The study results revealed that the TSP implementation can reduce system-wide total car and bus delays. However, it was also found that the presence of a downstream bottleneck can diminish the benefits of the TSP.

A mathematical model based on Brownian motion evaluated conditional signal priority where buses send priority request only when the request improves reliability (Dennis and Spulber, 2016). The outcomes showed that conditional priority improves reliability considerably as it reduces the number of priority requests. Another mathematically based method was applied to the effects of the TSP on bus service reliability (Anderson and Daganzo, 2019). The evaluation included both low (scheduled) and high-frequency (unscheduled) systems operated by headways. A mathematical model based on Brownian motion was proposed for the former. It was found that conditional priority improved reliability and also reduced the number of priority requests, especially for the high-frequency system of up to 50%. Also, for the high-frequency system by using conditional priority the average headway reduced by speeding up the buses.

A majority of the existing studies have described that the transit service benefitted after the deployment of TSP. However, most of the studies have focused on transit operational performance measures, while very few have focused on estimating the TSP's impact on all other vehicles. Additionally, in most studies cross-street analysis was not taken into consideration. One of the studies using a simulation approach did not guarantee system-wide TSP benefit, while another study on TSP using an analytical approach could reduce system-wide delay. This study analyzed the impact of the TSP on both the transit buses and all other vehicles on the corridor and by using real-world traffic data to calibrate the microscopic simulation models.

2.1.4 Calibration Benefits of Microscopic Simulation Model

Several previous studies have examined the calibration and validation of microscopic simulation models for use in traffic operation evaluation. Existing studies have shown well calibrated microscopic simulation model have benefits in terms of transferability (Bowman et al., 2017; Essa & Sayed, 2015; Gallelli et al., 2017; Koppelman & Wilmot, 1982; Sikder et al., 2014). Previous studies showed how well calibrated microscopic simulation model results may be transferred between two study locations. After proper calibration of the microscopic simulation model several studies used either the application-based or the estimation-based approaches for model results transferability (Bowman et al., 2017; Essa & Sayed, 2015; Gallelli et al., 2017; Koppelman & Wilmot, 1982; Sikder et al., 2014). Therefore, the transferability of calibrated parameters for TSP in a microscopic simulation environment is a positive step for research, especially for accumulating simulation evidence on what aspects of these models are transferable and understanding how best to transfer such models.

Essa and Sayed (2015) performed a study on the transferability of calibrated microsimulation model parameters for safety assessment using simulated conflicts. When applied to other sites, the study examined whether the calibrated parameters gave reasonable results in terms of the correlation between the field-measured and the simulated conflicts. Two signalized intersections were used in this transferability study. Calibrated VISSIM parameters obtained from the first intersection, which maximized the correlation between simulated and field-observed conflicts, were used to estimate traffic conflicts at the second intersection and compare the results to parameters optimized specifically for the second intersection. The study results showed that the VISSIM parameters were generally transferable between the two locations, as the transferred parameters provided better correlation between simulated and field-measured conflicts than using the default VISSIM parameters (Essa and Sayed, 2015).

Gallelli et al. (2017) investigated the transferability of calibrated microsimulation parameters for operational performance analysis in roundabouts. Transferability procedures were adopted to check whether calibrated parameters of one location were suitable for another location. The results showed that the application of Weidemann 99 parameters, calibrated for the first case study to the second case study, reduced the Root Mean Squared Normalized Error (RMNSE) by more than 50%, thus, confirming an acceptable level of transferability of these parameters between the two case studies (Gallelli et al., 2017).

Sikder et al. (2014) studied the spatial transferability of tour-based time-of-day choice models across different counties in the San Francisco Bay area in California.

Also tested was the hypothesis that pooling data from multiple geographic contexts helped in developing better transferability models than those estimated from a single context. An estimation-based approach was used that yielded encouraging results in favor of transferability for the time-of-day choice model, with a majority of the parameters estimated in the pooled model found to be transferable (Sikder et al., 2014). The study also emphasized that pooling data from multiple geographic context appears to help in developing better transferability models, with better transferability. However, attention is needed in selecting the geographic contexts from which to pool data.

Koppelman and Wilmot (1982) conducted a transferability analysis of disaggregate choice models. The study considered transferability from the perspective of the usefulness of information provided by a model that predicts in a context different from that in which it is estimated. The study observed inconsistency between general measures of error that indicate that transferability in this context was appropriate and the statistical analyses that reject hypotheses that support transferability. Results also indicated that model transferability is a property of the estimation and application context, as well as the specification of the model. Transferability is also substantially improved by the adjustment of alternative specific constants (Koppelman & Wilmot, 1982).

Bowman and Bradley (2017) examined the spatial transferability of an activity-based model (ABM), a travel forecasting model. Statistical tests were used to test transferability, including tests of regional differences in the model coefficients, likelihood ratio tests of model equivalence, and transferability indexes, which measure the degree of model differences. The study results indicated that parameters associated with travel time and cost caused the biggest problem with transferability. The study also concluded that agencies considering a transfer of an ABM from another region would do well to find a region within the same state (Bowman et al., 2017).

2.2 Safety Effectiveness of TSP

While the operational performance metrics have been considered the principal criteria while deploying TSP, little attention has been given to the TSP's anticipated safety impacts and is often qualitative (Li et al., 2017). Few studies that focused on determining the safety effectiveness of TSP have shown mixed outcomes. Some studies concluded that the TSP deployment improved road safety (Naznin et al., 2016; Song and Noyce, 2019, 2018), while others associated it with deteriorating safety (Li et al., 2017; Shahla et al., 2009). Although the key operational performance of a TSP system is through adjusting the traffic signal, they are often locally customized based on the demand of the transit vehicles, the capability of the respective traffic signal, and local traffic conditions. The fact that TSP may vary based on local conditions could explain the mixed findings from the previous studies (Song and Noyce, 2019).

Table 2-1 summarizes the adopted methods and key findings presented in the existing studies that explored the safety effectiveness of TSP. Of the seven studies presented in Table 2-1, three were conducted in Australia, two in the United States, and the remaining two were conducted in Canada.

As indicated in Table 2-1, all of the three studies conducted in Melbourne showed a reduction in crash frequency following the activation of TSP (Goh et al., 2014; Goh et al., 2013; Naznin et al., 2016). Specifically, Goh et al. (2013) used an aggregate analysis, i.e., EB before-after analysis and disaggregated level safety audit review, on 56 TSP corridors and observed a 14% and a 23% reduction in total crashes and rear-end crashes, respectively. Goh et al. (2014) analyzed 99 TSP sites using mixed effect negative binomial (MENB) and backpropagation neural network (BPNN) and estimated a 53.5% reduction in bus crash frequency. Naznin et al. (2016) conducted an empirical Bayes before-after analysis on 29 TSP sites in Melbourne, Australia, and concluded that TSP resulted in a 13.9% reduction in traffic crashes.

Consistent with the results from the safety studies conducted in Melbourne, Australia, the two studies conducted in the United States also concluded that TSP improved safety along the corridors (Song and Noyce, 2018, 2019). Song and Noyce (2018) evaluated the safety performance of TSP on 11 corridors with TSP in King County, Washington. The study used an empirical Bayes (EB) method, where a 13%, 16%, and 5% reduction in total crashes, PDO crashes, and FI crashes, respectively, was observed. Another study by Song and Noyce (2019) used an interrupted time series analysis (ITSA) conducted in Portland, Oregon, and observed a 4.5% reduction in total crashes and a 10% reduction in PDO crashes along the corridors with TSP. However, the decrease in FI crashes following the activation of TSP was not statistically significant. While the total crashes reduced, crashes involving pedestrians and bicyclists increased along the corridors with TSP. Both studies did not consider the influence of TSP on crash types.

While the studies in Australia and the United Stated reported enhanced safety due to TSP deployment, the two studies conducted in Toronto, Canada observed that safety deteriorated after the deployment of TSP (Li et al., 2017; Shahla et al., 2009). Li et al. (2017) used a microscopic simulation approach and negative binomial regression models and observed a 1.6%, 2.9%, 1.9%, and 2.1% increase in total crashes, angle crashes, rear-end crashes, and sideswipe crashes, respectively. Shahla et al. (2009) used a negative binomial regression approach and indicated that the number of traffic crashes increased on 24 TSP corridors in Toronto, Canada.

Table 2-1. Existing Studies on Safety Performance of TSP

Reference	Number of Study Sites	Factors	Key Study Findings	Method	Study Period	City, State
Goh et al. (2013)[P]	• Treatment corridors: 56 • Comparison Sites: 332	AADT	After TSP: overall crashes were reduced by 14%. Also, the number of fatal and serious injuries considerably dropped from 42 to 29 per year	Aggregate analysis, i.e., empirical Bayes before-after analysis and disaggregate-level safety audit review (corridor level assessment)	2003-2007	Melbourne, Australia
Goh et al. (2014)[P]	• Treatment corridors: 99 • Comparison Sites: NA	AADT, length of bus route segment, number of bus services per week, stop density, presence of TSP	With TSP: bus crash frequency reduced by 53.5%	Mixed effect negative binomial (MENB) and backpropagation neural network (BPNN) (corridor level assessment)	2009-2011	Melbourne, Australia
Naznin et al. (2016)[P]	• Treatment corridors: 29 • Comparison Sites: 82	AADT	After TSP: traffic crashes were reduced by 13.9%	Empirical Bayes before-after analysis (intersection level assessment)	2005-2012	Melbourne, Australia
Song and Noyce (2018)[P]	• Treatment corridors: 11 • Comparison Sites: 75	AADT, posted speed limit, number of lanes, segment length	After TSP: total crashes reduced by 13%, PDO crashes reduced by 16%, and FI crashes reduced by 5%	Empirical Bayes before-after analysis (corridor level assessment)	2002-2015	King County, Washington
Song and Noyce (2019)[P]	• Treatment corridors: 13 • Comparison Sites: 10	Number of lanes, trafficway characteristics (one-way or two-way street, section length, AADT, percentage of street section with median, number of bus routes, signal density	With TSP: total crashes reduced by 4.5%, PDO crashes reduced by 10%, and FI crashes did not significantly change compared to the non-treatment group	Controlled interrupted time series analysis (ITSA) (corridor level assessment)	1995-2010	Portland, Oregon
Shahla et al. (2009)[N]	• Treatment corridors: 24 • Comparison Sites: 35	AADT, number of signalized intersections, turning movements, bus stop locations (near-side or far-side), appearance of TSP	With TSP: number of traffic crashes increased	Negative binomial regression (intersection level assessment)	1999-2003	Toronto, Canada
Li et al., (2017)[N]	• 140 signalized intersections	Peak hour volume, number of signalized intersections	With TSP: total crashes increased by 1.6%, angle crashes increased by 2.9%, rear-end crashes increased by 1.9%, and sideswipe crashes increased 2.1%	Microsimulation and negative binomial regression (intersection level assessment)	2006-2010	Toronto, Canada

Note: [P]TSP has positive impacts on the safety effectiveness of roadways; [N]TSP has negative impacts on the safety effectiveness of roadways; NA is not applicable; AADT is Annual average daily traffic.

Excessive extended green time was reported as one of the possible reasons for the increase in crash frequency along the corridors with TSP.

As indicated in Table 2-1, previous studies that attempted to quantify the safety performance of deploying TSP have mainly used two types of methods: (1) crash frequency models such as negative binomial (Goh et al., 2014; Li et al., 2017; Shahla et al., 2009); and (2) safety effectiveness evaluation methods such as the before-after EB approach and controlled interrupted time series analysis (Goh et al., 2013; Naznin et al., 2016; Song and Noyce, 2019, 2018). Crash frequency models mainly focus on understanding factors that influence crash frequency along corridors with TSP. While developing crash frequency models, a negative binomial (NB) model has been conventionally used since it is better suited for modeling crash data. The NB model accounts for the over-dispersion of crash data (Srinivasan and Bauer, 2013). Instead of using the conventional NB model, Goh et al. (2014) considered a mixed-effects negative binomial model to account for unobserved location and time-specific factors. Li et al. (2017) explored the use of microscopic simulation and crash prediction models to investigate the safety performance of intersections with TSP. Nonetheless, microscopic simulation models are unable to mimic actual field representation as they are based on presumptions of safe driver behavior (Bevrani and Chung, 2012).

Three studies summarized in Table 2-1 applied the empirical Bayes (EB) before-after analysis to explore changes in expected crash frequency at locations where TSP was implemented (Goh et al., 2013; Naznin et al., 2016; Song and Noyce, 2018). The appeal of the EB methodology is that it accounts for the regression-to-the-mean effects, changes in traffic volume at the treatment corridors that might result from the treatment itself, and the influence of time trends in crash occurrence, i.e., changes over time due to factors such as weather, crash reporting practices, vehicle technology, and driving behavior. Regardless of the notable benefits of the EB method over other methods, it still suffers from methodological and statistical limitations, and inability to account for the uncertainty while computing the CMFs from the SPF's regression coefficients. That is, the EB method estimates the CMFs in two steps, i.e., (i) develop SPFs and (ii) use SPFs to estimate CMFs. Therefore, in the EB method, there is more chance of carrying the error to estimate the CMF. Moreover, the EB method is not suitable for small sample sizes.

A full Bayes (FB) method could potentially address these limitations. The FB approach integrates the process of estimating SPFs and treatment effects in a single step, incorporating the uncertainties of the SPFs in the final estimates (Park et al., 2016). Also, the FB method can yield robust result even with small sample size (Li et al., 2013; Persaud and Lyon, 2007). More detailed description of the FB method is presented in the methodology chapter (Section 4.2).

2.3 Summary

Proper evaluation of the mobility and safety benefits of transit signal priority is very essential to accurately report its effectiveness and deploy on the field. The following subsections discuss the research gaps pertaining to the mobility and safety benefits of TSP.

2.3.1 Challenges in the Evaluation of the Mobility Performance of TSP

There are several studies on the mobility performance of TSP. A majority of the existing studies have primarily focused on evaluating the impact of the TSP on transit vehicles, i.e., mostly buses, while very few have focused on estimating the TSP’s impact on all other vehicles. For instance, researchers have generally used transit travel time, reliability of transit vehicles, and transit delay as performance measures in evaluating the TSP. Note that these measures are all related to transit and are not related to all other vehicles on the network.

This study fills this gap by analyzing the impact of the TSP on both the transit buses and all other vehicles on the corridor and by using real-world traffic data to calibrate the microscopic simulation models. The impact of TSP is also analyzed for the cross-streets as well. Unlike other studies, this study also developed Mobility Enhancement Factors (MEFs) to better estimate the operational impact of the TSP on transit buses and all other vehicles along the corridor.

After the evaluation of the mobility performance of TSP, the importance of well calibrated VISSIM model with TSP integration was also studied. The critical question to answer is whether a well calibrated VISSIM model with TSP integration results are interchangeable between two similar transit corridors or not. There are so many transit corridors across the nation, however, it is difficult to conduct TSP studies by using microscopic simulation method for all transit corridors where TSP could be implemented. Therefore, the transit agencies may transfer the results of a well calibrated microscopic simulation model of an existing TSP corridor to a potential corridor where TSP could be implemented in the future to provide better transit service. Therefore, this study also showed the importance of calibration of the microscopic simulation TSP model. The study investigated the performance of calibrated parameters of the microscopic simulation model by using application and estimation-based approaches.

2.3.2 Challenges in the Evaluation of the Safety Performance of TSP

In addition to quantifying the mobility performance of TSP, evaluating the safety performance of TSP and understanding the contributing factors is vital. Existing safety studies on TSP are rare. The studies that have evaluated the safety benefits of TSP have shown mixed findings. Some studies indicated TSP improved safety, while others indicated it deteriorated safety. Unlike previous studies, this study will provide a comprehensive corridor level assessment considering crash frequencies i.e., for total traffic crashes, including PDO crashes and FI crashes, and crash types (i.e., rear-end, sideswipe, and angle crashes) by using a full Bayesian approach. CMFs were also developed for total crashes, specific crash severity levels, and crash types.

CHAPTER 3
DATA NEEDS

The data needs and study area were different for estimating the mobility and safety effects of TSP. VISSIM was used to model TSP to quantify the operational impacts on buses and all other vehicles along a corridor in mixed traffic condition. To replicate similar field scenario in the VISSIM model various data were needed, for instance, turning movement counts, signal timing plans, transit information, etc. For safety, crash data, geometric characteristics data, traffic volume data, etc. were need for the corridors where TSP was activated not activated. Therefore, the study area and the data needs were different to quantify the mobility and safety effects of TSP. Section 3.1 describes the data needs and study area for the operational impacts of TSP on buses and all other vehicles. Section 3.2 describes the data needs and study area for the safety effects of TSP.

3.1 Mobility Performance of TSP

The study area and the data required to estimate the mobility benefits of TSP are discussed in the following subsections.

3.1.1 Study Area

The analysis was based on a 4-mile corridor along Mayport Road, between Atlantic Boulevard and Edward Avenue, in Jacksonville, Florida. The study corridor serves bus route #24, which is a major transit route in the area in both the northbound (NB) and southbound (SB) directions. The bus circulates between the Atlantic Village Shopping Center (SB) and the Wonderwood Park-n-Ride (NB). Figure 3-1 shows the Mayport Road study corridor with 10 signalized intersections, between Wonderwood Drive and Atlantic Boulevard.

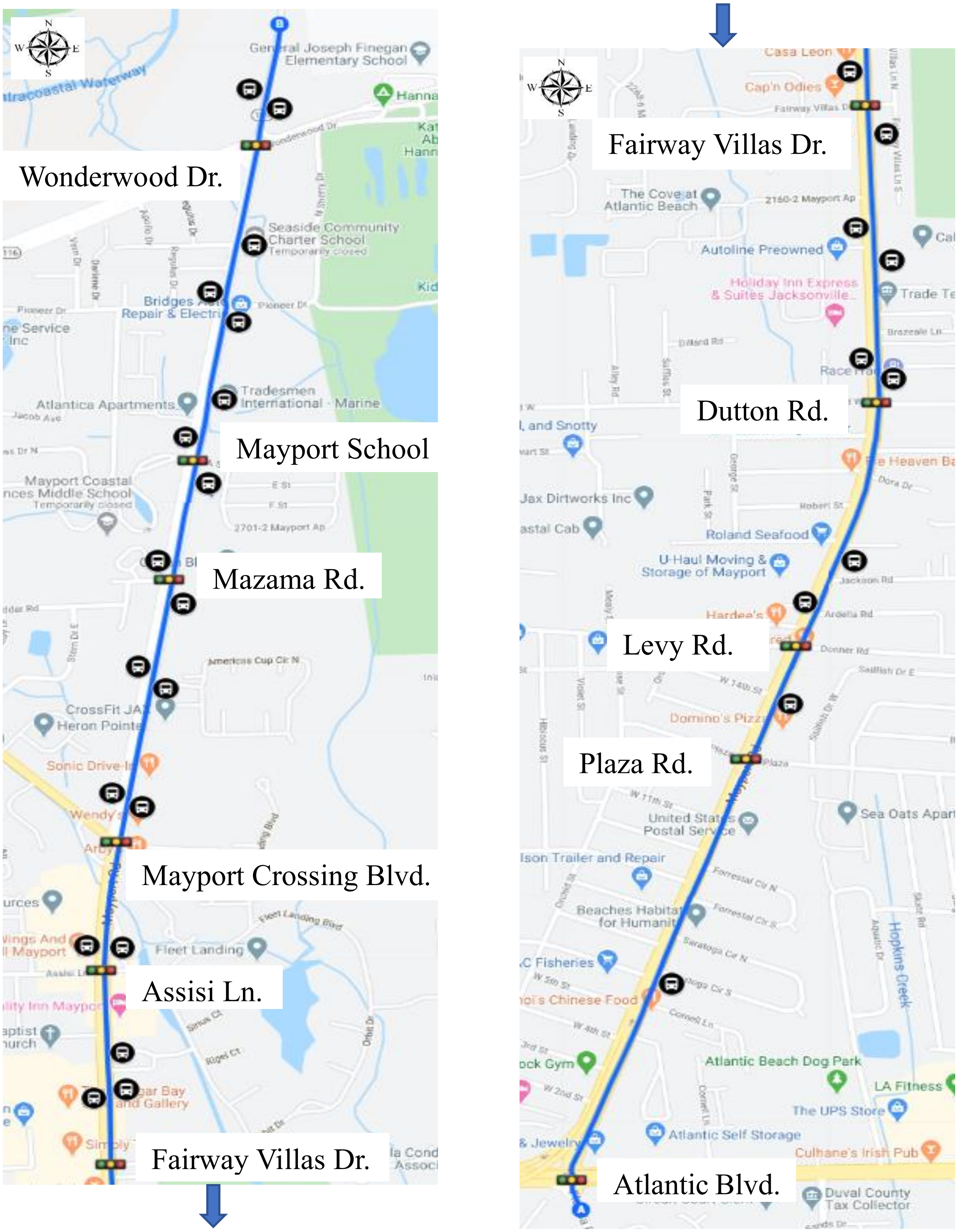


Figure 3-1: Mayport Road Study Corridor in Jacksonville, Florida

To demonstrate calibration benefits of TSP integrated VISSIM model the analysis was based on a 4-mile corridor along SW 8th Street, between SW 107th Avenue and SW 67th Avenue, in Miami, Florida. The study corridor serves bus route #8, which is a major transit route in the area in both the eastbound (EB) and westbound (WB) directions. The bus circulates between the FIU Terminal (WB) and the Brickell Station (EB). Figure 3-2 shows the SW 8th Street study corridor with 12 signalized intersections, where the top section is from SW 107th Ave. to SW 87th Ave., and the bottom section is from SW 87th Ave. to SW 67th Ave. As shown in Figure 3-2, the EB approach has a total of six nearside, two far side, and six mid-block bus stops, while the WB approach has three nearside, six far side, and four mid-block bus stops.

3.1.2 Data

To quantify the mobility benefits of TSP various data were needed, for instance, traffic flow data, geometric characteristics information, transit information, and signal timing data. For traffic flow data the travel time and travel speed were extracted from the BlueToad^{TM} paired devices. BlueToad pairs are Bluetooth signal receivers which read the media access control (MAC) addresses of active Bluetooth devices in vehicles passing through their area of influence. Traffic count data were collected manually from video recording.

For geometric characteristics information Google Maps and Google Earth-Street View were used to verify certain roadway geometric characteristics of the study site. For transit vehicle information transit information considered while developing the VISSIM simulation models include bus route, bus stops, bus schedule. This information was obtained from the Jacksonville Transportation Authority's official website (Jtafla, 2021).

For the signal timing data to replicate real-world conditions in the VISSIM model, the actual signal timing data for the evening peak period were obtained from the Florida Department of Transportation (FDOT) District 2.

Similarly, to demonstrate the calibration benefits of TSP integrated VISSIM model the traffic flow data, geometric characteristics data, transit information, and signal timing data were considered in the analysis. The traffic flow data, the travel time and travel speed were obtained from the HERE Technologies and INRIX. HERE Technologies and INRIX are companies that provide location-based traffic data and analytics. HERE Technologies capture location content, such as road networks, traffic patterns, etc. Similarly, INRIX collects anonymized data on congestion, traffic incidents, etc. Traffic count data were obtained from FDOT District 6.

Geometric characteristics information such as number of lanes, lane width, and presence and absence of median were obtained from Google Maps and Google Earth-Street View. Transit information such as bus route, bus stops, and bus schedule were obtained from the Miami-Dade County Transportation and Public Works official website (Miami-Dade Gov, 2021). Signal timing data such as, the actual signal timing data, i.e., green, yellow, and red intervals, turning movement counts, signal timing plans, signal split history, preemption logs, etc., for the evening peak period were requested from the Miami-

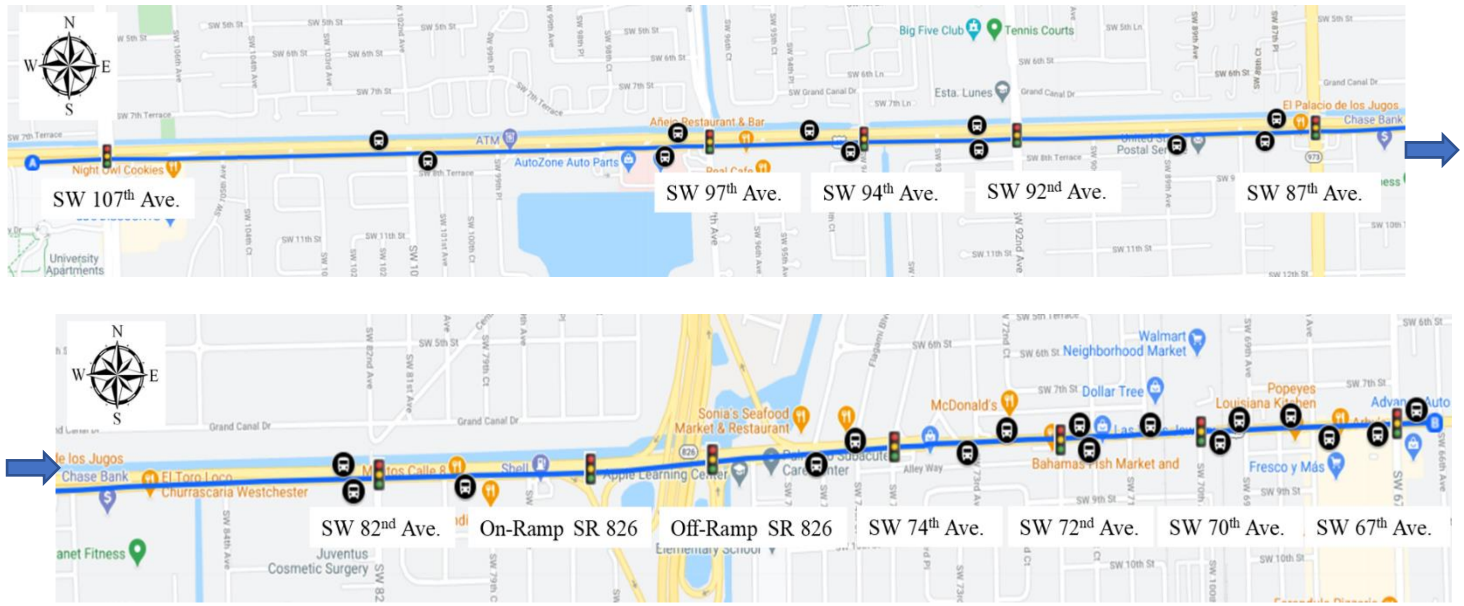
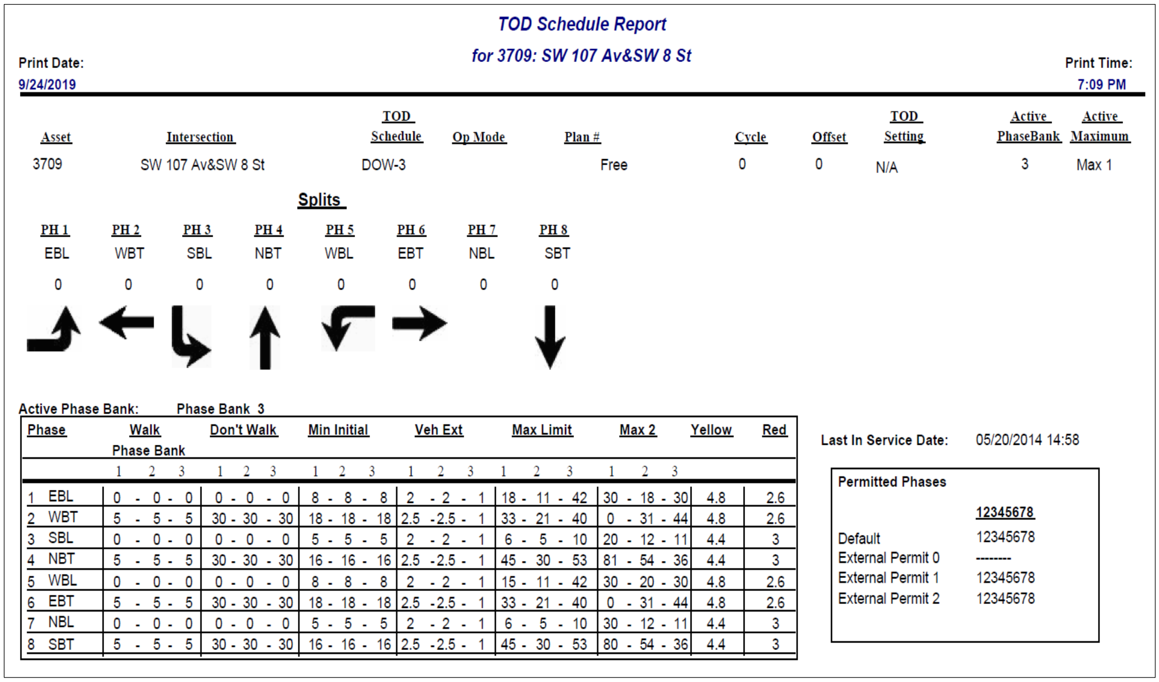


Figure 3-2: SW 8th Street Study Corridor in Miami, Florida

Dade County Traffic Signals and Signs Division and obtained from the FDOT District 6 offices. Figure 3-3 shows an example of a signal timing plan obtained from FDOT.



TOD Schedule Report
for 3709: SW 107 Av&SW 8 St

Print Date: 9/24/2019

Print Time: 7:09 PM

Asset	Intersection	TOD Schedule	Op Mode	Plan #	Cycle	Offset	TOD Setting	Active PhaseBank	Active Maximum
3709	SW 107 Av&SW 8 St	DOW-3		Free	0	0	N/A	3	Max 1

Splits

PH 1	PH 2	PH 3	PH 4	PH 5	PH 6	PH 7	PH 8
EBL	WBT	SBL	NBT	WBL	EBT	NBL	SBT
0	0	0	0	0	0	0	0

Active Phase Bank: Phase Bank 3

Phase	Walk (Phase Bank 1 2 3)	Don't Walk (1 2 3)	Min Initial (1 2 3)	Veh Ext (1 2 3)	Max Limit (1 2 3)	Max 2 (1 2 3)	Yellow	Red
1 EBL	0 - 0 - 0	0 - 0 - 0	8 - 8 - 8	2 - 2 - 1	18 - 11 - 42	30 - 18 - 30	4.8	2.6
2 WBT	5 - 5 - 5	30 - 30 - 30	18 - 18 - 18	2.5 -2.5 - 1	33 - 21 - 40	0 - 31 - 44	4.8	2.6
3 SBL	0 - 0 - 0	0 - 0 - 0	5 - 5 - 5	2 - 2 - 1	6 - 5 - 10	20 - 12 - 11	4.4	3
4 NBT	5 - 5 - 5	30 - 30 - 30	16 - 16 - 16	2.5 -2.5 - 1	45 - 30 - 53	81 - 54 - 36	4.4	3
5 WBL	0 - 0 - 0	0 - 0 - 0	8 - 8 - 8	2 - 2 - 1	15 - 11 - 42	30 - 20 - 30	4.8	2.6
6 EBT	5 - 5 - 5	30 - 30 - 30	18 - 18 - 18	2.5 -2.5 - 1	33 - 21 - 40	0 - 31 - 44	4.8	2.6
7 NBL	0 - 0 - 0	0 - 0 - 0	5 - 5 - 5	2 - 2 - 1	6 - 5 - 10	30 - 12 - 11	4.4	3
8 SBT	5 - 5 - 5	30 - 30 - 30	16 - 16 - 16	2.5 -2.5 - 1	45 - 30 - 53	80 - 54 - 36	4.4	3

Last In Service Date: 05/20/2014 14:58

Permitted Phases

	12345678
Default	12345678
External Permit 0	--------
External Permit 1	12345678
External Permit 2	12345678

Figure 3-3: An Example of a Signal Timing Plan

3.2 Safety Performance of TSP

The following types of data were required to estimate the safety performance of TSP: crash data, traffic volume data, and roadway characteristics data. These data were collected for 5 years, i.e., 2014-2018. The following subsections discuss the study area and each of the data types and its sources.

3.2.1 Study Area

The analysis was based on 41 transit corridors with lengths ranging between 0.5 miles and 2.8 miles in Orange and Seminole counties in Central Florida. The study corridors were divided into two categories: (i) 12 corridors with the TSP system, termed as "treatment sites"; and (ii) 29 corridors without the TSP system, termed as "non-treatment sites". The sites were selected based on the homogeneity criteria as recommended in the Highway Safety Manual (HSM) (AASHTO, 2010).

As the name implies, treatment sites are transit corridors where the TSP system was deployed. These corridors were manually selected after an extensive review of the Orange and Seminole counties' roadway network and operational status of the TSP system. All the identified treatment corridors had the TSP system operational either in 2016 or 2017. Therefore, for this study before-after study period considered was from 2014 through 2018 with the exclusion of the treatment year. None of the study sites had significant construction activity during the study period (2014-2018). The review was also conducted to ensure that there were no other countermeasures during the study period other than the TSP system.

The treatment corridors range from 0.5 miles to 2.8 miles in length with an average length of 1.47 miles. Table 3-1 provides more information about the treatment corridors including the total number of signalized intersections and density of signalized intersections with TSP along the treatment corridors.

Table 3-1: TSP-Enabled Corridors (Treatment Group)

County	ID	Treatment Corridors	TSP Activation Year	Corridor Length (miles)	Total Signalized Intersections	*Density of Intersections with TSP
Orange	1	Americana Boulevard	2016	1.0	4	2
	2	Church Street	2017	0.6	2	1
	3	Denning Drive	2017	1.0	5	3
	4	Fairbanks Avenue	2017	2.0	6	5
	5	Goldwyn Avenue	2016	0.5	3	1
	6	Metrowest Boulevard	2016	1.0	4	2
	7	Michigan Street	2016	1.6	6	3
	8	Raleigh Street	2016	1.8	5	3
	9	Rio Grande Avenue	2016	2.8	9	4
	10	Universal Boulevard	2016	1.0	5	3
	11	Vineland Road	2016	2.75	10	5
Seminole	12	State Road 46	2017	2.0	4	2

Note: *Per mile per direction

Figure 3-4 shows the locations of the treatment corridors in Orange and Seminole counties in Florida. In this figure, the locations of the 12 TSP treatment corridors are indicated by the treatment ID presented in Table 3-1.

Non-treatment sites, also known as comparison sites, are transit corridors that have similar traffic volume, roadway geometrics, and other site characteristics as the treatment sites, but without the TSP system. The non-treatment sites were identified either on the upstream or downstream of the treatment corridor or at the corridor adjacent to the treatment corridor. The non-treatment corridors selected have similar traffic patterns and geometric characteristics as the treatment corridors. The non-treatment corridors also accounted for unrelated factors such as time trends, traffic volume, vehicle technology, driver behavior, etc. (Gross et al., 2010). The non-treatment corridors range from 0.5 to 1.6 miles in length with an average of 0.9 miles.

3.2.2 Data

The following data were required to quantify the safety benefits of the TSP using the FB approach: crash data, traffic volume, and roadway geometric characteristics. These data were required both for treatment and non-treatment corridors. The analysis was based on 5 years of crash data. Since the TSP systems were deployed in 2016 and 2017, crash data from 2 years before the deployment of the TSP system and 2 years after the TSP system deployment were included in the analysis. Note that the TSP deployment year was not included in the analysis to exclude any disruption to traffic during the construction period and any ramp-up in bus operations after implementation.

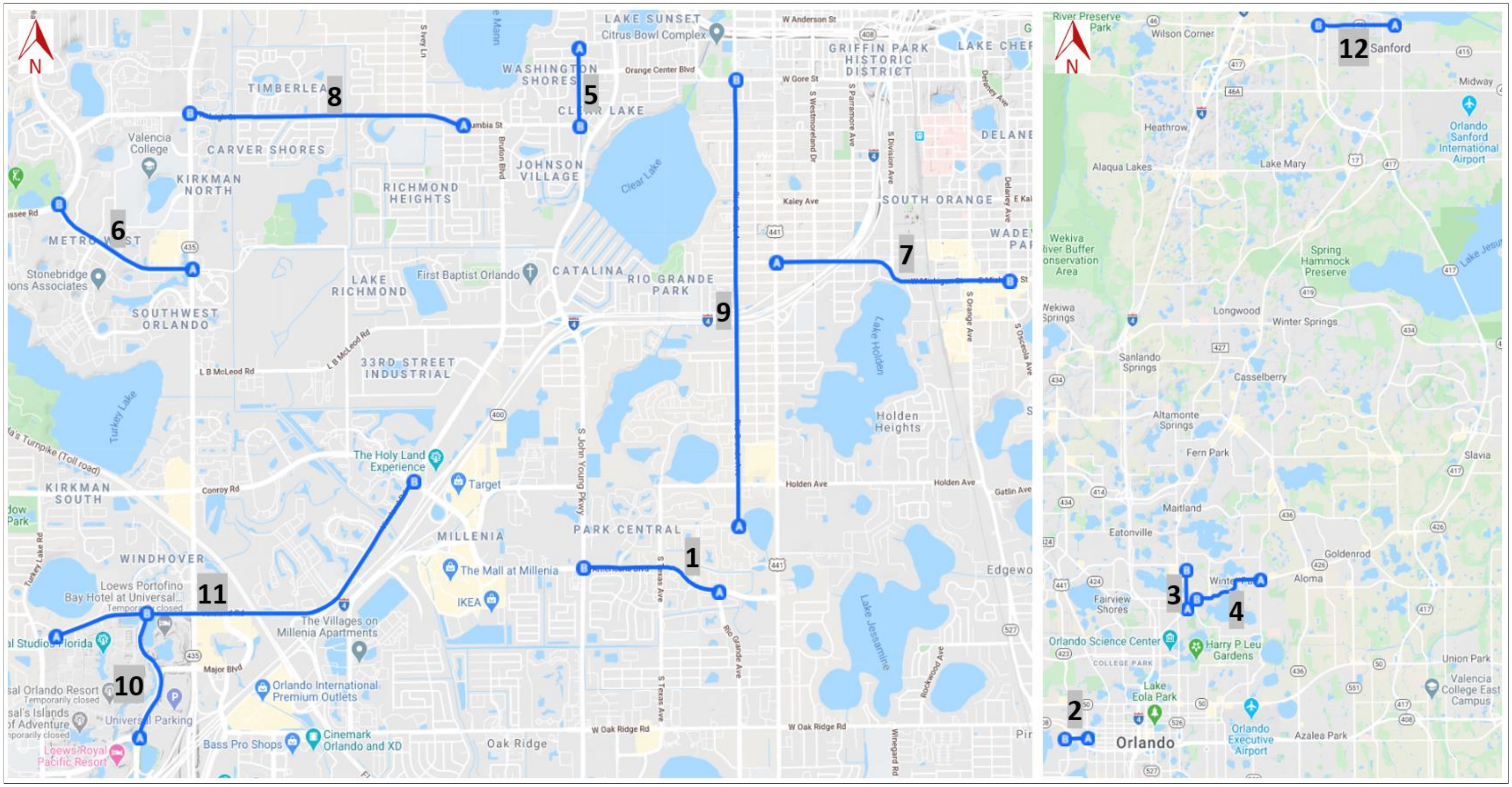


Figure 3-4: TSP Treatment Corridors in Central Florida

Excluding the deployment year from the analysis was deemed sufficient for bus drivers and motorists to fully adjust to the implementation of bus priority measures (Goh et al., 2013). Detailed explanation of the crash data, traffic volume, and roadway geometric characteristics used for the analysis is as follows:

- *Crash Data:* The crash data were extracted from Florida's Signal Four Analytics database and aggregated for each site by year as annual crash frequencies. Total crashes that occurred at treatment sites, and at non-treatment sites, during both the before and the after periods was extracted. Apart from the total crash frequency, which included crashes of all severity levels, separate analyses involving PDO and FI crash categories was also performed. Note that all injury severity levels (i.e., incapacitating, non-incapacitating, and possible injury) was grouped in the fatal/injury (FI) crash category. The following crash types were also extracted: rear-end crashes, sideswipe crashes, and angle crashes.
- *Traffic Volume Data:* The traffic volume data, i.e., annual average daily traffic (AADT), is included in traffic safety models because it is proven to be the main contributor to what is called crash exposure, i.e., as traffic volume increases there is a higher likelihood for crashes to occur. AADT data were obtained from Florida's Traffic Online database, a web-based mapping application that provides traffic count site locations and historical traffic count data. These data were collected for each year of the analysis period, i.e., 2014-2018. However, it is vital to note that traffic counts may not be available for all years and all roads due to high data collection costs. As such, reasonable assumptions to estimate missing traffic counts was made. For the missing data, AADT was obtained from parallel roads with

similar roadway geometric characteristics, and AADT for the missing years was extrapolated assuming that traffic volume increased by 3% each year.

- *Roadway Characteristics Data:* Roadway characteristics often influence the occurrence and severity of crashes on roadways. These data in the analysis helps understand the relationship, if any, between crash trends along the treatment corridors and deployment of the TSP system. Roadway functional classification was extracted using the ArcGIS geoprocessing tool from several shapefiles retrieved from the FDOT Transportation Data and Analytics Office website (FDOT, 2020). The extracted roadway functional classification was used to select similar treatment and non-treatment corridors. The roadway geometric characteristics that were collected for each corridor included: number of lanes, the presence of medians, and the speed limit. These data were collected from multiple sources, including the FDOT's Roadway Characteristics Inventory (RCI) database, Google Maps, Google Earth-Street View, and historical imagery tools. Descriptive statistics of variables used in the analysis are presented in Table 3-2.

Table 3-2: Descriptive Statistics

Variables	Period	Treatment Intersections			Comparison Intersections		
		Minimum	Maximum	Mean	Minimum	Maximum	Mean
Total Crashes (crash/year/corridor)	Before	12	995	320	6	183	45.80
	After	18	760	300.36	4	138	49.40
FI Crashes (crash/year/corridor)	Before	3	305	88.33	0	56	12.93
	After	9	232	83.47	1	39	15.08
PDO Crashes (crash/year/corridor)	Before	9	700	213.20	4	127	31.70
	After	9	545	200.52	3	99	32.08
Rear-end Crashes (crash/year/corridor)	Before	2	595	172.03	0	109	23.58
	After	5	469	154.63	1	78	23.95
Sideswipe Crashes (crash/year/corridor)	Before	0	114	40	0	24	5.68
	After	2	126	42.90	0	22	6.21
Angle Crashes (crash/year/corridor)	Before	4	154	47.24	0	36	8.60
	After	8	120	38.59	0	32	9.40
AADT (vehicle/day)	Before	4,400	57,000	24,198	4,400	57,000	24,302
	After	4,700	57,000	28,981	4,700	57,000	28,917
Length	All	0.5	2.8	1.47	0.47	1.6	0.90
Number of Lanes	All	2	6	3.42	2	6	3.59
Speed Limit (mph)	All	30	45	34.38	30	45	33.11

3.3 Summary

The goal of this research was to quantify the mobility and safety benefits of Transit Signal Priority. Table 3-3 summarizes the data needs for each of the tasks required to achieve the research goal.

Table 3-3: Data Needs for Evaluating the Mobility and Safety Benefits of TSP

Data Type	Mobility Benefits of TSP	Safety Benefits of TSP
Traffic flow	✓	✓
Transit vehicle information	✓	✓
Signal timing	✓	
Roadway geometrics characteristics	✓	✓
Crash data		✓

The study area to evaluate the mobility benefits of TSP was Mayport Road, Jacksonville, Florida. To evaluate the safety benefits of TSP, the study area comprised 12 corridors with the TSP system, and 29 corridors without the TSP system, in Orange and Seminole Counties in Florida.

CHAPTER 4
METHODOLOGY

The goal of this research was to quantify the mobility and safety benefits of TSP. To achieve this goal, the following two objectives were established: (1) assess the operational impacts of TSP on buses and all other vehicles along the corridor in mixed traffic condition using a microscopic simulation approach, and (2) evaluate the safety effects of TSP on total crashes, specific crash severity (i.e., FI and PDO crashes) and specific crash types (i.e., rear-end, sideswipe, and angle crashes) using a full Bayes before-after approach. This chapter is divided into three sections. Section 4.1 describes the methodology adopted to estimate the operational impacts of the TSP for buses and all other vehicles. Section 4.2 describes the methodology adopted to estimate the safety effects of TSP. Finally, Section 4.3 presents a summary of these methodologies.

4.1 Operational Impacts of TSP

VISSIM microscopic simulation model was used to quantify the operational impacts of the TSP. The following five steps were applied to quantify the operational impacts of TSP:

1. Develop a VISSIM microscopic simulation model with no TSP scenario to realistically represent the existing field conditions (i.e., Base Scenario).
2. Integrate the TSP scenario within the Base VISSIM microscopic simulation model.
3. Calibrate the Base VISSIM model to present the model's ability to replicate field conditions.

4. Analyze data and conduct statistical tests of the corridor performance to document and evaluate the performance of the corridor with and without TSP integration.
5. Develop Florida-specific MEFs for the TSP strategy

4.1.1 The Base VISSIM Model

The first VISSIM model was developed to represent the Base conditions, i.e., without TSP, by following the guidelines in the VISSIM manual and traffic analysis handbook (FDOT, 2014). The Base VISSIM model was developed accurately to closely match actual field conditions. First, the geometry of the corridor (i.e., number of lanes, lane widths) were extracted using Google Maps and Google Earth-Street View. Once the geometric technical drawing was defined in the VISSIM model, all links and connectors were set up with the real dimensions as per field. Detailed turning movement counts to represent all movements (i.e., through, left, and right) and the traffic composition (i.e., percentage of passenger cars, heavy vehicles, and buses) were then defined. Public transit (i.e., buses in this study) was defined in the VISSIM model by using real number of buses as per field condition.

In this Base VISSIM model, one transit line in each travel direction was added. Bus stops along the corridor in both travel directions was included in this model. All the traffic signals along the study corridor are actuated control. Actual traffic signal settings were defined in VISSIM using a ring barrier controller (RBC) in which, in addition to the signal cycle length, each phase minimum and maximum green time, yellow time, and all red time. Integrated into the VISSIM software, the RBC interface allows users to simulate actuated control in a VISSIM model. To represent the protected-permissive left turns, a detector was defined at each of the four left-turn lanes at four approaches of a signalized intersection. In each signal cycle, if the detector is occupied, a protected left turn phase will be called by the RBC, otherwise the left turn will be permissive.

The Base model was developed in VISSIM for the Mayport Road study corridor between Atlantic Boulevard and Edward Avenue, in Jacksonville, Florida. The analysis was conducted for the evening peak period (4:00 PM - 7:00 PM) and was based on the existing network geometry, traffic, and transit operations. An example of a Base VISSIM model is shown in Figure 4-1. The analysis period was 3.5 hours, with the first 30 minutes used as the warm-up period. The Base model will include transit vehicles operating in mixed traffic and will not consider any special transit treatment, for instance, TSP scenario in this case.

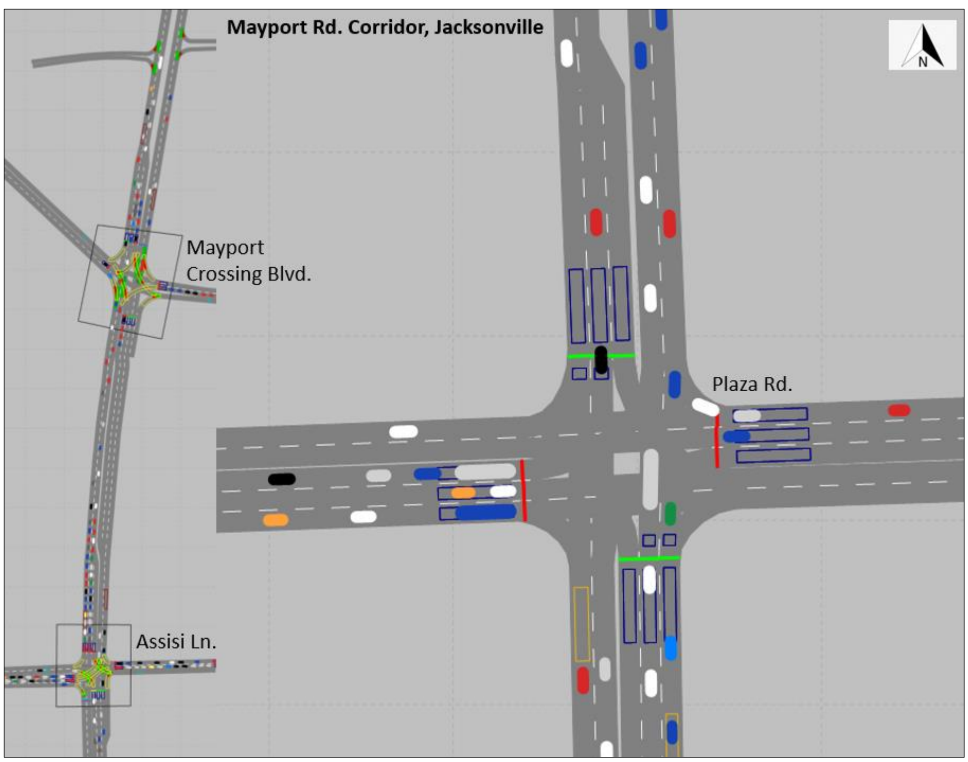


Figure 4-1: Illustration of the Base VISSIM Model

4.1.2 The TSP-integrated VISSIM Model

For the inclusion of the TSP operations along the same study corridor, the Base model was duplicated to create another microscopic simulation model where the TSP parameters was integrated into the signal groups (SG) of the ring barrier controller (RBC) in VISSIM. The RBC interface allows users to simulate actuated control in a VISSIM model. The RBC editor allows the user to set the timings used during the VISSIM simulation by the controller and stores these values in the external RBC data files with the ".rbc" file extension (PTV, 2010). Programmable transit priority options for each transit SG are present in the signal controller. When a transit SG operates in a priority options in a priority mode, the SGs that conflict with the parent SGs of a transit SG can be abbreviated or omitted. For transit priority, the controller attempts to adjust its operation to give a green signal, i.e., either early green or extended green, to the transit SG by the time the transit vehicle arrives at the intersection.

The graphical interface of RBC is shown in Figure 4-2. During the simulation, VISSIM passes the status of its detectors and signal heads to the RBC and the controller returns the state of the signal heads for the next period (PTV, 2010). The time used for this interaction is determined by the controller frequency and can be as small as one-tenth of a second (PTV, 2010). An example of the placement of detectors is shown in Figure 4-3. As shown in Figure 4-3, detectors 311 and 312 are check-in detectors, whereas detectors 321 and 322 are check-out detectors. Check-in detectors detect the bus to grant signal priority, whereas the check-out detectors detect the bus that was already granted priority and sends back information to the controller to resume to normal signal timing plan. As per Zhou et al. (2006), the optimal position of the check-in detector location was set 452 ft. for the medium-volume case and 531 ft. for the high-volume case away from the signalized intersection. The check-out detectors were placed immediately after the stop bar of the signalized intersection.

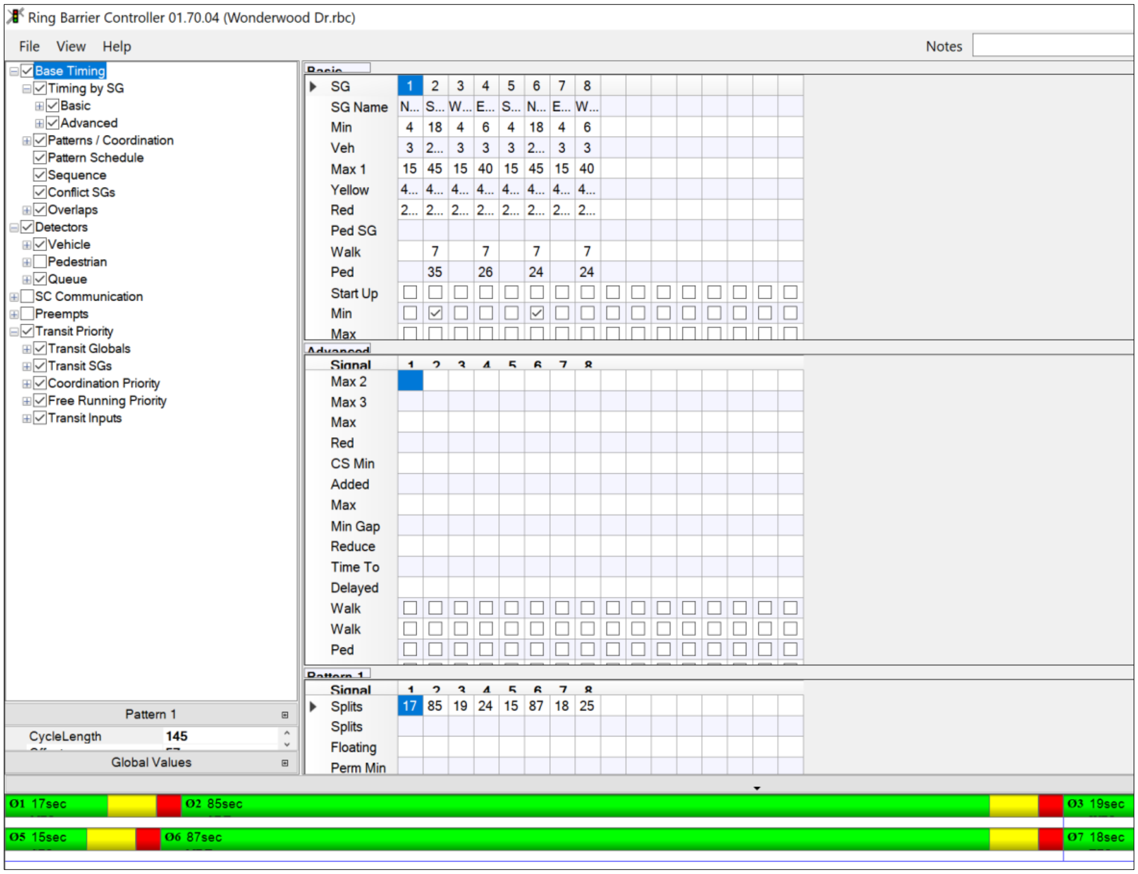


Figure 4-2: RBC Graphical Interface

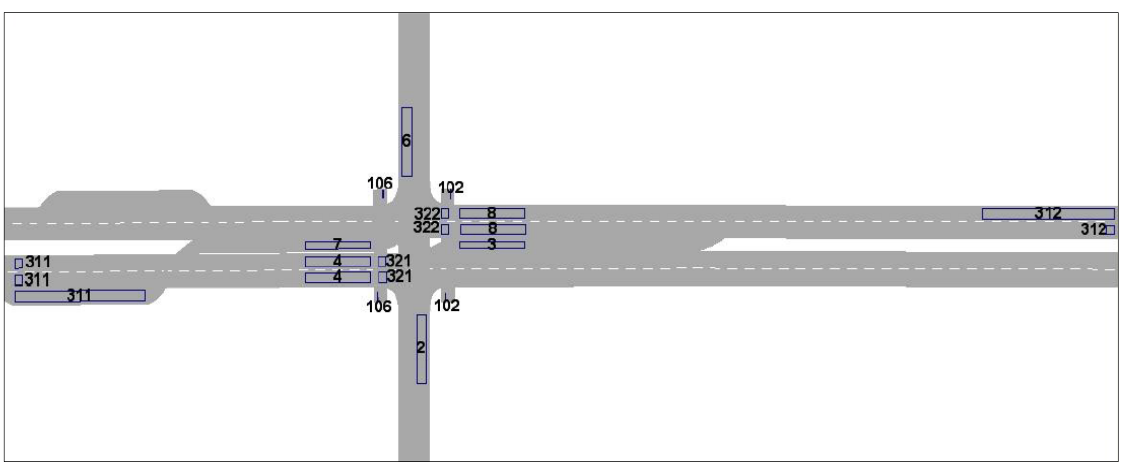


Figure 4-3: Detector Placement for the Signal Controller

Programmable transit priority options for each transit signal group are present in the signal controller. For the transit priority, the controller attempts to adjust its operation to give a green signal to the transit signal group by the time the transit vehicle arrives at the intersection.

The TSP was implemented at 10 signalized intersections along the study corridor. The model examined the scenario of transit vehicles operating in mixed traffic conditions using the TSP application. As mentioned earlier, the early green (early start or red truncation of priority phase) and extended green (or phase extension of priority phase) TSP strategies was implemented at the TSP-enabled signalized intersections. The early green strategy shows a green traffic light before the regular start of a priority movement phase. This strategy was applied by shortening the green time of the conflicting phases, without violating the minimum green time and clearance intervals, so the green time for the priority phase can start early. The extended green strategy was used when a transit vehicle approaches near the end of the green traffic light of a priority phase. This strategy holds the green light of the priority phase for a few additional seconds to allow the transit vehicle to pass through the intersection without further delay. Depending on the signal control policy, green times for conflicting phases may or may not be shortened to compensate for the extended green for the priority phase.

Both the abovementioned strategies are intended to decrease transit vehicle delays at the TSP-enabled intersections. An early green or an extended green was used to provide an appropriate TSP treatment to transit vehicles depending on its time of arrival upstream of the TSP-enabled signalized intersection. Travel time of transit buses and all other vehicles along the study corridor was extracted from the VISSIM models along each travel direction. The average vehicle delay for buses and all other vehicles was extracted from the models for each direction of travel.

4.1.3 The Required Number of VISSIM Simulation Runs

To replicate the stochasticity of traffic flow, VISSIM assigns different random seeds for each run. Random seeding returns different outputs for each run and effects parameters for instance when a vehicle enters into the network, which lane to use, the aggressiveness level of the driver, and interaction between vehicles (Radwan et al., 2009). VISSIM does not automatically calculate the required number of runs necessary to achieve good results that are within the tolerable error. Therefore, the number of runs was determined by using the Traffic Analysis handbook formula:

$$n = \left(\frac{s \times t_{\alpha/2}}{\mu \times \varepsilon}\right)^2 \tag{4-1}$$

where

n = the required number of simulations runs,

s = the standard deviation of the system performance measure based on the previous, simulation runs,

$t_{\alpha/2}$ = the critical value of a two-sided Student's *t*-statistic at the confidence level of α and n – 1 degree of freedom (df),

μ = the mean of the system performance measure, and

ε = the tolerable error, specified as a fraction of μ, desirable value of 10%.

To minimize the impact of the stochastic nature of the model on the results, the simulation model was run with different random number seeds. Note that the formula in

Equation 4-1 considers the standard deviation, the 95% confidence interval, the mean, and the tolerable error of 10%. A total of 15 simulation runs were determined for this study.

4.1.4 VISSIM Model Calibration

After the model was examined for completeness and verified for accuracy using the checklist suggested in the Traffic Analysis handbook FDOT (2014), the VISSIM Base model was calibrated using the turning movements counts data at each signalized intersection. Signal timing data, turning movement counts, and travel time data along the study corridor was used in the development of the VISSIM models. For each of the 10 signalized intersections along the study corridor, the signal timing data and the turning movement counts data were collected from the Jacksonville Transportation Authority and FDOT District 2, respectively. Signal timing data included the local time-of-day plans along with signal phasing information. Travel time along the corridor was extracted from the BlueToad paired devices.

The Base VISSIM model was calibrated using the turning movement counts data at each signalized intersection. The turning movement traffic counts of the simulation model and the collected field data for a simulation period of 3.5 hours during the evening peak hour was compared. The coefficient of determination (R^2) was calculated to assess the resemblance between the simulation and the field conditions. The value of R^2 was found to be 0.89, indicating similarity between the field and the simulated data. Figure 4-4 illustrates the comparison of turning movement traffic counts of the simulation model and the collected field data for a simulation period of 3.5 hours, during the evening peak hour. The Geoffrey E. Havers (GEH) empirical formula was also used as the acceptance criteria for the model as shown as follows:

$$GEH = \sqrt{\frac{2(M-C)^2}{M+C}} \quad (4\text{-}2)$$

where M is the traffic volume from the traffic simulation model, and C is the real-world traffic count in vehicles per hour. The acceptance criterion was GEH < 5.0 for at least 85% of intersections (FDOT, 2014). GEH < 5.0 was observed for 91% of the intersections in the model.

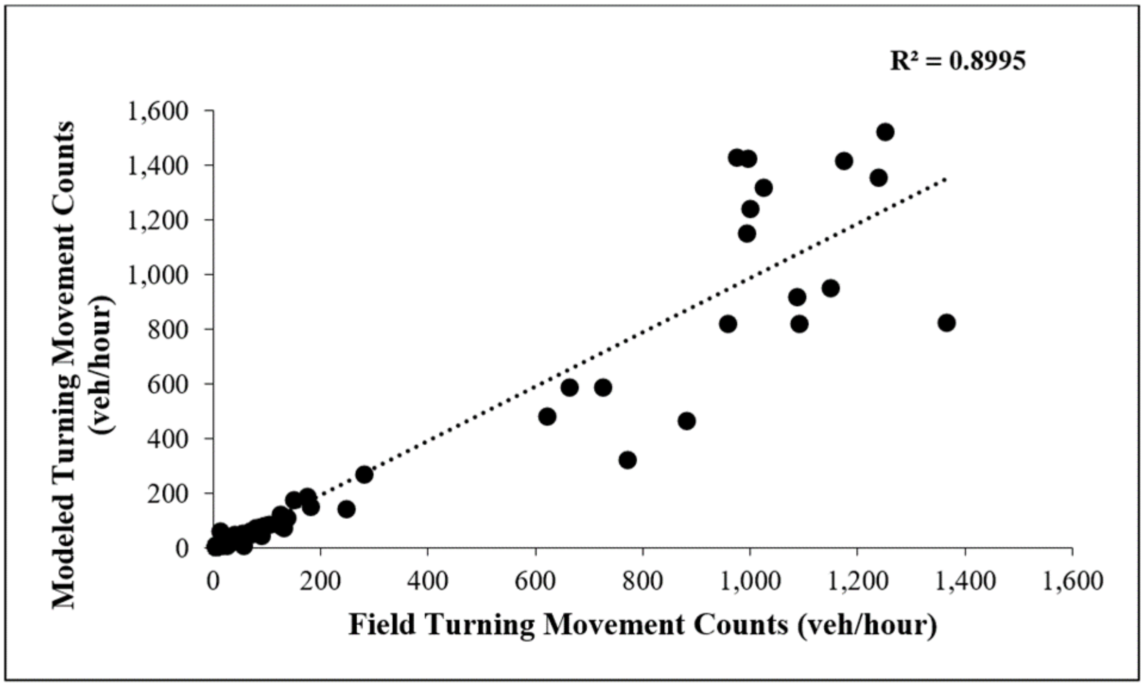


Figure 4-4: Calibration Results of VISSIM Base model

Also, this study developed Mobility Enhancement Factors (MEFs) to better estimate the operational impact of TSP on transit buses and all other vehicles along the corridor. MEFs relate to the operational performance of a strategy, as crash modification factors (CMFs) relate to the safety performance. Similar to CMFs, MEFs are multiplicative factors used to estimate the expected mobility level after implementing a certain strategy, such as TSP. A MEF < 1 implies that the TSP improves the operational performance of the corridor, while a MEF > 1 implies that the TSP deteriorates the corridor's operational performance for that particular performance measure.

4.1.5 Importance and Benefits of Calibration of TSP Integrated VISSIM Model

To comprehend the importance and benefits of calibration of microscopic simulation model, the study also explored different calibration process to check how well the calibrated VISSIM parameters performed between two study corridors. The benefits of calibrated parameters in the microscopic simulation model (VISSIM) for operational analysis between two different study corridors (Mayport Road, Jacksonville and SW 8th Street, Miami) were also explored. Specifically, the study investigated how well the calibrated VISSIM parameters of a TSP simulation model performed, in terms of the relationship (correlation) between the field-measured travel time and the simulated travel time, between the two study corridors.

To explore how well the calibrated VISSIM parameters performed, two VISSIM microscopic simulation models (Base model and TSP model) were developed for the SW 8th Street corridor in Miami. The Base model was developed based on regular traffic operations, whereas the TSP model was developed with the TSP strategy integrated. To develop the Base VISSIM models, geometry information (e.g., number of lanes, lane widths, and turning radius) was first extracted and then drawn in technical drawings. All links and connectors were set using the actual field dimensions. Detailed traffic counts were then defined in VISSIM using routes to represent all movements (i.e., left, right, and through) and traffic composition (i.e., percentage of cars, heavy vehicles, and buses). Public transit buses were defined using the number of buses as per field. Actual traffic signal settings were defined in VISSIM using the RBC. In the RBC, in addition to signal cycle length, the yellow time, red time, and each phase minimum and maximum green time was also defined. To represent the protected-permissive left turns, a detector was defined at each one of the four left-turn lanes for all approaches of a signalized intersection. Also, during a signal cycle, if the detector was occupied, a protected left-turn phase would be called by the RBC, otherwise the left turn was permissive. Finally, a visual inspection was performed to ensure there were no abnormal movements of the simulated vehicles. The TSP scenario was then integrated into the Base model to create the TSP model. The TSP model was developed by following the same procedure as explained in Section 4.1.2.

Microscopic simulation models contain numerous independent parameters that can be used to describe traffic flow characteristics, traffic control operations, and driver behavior. These models provide a default value of each parameter; however, they also allow users to change the values to represent local traffic conditions. The process of adjusting and fine-tuning model parameters, using real-world data to reflect traffic conditions, is referred to as model calibration. Simulation model-based analyses are often performed using default parameter values or manually adjusted values. Rigorous calibration procedures are often omitted because it requires a great deal of time, as well as a vast amount of field data. However, to achieve adequate simulation model results, it is crucial that a rigorous calibration is applied. The microscopic simulation models need to be well calibrated to give reasonable and realistic results. In this study, the first calibration process matched the actual field conditions (desired speed and travel time) to ensure that VISSIM produced field travel time. A second calibration step was performed to calibrate the identified VISSIM driving behavior parameters. Detailed explanation of the first and second calibration process is as follows:

- *First Calibration Process:* The primary goal of the first calibration process was to determine if the simulated travel time in VISSIM was similar to the field travel time. To better calibrate the travel time, the desired speeds were calibrated to match the field conditions. For the desired speed, the cumulative distribution curve for the microscopic simulation VISSIM model was also modified to match the field conditions. The coefficient of determination (R^2) was calculated to assess the resemblance between the simulation and the field conditions. The value of R^2 was found to be 0.84, indicating similarity between the field and the simulated data. Figure 4-5 illustrates the comparison of travel time of the simulation model and the collected field data for a simulation period of 3.5 hours, during the evening peak hour.

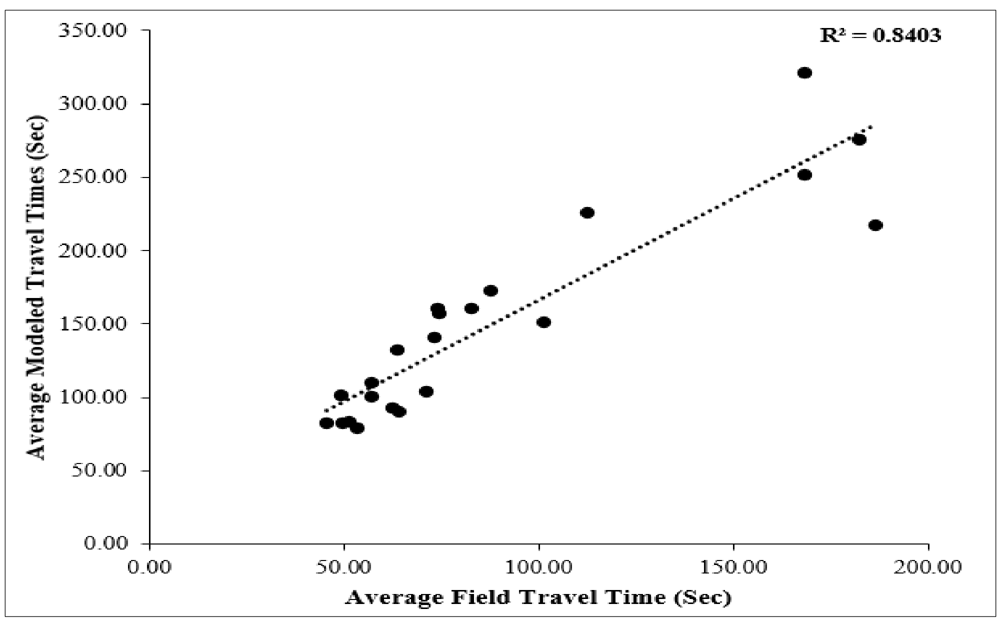


Figure 4-5: Calibration Results of VISSIM Base Model for SW 8th Street

The Geoffrey E. Havers (GEH) empirical formula was also used as the acceptance criteria for the model, and set as GEH < 5.0 for at least 85% of intersections (FDOT, 2014). From the calibration results, a GEH < 5.0 was observed for 92% of the intersections in the model. VISSIM does not automatically calculate the required number of runs necessary to achieve good results that are within the tolerable error. By using Equation 4-1, the total number of simulation runs were determined to be 17.

- *Second Calibration Process:* The main goal of second calibration process was to enhance the correlation between the simulated travel time and the field travel time by calibrating the VISSIM parameters. The most critical VISSIM parameters which had a significant effect on the simulation results were identified, as shown in Table 4-1. Since the Wiedemann 74 model is more suitable for urban traffic and merging areas, this model was used instead of the Wiedemann 99 model, which is more suitable for freeway traffic with no merging areas (PTV, 2010). Subsequently, a genetic algorithm technique was applied to estimate the optimized values of the identified parameters.

Table 4-1: Wiedemann 74 Model VISSIM Parameters

No.	**VISSIM Parameters**
	Car Following
1	Average standstill distance (w74ax)
2	Additive part of safety distance (w74bxAdd)
3	Multiplicative part of safety distance (w74bxMult)
	Lane Change
4	Lane change
5	Emergency stop

Note: W74ax = Average standstill distance; W74bxAdd = Additive part of safety distance; W74bxMult = Multiplicative part of safety distance.

The *average standstill distance* is the average desired distance between two cars (PTV, 2010). The tolerance lies from -1.0 meters to +1.0 meters, which is normally distributed around 0.0 meters, with a standard deviation of 0.3 meters. The default value is

2.0 meters (6.56 feet). The *additive part of safety distance* value, used for the computation of the desired safety distance (PTV, 2010), allows the time requirement values to be adjusted. The default value is 2.0 meters (6.56 feet). The *multiplicative part of safety distance* value, used for computation of the desired safety distance (PTV, 2010), also allows the time requirement values to be adjusted. A greater value reflects a greater distribution (i.e., standard deviation) of safety distance. The default value is 3.0 meters (9.84 feet).

For the lane changing parameters, *lane change* was used to model the lane change rule for vehicles that follow their route, or in a dynamic assignment, their path (PTV, 2010). The lane change rule applies to the distance before the connector from which those vehicles, whose route or path leads across the connector, try to choose the lane in which they reach the connector without changing lanes. The standard value is 200 meters (i.e., 565 feet and 2.016 inches), and the minimum value is 10 meters (i.e., 32 feet and 9.701 inches). The lane change value must be >= *Emergency Stop* + 5.0 meters (i.e, 16 feet and 4.85 inches). *Emergency Stop* is used to model the lane change rule of vehicles that follow their route, or in dynamic assignment, their path, and the default value is a minimum of 5.0 meters (PTV, 2010). If the lanes could not be reached before the connector at the emergency stop position, the vehicle stops and waits for a sufficiently large enough gap. The system measures upstream, starting from the beginning of the connector. When a vehicle has to make more than one lane change, 5.0 meters per lane is also taken into account in each case. If the current lane has an odd number, 2.5 meters are also added to the total length of the emergency stop distance. This prevents a conflict from occuring in the case of two vehicles, with identical positions, that are set to change lanes on neighboring lanes. Due to the uniqueness of the geometry of the signalized intersections along the corridor, there was no definite one value for lane change and emergency stop parameters. The value of the lane changing parameters differed as per the geometry and traffic pattern along the corridor. Therefore, the genetic algorithm (GA) technique was performed only for the VISSIM car following parameters.

After identifying the VISSIM car following parameters and their acceptable ranges, a GA process was used to calibrate and optimize the values of the selected parameters (Goldberg, 1989). A GA analysis is a heuristic optimization technique based on the mechanics of natural selection and evolution. It works with a population of individuals, each of which represents a possible solution to a given problem. The GA procedure was applied to find the best values of the selected parameters which gave the highest correlation between the simulated and field-measured travel times. The basic operators of the GA, i.e., reproduction, crossover, mutation, and elitism, were used to generate the next generation. The reproduction operator selects individuals with higher fitness. The crossover operator creates the next population from the intermediate population, and the mutation operator was used to explore areas that have not been searched. The initial population was created randomly, which means that all solutions have an equal chance to fall into the population. However, the random selection does not guarantee the uniform covering of each parameter space. Therefore, a Latin Hypercube Sampling method (LHS) was used to select the initial population. The relative error of the average travel time between the simulation output and field data was used as the fitness value of the GA. The fitness function takes the form as:

$$FV = \frac{|TTfield - TTsimulation|}{TTfield} \tag{4-3}$$

where

FV = the fitness value,

TTfield = the average travel time from the field, and

TTsimulation = average travel time from the simulation.

The automation access of VISSIM was completed using the VISSIM component object model (COM) interface that enables users to access VISSIM through many scripting languages. However, the VISSIM COM interface does not cover all VISSIM parameters selected for the study. To overcome this challenge, all of the parameter values were set to automatically change each time by editing the text contents in the VISSIM input (*.inp) files.

Assessment of calibrated parameters performance was conducted using two approaches: (a) the application-based approach, and (b) the estimation-based approach (Bowman et al., 2017; Essa & Sayed, 2015; Gallelli et al., 2017; Koppelman & Wilmot, 1982; Sikder et al., 2014). Each approach is discussed as follows:

- *Application-based approach:* In the application-based approach, the model parameters were calibrated using data from one location (the base context (i.e., Mayport Road Corridor)) and applied directly, with no change to the data, to the second location (the application context (i.e., SW 8th Street Corridor)) to assess how well the calibrated model predicts in the other location (i.e., SW 8th Street Corridor). This approach is more direct and generally tests the performance of the calibrated model as a whole, without examining which specific parameters.

- *Estimation-based approach:* In the estimation-based approach, the model parameters were calibrated using data from one location (i.e., Mayport Road Corridor) and recalibrated using data from the second location (i.e., SW 8^{th} Street Corridor). Model performance was determined by identifying whether the calibrated parameters values were different between the two locations. This approach was more comprehensive, as it can test whether each and every parameter in a model.

In order to avoid any influence of a random component or a lucky parameters' combination on the outcomes of the VISSIM calibrated parameters performance, both the application-based and the estimation-based approaches were used. Specifically, according to the application-based approach, the calibrated parameters obtained using data from first location (i.e., Mayport Road Corridor) were applied for the simulation of the second location (i.e., SW 8^{th} Street Corridor). For the estimation-based approach, the calibration process was applied also using the first location (i.e., Mayport Road Corridor) dataset and again recalibrated using the second location dataset (i.e., SW 8^{th} Street Corridor). The methodology was comprised of the following four scenarios to determine the correlation between field and simulated conditions:

- **Scenario 1 (without any calibration process):** In this scenario, the second location (i.e., SW 8^{th} Street Corridor) was modeled and simulated using default VISSIM values without any calibration. The correlation between field-measured and simulated travel time was estimated.
- **Scenario 2 (with only first calibration process):** In this scenario, the second location (i.e., SW 8^{th} Street Corridor) was simulated and only the first calibration

process was used. With the driving behavior parameters set at default values, the correlation between field-measured and simulated travel time was estimated.

- **Scenario 3 (application-based approach):** In this scenario, the second location (i.e., SW 8th Street Corridor) was simulated using the first calibration process (i.e., only the values of desired speeds of Mayport Road Corridor). The values of the second calibration process of the first location (i.e., Mayport Road Corridor) were used. The values of the Mayport Road corridor was used, without any recalibration, as per the application-based approach to estimate the correlation between field-measured and simulated travel time.
- **Scenario 4 (estimation-based approach):** Considering the estimation-based approach, the Wiedemann 74 significant factors (driving behavior parameters), calibrated for the second location (i.e., SW 8th Street Corridor), were compared with the same parameters calibrated for the first location (i.e., Mayport Road Corridor). In other words, the second location (i.e., SW 8th Street Corridor) was simulated using the values of the first and the second calibration process for the first location (i.e., Mayport Road Corridor). The values of the Mayport Road corridor was used, and a recalibration process for the local condition was also executed.

To further examine the performance of the VISSIM calibrated parameters, the performance of each parameter was investigated by comparing the calibrated values between the two locations. The calibrated values were the results of the GA procedure for both study locations. The percentage change for each parameter was determined as follows:

$$\%\ of\ change = \frac{V1 - V2}{X1 - X2} \times 100 \tag{4-4}$$

where

V1 = the calibrated value of the parameter from the first study location (i.e., Mayport Road Corridor),

V2 = the calibrated value of the parameter from the second study location (i.e., SW 8th Street Corridor),

X1 = the maximum value of the parameter, and

X2 = the minimum value of the parameter.

Table 4-2 provides the default values, range, and calibrated values of the VISSIM parameters.

Table 4-2: Maximum and Minimum Values of the VISSIM Parameters

#	Parameter	Default	Range
	Car-Following Parameters		
1	Average standstill distance (w74ax)	2.00 (m)	>1 (m)
2	Additive part of safety distance (w74bxAdd)	2.00 (m)	1 to 5.00 (m)
3	Multiplicative part of safety distance (w74bxMult)	3.00 (m)	1.00 to 6.00 (m)
	Lane Change Parameters		
4	Lane change	656.2 ft.	>656.2 ft.
5	Emergency stop	16.4 ft.	As per field observations

Note: m = meters; ft. = feet; parentheses refer to parameter identifiers in VISSIM.

The maximum and minimum values of the parameters were assumed, based on the information provided in the VISSIM User Manual (Park and Qi, 2005; PTV, 2010).

This research investigated the mobility benefits of TSP. To achieve this goal, a microscopic simulation approach was adopted. In VISSIM the TSP model was developed to evaluate the mobility benefits of TSP. Also, the importance and benefits of VISSIM calibration was also investigated. The next section, discusses the methodology adopted to evaluate the safety benefits of TSP.

4.2 Safety Effects of TSP

As stated in the earlier sections, an *observational full Bayesian before-after* evaluation was used to evaluate the safety effectiveness of TSP. Bayesian statistics is an inference method that uses probability distributions through Bayes' theorem to describe the state of knowledge about unknown quantities. Unlike the classical statistical approach, the Bayesian approach uses the maximum posterior method to estimate the posterior distributions of the parameters and treats parameters as random variables with known distributions (Ntzoufras, 2009). Figure 4-6 presents an overview of the analysis. The first step involved identifying sites with and without TSP. Then geometric characteristics and crash data were extracted for the identified sites. Data were then processed and cleaned. Crash contributing factors were identified and then the relationship between the crash frequency and different explanatory variables were determined. The frequency of crashes before and after the installation of TSP was compared. Finally, the safety benefits of TSP were quantified.

Unlike the EB method, the FB approach integrates the process of estimating SPFs and treatment effects in a single step, incorporating the uncertainties of the SPFs in the final estimates (Park et al., 2016). The properties of FB models allow the estimation of valid models with even smaller sample sizes (Li et al., 2013; Persaud and Lyon, 2007). Also, the FB approach divides the periods into time intervals and models each time interval as a separate data point to account for time variations, unlike the EB approach that averages the data into a single data point (Kitali and Sando, 2017). Moreover, a hierarchical FB model can allow crash counts from multiple time-points to inform predictions, with counts in more recent years lending more weight to predictions than counts from years further in the past (Fawcett et al., 2017).

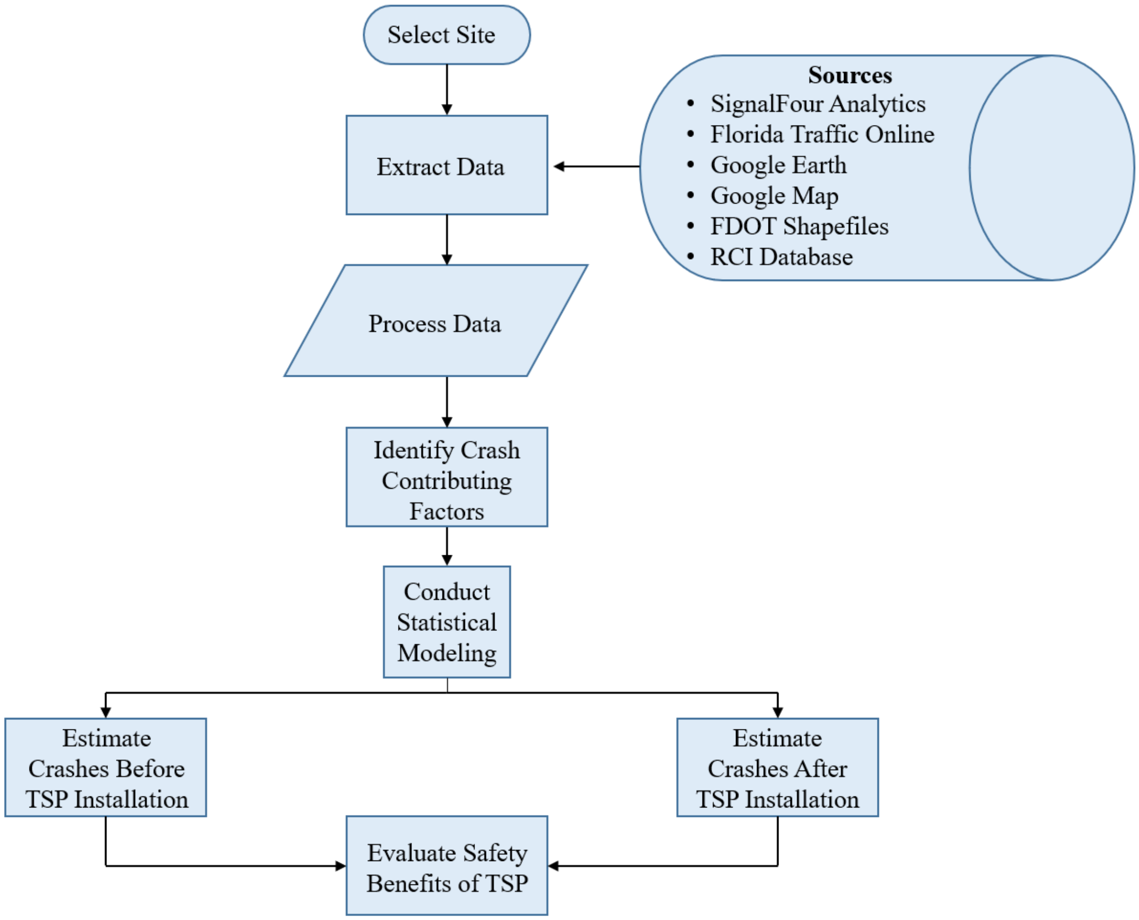


Figure 4-6: Overview of the Analysis Approach

Note: FDOT-Florida Department of Transportation, RCI-Roadway Characteristics Inventory

Furthermore, when compared to the EB approach, which is over-optimistic while quantifying the variability of estimates of crash frequency, the FB method provides a flexible and complete inferential procedure (Fawcett and Thorpe, 2013). The FB techniques can incorporate random parameters in the specification of SPFs which can account for the heterogeneity and found to improve the model fit (Anastasopoulos and Mannering, 2009; El-Basyouny and Sayed, 2012; Li et al., 2008). A jump parameter can also be incorporated in the FB techniques to account for the sudden change in the crash frequency (Kitali, 2017; Li et al., 2008). The process of FB methodology is shown in Figure 4-7.

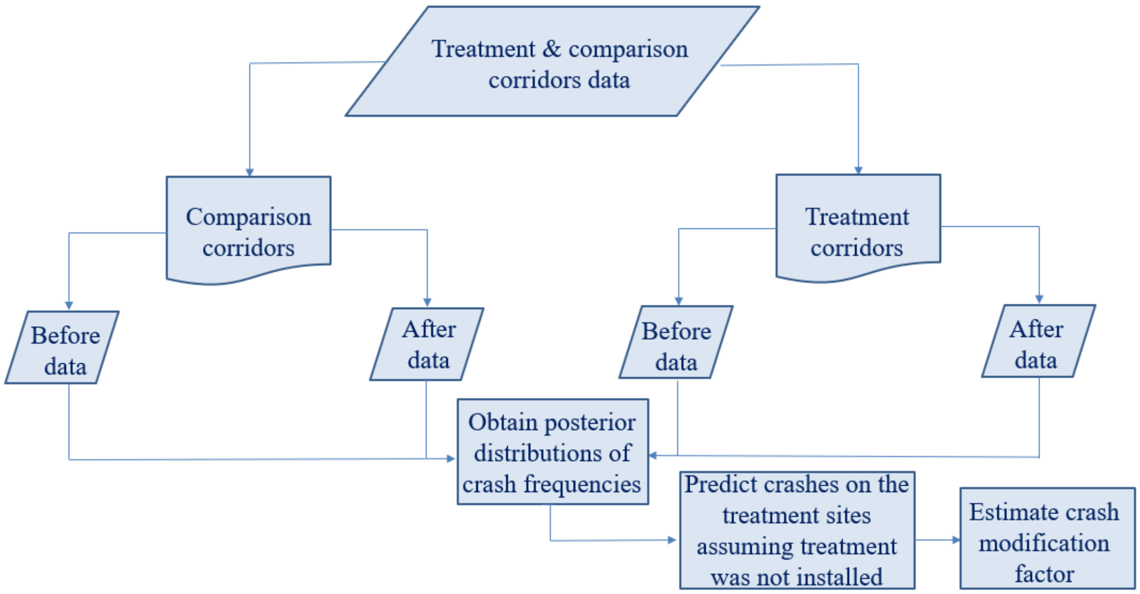


Figure 4-7: Full Bayesian Methodology

The following section describes the modeling approach and the estimation of the CMFs using the FB method.

4.2.1 Poisson Log-normal Model

The Poisson log-normal model, a statistical model to analyze crash counts of treatment corridors, was used to evaluate the safety effectiveness of TSP along the treatment corridors. In a Poisson log-normal model the crash counts were modeled using Poisson distribution as:

$$Y_{it}|\theta_{it} \sim Poisson\ (\theta_{it}) \tag{4-5}$$

where Y_{it} is the crash counts observed at TSP corridor *i* during year *t*, and θ_{it} is the mean of crash counts observed at TSP corridor *i* during year *t*. The Poisson mean can be written as:

$$\ln(\theta_{it}) = \ln(\mu_{it}) + \varepsilon_i \tag{4-6}$$

where μ is crash counts observed at TSP corridor *i* during year *t*, and ε is the random effects for the latent variables and heterogeneity across the sites. The parameter ε is assumed to be normally distributed, i.e.,

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2) \tag{4-7}$$

where *N* is normal distribution and σ_ε^2 is the extra-Poisson variation.

The posterior distribution contains the distribution of each of the variable coefficients presented as follows:

$$ln(\mu_{it}) = \alpha_0 + \alpha_1 T_i + \alpha_2 t + \alpha_3 \mathrm{T_i I_{t>t_{0i}}} + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + OFFSET \tag{4-8}$$

where

α_0 = the intercepts,

α_1 = difference in log crash frequency between treatment and non-treatment corridors,

T = treatment sites,

i = treatment year,

α_2 = variable coefficient of crash trend over years,

t = crash trend over years,

α_3 = variable coefficient for jump parameter,

$\mathrm{I_{(t>t_{0i})}}$ = indicator function that takes on the value of 0 if $t < t_{0i}$ and 1 if $t \geq t_{0i}$,

β_1 = variable coefficient of posted speed,

X_1 = posted speed,

β_2 = variable coefficient of annual average daily traffic (AADT),

X_2 = AADT,

β_3 = variable coefficient of proportion of TSP-enabled intersections,

X_3 = proportion of TSP-enabled intersection, and

$OFFSET$ = natural logarithm of corridor length.

The lognormal model for crash density is a piecewise linear function of the predictor variables, such that the function is continuous at the change point, t_{0i}. These variables are essential in quantifying changes in crash frequency brought by changes other than the treatment, which is the presence of TSP. The piecewise linear function was defined that applied to a different part of the domain (i.e., before and after deployment of the TSP). The linear intervention model allows for different slopes of crash frequency for times before and after the installation of the TSP, and across the treatment and non-treatment corridors. Note that the length of the corridor was used as an offset (i.e., $OFFSET = ln(Corridor\ length)$).

The Markov Chain Monte Carlo (MCMC) simulation was used to calibrate the parameters of the Poisson log-normal model. No U-Turn Sampling (NUTS) technique was adopted in the analysis. The NUTS is based on the Hamiltonian Monte Carlo (HMC) that avoids the random walk behavior which has a greater advantage over convergence during sampling compared to other sampling techniques such as Metropolis. More information regarding the comparison of NUTS and other techniques for sampling the posterior distribution can be found in the study by Hoffman and Gelman (Hoffman and Gelman, 2014). This approach requires assigning the prior distribution to each parameter in the model. Note that the non-informative priors were specified in this analysis. In Bayesian modeling, assigning the non-informative priors to model parameters is common especially in the absence of informative priors (Kruschke, 2013). The non-informative priors impose minimal influence over the estimates and allow the data characteristics to dominate instead (Ntzoufras, 2009).

For the regression coefficients, α and β, the Student's *t*-distribution with three degrees of freedom, a mean of zero, and a standard deviation of ten was assigned as the non-informative priors in the model. Moreover, the variance σ_{ε}^{2} was assumed to follow the Student's *t*-distribution, also with three degrees of freedom, mean of zero, and a standard deviation of ten.

As with the Bayesian estimation, the convergence of the MCMC simulations was assessed using the Gelman-Rubin Diagnostic statistic. Also, a visual diagnostics approach was used to assess the convergence of the chains including the use of the autocorrelation plot and the trace plot of each parameter. A total of 50,000 iterations including 20,000 for warmup and 30,000 for inference were sufficient to produce the desirable Gelman-Rubin statistic, which shows that the convergence has been reached. The model was implemented using the Bayesian Regression Models using Stan (BRMS), an R open-source package (Bürkner, 2018).

In this study, negative binomial, Poisson, and Poisson log-normal were fitted, and the model that best-fitted the data was considered for further analysis. The widely applicable information criterion (WAIC) was used to investigate the performance of the Poisson log-normal model in fitting the crash data. Note that the model with the lowest WAIC best fits the data characteristics (Elvik et al., 2009). As indicated in Figure 4-8, the Poisson log-normal model has the lowest WAIC value for total crashes, FI crashes, and

PDO crashes. Also, as indicated in Figure 4-9, the Poisson log-normal model has the lowest WAIC value for specific crash types (i.e., rear-end, sideswipe, and angle crashes).

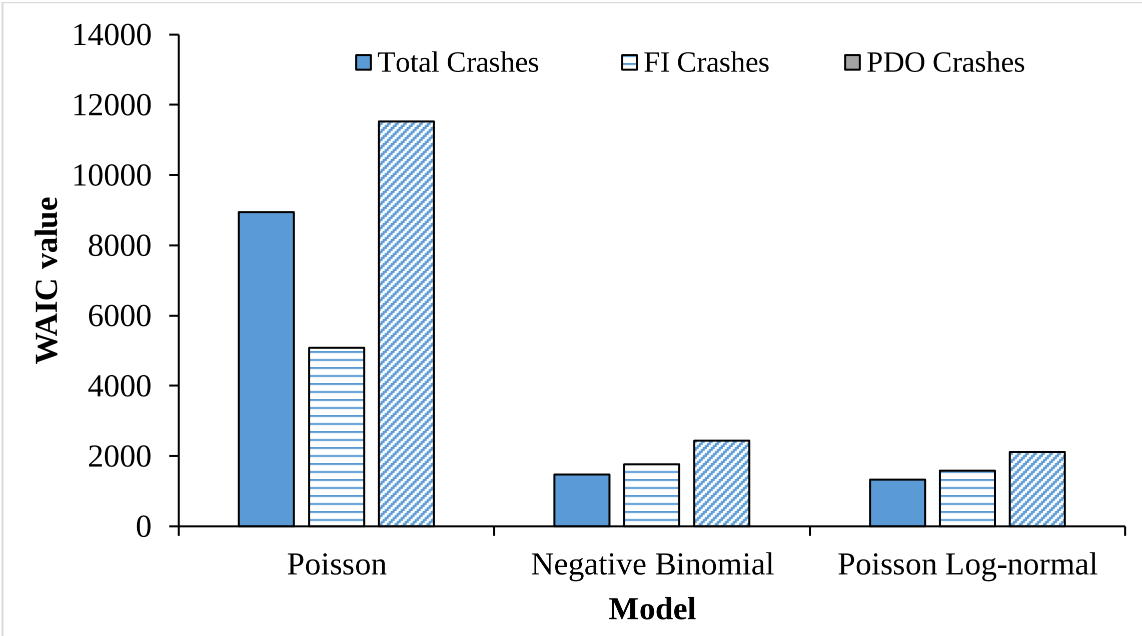


Figure 4-8: Comparison of the Fitted Models Using WAIC to Evaluate Safety Benefits of TSP for Crash Severity

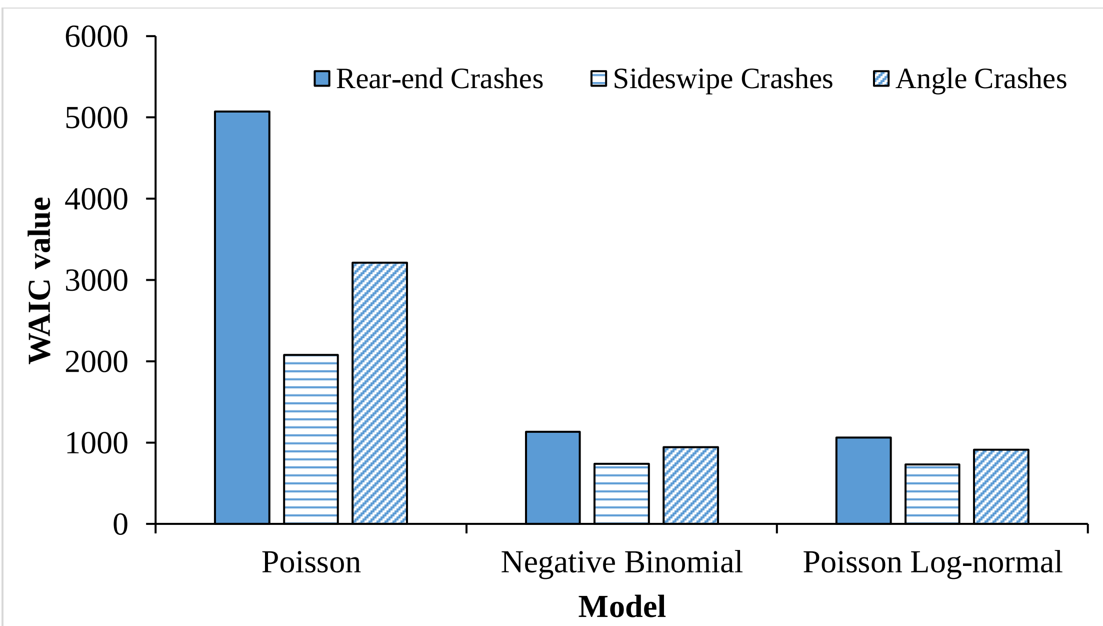


Figure 4-9: Comparison of the Fitted Models Using WAIC to Evaluate Safety Benefits of TSP for Crash Types

4.2.2 Estimation of Crash Modification Factors (CMF)

The posterior distribution was used to predict the crashes on treatment and non-treatment sites (i.e., comparison sites) during the before and after period. The CMFs were then derived from the predicted crashes as:

$$CMF_i = \frac{\mu_i^{TA}}{\pi_i^{TA}}, \text{where } \pi_i^{TA} = \mu_i^{TB}\left(\frac{\mu^{CA}}{\mu^{CB}}\right) \tag{4-9}$$

where

μ_i^{TB} and μ_i^{TA} = predicted crash counts for the i^{th} treatment corridor averaged over the years before and after deployment of the TSP system, respectively,

μ^{CB} and μ^{CA} = corresponding crash counts for the paired comparison corridors,

T and C = treatment and comparison corridors, respectively, and

A and B = after and before periods, respectively.

The safety effectiveness of the TSP systems was estimated using CMF, a parameter that was obtained using a fully Bayesian approach as stated in the earlier sections. The ratio μ^{CA}/μ^{CB}, conventionally known as the comparison ratio, is included during the evaluation of the safety effect of the countermeasure to account for other external non-quantifiable factors that may influence the change in the crash frequency (Kitali and Sando, 2017; Park et al., 2010). Potential external non-quantifiable factors include enhancements in vehicle safety technology, new traffic policies, education on traffic safety awareness, etc., that cannot be attributed to the treatment (i.e., TSP deployment). Explicitly, the estimate of the comparison ratio μ^{CA}/μ^{CB} was combined with the observed crashes during the before period on the treatment corridors to compute the expected crashes on the treatment corridors, assuming that the TSP was not deployed.

Finally, the overall CMF, was estimated using:

$$C = \frac{1}{n}\sum_{i=1}^{n} \ln\left(CMF_i\right) \tag{4-10}$$

where

C = natural logarithm of crash modification factors,

n = total number of treatment corridors, and

i = corridor with TSP.

Previous research indicated that although the estimate of CMF is subject to a small bias, it is ordinarily irrelevant (Hauer, 1997).

4.3 Summary

This chapter described the approach used to estimate the mobility and safety benefits of TSP. The operational impacts of TSP were quantified using a microscopic simulation approach. Specifically, VISSIM a microscopic simulation modeling software was used. Two separate VISSIM models were developed, i.e., the Base and the TSP model. As per the formula provided by the Traffic Analysis Handbook (FDOT, 2014), a total of 15 simulation runs were required for evaluation. The Base model was calibrated to reflect field conditions.

The importance and benefits of microscopic simulation model were also explored. A two-step VISSIM calibration process was used to calibrate the VISSIM model. The first calibration step matched the actual field conditions (desired speed and travel time), whereas the second calibration step was to calibrate the identified VISSIM driving behavior parameters.

An observational FB before-after evaluation was used to evaluate the safety effectiveness of TSP. The FB approach integrates the process of estimating SPFs and treatment effects in a single step, incorporating the uncertainties of the SPFs in the final estimates. The first step in the analysis identified sites with and without TSP. Next, the geometric characteristics and crash data were extracted for the identified sites. Then the data were processed and cleaned. Crash contributing factors were then identified, and the relationship between the crash frequency and different explanatory variables were determined. The crash frequency before and after the installation of TSP was compared. Lastly, the safety benefits of TSP were quantified.

CHAPTER 5
RESULTS AND DISCUSSION

This chapter presents the results from the study analyses. The first section discusses the results of the operational impacts of TSP for buses and all other vehicles along a corridor in mixed traffic condition using a microscopic simulation approach. The second section presents the results of the analysis on the safety effects of TSP on total crashes, crash severity levels (i.e., FI and PDO crashes) and specific crash types (i.e., rear-end, sideswipe, and angle crashes) using a full Bayes before-after method. The final section provides a summary of the research findings.

5.1 Operational Impacts of TSP

Two VISSIM models, one with no TSP strategy (i.e., Base model), and a second model with only TSP strategy (i.e., TSP-integrated model), were developed for a 4-mile corridor in Jacksonville, Florida. The mobility benefits were quantified based on travel time, average vehicle delay, average cross-street delay, and overall network performance of buses and all other vehicles. The two VISSIM models were run for 15 differently seeded simulations. Each model was run for 3.5 hours, where the first 30-minute period was used as the warm-up time. The following subsections discuss the simulation results.

5.1.1 Travel Times

Travel times were measured for segments between each pair of signalized intersections along the study corridor in both directions of travel. The data collection points were set in VISSIM from one signalized intersection to the next signalized intersection, for each travel direction. Travel times collected from the two models were analyzed and compared. Travel time results for all other vehicles and buses are shown in Tables 5-1 and

5-2 for the NB and SB segments, respectively. It can be inferred from the tables that the TSP scenario resulted in lower travel times for all other vehicles and buses, for both the NB and SB approaches. These results are statistically significant at a 95% confidence level.

Table 5-1: Corridor Travel Time for All Other Vehicles and Buses Along NB

	Northbound Approach	Base Scenario		TSP-integrated Scenario			
Seg-ment No.	Segment Name	All Other Vehicles (s)	Buses (s)	All Other Vehicles (s)	% Increase/ Decrease Compared to Base	Buses (s)	% Decrease Compared to Base
1.	Atlantic Blvd.-Plaza Rd.	62.9	136.9	67.0	6.51	125.9	-8.03
2.	Plaza Rd.-Levy Rd.	22.3	50.9	21.1	-5.38	45.7	-10.21
3.	Levy Rd.-Dutton Rd.	45.4	76.3	41.0	-9.69	65.4	-14.28
4.	Dutton Rd.-Fairway Villas Dr.	58.2	161.9	56.0	-3.78	146.9	-9.26
5.	Fairway Villas Dr.-Assisi Ln.	48.4	135.6	45.0	-7.02	122.8	-9.43
6.	Assisi Ln.-Mayport Crossing Blvd.	31.8	54.8	27.6	-13.20	50.4	-8.02
7.	Mayport Crossing Blvd.-Mazama Rd.	56.5	149.0	59.1	4.60	135.1	-9.32
8.	Mazama Rd.-Mayport School	21.2	67.2	19.1	-9.90	59.8	-11.01
9.	Mayport School-Wonderwood Dr.	47.4	63.3	42.5	-10.33	58.2	-8.05
	Total	**394.07**	**895.9**	**378.40***		**810.2***	
	Compared to Base	**N/A**	**N/A**		**-4.0%**		**-9.5%**

* Value is statistically lower than the corresponding Base value. (s)-seconds

Table 5-2: Corridor Travel Time for All Other Vehicles and Buses Along SB

	Southbound Approach	Base Scenario		TSP-integrated Scenario			
Seg-ment No.	Segment Name	All Other Vehicles (s)	Buses (s)	All Other Vehicles (s)	% Increase/ Decrease Compared to Base	Buses (s)	% Decrease Compared to Base
9.	Wonderwood Dr.-Mayport M. School	46.2	126.2	43.1	-6.70	115.7	-8.32
8.	Mayport School-Mazama Rd.	21.0	41.6	18.8	-10.47	38.5	-7.45
7.	Mazama Rd.-Mayport Crossing Blvd.	43.4	94.5	45.2	4.14	87.4	-7.51
6.	Mayport Crossing Blvd.-Assisi Ln	39.8	60.0	37.5	-5.77	54.8	-8.66
5.	Assisi Ln.-Fairway Villas Dr.	52.0	116.3	46.3	-10.96	106.6	-8.10
4.	Fairway Villas Dr.-Dutton Rd.	49.0	97.5	41.7	-14.89	90.2	-7.01
3.	Dutton Rd.-Levy Rd.	44.9	61.0	44.8	-0.22	55.4	-9.18
2.	Levy Rd.- Plaza Rd.	23.1	18.2	19.5	-15.58	15.8	-13.18
1.	Plaza Rd.- Atlantic Blvd.	90.0	112.0	100.3	11.44	103.6	-10.44
	Total	**409.43**	**727.3**	**397.17***		**668***	
	Compared to Base	**N/A**	**N/A**		**-3.0%**		**-8.1%**

* Value is statistically lower than the corresponding Base value. (s)-seconds

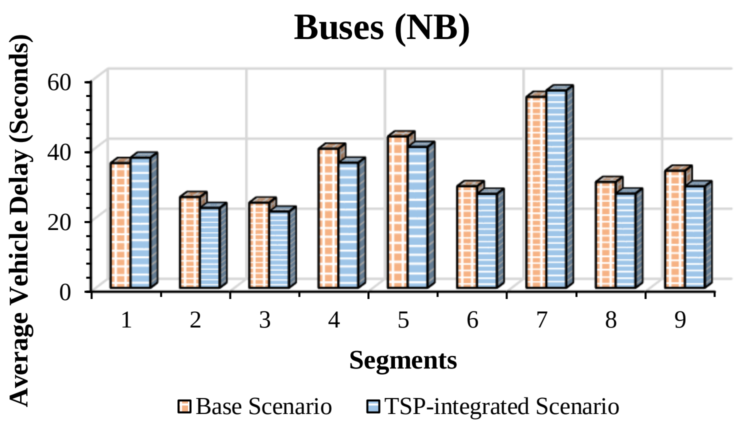
Overall, the TSP scenario outperformed the Base scenario in terms of travel times. Compared to the Base scenario, the implementation of TSP generated better travel time results. For the NB approach, a 9.5% reduction in travel time for buses was observed with TSP, compared to the Base scenario. A similar trend, although not to this extent, was observed for all other vehicles in the NB direction. All other vehicles experienced a 4.0%, reduction in travel time with TSP, compared to the Base scenario.

Travel times along the SB approach showed similar trends for both buses and all other vehicles. For SB approach buses, TSP implementation resulted in a travel time reduction of 8.1%, compared to the Base scenario. For all other vehicles, the reduction in travel time with TSP was found to be 3%.

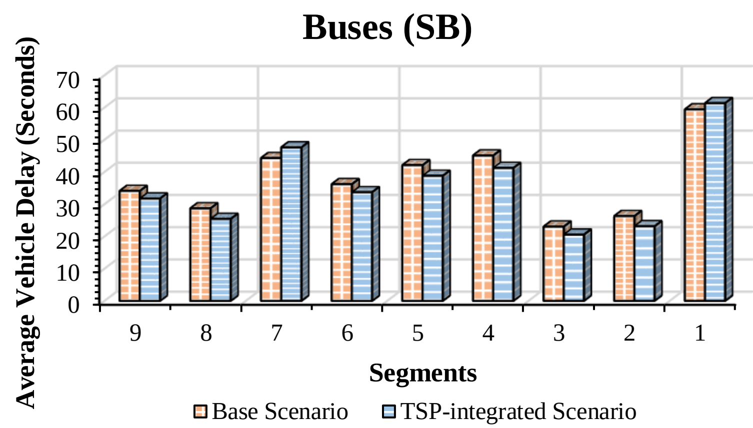
5.1.2 Delay

Average vehicle delay time and average cross-street delay were also considered as the performance measures to quantify the mobility benefits of TSP. Delay, due to deceleration before a bus stop and/or the subsequent acceleration after a bus stop, was included in the average vehicle delay time. Figure 5-1 shows the average vehicle delay times along the main street for all other vehicles and buses in the NB and SB directions, respectively. From Figure 5-1, it can be inferred that the TSP-integrated scenario resulted in lower average vehicle delay time for all other vehicles and buses.

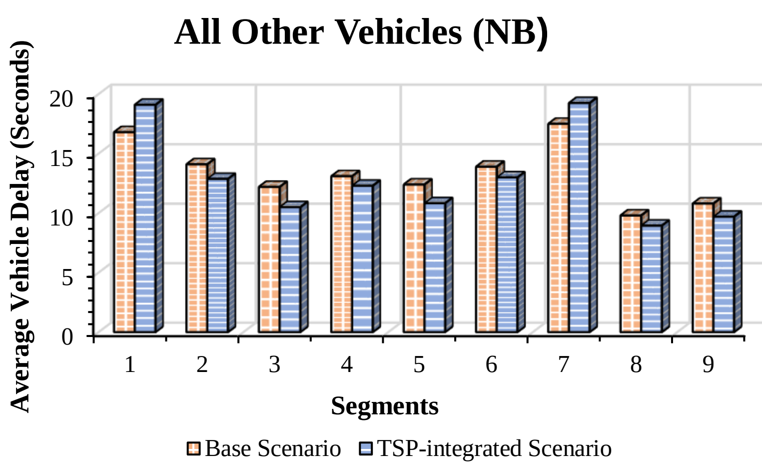
For the NB direction, the average vehicle delay time for buses in the Base scenario was 315.80 seconds, which was 6% higher than the average vehicle delay for buses in the scenario with TSP-integration (see Figure 5-1(c)). For the same direction of travel, the average vehicle delay for all other vehicles in the Base scenario was 120.6 seconds, which was 2% higher than TSP-integration (see Figure 5-1(a)).



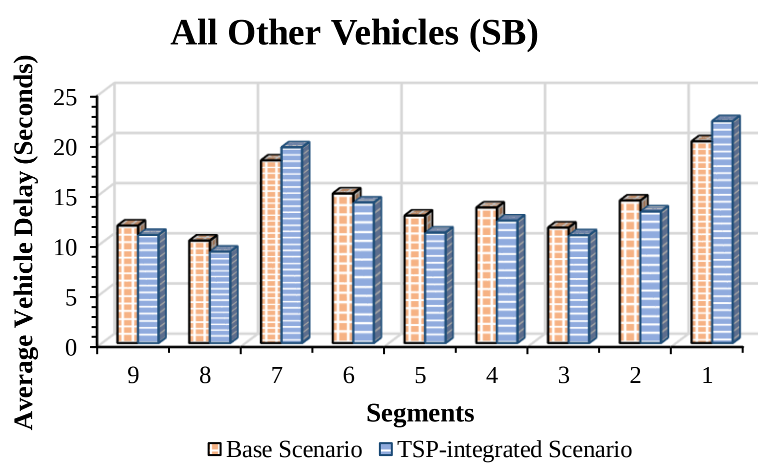
a.



b.



c.



d.

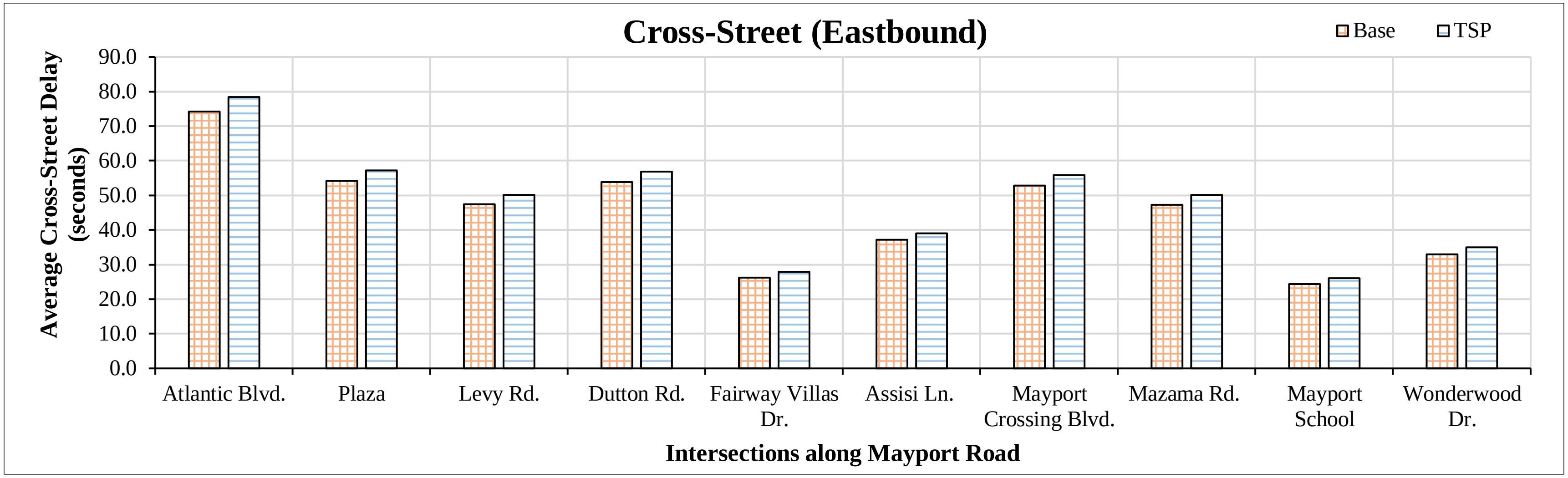
Figure 5-1: Delay Time Measurement Along the Main Street for All Other Vehicles and Buses for Both Travel Directions

Note: segment 1(Atlantic Blvd.-Plaza Rd.), segment 2 (Plaza Rd.-Levy Rd.), segment 3 (Levy Rd.-Dutton Rd.), segment 4 (Dutton Rd.-Fairway Villas Dr.), segment 5 (Fairway Villas Dr.-Assisi Ln.), segment 6 (Assisi Ln.-Mayport Crossing Blvd.), segment 7 (Mayport Crossing Blvd.-Mazama Rd.), segment 8 (Mazama Rd.-Mayport School), segment 9 (Mayport School-Wonderwood Dr.)

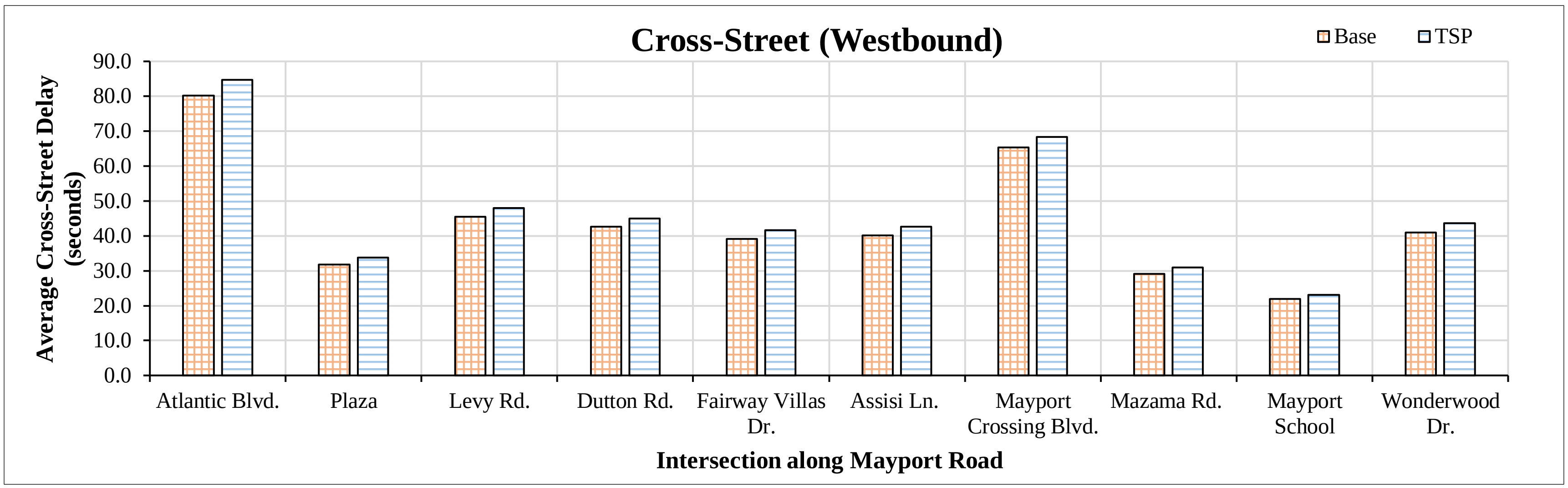
Similar results, although with slightly different magnitudes, were observed for the SB direction. The average vehicle delay time for buses in the Base scenario was found to be 339.3 seconds, which was 5% higher than the average vehicle delay with TSP-integration (see Figure 5-1(d)). It can be inferred that the TSP-integrated scenario generated better results. Similarly, the average vehicle delay in the SB direction for all other vehicles in the Base scenario was 127 seconds, which was 3% higher than the TSP-integration (see Figure 5-1(b)).

5.1.3 Impacts on Cross-Street Traffic

Another crucial factor in the performance evaluation of transit-preferential treatments is the cross-street delay. VISSIM recorded these delays at signalized intersections for the two scenarios (i.e., Base, and TSP-integrated). Figure 5-2 show the average cross-street delays at the signalized intersections in the study corridor. From Figure 5-2, it is evident that transit-preferential treatment (i.e., TSP) caused delay on the cross-streets. The delays at cross-streets varies as it is site-specific. It is also worth noting that due to much lower demand on the cross-street compared to other intersections, the average cross-street delay at the Mayport School intersection was almost equal for the Base and TSP-integrated scenarios.



a.



b.

Figure 5-2: Cross-Street Delays

5.1.4 Statistical Analysis of the Measures of Effectiveness

Student's *t*-tests were performed on the raw output data from the 15 simulation runs for each scenario. The *t*-test was used to compare the performance of two models (i.e., Base, and TSP). Note that the performance measures used in this study were travel time, average vehicle delay, and cross-street delay. The hypothesis testing for the means of the performance measures between the two scenarios, i.e., the Base and the TSP model, were as follows:

$$\text{Null hypothesis; } H_0: \mu_{Base} = \mu_{TSP} \tag{5-1}$$

$$\text{Alternative hypothesis; } H_a: \mu_{Base} \neq \mu_{TSP} \tag{5-2}$$

where μ_{Base} is the mean of the performance measure for the Base model, and μ_{TSP} is the mean of the performance measure for TSP-integrated model. Table 5-3 presents the results of the *t*-test statistics.

Table 5-3: Results of the *t*-test Statistics

Travel Time					
		All Other Vehicles		Buses	
		Base	TSP	Base	TSP
Base and TSP	Mean	44.638	42.797	90.177	82.908
	t-statistic value	2.319		9.588	
	P-value	0.016		0.0	
	t-critical value	1.739		1.739	
Average Vehicle Delay					
		All Other Vehicles		Buses	
		Base	TSP	Base	TSP
Base and TSP	Mean	13.755	13.409	36.391	34.455
	t-statistic value	1.196		3.4972	
	P-value	0.123		0.001	
	t-critical value	1.739		1.739	

The t-statistic value was found to be greater than the critical t-values at a 95% confidence level for all the performance measures for buses. This indicates that there was a significant difference in the performance measures among the Base and TSP-integrated scenarios. More specifically, travel time and average vehicle delay were significantly lower for the TSP-integrated scenario, compared to the Base scenario, at a 95% confidence level.

5.1.5 Corridor Performance

Table 5-4 summarizes the performance results of the entire corridor and shows the travel time, average vehicle delay, and average cross-street delay in seconds. Results are shown for the Base scenario and the TSP scenario for each direction of travel.

Table 5-4: Performance Results of the Entire Corridor

		Northbound		**Southbound**	
	Corridor Performance	**Base**	**TSP**	**Base**	**TSP**
All Other Vehicles	Total Travel Time (s)	394.07	378.4	409.4	397.1
	Average Vehicle Delay (s)	120.6	117.0	127.0	123.3
Buses	Total Travel Time (s)	1066.4	820.3	727.3	672.1
	Average Vehicle Delay (s)	315.8	296.63	339.3	323.5
		Eastbound		**Westbound**	
	Corridor Performance	**Base**	**TSP**	**Base**	**TSP**
Cross-Street	Average Cross-Street Delay (s)	450.5	476.5	436.4	461.6

The implementation of any transit-preferential treatment, such as TSP, can impact vehicular traffic at the network level, including cross-street traffic and through traffic. The corridor-level travel time reduced significantly for buses and all other vehicles in both directions of travel for the TSP scenario, compared to the Base scenario. The TSP scenario resulted in decreased travel time along the main street. However, it reduced the available green time for turning vehicles and cross-street traffic. Consequently, increased delays were observed for the cross-street movements, especially where cross-street traffic volumes exceeded capacity.

5.1.6 Mobility Enhancement Factors (MEFs)

MEFs were developed to quantify the operational effectiveness of TSP. As discussed earlier, an MEF is a multiplicative factor used to estimate the expected mobility level after implementing a given TSM&O strategy at a specific site, such as TSP in this case. A MEF of 1.0 serves as a reference, where below or above indicates an expected increase or decrease in mobility, respectively, after implementation and depending on the performance metric. These MEFs will assist agencies and professionals in evaluating the effectiveness of the TSP. In this study, MEFs for implementing TSP were estimated based on travel time and delay measurements.

The MEFs based on the travel time and average vehicle delay was estimated using the following equations:

$$MEF_{travel-time,i} = \frac{tt_{i,TSP}}{tt_{i,NOTSP}} \tag{5-3}$$

$$MEF_{delay,i} = \frac{avdt_{i,TSP}}{avdt_{i,NOTSP}} \tag{5-4}$$

$$MEF = \frac{\sum_{i=1}^{n} MEF_i}{n} \tag{5-5}$$

where

$MEF_{travel\text{-}time,i}$ = the MEF based on travel time for a particular i^{th} corridor,

$MEF_{delay,i}$ = the MEF based on average vehicle delay for a particular i^{th} corridor,

$tt_{i,TSP}$ = the travel time along the TSP-enabled corridor,

$tt_{i,NOTSP}$ = the travel time along a corridor with no TSP (Base scenario),

$avdt_{i,TSP}$ = the average vehicle delay time along the TSP-enabled corridor,

$avdt_{i,NOTSP}$ = the average vehicle delay time along a corridor with no TSP (Base scenario), and

n = total number of corridors.

Figure 5-3 presents the estimated MEFs for travel time for all other vehicles and buses. The MEFs for TSP, in terms of travel time, for all other vehicles and buses were estimated to be 0.965 and 0.911, respectively. This implies that with TSP along a corridor would result in a 3.5% and a 9% decrease in travel time for all other vehicles, and buses, respectively. The MEFs in terms of average vehicle delay for all other vehicles and buses were estimated to be 0.962 and 0.946, respectively, suggesting that deploying TSP along a corridor would result in a 3.8% and 5.4% decrease in average vehicle delay for all other vehicles and buses, respectively. The study results show that TSP improves the operational performance of the corridor.

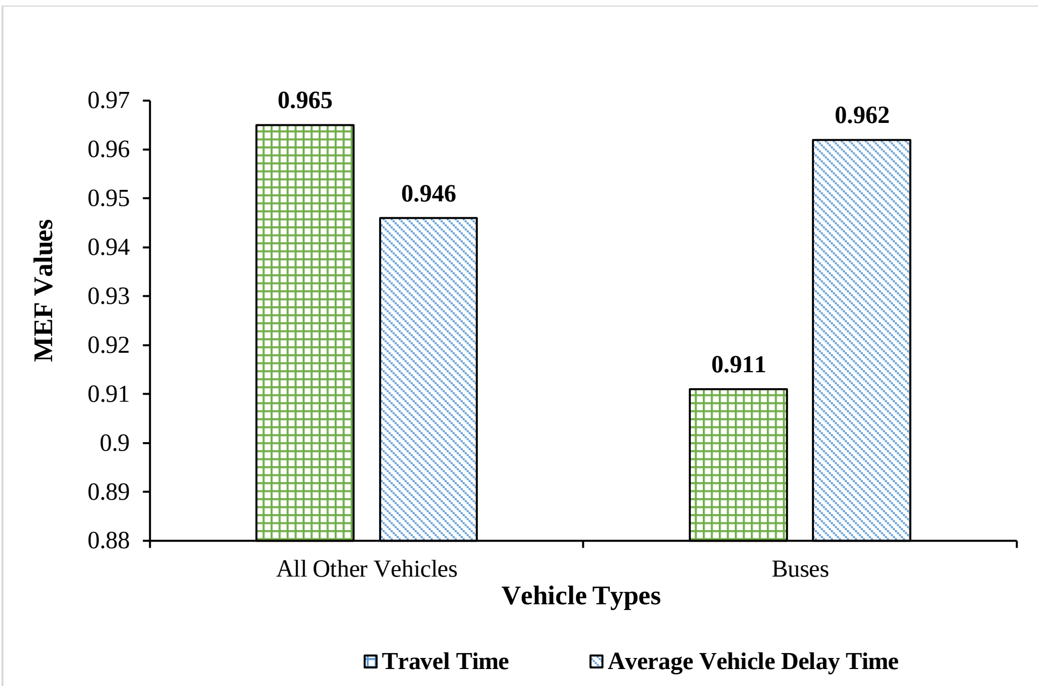


Figure 5-3: MEFs of TSP for the Performance Measures

5.1.7 Importance and Benefits of VISSIM Model Calibration

The following paragraph discuss the importance and benefits of microscopic simulation model calibration. It specifically investigated how well the calibrated VISSIM parameters performed between two TSP corridors. Therefore, the performance analysis results for the calibrated VISSIM TSP model, the four simulation scenarios, and the performance of individual parameters are discussed in the following paragraphs.

5.1.8 Investigation of Calibrated TSP Integrated VISSIM Model

The data from the calibrated VISSIM models for the Mayport Road corridor in Jacksonville were used to investigate the performance of the simulated model for the SW 8th Street corridor in Miami. The correlation between simulated and field travel time was calculated for the VISSIM model of the SW 8th Street corridor for four scenarios.

For the first scenario, the default values of the VISSIM driving behavior parameters were used for the SW 8th Street corridor. In the second scenario, only the first calibration process was applied, and the default values of the VISSIM parameters were used for the SW 8th Street corridor. In the third scenario, the SW 8th Street corridor was simulated using the calibrated values from the Mayport Road corridor. Finally, in the fourth scenario, the SW 8th Street corridor was simulated using the calibrated values from the Mayport Road corridor, and also, the SW 8th Street corridor was recalibrated as per local conditions. Table 5-5 summarizes the values used for the VISSIM parameters, and which calibration process was applied.

Table 5-5: Four Scenarios of SW 8th Street for Calibration Performance

Scenario	VISSIM Parameters			Description	First Calibration Process	Second Calibration Process
	W74ax	W74bx Add	W74bx Mult			
1	2.0	2.0	3.0	Default	No	No
2	2.0	2.0	3.0	Default	Yes	No
3	3.82	4.97	5.74	Application-based	Yes	No
4	3.45	4.23	4.55	Estimation-based	Yes	Yes

Note: W74ax = Average standstill distance; W74bxAdd = Additive part of safety distance; W74bxMult = Multiplicative part of safety distance.

- *Scenario 1 - Without Any Calibration Process:* In this scenario, the default VISSIM parameters were used to model the SW 8th Street corridor in Miami, without the first and second calibration process. The correlation between field and simulated travel time was estimated. The results, illustrated in Figure 5-4, revealed that using the default values of the VISSIM parameters, the field and simulated travel time were not correlated. Thus, using simulation models without proper calibration can lead to subjective results and should be avoided.

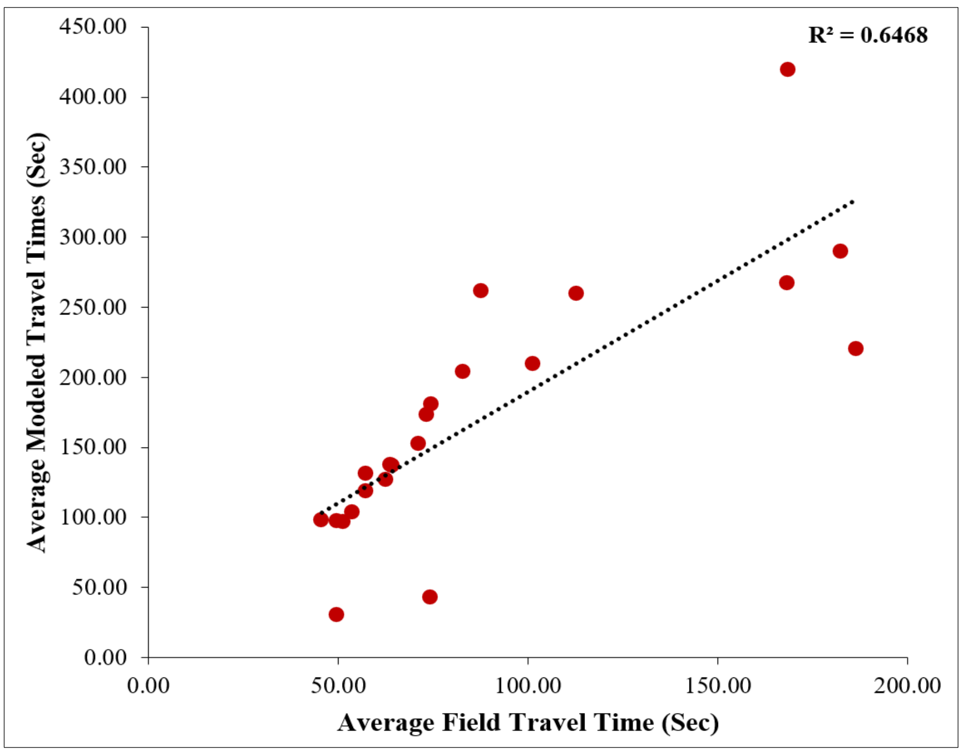


Figure 5-4: Result Using Only the Default VISSIM Parameters Value

- *Scenario 2 – With Only First Calibration Process:* In this scenario, the SW 8th Street was simulated using only the first calibration process to estimate the correlation between field and simulated travel time. The results, illustrated in Figure 5-5, showed improvement in the correlation between field and simulated travel time, compared to Scenario 1. This result significantly emphasized the need and importance of the first calibration process to match the travel time, where the desired speeds were also matched. For the desired speeds, the cumulative distribution curve of the VISSIM model was modified as per field conditions. Better results could be realized if the default driver behavior, simulated by Wiedemann 74 car following model in VISSIM, was also calibrated.

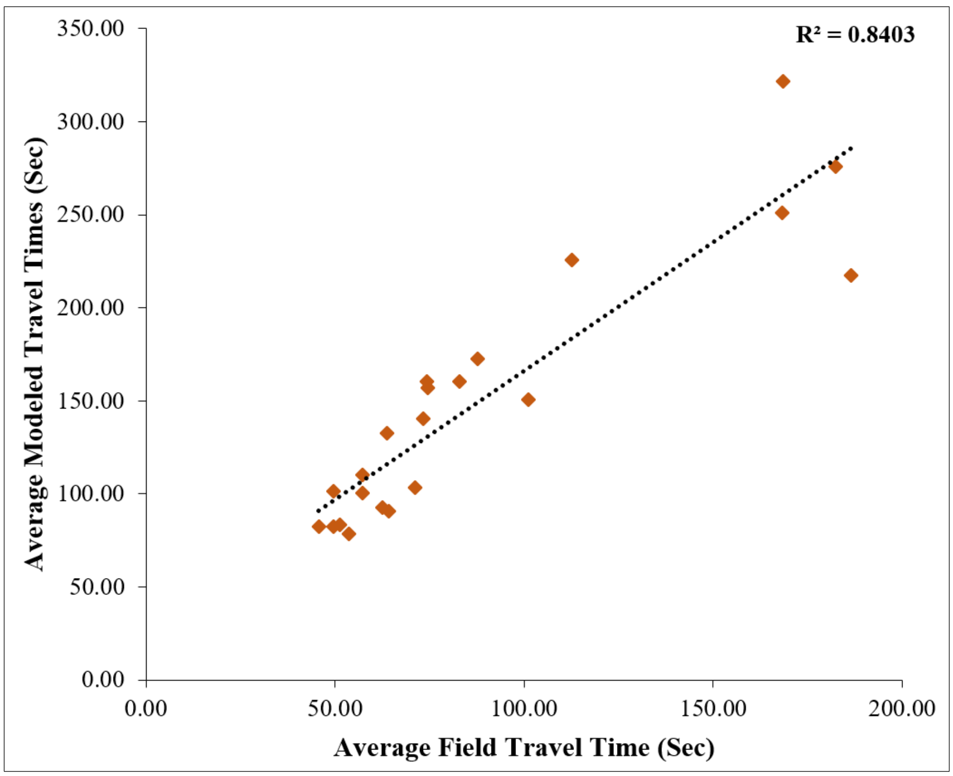


Figure 5-5: Result With Only First Calibration Process

- *Scenario 3 – Application-Based Approach:* In this scenario, the SW 8th Street was simulated using the desired speeds from the Mayport Road corridor as a part of the first calibration process. The values of the second calibration process for the Mayport Road corridor were also used for the SW 8th Street simulation model, according to the application-based approach, to estimate the correlation between field and simulated travel time. The results, illustrated in Figure 5-6, showed that the correlation between field and simulated was enhanced when the calibrated values of the Mayport Road corridor were used instead of the default values. This finding confirms that the main VISSIM parameters that affect travel time could be used at similar, or close to similar, corridors. Thus, results reveal an acceptable level of performance of the Wiedemann 74 driving behavior parameters between the two study corridors.

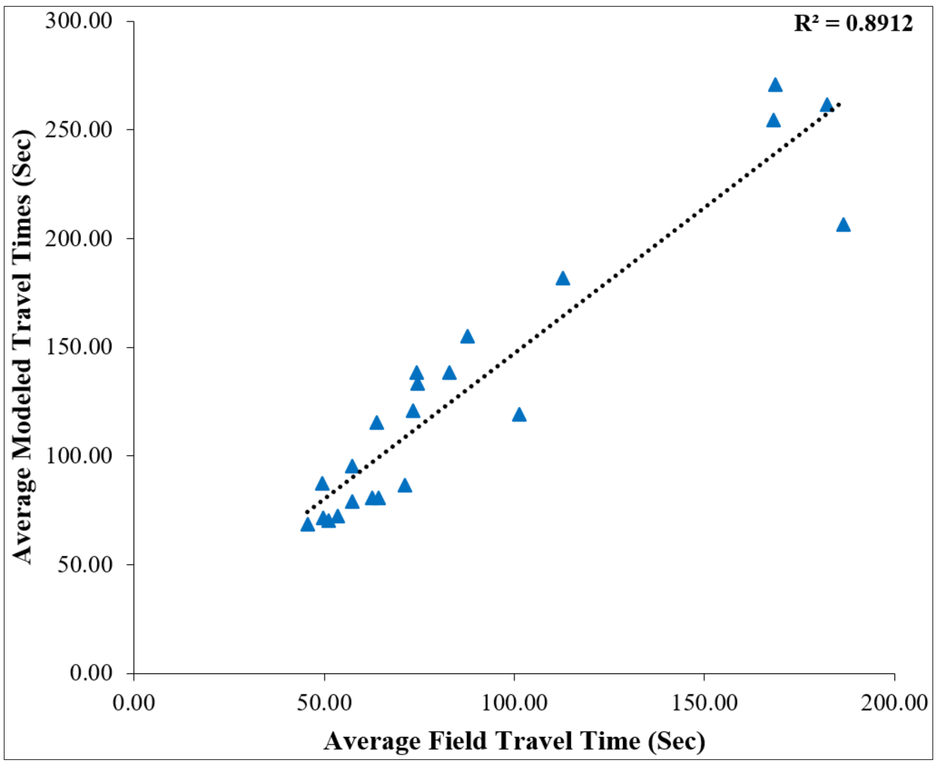


Figure 5-6: Result of Application-Based Approach

- *Scenario 4 – Estimation-Based Approach:* In this Scenario, the SW 8th Street was simulated using the desired speeds from the Mayport Road corridor as a part of the first calibration process. Also, the values of the second calibration process of the Mayport Road corridor were used for the SW 8th Street simulation model. Per the estimation-based process, the SW 8th Street corridor was recalibrated for local conditions by following both the first and second calibration process. The results, illustrated in Figure 5-7, showed the correlation between field and simulated travel time was higher for Scenario 4 than in all other Scenarios. This enhancement in correlation was expected, due to the local calibration process. The difference between Scenarios 3 and 4 was evident.

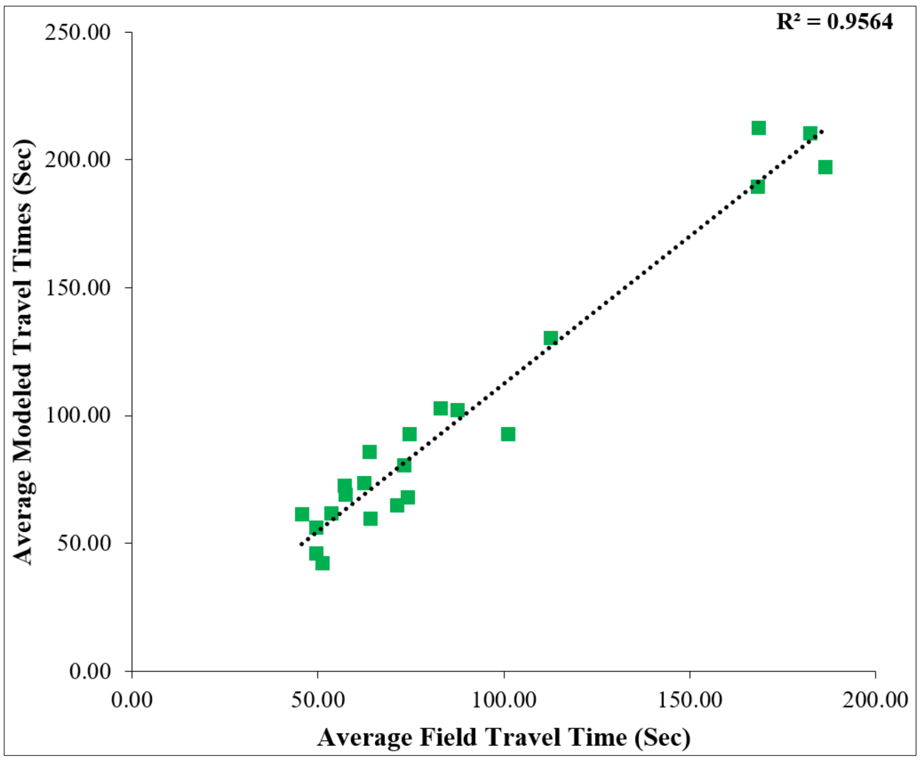


Figure 5-7: Result of Estimation-Based Approach

Therefore, although local calibration of model parameters was crucial, using calibrated parameters from similar, or close to similar, corridors can lead to good results. The next section discusses the performance of individual parameters used in the estimation-based approach.

5.1.9 Performance Results of Individual Calibrated Parameters

Table 5-6 shows the results of individual calibrated parameters performance. As shown in Table 5-6, when the calibration process was applied for both corridors, the parameter ‘W7ax’ had a value of 9.25%. Which signifies even if the calibrated value of this parameter ‘W7ax’ when interchanged between the two study corridor it would perform better than the default value. For the ‘W74bxAdd’ parameter, a value of 18.50% was observed, which signifies that the calibrated parameter value could be interchangeable between the two study corridor to some degree (Essa & Sayed, 2015). However, for the ‘W74bxMult’ parameter, a higher value of 23.80% was observed. This high change indicates that this calibrated parameter value cannot be interchangeable between the two study corridors and needs a new calibration to enhance the results (Essa & Sayed, 2015).

Table 5-6: Performance Results of Individual Calibrated Parameters

#	Parameter Name	Calibrated value		Difference	% of Change
		Mayport Road Corridor	SW 8th Street Corridor		
1.	W74ax	3.82	3.45	0.37	09.25
2.	W74bxAdd	4.97	4.23	0.74	18.50
3.	W74bxMult	5.75	4.55	1.20	23.80

Note: W74ax = Average standstill distance; W74bxAdd = Additive part of safety distance; W74bxMult = Multiplicative part of safety distance.

The importance and benefits of VISSIM model calibration were assessed using two different approaches: (a) the application-based approach, and (b) the estimation-based approach. The application-based approach tests the performance of a calibrated model as a whole, while the estimation-based approach tests the performance of each calibrated parameter. Based on the assessment of the two approaches, the estimation-based approach was observed to be more comprehensive.

5.2 Safety Effects of TSP

5.2.1 Posterior Distribution

The posterior distribution summaries for total, FI, PDO crashes and specific crash type (i.e., rear-end, sideswipe, and angle crashes), along with the means and the 95th percentile Bayesian credible intervals (BCIs), are presented in Table 5-7. The predictor variable is significant at a 95% BCI if the values of the 2.5% and 97.5% percentiles do not include zero (i.e., they are both either negative or positive). Overall, the results of the posterior means indicate a decreasing trend in crashes for treatment corridors over the years.

The treatment indicator variable represents the difference in log crash frequency between treatment and non-treatment corridors. It helps determine the crash trend in treatment corridors versus non-treatment corridors. The crash trend over years variable determines whether the crash frequency in the study corridors (treatment and non-treatment corridors) has increased or decreased over time. The jump parameter variable accounts for a possible sudden change in crashes at the treatment corridor after installing and activating TSP. Whereas, the posted speed > 40 mph indicates if the crashes increased or decreased when the posted speed > 40 mph for both treatment and non-treatment sites. AADT indicates the AADT for both treatment and non-treatment sites. Lastly, the proportion of TSP-enabled intersections indicates whether the crashes with proportion of signalized intersection with TSP increased or decreased for the treatment sites.

As per the posterior distribution summaries in Table 5-7 the jump parameters for the total crashes, FI crashes, PDO crashes, and angle crashes indicate a sudden drop in crashes following the deployment of TSP. For instance, for the total crashes the mean value of jump parameter “-0.08” indicated a sudden decrease in crashes on treatment corridors after the deployment of TSP. The probability of the coefficient being negative was 100%.

Table 5-7: Posterior Distribution Summaries for Different Crash Categories

Variable/Parameter	Mean	2.5%	97.5%
Total Crashes			
Intercept	2.83	1.83	3.85
Treatment indicator	1.08	-0.54	2.71
Crash trend over years	-0.01	-0.02	0.01
Jump parameter	-0.08	-0.13	-0.03
Posted speed > 40 mph	0.18	-0.30	0.65
Ln AADT	0.02	-0.08	0.12
Proportion of TSP-enabled intersections	-2.24	-4.79	0.29
FI Crashes			
Intercept	-6.491	-7.447	-5.559
Treatment indicator	4.314	3.844	4.786
Crash trend over years	-0.055	-0.087	-0.024
Jump parameter	-0.130	-0.202	-0.057
Posted speed > 40 mph	0.292	0.002	0.594
Ln AADT	0.855	0.766	0.946
Proportion of TSP-enabled intersections	-8.183	-9.040	-7.347
PDO Crashes			
Intercept	-4.935	-5.595	-4.291
Treatment indicator	3.940	3.639	4.253
Crash trend over years	-0.056	-0.077	-0.035
Jump parameter	-0.116	-0.163	-0.070
Posted speed > 40 mph	0.580	0.381	0.785
Ln AADT	0.773	0.717	0.830
Proportion of TSP-enabled intersections	-7.988	-8.564	-7.434
Rear-end Crashes			
Intercept	1.35	0.05	2.68
Treatment indicator	0.42	-1.51	2.30
Crash trend over years	-0.03	-0.05	-0.01
Jump parameter	-0.06	-0.13	0.01
Posted speed > 40 mph	0.35	-0.20	0.90
Ln AADT	0.08	-0.05	0.21
Proportion of TSP-enabled intersections	-1.25	-4.13	1.75
Sideswipe Crashes			
Intercept	-1.86	-4.24	0.60
Treatment indicator	0.13	-2.23	2.45
Crash trend over years	-0.02	-0.06	0.02
Jump parameter	0.04	-0.09	0.18
Posted speed > 40 mph	0.13	-0.50	0.78
Ln AADT	0.27	0.02	0.51
Proportion of TSP-enabled intersections	-0.64	-4.23	3.02
Angle Crashes			
Intercept	0.60	-1.61	2.85
Treatment indicator	1.79	0.07	3.51
Crash trend over years	0.02	-0.01	0.06
Jump parameter	-0.26	-0.38	-0.13
Posted speed > 40 mph	0.05	-0.47	0.56
Ln AADT	0.08	-0.15	0.31
Proportion of TSP-enabled intersections	-3.48	-6.17	-0.80

Results for the jump parameters in Figures 5-8, 5-13 and 5-11 also show that after the deployment of TSP the probability of decrease in crashes is 100% for total and angle crashes, and 92% for rear-end crashes. However, the plots for the jump parameter in Figures 5-9, 5-10, and 5-12 results show that after the deployment of TSP the probability of a sudden increase in crashes is 99%, 86%, and 71% for FI, PDO and sideswipe crashes respectively.

As shown in Table 5-7, the mean of the treatment indicator coefficient for total, rear-end, and sideswipe crashes are positive, although not significant at the 95% BCI. For instance, for total crashes the mean of the treatment indicator "1.08" indicated that there were more crashes in the treatment corridor during the analysis period. The probability of coefficient being positive was 87%. Figures 5-8, 5-11, and 5-12 indicated that the probabilities of this coefficient being positive for the total, rear-end, and sideswipe crashes were found to be 87%, 65%, and 54%, respectively. On the other hand, the probability of the treatment indicator for the FI and PDO crashes being positive is 94% (Figure 5-9) and 73% (Figure 5-10), respectively. Also, the probability of the treatment indicator for the angle crashes being positive is 96% (Figure 5-13) and thus the mean of this coefficient being positive is significant at the 95% BCI (Table 5-7). This implies that, compared to comparison corridors, treatment corridors experienced a higher frequency of angle crashes during the study period.

The crash trend over the years for the study corridors showed a significant decrease in FI crashes, PDO crashes, and rear-end crashes. For instance, for total crashes the mean value of the crash trend over years coefficient "-0.01" indicated the crashes reduced over the years for both treatment and non-treatment corridors. The probability of coefficient being negative was 80%. The results in Figures 5-8, 5-11, and 5-12 also show that after the deployment of TSP the probability of a reduction in crash trend is 80%, 100%, and 77% for total, rear-end, and sideswipe crashes, respectively. However, the results in Figures 5-9, 5-10, and 5-13 show that after the deployment of TSP the probability of an increase in crash trend is 54%, 97%, 85% for FI, PDO, and angle crashes, respectively.

As shown in Table 5-7, the regression coefficient for the proportion of signalized intersections with the TSP parameter (parameter accounting for a higher proportion of TSP-enabled signalized intersections) is significantly negative for FI crashes, PDO crashes, and angle crashes. For instance, for total crashes the mean value of proportion of signalized intersection with TSP "-2.24" indicated a decrease in the crashes for the treatment sites. The probability of coefficient being negative was 93%. Also, the results in Figures 5-8, 5-11 to 5-13 show that after the deployment of TSP the probability of a reduction in crashes for the proportion of signalized intersection with TSP is 93%, 76%, 62%, and 98% for total, rear-end, sideswipe, and angle crashes, respectively.

With higher AADT, the resulting posterior means also indicate a significant increase in FI crashes, PDO crashes, and sideswipe crashes. For instance, for total crashes the mean value of AADT "-0.02" indicated an increase in the crashes for the treatment and non-treatment sites with higher AADT. The probability of coefficient being positive was 63%. After the deployment of TSP, the probability of an increase in crashes with higher AADT is 63%, 99%, 65, 85%, 96%, and 73% for total, FI, PDO, rear-end, sideswipe, and angle crashes, respectively, (see Figures 5-8 through 5-13). A higher traffic volume is accompanied by an increase in heterogeneity in driving behavior, a situation that increases the probability of a crash to occur (Kitali and Sando, 2017). With higher speed, the resulting posterior means in Table 5-7 also indicate a significant increase in FI crashes and PDO crashes. For instance, for total crashes the mean value of posted speed > 40 mph “0.18” indicated an increase in the crashes for the treatment and non-treatment sites with posted speed limit > 40 mph. The probability of the coefficient being positive was 73%. Figure 4 through Figure 7 also present that after the deployment of TSP the probability of an increase in crashes with higher speed (i.e., speed limit > 40 mph) is 73%, 59%, 77%, 85%, 63%, and 57% for total, FI, PDO, rear-end, sideswipe, and angle crashes, respectively. Higher posted speed limits on urban arterials are also associated with an increase in crashes (Wang et al., 2018).

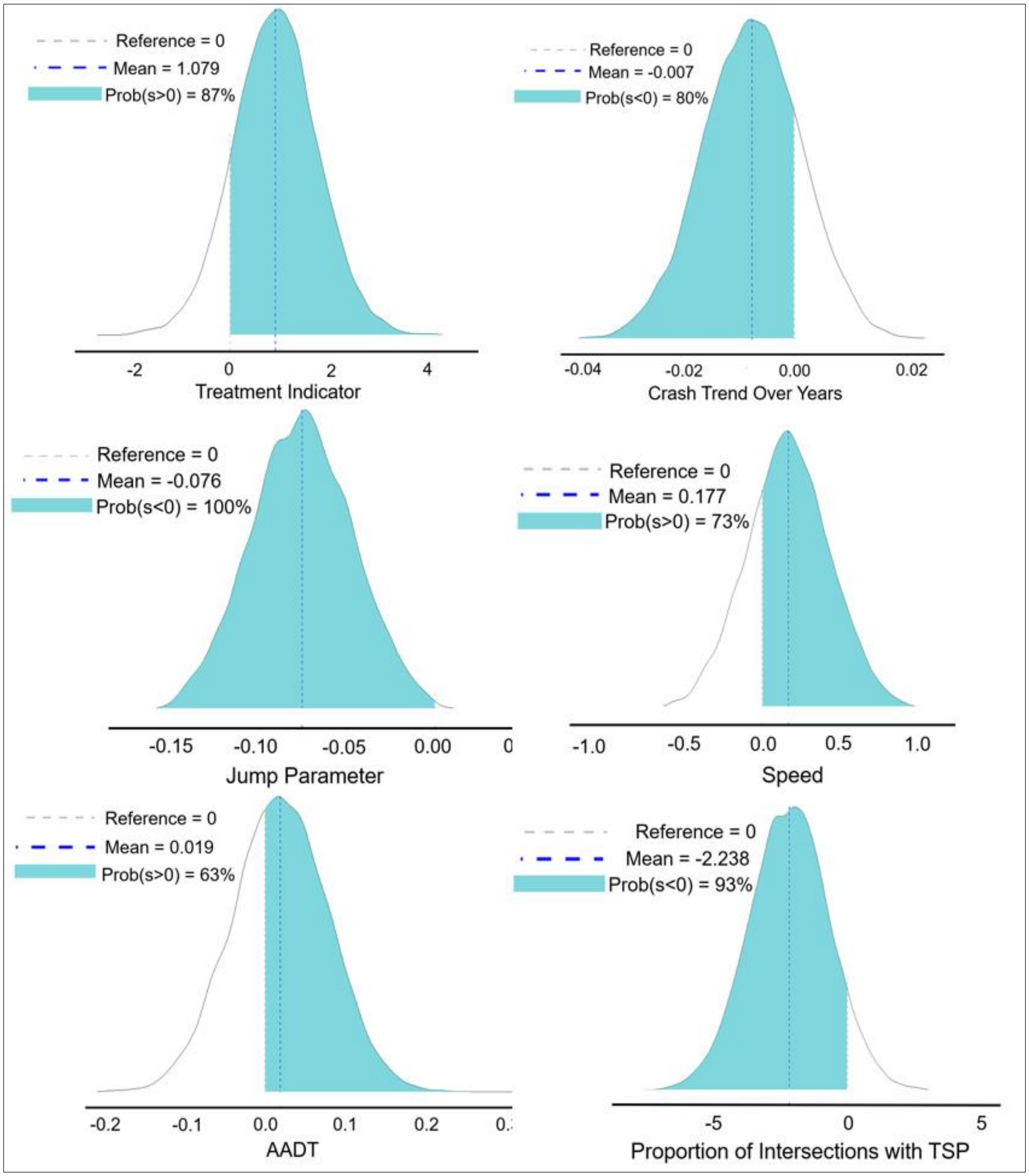


Figure 5-8: Posterior Probability Results for Total Crashes

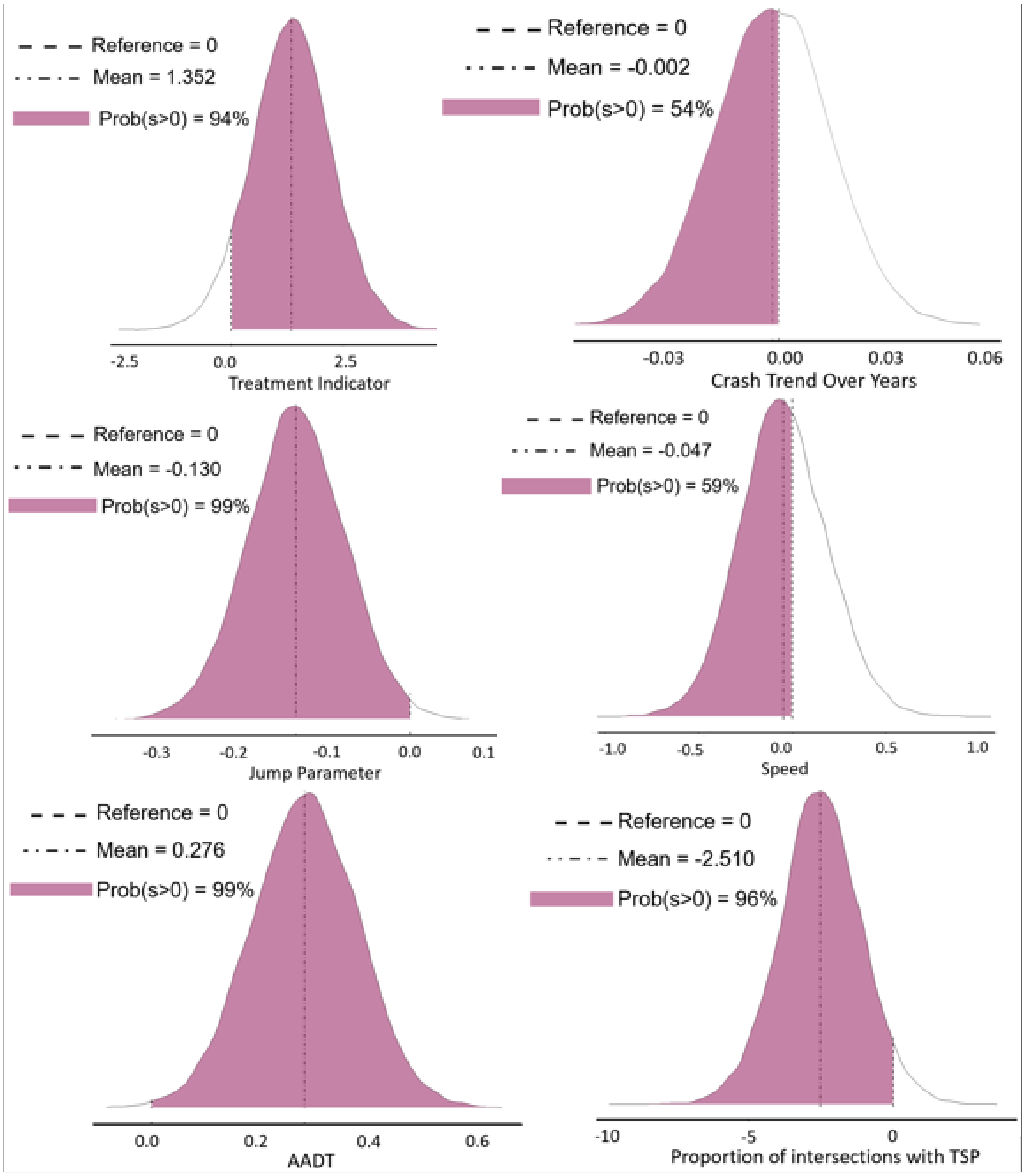


Figure 5-9: Posterior Probability Results for FI Crashes

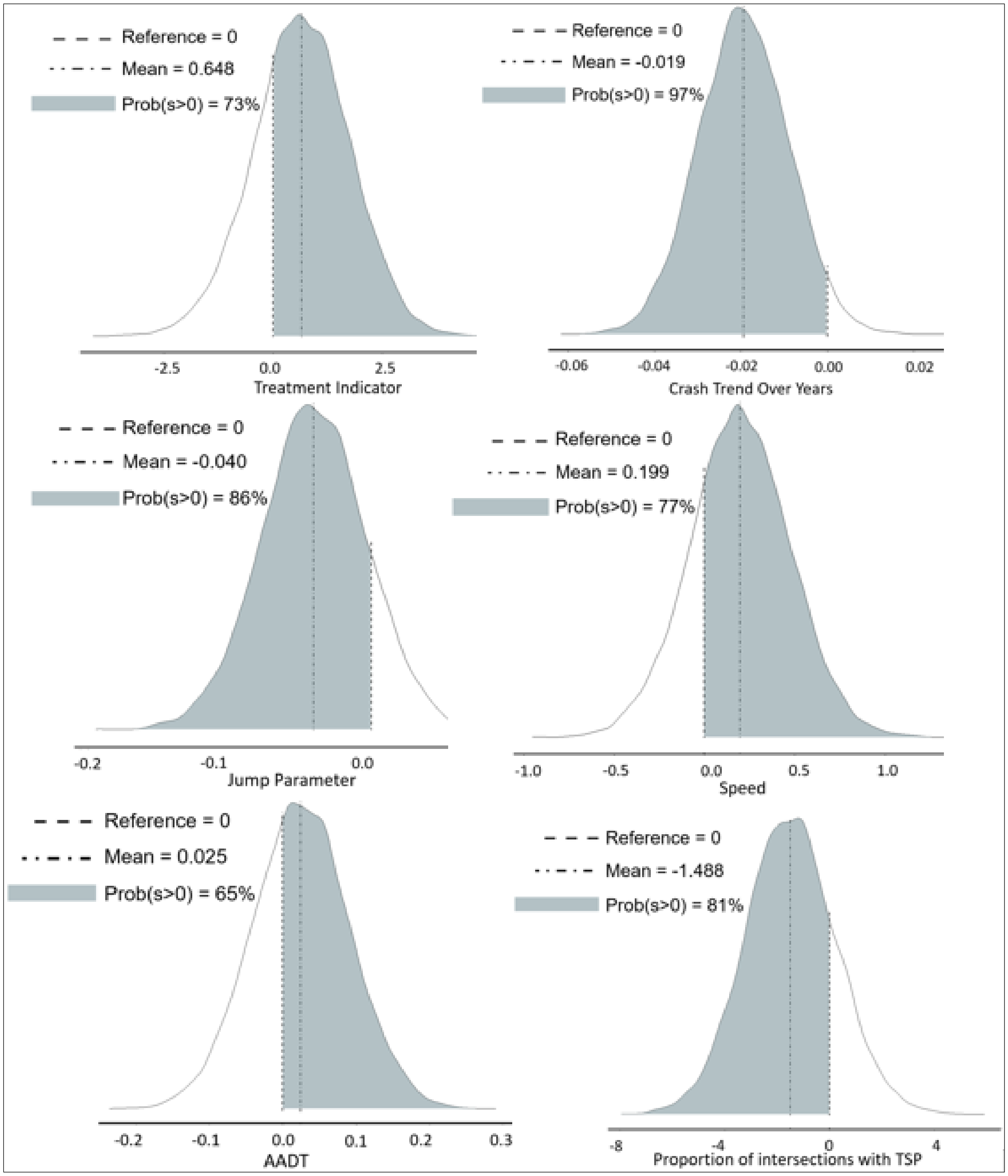


Figure 5-10: Posterior Probability Results for PDO Crashes

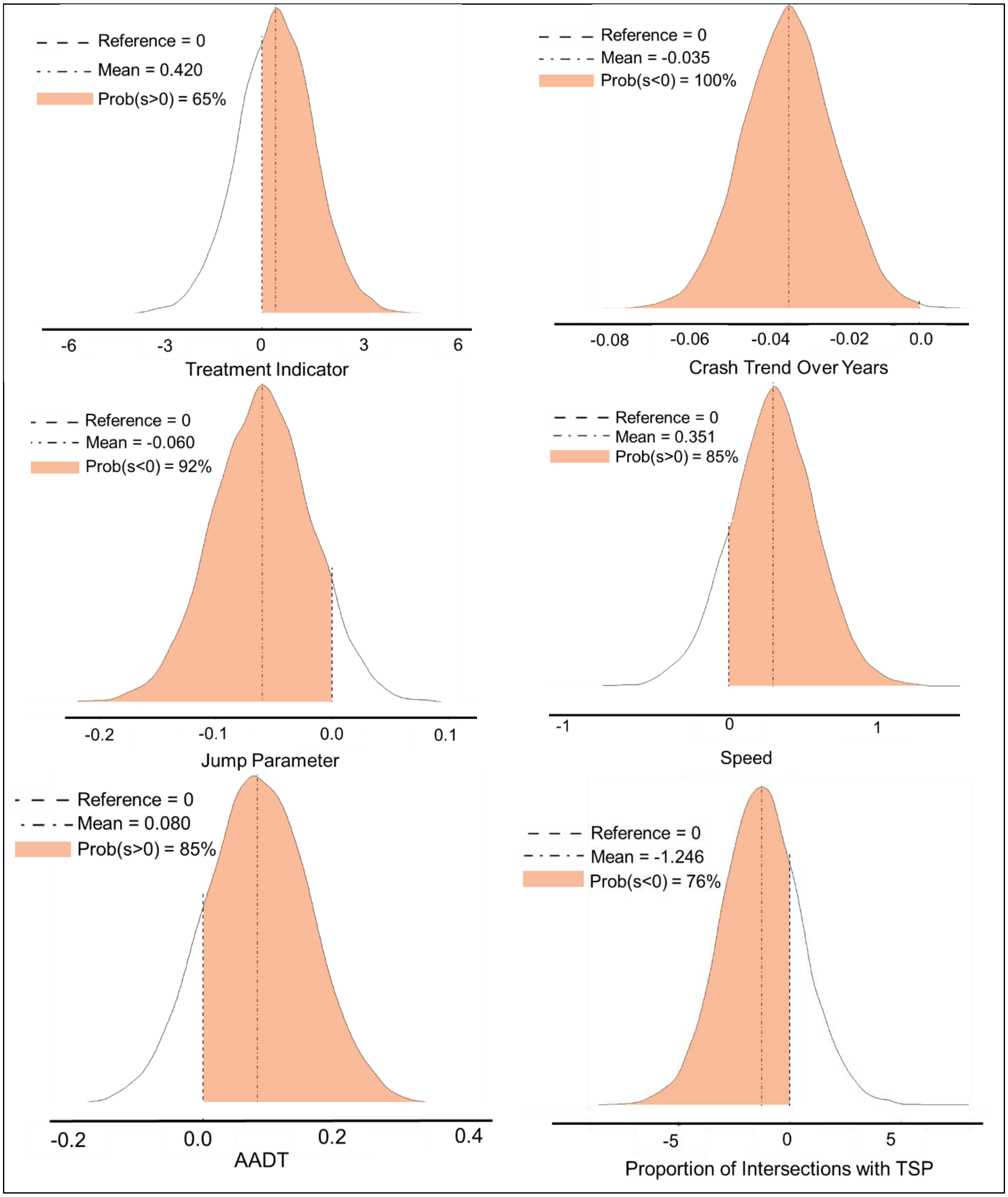


Figure 5-11: Posterior Probability Results for Rear-end Crashes

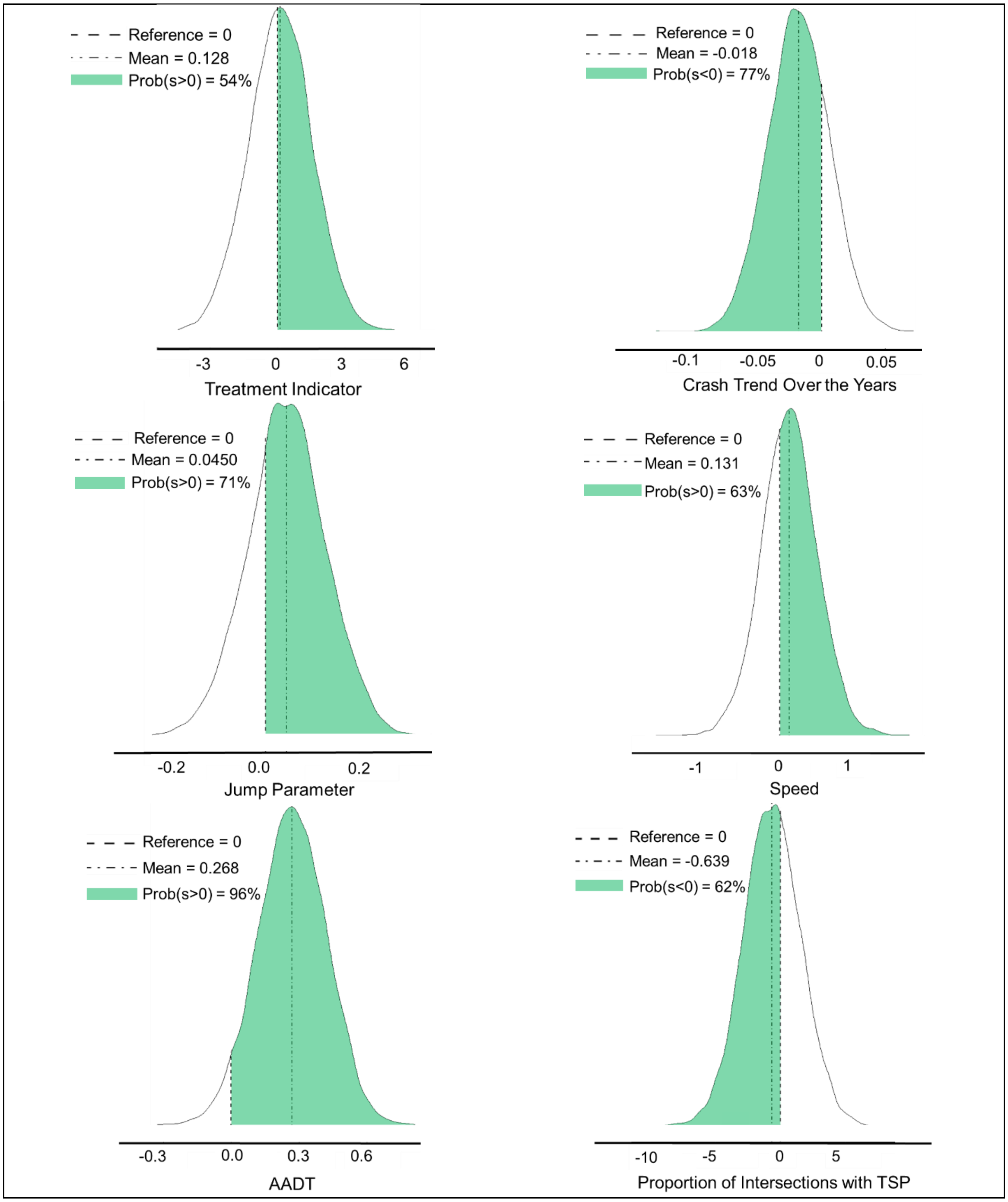


Figure 5-12: Posterior Probability Results for Sideswipe Crashes

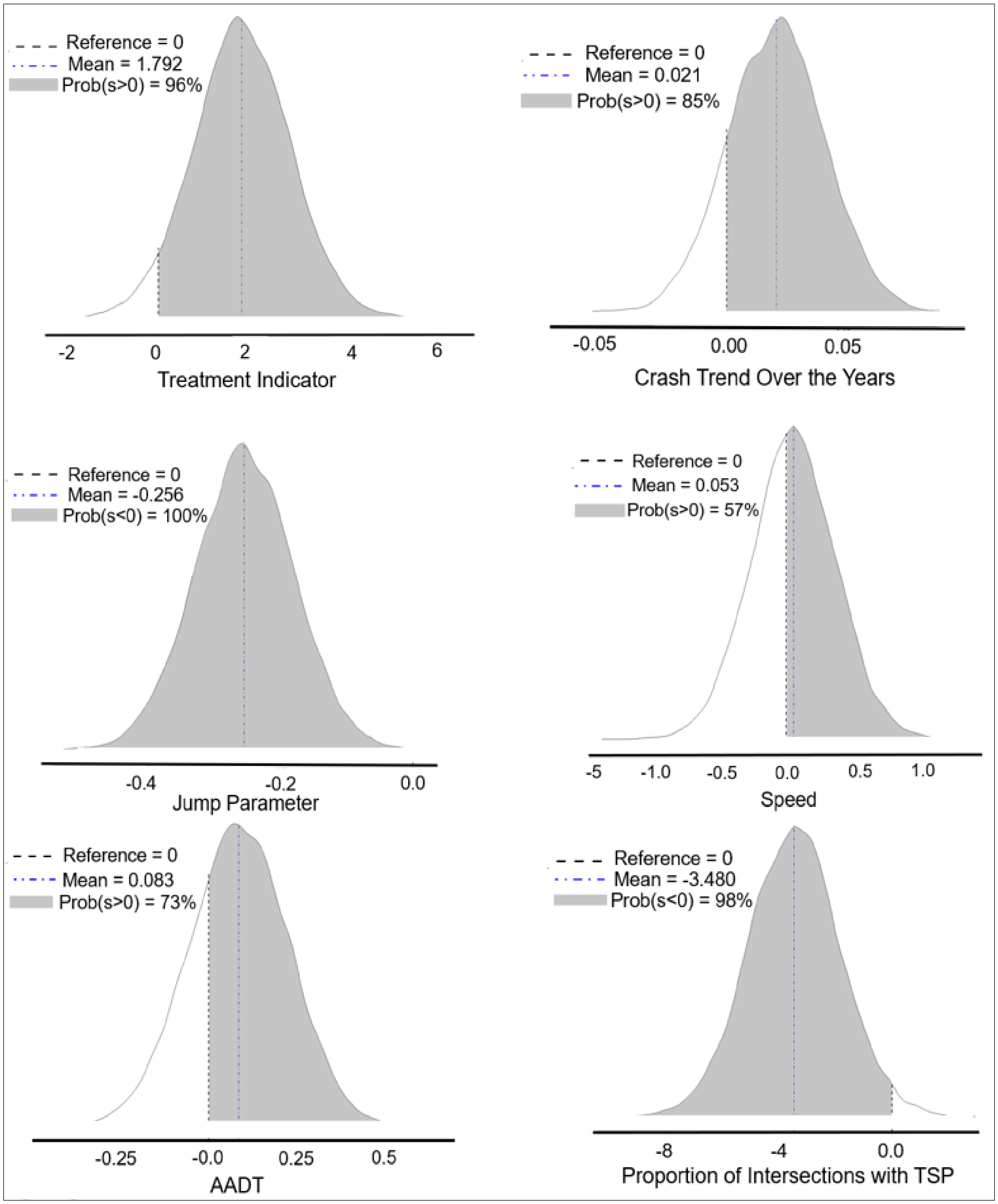


Figure 5-13: Posterior Probability Results for Angle Crashes

5.2.2 Crash Modification Factors (CMFs)

The safety effectiveness of TSP was determined using the CMFs presented in Table 5-8. The table summarizes the CMFs for total, FI, PDO, rear-end, sideswipe, and angle crashes and the associated 95% credible intervals. The CMF is considered significant at a 95% BCI if the lower and upper values do not include 1, i.e., they are either less than one or greater than one.

Table 5-8: CMFs for Different Crash Types

Crash Types	Mean	95% Bayesian Credible Interval		% Change in Crashes
		2.5	97.5	
Total crashes	0.928	0.883	0.985	7.2% (reduction)
FI crashes	0.860	0.790	0.920	14% (reduction)
PDO crashes	0.920	0.880	0.970	8% (reduction)
Rear-end crashes	0.948	0.883	1.030	5.2% (reduction)
Sideswipe crashes	1.060	0.919	1.245	6.0% (increase)
Angle crashes	0.781	0.689	0.899	21.9% (reduction)

Note: total, FI, PDO, and angle crashes were statistically significant at 95% BCI.

The CMF for total crashes is 0.928, indicating a 7.2% reduction in total crashes following the deployment of TSP along the treatment corridors. This finding is consistent with previous studies (Song and Noyce, 2019, 2018). These results may indicate that after the TSP deployment the corridors that received extra green time because of signal priority helped to clear all other vehicles along with buses from an intersection, thus, the crashes were reduced. The extra green time reduces the number of stops for transit and other vehicles upstream of a signalized intersection. The stopping of vehicles in a platoon at a signalized intersection sometimes causes differential speed between vehicles and sometimes may result in hard braking which may potentially lead to a crash.

The CMF for FI and PDO crashes are 0.860 and 0.920, respectively. Reduction of 14% and 8% was observed for FI and PDO crashes, respectively. The deployment of the

TSP provides a little extra green time to transit and all other vehicles to cross the intersection because of signal priority. The extra green time decreases the number of stops for transit and other vehicles upstream of a signalized intersection. These findings were expected as drivers have more green time along the TSP corridors to navigate through the signalized intersections, thereby reducing the queue formation upstream of an intersection stop bar and avoiding potential crashes that may occur during deceleration, hard-braking, and acceleration. Some previous studies reported a similar observation (Goh et al., 2014, 2013; Naznin et al., 2016; Song and Noyce, 2019, 2018).

The CMF for rear-end crashes is 0.948, indicating a 5.2% reduction in rear-end crashes following the TSP deployment. The TSP system operates intending to give green traffic light to the TSP-enabled transit buses along the corridor. When there is more green time along the corridor, ultimately, the stop-and-go traffic is reduced which has the potential to cause a rear-end crash (USDOT, 2006). Moreover, due to the extended green time, the vehicles approaching in a platoon from upstream of an intersection do not have to stop. At times failing to yield to a stopped vehicle before an intersection can also cause a rear-end crash, as these types of crashes mostly occur immediately upstream of the intersection (Polders et al., 2015).

The CMF for sideswipe crashes is 1.06 indicating about a 6% increase in sideswipe crashes following the TSP deployment however, it is not significant at a 95% confidence level. This finding is consistent with Li et al. (2017). When there is a provision of bus stop bay, instead of on-street parking, then when the bus tries to merge back from the bus stop bay to the roadway of the corridor with higher AADT there is also a chance of a sideswipe crash. Green truncation on the cross-street may also be one of the reasons for the increase in sideswipe crashes. Moreover, excessively extended green time can be one of the possible reasons for the increase in sideswipe crashes along the corridors with TSP. Provision of excessive green time on transit corridors will reduce green time on the cross-street, a situation that may impose frustration on cross-road users. Also, the pedestrians intended to cross the transit corridor on arterial may be tempted to jay-walk due to excessive waiting time (Shahla et al., 2009).

The CMF for angle crashes is 0.781, indicating a 21.9% reduction in rear-end crashes following the TSP deployment. Traffic signals can prevent crashes at an intersection by decreasing angle crashes (Elvik et al., 2009; Kenneth, 1996). At an intersection with the permitted left turns, the extended green will provide a bigger gap for left turners to traverse through the intersection, therefore, avoiding a potential crash occurrence. These findings are expected as drivers have more green time along the TSP corridors to navigate through the signalized intersections, thereby reducing the queue formation upstream of an intersection stop bar and avoiding potential crashes that may occur during deceleration, hard-braking, and acceleration. Some previous studies reported similar observations (Goh et al., 2014, 2013; Naznin et al., 2016; Song and Noyce, 2019, 2018).

5.3 Summary

This research investigated the mobility and safety benefits of TSP. To estimate the operational impacts, two VISSIM models, i.e., the Base and TSP model, were developed for a 4-mile corridor in Jacksonville, Florida and were run for a period of 3.5 hours. The mobility performance measures were travel time, average vehicle delay, and average cross-street delay. Along NB approach, a reduction in travel time of 9.5% and 4% was observed for buses and all other vehicles, respectively. Similarly, along SB approach, a reduction of 8.1% and 3% was observed for buses and all other vehicles, respectively. This indicates that TSP improved travel time when compared to the Base Scenario. For average vehicle delay, along NB approach, a reduction of 6% and 2% was observed for buses and all other vehicles, respectively. Similarly, along SB approach, a reduction of 5% and 3% was observed for buses and all other vehicles, respectively. TSP resulted in a reduction in average vehicle delay when compared to the Base scenario. However, the average cross-street delay was higher with TSP when compared to the Base scenario.

The study also investigated the importance and benefits of microscopic simulation model calibration. Specifically, the study investigated how well the calibrated VISSIM parameters performed between two study corridors (the Mayport Road corridor in Jacksonville and the SW 8th Street corridor in Miami). Four different scenarios were created for the SW 8th Street to investigate the performance of VISSIM calibrated parameters. In the first scenario, the simulation results were recorded without any calibration of the TSP VISSIM model. The R^2 value was observed to be 0.6468, indicating that the field and the simulated travel times were not correlated. In the second scenario, the SW 8th Street corridor was simulated by using only the first calibration process. The R^2 value was observed to be 0.8403, indicating that the field and the simulated travel times improved compared to scenario one and the importance of first calibration process. In the third scenario, the SW 8th Street corridor was simulated using the values of the first and the second calibration process of the Mayport Road corridor based on the application-based approach. The R^2 value was observed to be 0.8912, indicating an acceptable level of performance. In the fourth scenario, first the SW 8th Street corridor was simulated using the values of the first and the second calibration process of the Mayport Road corridor, then the SW 8th Street corridor was recalibrated using the first and the second calibration process as per local conditions as per the estimation-based approach. The R^2 value was observed to be 0.9564, indicating the importance of the first and the second calibration process as per local conditions. The percentage change between the average standstill distance, additive part of safety distance, and multiplicative part of safety distance parameters of the two corridors were 9.25%, 18.50%, and 23.80%, respectively.

The safety performance of TSP was estimated using an observational before-after full Bayesian approach with comparison group. The safety benefits of TSP were evaluated using the crash data for the years 2014 through 2018 in Orange and Seminole Counties in Florida. The analysis was based on 12 treatment corridors with TSP and 29 corresponding comparison corridors without TSP. The CMFs were estimated for total, FI, PDO, rear-end, sideswipe, and angle crashes. The CMF for total crashes was 0.928 which indicated a 7.2% in total crashes after TSP deployment. Similarly, the CMFs for FI, PDO, rear-end, and angle crashes were 0.860, 0.920, 0.948, and 0.781, respectively. However, the CMF for sideswipe crashes was 1.060, indicating a 6% increase in sideswipe crashes with TSP, although it was not statistically significant at 95% BCI.

CHAPTER 6
SUMMARY AND CONCLUSIONS

The goal of this research was to investigate the mobility and safety benefits of TSP. This goal was achieved through the following two objectives: (1) assess the operational impacts of TSP on buses and all other vehicles along the corridor in mixed traffic condition using a microscopic simulation approach, and (2) evaluate the safety effects of TSP on total crashes, crash severity levels (i.e., FI and PDO crashes) and specific crash types (i.e., rear-end, sideswipe, and angle crashes) using a full Bayes before-after approach. This chapter provides a summary of this effort, research contributions, and potential future research.

6.1 Summary and Conclusions

6.1.1 Operational Impacts of TSP

To evaluate the mobility benefits of TSP, this study used a microscopic simulation approach. VISSIM microscopic simulation software with Ring Barrier Controller was used for the analysis. The analysis was based on a 4-mile corridor along Mayport Road, between Atlantic Boulevard and Edward Avenue, in Jacksonville, Florida. The study corridor has a total of 10 signalized intersections and serves bus route #24. The bus circulates between the Atlantic Village Shopping Center and the Wonderwood Park-n-Ride facility. Two microscopic simulation VISSIM models were developed: a Base model with no TSP, and a TSP-integrated model. This study fills the gap in the existing research by analyzing the operational effectiveness of TSP for the transit buses and all other vehicles, for both the main and cross-streets.

A key finding observed from the evaluation was that TSP offers benefits not only for the transit buses, but also for all other vehicles along the corridor. TSP was found to provide savings in travel time and average vehicle delay. Based on the evaluation, results of the performance of TSP, with respect to travel time, include:

- For transit buses, TSP resulted in a 9.5% reduction in travel time for the NB direction, and an 8.1% reduction in travel time for the SB direction.
- For all other vehicles, a 4% reduction in travel time for the NB direction, and a 3% reduction in travel time for the southbound direction was observed after TSP integration.
- Travel time of all other vehicles was better in the Base scenario on the segment between Atlantic Boulevard and Plaza Road, for both the NB and SB approaches. This result may be attributed to congestion during the evening peak in the SB direction, leading to a higher volume to capacity (v/c) ratio (i.e., v/c > 1).
- Travel time between Mayport Crossing Boulevard and Mazama Road in the Base scenario was similar to the TSP scenario for both the approaches. For this segment, this finding may be the result of more bus stops between the two intersections (i.e., three bus stops) and higher dwell times, especially during peak hours.

TSP also provided significant reductions in average vehicle delay. Results of the performance of TSP, with respect to average vehicle delay, include:

- For transit buses, the presence of TSP resulted in a reduction in average vehicle delay of 6% and 5% for NB and SB directions, respectively.
- For all other vehicles, a reduction in the average vehicle delay of 2% and 3% for NB and SB directions, respectively, was observed. However, for both the NB and

SB approaches, the average vehicle delay time of all other vehicles and buses between Atlantic Boulevard and Plaza Road was better in the Base scenario, when compared to the TSP-integrated scenario. This finding may be the result of more access points and throughput vehicle volume along this segment.

- Average vehicle delay between Mayport Crossing Boulevard and Mazama Road was better in the Base scenario, compared to the TSP-integration scenario, for both the approaches. This finding may be the result of higher demand on the side streets at both the intersections and the presence of three bus stops along that segment in both the travel directions.

Transit-preferential treatments typically cause cross-street delay. The results indicated that TSP did result in delays on the cross-streets. However, the amount of delay varied, and was found to be site-specific. Also, due to the low demand on the cross-street at the Mayport School intersection, delay was almost equal for the Base and TSP-integrated scenarios.

This study also developed MEFs for TSP. The MEF based on travel time was 0.965 for all other vehicles and 0.911 for buses, and the MEF based on average vehicle delay was 0.962 for all other vehicles and 0.946 for buses. As can be inferred from the MEFs, TSP was found to improve the operational performance of the corridor. The estimated MEFs could provide researchers and practitioners with an effective method for analyzing the benefits of the TSP.

This study also investigated the importance and benefits of calibration of a TSP integrated microscopic simulation model. Specifically, the study focused on how well the calibrated VISSIM parameters performed between two study corridors. The performance analysis was conducted using VISSIM, with the Ring Barrier Controller option, and calibrated simulation model parameters. The calibrated parameters were utilized to estimate the mobility benefits of TSP and check how well the calibrated TSP VISSIM parameters performed between two study corridors. The two corridors were Mayport Road corridor in Jacksonville, Florida and SW 8th Street corridor in Miami, Florida. For both corridors two microscopic simulation VISSIM models were developed: a Base model with no TSP and a TSP-integrated model. This study fills a gap in existing research by analyzing the performance of the calibrated TSP VISSIM parameters, using application and estimation-based approaches.

In this study, a two-step VISSIM calibration process was used. The first calibration process matched the actual field conditions (i.e., desired speed and travel time) to ensure that VISSIM produced field travel time. A second calibration step was performed to calibrate the identified VISSIM driving behavior parameters. The calibrated value of the VISSIM driving behavior parameters was obtained using a genetic algorithm technique. The study proposed and assessed four exploration scenarios of the calibrated parameters. The four Scenarios and their findings are as follows:

- In scenario 1, the SW 8th Street corridor was modeled and simulated using the default values without any calibration. The R^2 value was 0.6468, indicating that the field-measured and simulated travel times were not correlated.
- In scenario 2, the SW 8th Street corridor was simulated and only the first calibration process was used. The R^2 value was 0.8403, revealing the importance of first calibration step, and also indicating that the correlation between field-measured and simulated travel time improved.

- In scenario 3, the SW 8th Street corridor was simulated using the values of the first and second calibration process of the Mayport Road corridor, as a part of the application-based approach. The R^2 value was 0.8912, indicating a better correlation between field-measured and simulated travel time. Moreover, findings from the application-based approach confirmed that the main VISSIM parameters that affect travel time perform well between two study corridors. The results also revealed an acceptable performance of the calibrated VISSIM parameters.
- In scenario 4, the SW 8th Street corridor was simulated using the values of the first and second calibration process of the Mayport Road corridor, and then recalibrated with local conditions, to conduct an estimation-based analysis. The R^2 value was 0.9564, indicating the best correlation between field-measured and simulated travel time, compared to all other scenarios.

Furthermore, the performance of individual parameters was also investigated using the estimation-based approach. After both calibration processes were applied to the two corridors, the difference in the calibrated values for the average standstill distance, the additive part of the safety distance, and the multiplicative part of the safety distance were 0.37, 0.74, and 1.20, respectively. The percentage change between both corridors in terms of the average standstill distance was less than one 0.925%. The percentage change between both corridors in terms of the additive part of the safety distance was 18.50%. Finally, the percentage change between both corridors in terms of the multiplicative part of the safety distance was 23.80%.

6.1.2 Safety Effects of TSP

TSP is increasingly being recognized as a crucial TSMO strategy that improves the operational performance of transit vehicles on urban arterials. As such, most of the consideration has been given to the operational impacts of TSP. Although TSP is meant for improving the operational performance of transit vehicles, such treatment may have some direct or indirect impacts on the traffic safety performance of signalized intersections and their adjacent roadway segments. Few previous studies have explored the safety impacts of TSP, with considerably fewer studies from the United States.

This study quantified the safety effectiveness of TSP, a transit preferential treatment that targets improving the travel time reliability of the transit system. The evaluation examined the safety benefits of TSP using crash data for the years 2014 through 2018 in Orange and Seminole Counties, Florida. The analysis was based on 12 treatment corridors with TSP and 29 corresponding comparison corridors without TSP. The study used an observational before-after full Bayesian (FB) approach with a comparison-group to determine the safety effectiveness of the TSP strategy. To the best of the author’s knowledge, the safety effectiveness of TSP has not been analyzed using the FB approach in previous studies. The proposed approach used a novel intervention model to account for temporal trends, as well as random parameters, to account for unobserved heterogeneity among treatment and comparison corridors.

The safety effectiveness of the TSP system was quantified using crash modification factors (CMFs) as the index measure of the treatment’s effectiveness. The deployment of TSP was found to significantly reduce total crashes by 7.2% (CMF=0.928), FI crashes by 14% (CMF=0.860), PDO crashes by 8% (0.920), and angle crashes by 21.9%

(CMF=0.781). A 5.2% (CMF=0.948) reduction in rear-end crashes was also observed, although the reduction was not significant at a 95% Bayesian credible interval. Additionally, nearly a 6% (CMF=1.060) increase in sideswipe crashes was observed, although the increase was not significant at a 95% Bayesian credible interval.

Overall, the research study results indicate that TSP improves safety. A major implication of this research is that bus priority measures improve the overall safety along the corridor, which is a strong rationale for implementing this TSM&O strategy. The findings of this study also present key considerations for transportation agencies and practitioners when planning future TSP deployments.

6.2 Research Contributions

Transit agencies have invested a substantial amount of time and resources to evaluate the mobility and safety benefits of TSP. A number of studies have been conducted on the mobility benefits of TSP; however, unlike previous research, this study estimated the mobility enhancement factors (MEFs) for transit buses and all other vehicles for TSP. The MEFs could potentially provide researchers and practitioners with an effective method for analyzing the operational and economic benefits of TSP.

Several previous studies have also focused on the importance and benefits of VISSIM calibration; however, to the best knowledge of the author, there are no studies on how proper calibration of TSP VISSIM parameters between two TSP integrated corridors the parameters may be interchangeable. This study evaluated the performance of the TSP VISSIM parameters using application-based and estimation-based approaches. The findings of the study revealed that calibrated microscopic simulation model parameters between two TSP corridors could be used between each other and produced better results compared to the default values.

This research also discussed the shortcomings of the existing approaches used to estimate the safety benefits of TSP. Previous studies on the safety effectiveness of TSP showed mixed results. Therefore, this study, for the first time, evaluated the safety effectiveness of TSP using a more comprehensive approach, i.e., the observational full Bayesian before-after approach. This study estimated the CMFs using the FB approach for the total, FI, PDO, rear-end, sideswipe, and angle crashes.

6.3 Future Work

Although this research has quantified the operational performance of TSP, future work could consider evaluating the mobility benefits of TSP using a passenger-based approach for TSP with GPS technology to provide a broader perspective. In addition, a rule-based TSP, that is set to assign priority to scheduled-based transit vehicles based on their schedule, passenger occupancy, and passenger waiting at downstream stops, could be evaluated.

Furthermore, for the safety effectiveness of TSP, future work could focus on evaluating the impact of TSP on pedestrian and bicycle crashes. Also, evaluating the safety benefits of TSP using safety surrogate measures could be a fruitful avenue to investigate.

REFERENCES

Ahn, K., Rakha, H. (2006). System-Wide Impacts of Green Extension Transit Signal Priority. *IEEE Conference Intelligent Transportation System Proceedings*, 91–96.

Alluri, P., T. Sando, C. Kadeha, H. Haule, J. H. Salum, M. S. Ali, J. H. Kodi, and A. E. Kitali. (2020). *Developing Florida-Specific Mobility Enhancement Factors (MEFs) and Crash Modification Factors (CMFs) For TSM&O Strategies.* Final Research Report.

Ali, M.S., Kaisar, E.I., Hadi, M. (2017). Guidance for Identifying Corridor Conditions that Warrant Deploying Transit Signal Priority and Queue Jump. *5th IEEE International Conference Model Technology Intelligent Transportation System Proceedings*, 657–662. DOI: 10.1109/MTITS.2017.8005595

Ali, M.S., Zerpa, L.A., Kaisar, E.I., Masters, K.O. (2018). Guidance for Identifying Corridor Conditions that Warrant Deploying Transit Signal Priority. In *Transportation Research Board 97th Annual Meeting*. (No. 18-05194).

Ali, MD Sultan, Angela E. Kitali, John H. Kodi, Priyanka Alluri, and Thobias Sando. (2021). "Safety Impacts of Transit Signal Priority Using a Full Bayesian Approach." *Transportation Research Record*: 03611981211025285.

American Association of State Highway and Transportation Officials [AASHTO]. (2010). *Highway Safety Manual* (1st ed.). Transportation Research Board of the National Academies.

Anastasopoulos, P.C., Mannering, F.L. (2009). A Note on Modeling Vehicle Accident Frequencies with Random-Parameters Count Models. *Accident Analysis & Prevention*, *41*(1), 153–159.

Anderson, P., Daganzo, C.F. (2019). Effect of Transit Signal Priority on Bus Service Reliability. *Transportation Research Part B Methodological*, *132*, 2–14.

Associates, S.W.&. (2014). *Countywide Transit Signal Priority Phase III : Corridor and Intersection Priority Ranking and Selection*. Montgomery County Department of Transportation.

Bevrani, K., Chung, E. (2012). An Examination of the Microscopic Simulation Models to Identify Traffic Safety Indicators. *Journal of Intelligent Transportation System Research*, *10*(2), 66–81.

Bowman, John L, Bradley, Mark. (2017). Testing Spatial Transferability of Activity-Based Travel Forecasting Models. *Transportation Research Record: Journal of the Transportation Research Board*, *2669*(1), 62–71.

Bürkner, P.-C. (2018). *Advanced Bayesian Multilevel Modeling with the R Package Brms.* Retrieved June 1, 2020, from https://arxiv.org/abs/1705.11123

Cesme, B., Altun, S.Z., Lane, B. (2015). Queue Jump Lane, Transit Signal Priority, and Stop Location Evaluation of Transit Preferential Treatments Using Microsimulation. *Transportation Research Record: Journal of the Transportation Research Board*, *2533*(1), 39–49.

Consoli, F.A., Alomari, A.H., Al-Deek, H., Rogers, J.H., Sandt, A., Noori, M., Tatari, O., Hadi, M. (2015). Evaluation of Conditional Transit Signal Priority Technology for Regional Implementation. *Transportation Research Record: Journal of the Transportation Research Board*, *2484*(1), 140–148.

Dennis, E.P., Spulber, A. (2016). *International Scan of Connected and Automated Vehicle Technology Deployment Efforts.* Center of Automative Research. Retrieved March 5, 2020, from https://www.cargroup.org/wpcontent/uploads/2017/04/CAV_International_Survey_2017_555402_7.pdf

El-Basyouny, K., Sayed, T. (2012). Measuring Safety Treatment Effects Using Full Bayes Non-Linear Safety Performance Intervention Functions. *Accident Analysis & Prevention*, *45*, 152–163.

Elvik, R., Hoye, A., Vaa, T., Sorensen, M. (2009). *The Handbook of Road Safety Measures.*

Essa, M., Sayed, T. (2015). Transferability of Calibrated Microsimulation Model Parameters for Safety Assessment Using Simulated Conflicts. *Accident Analysis & Prevention*, *84*, 41–53.

Fawcett, L., Thorpe, N. (2013). Mobile Safety Cameras: Estimating Casualty Reductions and the Demand for Secondary Healthcare. *Journal of Applied Statistics*, *40*(11), 2385–2406.

Fawcett, L., Thorpe, N., Matthews, J., Kremer, K. (2017). A Novel Bayesian Hierarchical Model for Road Safety Hotspot Prediction. *Accident Analysis & Prevention*, *99*, 262–271.

Florida Department of Transportation [FDOT]. (2020). *Geographic Information System (GIS)*. Retrieved January 8, 2020, from https://www.fdot.gov/statistics/gis/default.shtm

Florida Department of Transportation [FDOT]. (2014). *Traffic Analysis Handbook*. Retrieved October 9, 2019, from https://www.fdot.gov/planning/systems/documents/sm/default.shtm

Federal Transit Administration [FTA]. (2010). *Bus and Rail Transit Preferential Treatments in Mixed Traffic*. Transportation Research Board, Washington, D.C.

Gallelli, V., Iuele, T., Vaiana, R., Vitale, A. (2017). Investigating the Transferability of Calibrated Microsimulation Parameters for Operational Performance Analysis in Roundabouts. *Journal of Advanced Transportation*.

Goh, K.C.K., Currie, G., Sarvi, M., Logan, D. (2014). Bus Accident Analysis of Routes With/Without Bus Priority. *Accident Analysis & Prevention*, *65*, 18–27.

Goh, K.C.K., Currie, G., Sarvi, M., Logan, D. (2013). Road Safety Benefits from Bus Priority. *Transportation Research Record: Journal of the Transportation Research Board*, *2352*(1), 41–49.

Gross, F., Persaud, B., Lyon, C. (2010). *A Guide to Developing Quality Crash Modification Factors*. No. FHWA-SA-10-032.

Hauer, E. (1997). *Observational Before/After Studies in Road Safety*. *Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety.*

Haule, H. J., Ali, M. S., Alluri, P., & Sando, T. (2021). Evaluating the effect of ramp metering on freeway safety using real-time traffic data. *Accident Analysis & Prevention*, *157*, 106181.

Hoffman, M.D., Gelman, A. (2014). The No-U-turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, *15*(1), 1593–1623.

Hu, J., Park, B.B., Lee, Y.J. (2015). Coordinated Transit Signal Priority Supporting Transit Progression Under Connected Vehicle Technology. *Transportation Research Part C Emerging Technologies*, *55*, 393–408.

INRIX. (2019). *INRIX: Congestion Costs Each American 97 hours, $1,348 A Year*. Retrieved July 11, 2020, from http://inrix.com/press-releases/scorecard-2018-us/

Jacksonville Transportation Authority [JTAFLA]. (2021). Retrieved January 11, 2020, from https://www.jtafla.com/

Kadeha, C., Haule, H., Ali, M. S., Alluri, P., & Ponnaluri, R. (2021). Modeling wrong-way driving (WWD) crash severity on arterials in Florida. *Accident Analysis & Prevention*, *151*, 105963.

Kenneth, O. (1996). *Safer Roads: A Guide To Road Safety Engineering*.

Kitali, A.E. (2017). *Bayesian Approach on Quantifying the Safety Effects of Pedestrian Countdown Signals to Drivers*. Retrieved November 11, 2020 from https://digitalcommons.unf.edu/cgi/viewcontent.cgi?article=1782&context=etd

Kitali, A.E., Sando, P.E.T. (2017). A Full Bayesian Approach to Appraise the Safety Effects of Pedestrian Countdown Signals to Drivers. *Accident Analysis & Prevention*, *106*, 327–335.

Kodi, J. H., Kitali, A. E., Ali, M. S., Alluri, P., & Sando, T. (2021). Estimating Safety Impacts of Adaptive Signal Control Technology Using a Full Bayesian Approach. *Transportation Research Record*, 03611981211025281.

Koppelman, F.S., Wilmot, C.G. (1982). Transferability Analysis of Disaggregate Choice Models. *Transportation Research Record: Journal of the Transportation Research Board*, *895*, 18–24.

Kruschke, J.K.. (2013). Bayesian Estimation Supersedes the *t* test. *Journal of Experimental Psychology*, *142*(2), 573-603.

Lee, Y.-J., Dadvar, S., Hu, J., Park, B.B. (2017). Transit Signal Priority Experiment in a Connected Vehicle Technology Environment. *Journal of Transportation Engineering. Part A System*, *143*(8), 215-227.

Li, L., Persaud, B., Shalaby, A. (2017). Using Micro-Simulation to Investigate the Safety Impacts of Transit Design Alternatives at Signalized Intersections. *Accident Analysis & Prevention*, *100*, 123–132.

Li, S., Sayed, T., El-Basyouny, K. (2013). Full Bayes Before-and-After Evaluation of Traffic Safety Improvements in City of Edmonton, Canada. *Transportation Research Record: Journal of the Transportation Research Board*. *2386*(1), 189–194.

Li, W., Carriquiry, A., Pawlovich, M., Welch, T. (2008). The Choice of Statistical Models in Road Safety Countermeasure Effectiveness Studies in Iowa. *Accident Analysis & Prevention*, *40*(4), 1531–1542.

Lian, P., Wu, Y., Li, Z., Keel, J., Guo, J., Kang, Y. (2019). An Improved Transit Signal Priority Strategy for Real-World Signal Controllers that Considers the Number of Bus Arrivals. *Sustainability*, *12*(1), 1-22.

Lin, Y., Yang, X., Zou, N., Franz, M. (2015). Transit Signal Priority Control at Signalized Intersections: A Comprehensive Review. *The International Journal of Transportation Research*, *7*(3), 168–180.

Miami-Dade Gov. (2021). *Transportation & Public Works*. Retrieved May 5, 2020 from https://www.miamidade.gov/global/transportation/home.page

Mishra, S., Kattan, L., Wirasinghe, S.C. (2020). Transit Signal Priority Along a Signalized Arterial: A Passenger-Based Approach. *ACM Transaction on Spatial Algorithms and Systems*. *6*(1). 1-19.

Naznin, F., Currie, G., Sarvi, M., Logan, D. (2016). An Empirical Bayes Safety Evaluation of Tram/Streetcar Signal and Lane Priority Measures in Melbourne. *Traffic Injury Prevention*, 17(1), 91–97.

Ntzoufras, I. (2009). *Bayesian Modeling Using WinBUGS*.

Park, B., Qi, H. (2005). Development and Evaluation of a Procedure for the Calibration of Simulation Models. *Transportation Research Record: Journal of the Transportation Research Board*, *1934*(1), 208–217.

Park, E.S., Park, J., Lomax, T.J. (2010). A Fully Bayesian Multivariate Approach to Before–After Safety Evaluation. *Accident Analysis & Prevention*, 42(4), 1118–1127.

Park, J., Abdel-Aty, M., Lee, J. (2016). Use of Empirical and Full Bayes Before–After Approaches to Estimate the Safety Effects of Roadside Barriers with Different Crash Conditions. *Journal of Safety Research*, *58*, 31–40.

Persaud, B., Lyon, C. (2007). Empirical Bayes Before-After Safety Studies: Lessons Learned from Two Decades of Experience and Future Directions. *Accident Analysis & Prevention*, *39*(3), 546–555.

Pessaro, B., Van Nostrand, C. (2012). Measuring the Impacts of Transit Signal Priority by Synchronizing Manually Collected Data with APC Data. In *Transportation Research Board 91st Annual Meeting*. (No. 12-0949).

Polders, E., Daniels, S., Hermans, E., Brijs, T., Wets, G., 2015. Crash Patterns at Signalized Intersections. *Transportation Research Record: Journal of the Transportation Research Board*, *2514*(1), 105-116.

PTV. (2010). *PTV VISSIM 10 User Manual*. Retrieved May 5, 2019 from https://usermanual.wiki/Document/Vissim20102020Manual.1098038624.pdf

PTV. (2020). *Traffic Flow Simulation with PTV Vissim*. Retrieved April 3, 2020 from https://www.ptvgroup.com/en/solutions/products/ptv-vissim/areas-of-application/traffic-flow-simulation/

Radwan, E., Shankar Ramasamy, P., Harb, R., Russo, C., Zarillo, M., & Gordin, E. (2000). *Calibration and Validation of Shaker and TNCC for Deployment on Florida's Turnpike*. Final Research Report.

Shaaban, K., Ghanim, M. (2018). Evaluation of Transit Signal Priority Implementation for Bus Transit Along a Major Arterial Using Microsimulation. *Procedia Computer Science*, *130*, 82–89.

Shahla, F., Shalaby, A.S., Persaud, B.N., Hadayeghi, A. (2009). Analysis of Transit Safety at Signalized Intersections in Toronto, Ontario, Canada. *Transportation Research Record: Journal of the Transportation Research Board*, *2102*(1), 108–114.

Sikder, S., Augustin, B., Pinjari, A.R., Eluru, N. (2014). Spatial Transferability of Tour-Based Time-Of-Day Choice Models: Empirical Assessment. *Transportation Research Record: Journal of the Transportation Research Board*. *2429*(1), 99–109.

Skabardonis, A., Christofa, E. (2011). Impact of Transit Signal Priority on Level of Service at signalized intersections. *Procedia Social and Behavioural Sciences*, *16*, 612–619.

Smith, H.R., Hemily, B., Ivanovic, M. (2005). *Transit Signal Priority: A Planning and Implementation Handbook*.

Song, Y., Noyce, D. (2019). Effects of Transit Signal Priority on Traffic Safety: Interrupted Time Series Analysis of Portland, Oregon, Implementations. *Accident Analysis & Prevention*, *123*, 291–302.

Song, Y., Noyce, D. (2018). Assessing Effects of Transit Signal Priority on Traffic Safety: Empirical Bayes Before–After Study using King County, Washington, Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(8), 10-18.

Song, Y., Zlatkovic, M., Porter, R.J. (2016). Evaluation of GPS-Based Transit Signal Priority for Mixed-Traffic Bus Rapid Transit. *Transportation Research Record: Journal of the Transportation Research Board*, *2539*(1), 30–39.

Srinivasan, R., Bauer, K. (2013). *Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs*. (No. FHWA-SA-14-005)

Treiber, M., Kesting, A., Thiemann, C. (2008). How Much does Traffic Congestion Increase Fuel Consumption and Emissions? Applying a Fuel Consumption Model to the NGSIM Trajectory Data. In *Transportation Research Board 87th Annual Meeting*. (No. 08-0519).

United States Department of Transportation [USDOT]. (2006). *National Strategy to Reduce Congestions on America's Transportation Network*.

Wang, X., Zhou, Q., Quddus, M., Fan, T., Fang, S. (2018). Speed, Speed Variation And Crash Relationships for Urban Arterials. *Accident Analysis & Prevention*, *113*, 236–243.

Wu, K., Guler, S.I. (2019). Estimating the Impacts of Transit Signal Priority on Intersection Operations: A Moving Bottleneck Approach. *Transportation Research Part C Emerging Technologies*, *105*, 346–358.

Zhou, G., Gan, A., Zhu, X. (2006). Determination of Optimal Detector Location for Transit Signal Priority with Queue Jumper Lanes. *Transportation Research Record: Journal of the Transportation Research Board*, *1978*(1), 123–129.

Zlatkovic, M., Stevanovic, A. (2013). Effects of Queue Jumpers and Transit Signal Priority on Bus Rapid Transit. In *Transportation Research Board 92nd Annual Meeting*. (No. 13-0483).

Zlatkovic, M., Stevanovic, A., Martin, P.T., Tasic, I. (2013). Evaluation of Transit Signal Priority Options for Future Bus Rapid Transit Line in Utah. *Transportation Research Record: Journal of the Transportation Research Board*, *2311*(1), 176-185.

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- *Recipient*, 2020 Traffic Safety Scholar Award
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- *Winner*, 2019 FSITE Student Poster Competition
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PUBLICATIONS

1. Ali, M. S., Kitali, A., Kodi, J., Alluri, P., & Sando, T. (2021). Safety Impacts of Transit Signal Priority Using the Full Bayesian Approach. *Transportation Research Record*.
2. Ali, M. S., Haule, H., Alluri, P., & Kaisar, E. (2021). Evaluating the Potential Mobility Benefits of Transit Signal Priority with Connected Vehicle Technology. *Advances in Transportation Studies*.
3. Kodi, J., Kitali, A., Ali, M. S., Alluri, P., & Sando, T. (2021). Estimating Safety Effects of Adaptive Signal Control Technology Using the Full Bayesian Approach Using the Full Bayesian Approach. *Transportation Research Record*.
4. Kadeha, C., Haule, H., Ali, M. S., Alluri, P., & Ponnaluri, R. (2021). Modeling Wrong-Way Driving (WWD) Crash Severity on Arterials in Florida. *Accident Analysis & Prevention.*

5. Haule, H., Ali, M. S., Alluri, P., & Sando, Thobias. (2021). Evaluating the Effect of Ramp Metering on Freeway Safety Using Real-Time Traffic Data. *Accident Analysis & Prevention.*
6. Yan, X., Ali, M. S., Kaisar, E., & Hadi, M. (2021). (under review). Developing of Planning-Level Guidelines for Deploying Transit Signal Priority. *IEEE Transactions on Intelligent Transportation Systems*.
7. Ali, M. S., Kitali, A., Alluri, P., & Sando, T. (2021). (under review). Quantifying the Safety Benefits of Transit Signal Priority Using Full Bayes Before-After Study. *Journal of Transportation Engineering: Part A*
8. Ali, M. S., Alluri, P., & Sando, T. (2021). (under review). Quantifying the Mobility Benefits of Transit Signal Priority. *Journal of Public Transportation*.
9. Ali, M. S., Kodi, J., Alluri, P., & Sando, T. (2021). (under review). Operational Impacts of Transit Signal Priority (TSP) in Adaptive Signal Control Technology (ASCT) Environment. *Advances in Transportation Studies*.
10. Alluri, P., Sando, T., Kadeha, C., Haule, H., Salum, J., Ali, M. S., Kodi, J., & Kitali, A. (2020). Developing Florida-specific Mobility Enhancement Factors (MEFs) and Crash Modification Factors (CMFs) for TSM&O Strategies. Final Research Report. Florida Department of Transportation, Transit Office, Tallahassee, Florida.
11. Kaisar, E., Hadi, M, Ali, M. S., & Yan, X. (2017). Guidance for Identifying Corridor Conditions that Warrant Deploying Transit Signal Priority. Final Research Report. Florida Department of Transportation, Tallahassee, Florida.
12. Ali, M. S., Kodi, J., Alluri, P., & Sando, T. (2021). Mobility Benefits of Transit Signal Priority (TSP) in Adaptive Signal Control Technology (ASCT) Environment. Proceedings of the 100th Annual Meeting of the Transportation Research Board, Washington, DC.
13. Kodi, J., Kitali, A., Ali, M. S., Alluri, P., & Sando, T. (2021). Estimating Safety Effects of Adaptive Signal Control Technology Using the Full Bayesian Approach Using the Full Bayesian Approach. Proceedings of the 100th Annual Meeting of the Transportation Research Board, Washington, DC.
14. Ali, M. S., Zerpa, L. A., Kaisar, E. I., & Masters, K. O. (2018). Guidance for Identifying Corridor Conditions that Warrant Deploying Transit Signal Priority. Proceedings of the 97th Annual Meeting of the Transportation Research Board, Washington, DC.
15. Ali, M. S., Kaisar, E. I., & Hadi, M. (2017). Guidance for Identifying Corridor Conditions that Warrant Deploying Transit Signal Priority and Queue Jump. Proceedings of the 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), Naples, Italy.