Developing Florida-specific Mobility Enhancement Factors (MEFs) and Crash Modification Factors (CMFs) for TSM&O Strategies

Final Report

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DISCLAIMER

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

METRIC CONVERSION TABLE

U.S. UNITS TO SI* (MODERN METRIC) UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.400	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.610	kilometers	km
mm	millimeters	0.039	inches	in
m	meters	3.280	feet	ft
m	meters	1.090	yards	yd
km	kilometers	0.621	miles	mi

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		AREA		
in^2	square inches	645.200	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.590	square kilometers	km^2
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.470	acres	ac
km^2	square kilometers	0.386	square miles	mi^2

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		VOLUME		
fl oz	fluid ounces	29.570	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
NOTE: volumes greater than 1,000 L shall be shown in m^3.				

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.

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16. Abstract

Transportation Systems Management and Operations (TSM&O) focus on improving the safety and operational performance of the transportation network by integrating proven transportation management strategies and Intelligent Transportation Systems (ITS) applications. The Florida Department of Transportation (FDOT) has been a pioneer in adopting TSM&O strategies to improve safety and mobility of Florida's roadways. The primary goal of this research was to develop resources that can assist FDOT and other agencies in evaluating the effectiveness of the deployed TSM&O strategies.

This research focused on quantifying the mobility and safety benefits of the following TSM&O strategies: ramp metering systems, dynamic message signs (DMSs), Road Rangers, express lanes, transit signal priority (TSP), and adaptive signal control technology (ASCT). The operational performance of the aforementioned strategies was evaluated using mobility performance measures such as travel time, travel time reliability, average speed adjustment, incident clearance duration, etc. Safety benefits were evaluated using the crash occurrence risk, secondary crash occurrence risk, and crash frequency as the performance measures.

In general, all the evaluated TSM&O strategies were found to have resulted in safety and mobility improvements. The study results were incorporated into a spreadsheet application, the *TSM&O Strategies Assessment Tool*. The Tool was developed to automatically estimate the safety and mobility benefits of deploying the studied TSM&O strategies. The developed resources will enable FDOT and local agencies to prioritize TSM&O strategies using quantifiable safety and mobility metrics.

17. Key Word
Mobility Enhancement Factors (MEFs), Crash Modification Factors (CMFs), TSM&O strategies.

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EXECUTIVE SUMMARY

Transportation Systems Management and Operations (TSM&O) is a program based on actively managing the multimodal transportation network, measuring performance, and streamlining and improving the existing system to deliver positive safety and mobility outcomes to the traveling public. TSM&O comprises a set of strategies that focus on operational improvements that can maintain or restore the performance of the existing transportation system before extra capacity is needed.

The Florida Department of Transportation (FDOT) has been a pioneer in adopting TSM&O strategies to improve safety and mobility along Florida's highways. A key FDOT milestone was the development and adoption of the *2017 TSM&O Strategic Plan*, which outlines the agency's vision, mission, goals, objectives, and priority TSM&O focus areas. The primary goal of this research was to develop resources to assist FDOT and other agencies in evaluating the mobility and safety effectiveness of some of the strategies identified in Florida's TSM&O Strategic Plan.

To accomplish the research goal, a comprehensive literature review was conducted on TSM&O strategies deployed in Florida. Various analysis methods were then employed, depending on the strategy being analyzed, to quantify the safety and mobility benefits of each strategy. The developed resources will enable FDOT and local agencies to prioritize TSM&O strategies using quantifiable safety and mobility metrics.

The following TSM&O strategies were included in the evaluation:

Freeways
- Ramp Metering Systems
- Dynamic Message Signs (DMSs)
- Road Rangers
- Express Lanes (ELs)

Arterials
- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

Ramp Metering System (RMS)

Ramp metering or signaling is a traffic management strategy that installs traffic signals along freeway on-ramps to control and regulate the frequency at which vehicles enter the flow of traffic on the freeway mainline (Gan et al., 2011; Mizuta et al., 2014). The operational performance of ramp metering systems was quantified using a Mobility Enhancement Factor (MEF), which is a multiplicative factor used to describe the mobility benefits of a TSM&O strategy on a specific infrastructure element, i.e., intersection, corridor, etc. Travel time reliability was selected as the mobility performance measure for estimating the MEFs of the ramp metering system.

The MEFs were developed based on the analysis of a corridor with system-wide ramp metering in Miami-Dade County, Florida. Buffer index (BI), estimated using the 95th percentile travel time and average travel time, was adopted as the travel time reliability measure for the analysis. The MEF for ramp metering at levels of service C and D (LOS C&D) was 0.784, indicating a 22% reduction in the BI values. The MEF for ramp metering operations during LOS E&F was 0.701, indicating a 30% reduction in the BI values. These results indicate that ramp metering operations improve mobility on the freeway mainline.

The study analyzed the safety benefits of the ramp metering system using the crash occurrence risk on the freeway mainline. The risk of traffic crashes was estimated using a *case-control* study design of crash and non-crash cases. Results showed that the crash occurrence risk at a particular time was significantly affected by the standard deviation of speed 30 minutes before the time, standard deviation of occupancy 30 minutes before the time, and the ramp metering operations during that time. Moreover, results revealed a 41% decrease in the risk of crashes when RMSs were operational compared to when they were not operational. Based on the study results, it can be concluded that ramp metering operations improve safety on the freeway mainline.

Dynamic Message Signs

Dynamic message signs (DMSs) are programmable electronic signs that appear along highways and typically display information about real-time alerts related to unusual traffic conditions, such as adverse weather conditions, construction activities, travel times, road closures or detours, advisory phone numbers, roadway incidents, etc.

The methodology for quantifying the mobility benefits of DMSs involved assessing the reaction of drivers to *crash* messages by observing their speed adjustments between the *clear* and *crash* message display durations. The average speed ratio (calculated as the ratio of the average speed during *crash* messages to the average speed during *clear* messages) was used as a performance measure to estimate the MEFs for DMSs. The overall MEF was found to be 0.94, implying that there was a 6% reduction in average speeds when the DMSs displayed *crash* information. Results also revealed that among messages displaying *crash* information, if secondary information required drivers to "use caution", there were less speed reductions compared to lane blockage information. This implies that the drivers were more willing to reduce speeds if lanes were blocked downstream as a result of a crash.

The safety benefits of DMSs were quantified using the coefficient of variation of speeds (CVS) as a surrogate safety measure. The CVS when the displayed messages on DMSs did not require drivers to take action (clear condition/information messages) were compared to the CVS when the DMSs displayed messages about downstream crashes. Overall, displaying crash messages on DMSs was found to result in fewer crashes despite the increase in speed variations. The analysis did not consider other potential factors such as incidents downstream which may result in speed reduction and variations.

Road Rangers

Road Rangers are a crucial component of incident management systems that facilitate a quick clearance of incidents through faster response and reduced clearance time. Florida's Road Rangers provide free highway assistance services during incidents on Florida's roadways to reduce delays and improve safety for the motorists and incident responders. Incident clearance duration was selected as the performance measure to quantify the mobility benefits of Road Rangers. Quantile regression was applied to predict incident clearance duration and identify factors that may affect the clearance duration. The following seven factors were found to be significantly associated with longer incident clearance durations: crashes, severe incidents, shoulder blockage, peak hours, weekends, nighttime, number of responding agencies, and towing involvement. Analysis results revealed incidents first detected by responding agencies other than Road Rangers were associated with longer incident clearance durations.

The likelihood of secondary crash (SC) occurrence was used as a surrogate safety measure to evaluate the safety benefits of Road Rangers. A complimentary log-log regression model was developed to associate the probability of SC with potential contributing factors. Of the factors analyzed, traffic volume, incident impact duration, moderate and severe crashes, weekdays, peak periods, percentage of lane closure, shoulder blockage, and towing involving incidents were found to significantly increase the likelihood of SCs. Road Ranger involvement, weekend days, off-peak periods, minor incidents, vehicle problems, and traffic hazard-related incidents were associated with relatively lower probabilities of SC. Based on the average incident duration reduction, the results suggest that the Road Ranger program may reduce the SC likelihood by 20.9%. Note that this value does not mean the number of secondary crashes, but it means the likelihood of SC occurrence.

Express Lanes

Express lanes are a type of managed travel lanes physically separated from general-purpose or general toll lanes within a roadway corridor. They use dynamic pricing through electronic tolling in which toll amounts are set based on traffic conditions (Neudorff, 2011). Buffer index (BI) was selected as the performance measure to quantify the mobility benefits of express lanes. Overall, on 95Express northbound lanes, the express lanes resulted in a 50% reduction in BI (MEF = 0.5), compared to their adjacent general-purpose lanes, while the reduction was 60% (MEF = 0.4) for southbound lanes. When the express lanes were operational (i.e., open for use), the performance of the adjacent general-purpose lanes improved. The BIs for the general-purpose lanes improved by 20% (MEF = 0.8) and 60% (MEF = 0.4) for the northbound and the southbound directions respectively, when the express lanes were operational, compared to when they were closed. Overall, the general-purpose lanes were found to perform better when the express lanes were operational. The study results showed mobility improvements on both the express lanes and the general-purpose lanes, although the extent of the improvement varied by direction and the time-of-day (i.e., AM peak, PM peak, off-peak).

Transit Signal Priority

Transit signal priority (TSP) modifies the signal timing at intersections to better accommodate transit vehicles. Average travel time and average delay time were used as the performance measures to quantify the operational performance of TSP. The analysis was based on a 10-mile corridor along US-441 between SW 8th Street and the Golden Glades Interchange in Miami, Florida. The MEFs based on travel time were 0.96 for all vehicles and 0.91 for buses, and the MEF based on average vehicle delay time was 0.87 for all vehicles and buses. Based on the analysis results, TSP was found to improve the operational performance of the corridor.

A full Bayesian (FB) before-after approach was used to quantify the safety benefits of TSP; the safety performance of TSP-enabled corridors (i.e., treatment corridors) was compared to the safety performance of non-TSP corridors (i.e., non-treatment corridors). The study results indicated that the implementation of TSP resulted in a 12% reduction in total corridor-level crashes, 8% reduction in Property Damage Only (PDO) crashes, and 15% reduction in Fatal and Injury (FI) crashes.

Adaptive Signal Control Technology

Adaptive signal control technology (ASCT) is an Intelligent Transportation Systems (ITS) strategy that optimizes signal timings in real time to improve traffic flow along the corridor. Average speed was selected as the performance measure to quantify the mobility benefits of ASCT. The Bayesian Switch-point Regression (BSR) model was used to evaluate the operational benefits of the ASCT. The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida. ASCT was found to improve the average travel speeds by 4% during a typical weekday, 7% during AM peak hours, 5% during off-peak hours, and 2% during PM peak hours, in the northbound direction.

Mixed results were observed in the southbound direction. The overall MEFs for the southbound direction indicated no improvement with ASCT on Tuesdays and Thursdays and a 2% decrease in average travel speed on Wednesdays. Conversely, ASCT was found to increase the average travel speed by 3% and 2% during AM peak and off-peak hours, respectively. However, during PM peak hours, ASCT showed a 5% reduction in average travel speeds in the southbound direction. The inconsistent results in the southbound direction may be attributed to traffic congestion and the relatively higher driveway density in the southbound direction.

The Bayesian negative binomial (BNB) model was used to develop safety performance functions (SPFs) for total crashes, rear-end crashes, and FI crashes. The crash modification factors (CMFs) were developed using an empirical Bayes before-after approach with comparison group. The analysis revealed that the deployment of ASCT reduces total crashes by 5.2% (CMF = 0.948), rear-end crashes by 12.2% (CMF = 0.878), FI crashes by 4.2% (CMF = 0.958), and PDO crashes by 5.7% (CMF = 0.943).

TSM&O Strategies Assessment Tool

The TSM&O Strategies Assessment Tool is a spreadsheet application that was developed to automatically estimate the safety and mobility benefits of TSM&O strategies. The Tool contains a total of nine worksheets:

- Preface - includes a foreword, acknowledgments, and a disclaimer
- Info - includes a brief overview of TSM&O strategies
- Worksheets for each TSM&O strategy - includes a separate worksheet for each TSM&O strategy (ramp metering, dynamic message signs, Road Rangers, express lanes, adaptive signal control technology, and transit signal priority)
- Input Data Description – includes step-by-step procedures to calculate the input values for the Tool.

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ACRONYMS AND ABBREVIATIONS

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AIC	Akaike's Information Criterion
ASCT	Adaptive Signal Control Technology
ATMS	Advanced Traffic Management System
B/C	Benefit-to-Cost
BCI	Bayesian Credible Interval
BCT	Broward County Transit
BHT	Bayesian Hypothesis Test
BI	Buffer Index
BNB	Bayesian Negative Binomial
BRT	Bus Rapid Transit
BSR	Bayesian Switch-point Regression
CCTV	Closed-Circuit Television
CMF	Crash Modification Factor
CMS	Changeable Message Sign
CTOD	Central Time of Day
CVS	Coefficient of Variation of Speed
DHSMV	Department of Highway Safety and Motor Vehicles
DMS	Dynamic Message Sign
DUI	Driving under the Influence
EL	Express Lane
FB	Full Bayes
FDOT	Florida Department of Transportation
FGDL	Florida Geographical Data Library
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
FI	Fatal/Injury (crash)
FSP	Freeway Service Patrol
FSPE	Freeway Service Patrol Evaluation
FTE	Florida Turnpike Enterprise
GEH	Geoffrey E. Havers
GIS	Geographic Information System
GPL	General-purpose Lane
GPS	Global Positioning System
HDI	Highest Density Interval
HMC	Hamiltonian Markov Chain
HOT	High-occupancy Toll
HOV	High-occupancy Vehicle
HSM	Highway Safety Manual
ICM	Integrated Corridor Management
ITS	Intelligent Transportation Systems
JSO	Jacksonville Sheriff's Office
KDOT	Kansas Department of Transportation

LASSO	Least Absolute Shrinkage and Selection Operator
LOS	Level of Service
LTOD	Local Time of Day
MAC	Media Access Control
MCMC	Markov Chain Monte Carlo
MDT	Miami-Dade Transit
MEF	Mobility Enhancement Factor
MENB	Mixed Effects Negative Binomial
MLR	Multiple Linear Regression
MoDOT	Missouri Department of Transportation
MSE	Mean-Squared Error
MUTCD	Manual on Uniform Traffic Control Devices
NB	Northbound
OLS	Ordinary Least Square
PDO	Property Damage Only (crash)
PI	Primary Incident
PSA	Public Service Announcement
QJ	Queue Jumpers
RCI	Roadway Characteristics Inventory
RITIS	Regional Integrated Transportation Information System
RMS	Ramp Metering Signal
RMSE	Root Mean-Squared Error
RTMC	Regional Transportation Management Center
SB	Southbound
SC	Secondary Crash
SPaT	Signal Phasing and Timing
SPF	Safety Performance Function
SR	State Road
SSAM	Surrogate Safety Assessment Model
SSP	Safety Service Patrol
TIM	Traffic Incident Management
TMC	Transportation Management Center
TOD	Time of Day
TSM&O	Transportation Systems Management and Operations
TSP	Transit Signal Priority
v/c	Volume-to-Capacity
VBA	Visual Basic for Applications
VMS	Variable Message Sign
vphpl	Vehicles per Hour per Lane
VSL	Variable Speed Limit
WAIC	Widely Applicable Information Criterion

CHAPTER 1
INTRODUCTION

Transportation Systems Management and Operations (TSM&O) is a program based on actively managing the multimodal transportation network, measuring performance, and streamlining and improving the existing system to deliver positive safety and mobility outcomes to the traveling public. TSM&O comprises a set of strategies that focus on operational improvements that can maintain or restore the performance of the existing transportation system before extra capacity is needed. Operational improvements are attained by applying TSM&O strategies to maximize the efficiency, safety, and utility of the existing and/or planned transportation infrastructure (Williams & Hazley, 2017).

TSM&O initiatives have gained momentum recently because of the benefits associated with their deployments. TSM&O strategies allow transportation agencies to realize their goals through the use of available real-time traffic information, improved condition monitoring and detection of disruptions, and coordination of transportation needs. As a result, TSM&O strategies have been observed to offer cost-effective and less invasive solutions for congestion and safety issues than the large-scale expansion alternatives (Zeeger et al., 2014).

The Florida Department of Transportation (FDOT) has been a pioneer in adopting TSM&O strategies to improve safety and mobility along Florida’s highways. A key FDOT milestone was the development and adoption of the *2017 TSM&O Strategic Plan* which outlines the agency’s vision, mission, goals, objectives, and priority TSM&O focus areas (Florida Department of Transportation [FDOT], 2017a). Potential strategies include the use of express lanes, dynamic message signs (DMSs), ramp metering, transit signal priority (TSP), and Advanced Traffic Management Systems (ATMS), of which a number have been deployed throughout the state. Since each project is unique, the selection of the most suitable TSM&O strategy and its deployment depends on the region’s needs and requirements.

The primary goal of this research was to develop resources to assist FDOT and other agencies in evaluating the effectiveness of the strategies identified in Florida’s TSM&O Strategic Plan (FDOT, 2017a). The developed resources will enable FDOT and local agencies to prioritize TSM&O strategies using quantifiable safety and mobility metrics.

The rest of the report is organized as follows:

- Chapter 2 identifies and discusses the existing TSM&O strategies that have been deployed in Florida.
- Chapter 3 discusses the data sources used to obtain data for quantifying the safety and mobility benefits of the identified TSM&O strategies.
- Chapter 4 discusses the mobility benefits of the identified TSM&O strategies.
- Chapter 5 discusses the safety benefits of the identified TSM&O strategies.
- Chapter 6 presents the user manual for the *TSM&O Strategies Assessment Tool.*
- Chapter 7 summarizes the findings of this research.

CHAPTER 2
EXISTING TRANSPORTATION SYSTEMS MANAGEMENT AND OPERATIONS (TSM&O) STRATEGIES

This chapter focuses on the following TSM&O strategies that are currently deployed in Florida:

Freeways
- Ramp Metering System (RMS)
- Dynamic Message Signs (DMS)
- Road Rangers
- Express Lanes (ELs)

Arterials
- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

The chapter also includes a detailed discussion on the available safety and operational performance measures, as well as the quantitative safety and mobility benefits of the above-listed TSM&O strategies.

2.1 Ramp Metering System

Ramp metering or signaling is a traffic management strategy that installs traffic signals along freeway on-ramps to control and regulate the frequency at which vehicles enter the flow of traffic on the freeway mainline (Gan et al., 2011; Mizuta et al., 2014). The primary operational objectives of ramp metering include: controlling the frequency of vehicles entering the freeway, reducing freeway demands, and breaking up platoons of vehicles released from the upstream traffic signals (Balke et al., 2009).

With ramp metering, vehicles traveling from the adjacent arterials to the freeway mainline on the on-ramp segment are stopped and released at a determined metered rate. As illustrated in Figure 2-1, a typical ramp metering configuration has an on-ramp stop line where vehicles are stopped and released onto the mainline at a rate that depends on the prevailing mainline traffic conditions. Ramp metering is set to optimize traffic flow on the mainline and on-ramp queue using signal timing algorithms and real-time data from a network of loop detectors.

Ramp metering helps relieve traffic congestion (Mizuta et al., 2014) by keeping the freeway density as close to but below the critical density value (Hadi et al., 2017). It reduces delay and maintains capacity flow on freeways by regulating access of ramp traffic to the mainline (Lee et al., 2006). Nonetheless, effective ramp metering has to ensure queues are prevented from spilling onto the adjacent arterial with stopped vehicles waiting to access the freeway (Mizuta et al., 2014). Apart from reducing congestion, ramp metering can also improve traffic safety by reducing the frequency of rear-end and sideswipe crashes due to less turbulence and speed variability in merging zones (Lee et al., 2006). In general, ramp metering is intended to improve mobility, reliability, safety, and the environment while preserving freeway capacity at a significantly lower cost than traditional capacity improvement measures, such as adding a new lane (Mizuta et al., 2014).

Overall, the widespread benefits of ramp metering, relative to its costs, make it one of the most cost-effective freeway management strategies (Mizuta et al., 2014).

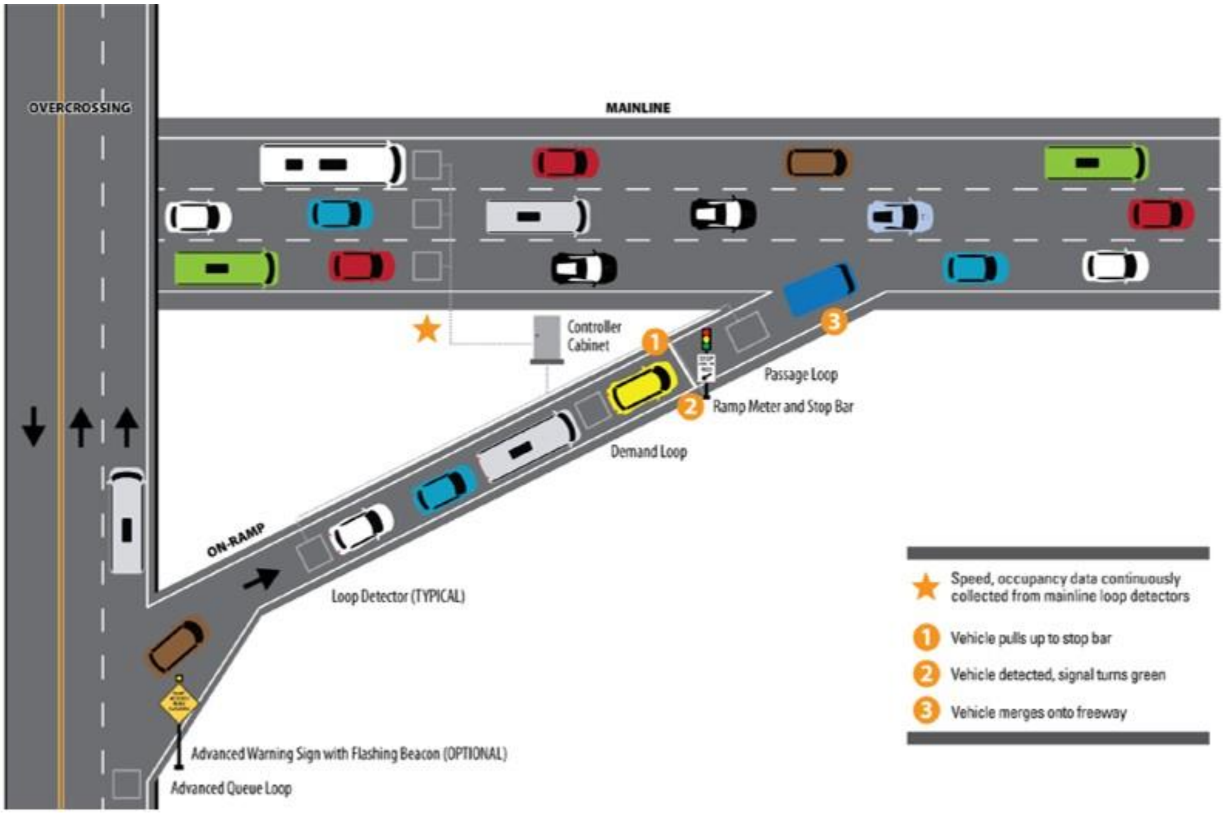


Figure 2-1: Ramp Metering Configuration (Mizuta et al., 2014)

2.1.1 Current Deployments in Florida

In Florida, the first ramp metering system was deployed in 2009 along a northbound (NB) section of I-95 in Miami-Dade County (Gan et al., 2011). An additional 14 ramp meters were deployed in 2010 along the corridor, both NB and southbound (SB), for a total of 22 ramp meters (Gan et al., 2011). Figure 2-2 shows the location of the existing ramp meters along the I-95 section in Miami-Dade County. FDOT District 6 currently operates the ramp meters between Ives Dairy Road and NW 62nd Street.

Another ramp metering deployment is underway in District 6 on SR 826 from SR 836 to NW 154th Street (Hadi et al., 2017). FDOT District 4 is also considering deploying ramp meters at over 60 ramps in Broward and Palm Beach Counties (Hadi et al., 2017).

2.1.2 Safety Performance Measures

Research on the safety benefits of ramp metering is sparse (Sun et al., 2013). The limited available studies have focused on analyzing the safety implications of the deployment of ramp metering using the following approaches: crash occurrence (Cohen et al., 2017; Liu & Wang, 2013) and safety surrogate measures (Karim, 2015; Lee et al., 2006; Sun et al., 2013).

2.1.2.1 Crash Occurrence

Ramp metering is considered to reduce the number of crashes in acceleration lanes and merging areas (Gan et al., 2011). Gan et al. (2011) discussed the justification for installing ramp meters based on the rate of crashes near the ramps that exceeded the mean crash rate for comparable sections of a freeway. The authors suggested that safety concerns should be considered as one of the reasons for installing ramp meters. Gan et al. (2011) observed that many agencies consistently agreed that ramp metering should be warranted when there is a high frequency of crashes near freeway entrances due to platooning of on-ramp traffic, inadequate merge area, and congestion.

Liu and Wang (2013) analyzed the influence of ramp metering on safety near on-ramp exits using crash rates. Crash records were collected from 19 ramp metering locations in California, and the following three indicators were introduced to assess the operational safety of the ramp metering before and after deployment: percentage of reduction in crash frequency regardless of the traffic volume (ψ), percentage of the crash rate including the traffic flow characteristics near the on-ramp exit (λ), and percentage of crash rate reduction considering the number of interactions among the on-ramp and mainline vehicles (γ). Results suggested that the average crash rate reductions of 38%, 37%, and 35% were observed for the ψ, λ, and γ, respectively, after the deployment of ramp meters.

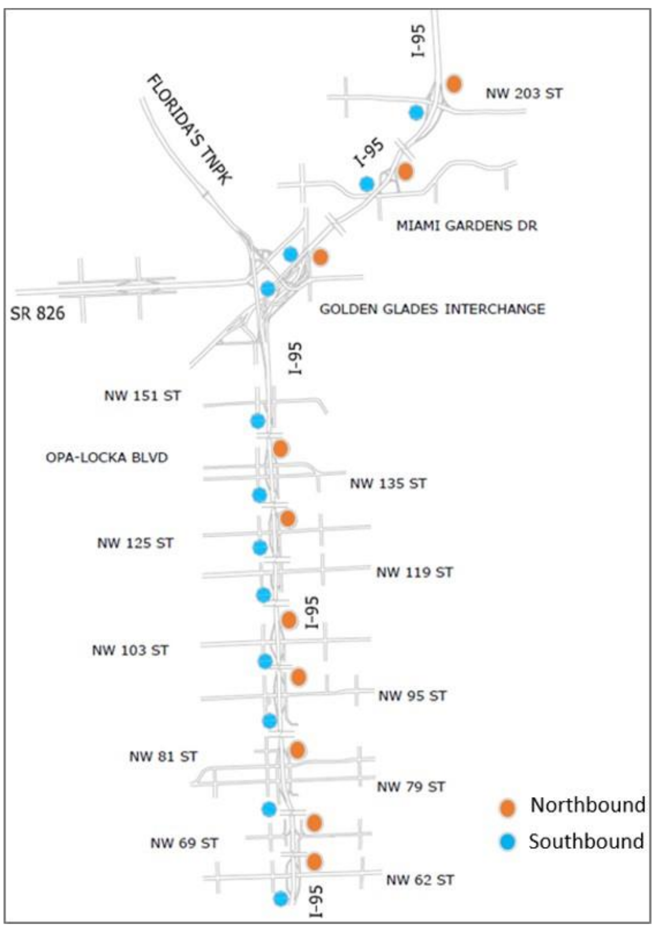


Figure 2-2: Ramp Meters along I-95 in Miami-Dade County, Florida (Zhu et al., 2010)

2.1.2.2 Safety Surrogate Measures

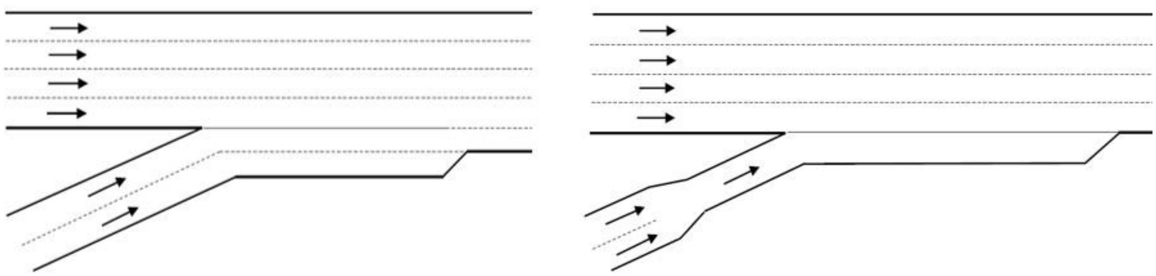
Surrogate measures have been used in several studies to evaluate the safety performance of a facility where challenges existed with the collection of crash data and prediction of crash frequencies. For instance, safety surrogate measures were used to evaluate the performance of ramp meters that were temporarily deployed in work zones in Columbia, Missouri (Sun et al., 2013). Crash data could not be used since the ramp meters were deployed for a short period in the work zones. The surrogate measures used in this study included driver compliance rates, speed statistics along the mainline, ramp traffic, speed differences between merging and mainline vehicles, merging headways, lane changes, and braking events along the mainline (Sun et al., 2013). These surrogate measures were obtained from video data collected at each study site, and data extraction was performed using different criteria for each specific surrogate measure. For example, when assessing driver compliance rates, a vehicle was considered to comply if it went through the ramp meter only when the signal displayed green. Results indicated that the compliance rate was 63.6% when few vehicles were on the ramps, and 67.3% under congested conditions, which suggested that ramp meters should not be operated under low ramp volume conditions (Sun et al., 2013).

Lee et al. (2006) quantified the safety benefits of local-traffic responsive ramp metering in terms of the reduced crash potential estimated from a real-time crash prediction model. Local-traffic responsive ramp meters select the metering rate by monitoring the volume and speed of traffic flow in the mainline lanes adjacent to the ramp meter. The model used real-time traffic flow data from road sensors to estimate the values of surrogate measures of traffic turbulence that contribute to crash occurrence. The surrogate measures analyzed included coefficient of variation of speed, calculated as the standard deviation of the speed divided by the average speed over certain time intervals, the average speed difference between the upstream and downstream traffic at a specific location, and the average covariance of volume difference between the upstream and downstream traffic at a specific location, between adjacent lanes.

Lee et al. (2006) used a microscopic simulation model coupled with the crash prediction model to generate values of the surrogate measures for a freeway section with an on-ramp exit along I-880 in Hayward, California. Results showed that although ramp metering can benefit the road sections upstream of the ramp merge area, it also led to an increased crash potential on the road sections downstream of the ramp merge area. Therefore, the potential crash reduction along the upstream sections was offset by the increased crash potential along the downstream road sections. Thus, the overall safety benefit of ramp metering was a 5% reduction in total crash potential. However, these results were influenced by the study locations' attributes, such as the formation of queue spillback during the study period due to downstream bottlenecks, etc.

Karim (2015) analyzed the frequency, type, and severity of vehicle conflicts that occurred on a 3000-ft freeway segment to measure the ramp metering system's operational and safety effectiveness. Surrogate Safety Assessment Model (SSAM) software was used to estimate the frequency and type of conflicts from the simulation model. The severity of the vehicle conflicts was obtained using two measures of conflict: time to collision and maximum speed difference between conflicting vehicles. Different results were observed regarding the efficiency and safety benefits of ramp metering depending on the geometric configuration and signal timing scenarios.

For example, a ramp with geometric configuration (Figure 2-3(a)) that has two on-ramp lanes and using two different signal timing scenarios with traffic volume ≥ 1,250 vphpl and ramp traffic volume ≥ 800 vphpl, led to a decrease in traffic conflicts. However, for the same signal timing scenarios and traffic volume attributes, the on-ramp geometric configuration of two lanes that merged to form one lane (Figure 2-3(b)) led to an increase in traffic conflicts. Karim (2015) concluded that ramp metering increases efficiency and improves the safety of freeways only at specific situations defined by the geometric configuration, freeway and ramp traffic volume, and the ramp metering algorithm.



(a) (b)

Figure 2-3: Examples of Geometric Configurations for Freeway On-ramps (Karim, 2015)

2.1.3 Mobility Performance Measures

Several studies have evaluated the mobility benefits of ramp metering. In general, most of the studies observed that ramp metering increases travel speeds, increases freeway throughput, sustains higher traffic volumes, and improves traffic flow by reducing the impact of recurring congestion (Karim, 2015). Several studies have analyzed the mobility impact of ramp metering using the following performance measures: travel time (Cohen et al., 2017; Karim, 2015), travel time reliability (Cambridge Systematics, Inc., 2001; Levinson and Zhang, 2006), traffic delays (Sun et al., 2013), and capacity and level of service (Cohen et al., 2017).

2.1.3.1 Travel Time

Travel time is a common measure of mobility improvement effectiveness. Cohen et al. (2017) used baseline travel times that were estimated from loop detector measurements (i.e., flow, occupancy, and speed) on a 40-mile section of the A25 roadway linking Socx and Lille in France. The estimated travel times were validated based on the data collected from the floating car studies. Travel times were collected on weekdays during the months of May, June, October, and November when ramp meters were not operational, and for 11 days in February and March when ramp meters were operational. Although data were collected for the entire day on each specified day, the analysis focused on the morning peak hour (6:30 a.m. to 10:30 a.m.) when ramp meters were operational and non-operational. Cohen et al. (2017) used descriptive statistics to compare the travel time of the study segment with and without ramp meters, and observed that the average travel time with ramp metering was 95 seconds less than the average travel time without ramp metering. This result was found to be statistically significant at the 95% confidence level.

Karim (2015) used VISSIM, the microscopic simulation software, to explore the effectiveness of ramp metering on the operational efficiency of the freeway. The study used the average speed in the ramp influence area and the average travel time on a 3000-ft freeway segment adjacent to the ramp as the measure of freeway efficiency. The study evaluated three geometric configurations of ramp freeway junctions with different traffic volumes on the ramp and freeway and different signal timing scenarios. Karim (2015) considered that ramp meters improved the efficiency of the freeway if the percentage decrease in the average travel time was ≥ 5%. Results suggested that ramp metering efficiency depended on the traffic volume on both the on-ramp and freeway, signal timing scenarios, and the geometric configuration of the on-ramp. For example, using ramp metering for on-ramps with a geometric configuration that has two lanes merging into one lane, as shown in Figure 2-3(b), is not recommended. However, ramp metering was observed to be beneficial for a single lane on-ramp during the peak period or when the ramp traffic volume is ≥ 800 vphpl, and the freeway traffic volume is ≥ 1,250 vphpl.

2.1.3.2 Travel Time Reliability

Travel time reliability is a measure of the expected range in travel time and provides a quantitative measure of travel time predictability (Cambridge Systematics, Inc., 2001). Travel time reliability has been used to assess various transportation improvement deployments. A higher value is assigned to travel time reliability than to average travel time due to the usefulness of predictable travel times (Cambridge Systematics, Inc., 2001). Cohen et al. (2017) used travel time reliability to investigate the impact of ramp metering for traffic on the A25 roadway connecting Socx to Lille in France during morning peak hours (6:30 a.m. to 10:30 a.m.). The *F*-test was used to test the hypothesis of equal variances of travel time with and without ramp metering. Results indicated that more variability in travel time was present when the facility operated without ramp metering compared to when ramp metering was operational.

Levinson and Zhang (2006) analyzed the operations of freeways, based on travel time variation, with and without ramp metering during the afternoon peak period. Travel time variation is considered as the standard deviation of travel times and is used as a measure of travel time reliability. In the study, the travel time variation was estimated for two scenarios, inter-day, and intra-day. The inter-day travel time variation was estimated from trips that were made across different days, while intra-day travel time variation was estimated from trips that occurred only on a specific day. Results indicated the absence of spillover effects on local connecting streets during the analyzed peak periods since all ramp arrival detectors showed low occupancy readings. This scenario implies that delays at on-ramps represented the total delays caused by ramp meters. Results also suggested that ramp meters are more helpful for long trips (i.e., trips where a driver passed more than three exits), compared to short trips (i.e., trips where a driver passed three exits or less). However, although beneficial to freeway operations, ramp metering may not improve trip travel time, including on-ramp delays.

2.1.3.3 Traffic Delays

Sun et al. (2013) evaluated the effectiveness of ramp metering at work zones in Columbia, Missouri. Traffic demand observed on the mainline and ramps at the study locations was not consistently high enough for the ramp meters to have a sustained effect on mobility; therefore, traffic simulation was used in the analysis. The analyzed scenario involved a two-to-one lane work zone with an entrance ramp located upstream of the work zone. Three different traffic volumes (900 vph, 1,240 vph, and 1,754 vph) and two truck percentage levels (10% and 40%) were evaluated, and VISSIM models were developed for the five work zone scenarios for metered and unmetered ramp conditions. The models were calibrated using field data collected at the congested work zone sites. The total vehicular delay was used to measure the impact of ramp metering on the mobility of the corridor. The total vehicular delay considered the delay caused by both the mainline and ramp traffic. Simulation models provided the results in terms of total delay during under-capacity, at capacity, and over-capacity conditions. Results suggested that ramp metering decreased traffic delays in work zones when traffic volume exceeded capacity. On average, a 24% decrease in delay with low truck percentage and a 19% decrease in delay with high truck percentage conditions resulted from metering ramps near work zones operating above capacity. Note that ramp metering was not recommended for flows below capacity in work zones because it increased total delays.

2.1.3.4 Capacity and Level of Service (LOS)

Cohen et al. (2017) collected and used conventional traffic data, i.e., flow, occupancy, and speed, to estimate the level of service (LOS). Additional contextual data were also collected to give further insights into conditions with and without ramp metering. The contextual data included incidents, planned works, and adverse weather conditions. Capacity and LOS were estimated using fundamental diagrams to assess the mobility improvements due to ramp metering in combination with variable speed limit (VSL) (Cohen et al., 2017). Findings suggested that there was no significant change in the capacity as a result of ramp metering and VSL. However, traffic conditions were found to improve when both ramp metering and VSL were deployed, compared to deploying ramp meters alone (Cohen et al., 2017).

2.1.4 Quantitative Benefits

Ramp metering was found to improve safety by decreasing the number of crashes that are likely to be attributed to merging maneuvers. A study by the Kansas Department of Transportation (KDOT) and Missouri Department of Transportation (MoDOT) (2011) observed a reduction in crashes per year from 44 crashes (prior to the deployment of ramp meters) to 16 crashes (after the deployment of ramp meters). Lee et al. (2006) indicated that ramp metering reduced the crash potential by 5 - 37% compared to locations without ramp metering. Cambridge Systematics, Inc. (2001) estimated a 26% reduction in the crash rate attributable to the ramp metering system. The majority of reduced crashes were classified as minor with personal injury. Piotrowicz & Robinson (1995) concluded that ramp metering decreased crashes in the peak period by 24% in Minneapolis, MN. The authors also summarized the safety benefits of ramp metering deployment in various states. For example, ramp metering contributed to a 50% reduction in rear-end and side-swipe collisions in Denver, CO, and led to a 50% reduction in total collisions and a 71% reduction in injury collisions in Detroit, MI. However, the safety benefits of the ramp metering were restricted to the freeway sections in the vicinity of the ramp and were dependent on the existing traffic conditions, as well as the spatial extent of the evaluation (Lee et al., 2006).

Cambridge Systematics, Inc. (2001) concluded that, in general, ramp metering led to significantly longer delays on ramps. However, with the improved travel condition on the freeway facilities, the overall system exhibited a decrease in total vehicle delays. Ramp meters led to a system-wide reduction of 25,100 person-hours of travel time per year due to improved travel speeds and lower travel times on freeways. Interestingly, ramp meters did not cause any significant impact on the arterials.

Piotrowicz and Robinson (1995) summarized the mobility benefits observed from ramp metering projects in several cities: a 173% increase in average travel speed in Portland, OR; an 8% increase in average travel speed, and a 14% increase in traffic volume in Detroit, MI; and a 52% reduction in average travel time, and a 74% increase in traffic volume in Seattle, WA. Also, ramp meters improved the travel time reliability which resulted in an annual benefit of over $25 Million (Cambridge Systematics, Inc., 2001). The study by KDOT and MoDOT (2011) observed a decrease in the travel time index, which is a measure of travel time before and after the installation of ramp meters. The average travel time index for both directions of a freeway (i.e., I-435) during peak hours was 1.17 in the before-period and 1.14 in the after-period (KDOT & MoDOT, 2011).

2.2 Dynamic Message Sign (DMS)

Dynamic Message Signs, or DMSs, also referred to as Changeable Message Signs (CMSs) or Variable Message Signs (VMSs), are programmable electronic signs that appear along highways and typically display information about real-time alerts related to unusual traffic conditions such as adverse weather conditions, construction activities, travel times, road closures or detours, advisory phone numbers, roadway incidents, etc. These messages are intended to affect the behavior of drivers by providing real-time traffic-related information to warn drivers, regulate traffic flow, and manage congestion on the roadways (Edara et al., 2011; Wang et al., 2017). DMSs are usually permanently mounted, while VMSs are commonly used in work zones, or where temporary messaging is needed.

The effectiveness of a DMS system depends on factors such as accuracy of travel time forecast, the driving public's knowledge of the prevailing traffic conditions, and their ability to infer travel times from these conditions (Yin et al., 2011). DMSs are expected to reduce secondary crashes, travel delays, fuel consumption, and emissions by assisting motorists with making informed routing decisions in response to incidents (Montes et al., 2008).

2.2.1 Current Deployments in Florida

DMSs have been deployed statewide on all major freeways and several arterial highways in Florida. As of December 2018, there are 760 permanently mounted DMSs displaying information to motorists – 188 in Central Florida, 98 in the Northeast region, 40 in the panhandle region (Northwest), 156 in the Southeast region, 57 in the Southwest region, and 147 in the Tampa Bay area. These DMSs are operational 24/7 to convey time-sensitive information to motorists and are generally updated every minute. In District Six alone, there were 33,944 messages posted with 10,276 DMS activations for 1,418 events during the month of December 2018. The displayed messages included incidents (14,952), construction (5,402), safety (10,033), and vehicle alerts

(3,557). The DMS efficiency was 99.72% (i.e., 1,414 of the 1,418 events had DMS messages posted) for all roadways.

2.2.2 Safety Performance Measures

With the dynamic nature of the messages that can be displayed, DMSs serve as an ideal tool for improving roadway efficiency and safety. The safety benefits of DMSs relate to the nature of the messages that are displayed. When displaying FDOT-approved safety messages shown in Figure 2-4, safety performance measures must consider the purpose of the message, location, time, and period of use, as well as the expected responses from drivers (Mounce et al., 2007).

Safety benefits of DMSs include the potential reduction in crash frequency and/or severity, as well as fewer secondary crashes, when drivers are well informed of incidents ahead, using real-time information. However, the drivers' comprehension of the DMS message may result in slower vehicle approach speeds and avoidance maneuvers (Mounce et al., 2007). Nevertheless, informing road users of traffic conditions in real-time, such as crashes, congestion, or roadwork ahead, can promote crash avoidance and improve the overall safety of the corridor.

Several previous studies have estimated the effectiveness of messages displayed on DMS using road users' perception surveys (Tay and de Barros, 2008; Peng et al., 2004; Richards and McDonald, 2007). Boyle et al. (2014) assessed the usefulness and effectiveness of safety and public service announcement (PSA) messages through surveys conducted in four urban areas in the United States (U.S.): Chicago, IL; Houston, TX; Orlando, FL; and Philadelphia, PA. The surveys were designed to specifically address the types of safety and PSA messages used in each respective city. A total of 2,088 survey responses were received and analyzed. Based on the information gathered, Boyle et al. (2014) recommended that safety and PSA messages displayed on DMSs should be useful and effective to maximize their influence on driver behavior.

2.2.3 Mobility Performance Measures

The mobility performance resulting from DMSs can be evaluated quantitatively or qualitatively depending on the type of motorist response to the displayed information (Mounce et al., 2007). Qualitative measures include public acceptance and satisfaction with DMS operations (Mounce et al., 2007). The reliability of the messages is one of the factors that can promote positive responses from drivers. Subjective performance measures obtained from drivers can be grouped into the effectiveness and usefulness of the DMS. Mobility benefits can be measured by shorter queues, less average delay per vehicle, shorter travel times for a given trip length, reduced total vehicle delay, higher travel speeds, increased throughput at bottlenecks, and improved LOS.

Schroeder and Demetsky (2010) investigated the impacts of existing DMSs to identify the messages that maximize diversion of motorists and develop new messages to be deployed using data collected on I-95 and I-295 in Richmond, Virginia. The percentage of diverted traffic was identified as a performance measure for diversion messages. The study concluded that increased traffic diversion was more likely when drivers were alerted to certain situations, such as a highway closure or incident ahead.

Figure 2-4: FDOT-approved Safety Messages on DMS (FDOT, 2018)

2.2.4 Quantitative Benefits

Rämä and Kulmala (2000) investigated the effect of DMSs for slippery road conditions on driving speed and headways in Finland during winter seasons. The results indicated that drivers reduced their speeds and decreased the proportion of short headways when a slippery road condition message and a recommended minimum headway between vehicles message were displayed. The majority of drivers regarded both signs useful: 65% approved of the slippery road condition sign, and 72% approved of the minimum headway sign. The slippery road condition sign decreased driving speeds by 1–2 km/h at a distance of 500-1,100 m after the signs (Rämä and Kulmala, 2000).

Tay and de Barros (2010) examined the impacts of anti-speeding messages on driver attitudes and traffic speed on an inter-city highway using a questionnaire survey. Study results suggested that DMSs had a relatively small beneficial effect on driver attitudes and traffic speed.

Haghani et al. (2013) used crash data, weather information, and DMS logs in Maryland for the years 2007-2010 to evaluate the crash patterns in the vicinity of DMSs. Of the 23,842 crashes in the study area for a sample of 70 road segments, only 50 crashes (35 property damage only (PDO) and 15 personal injuries) occurred when the DMSs were displaying messages. Of these 50 crashes, 11 occurred while danger/warning messages were displayed on DMSs. Overall, findings suggested that DMSs are a safe and effective tool for disseminating real-time travel information.

2.3 Road Rangers

Traffic incident management, as a planned and coordinated process to detect, respond to, and remove traffic incidents to restore traffic capacity as safely and quickly as possible, has emerged as a proven solution to ensure highway efficiency and reliability (Farradyne, 2000). As one component of a comprehensive incident management system, Freeway Service Patrols (FSPs) facilitate a quick clearance of incidents through faster response and reduced clearance time.

FSPs are present in at least 40 states nationwide under different names. The first FSP program started in Chicago, Illinois in 1960. Currently, many metropolitan areas implement FSP programs such as Road Rangers in Florida, FIRST (Freeway Incident Response Service Team) in Ohio, HELP (Highway Emergency Local Patrol) in New York and Tennessee, CHART (Coordinated Highway Action Response Team) in Maryland, HERO (Highway Emergency Response Operators) in Georgia, Hoosier Helper Program in Indiana, Texas's Courtesy Patrol, and California's Freeway Service Patrol (Baird, 2008).

2.3.1 Current Deployments in Florida

Florida's Road Rangers, in particular, provide free highway assistance services during incidents on Florida's roadways to reduce delay and improve safety for the motorists and incident responders. The objectives of the Road Ranger program include assisting the Florida Highway Patrol to reduce incident duration, provide assistance to disabled or stranded vehicles, remove road debris, and increase safety at incident sites. To meet these goals, Road Ranger probe vehicles monitor congested areas and high incident locations along urban expressways for road debris, traffic crashes or incidents, and stranded vehicles (Laman et al., 2018). With the exception of District Three, all other FDOT Districts and the Florida Turnpike Enterprise (FTE) provide Road Ranger services. The hours of operation for FDOT Districts 1, 4, 5, 6, and 7 are 24 hours a day, seven days a week; FDOT District 2 operates daily from 5:30 AM to 7:30 PM (Hagen et al., 2005).

2.3.2 Safety Performance Measures

Although FSPs are deployed to primarily mitigate traffic congestion, they are widely believed to improve traffic safety as well. However, little is known about the safety benefits or the magnitude of the safety effects of these programs, and the resulting cost benefits. There is limited literature on the safety implications of FSP programs, especially with a focus on secondary crashes.

2.3.2.1 Secondary Crashes

Secondary crashes result from a change in traffic characteristics caused by a primary incident. A critical element in estimating the benefits of FSP programs is the reduction in secondary crashes. The probability of occurrence of a secondary crash is a function of the duration of the primary incident. Several studies estimated the reductions in secondary crashes by assuming a linear relationship between the number of secondary crashes and the total savings in incident duration (Chou et al., 2009; Guin et al., 2007). According to Guin et al. (2007), FSP deployment helped to reduce incident duration time, thus reducing the occurrence of secondary crashes. The study assumed that 15% of crashes that occur on highways patrolled by FSPs were secondary crashes. Accordingly, a reduction in the primary incident duration from FSP response results in a decrease in the probability of secondary crash occurrence.

Olmstead (2004) used a fixed-effects negative binomial regression model to show that FSP programs significantly reduce secondary crashes. According to the study, FSP programs can reduce secondary crashes by reducing the non-recurring congestion associated with incidents and alerting motorists to exercise caution in the vicinity of incidents (either explicitly via portable DMSs or implicitly via flashing lights) (Olmstead, 2004).

2.3.3 Mobility Performance Measures

In addition to improved safety, FSP programs provide several benefits, including reduced incident durations (delay savings), reduced fuel consumption, reduced air pollutant emissions, motorist assistance, and freeway operator assistance. Improved average freeway travel speeds and freeway throughput also promote better public perception. FSP programs are widely used to help mitigate the effects of non-recurring congestion and have become an increasingly vital element of incident management programs (Skabardonis and Mauch, 2005).

While many studies evaluated and analyzed the operational performance of FSP programs by using incident duration and/or its components, several studies have conducted benefit-cost analyses to illustrate the return on investment of these programs (Dougald and Demetsky, 2008; Lin et al., 2012a). Since the FSP programs are developed primarily to reduce traffic congestion (mobility benefit), a primary measure of effectiveness is delay savings.

2.3.3.1 Delay Savings

Over the last decade, various methodologies have been used to calculate delays caused by incidents and savings in delay resulting from service patrols. There are certain challenges in estimating such benefits, primarily related to the measurement and collection of certain important variables, such as incident detection and response times (with and without FSPs), reduction in roadway capacities, travel time value, and the approach for calculating delay.

According to Lin et al. (2012a), delay savings are determined based on detection and response times and the amount of capacity reduction imposed by an incident. Figure 2-5 illustrates this concept by comparing incident delay (a) without and (b) with Road Ranger assistance. The horizontal axis in Figure 2-5 represents incident time, while the vertical axis represents the cumulative traffic volume for a freeway segment.

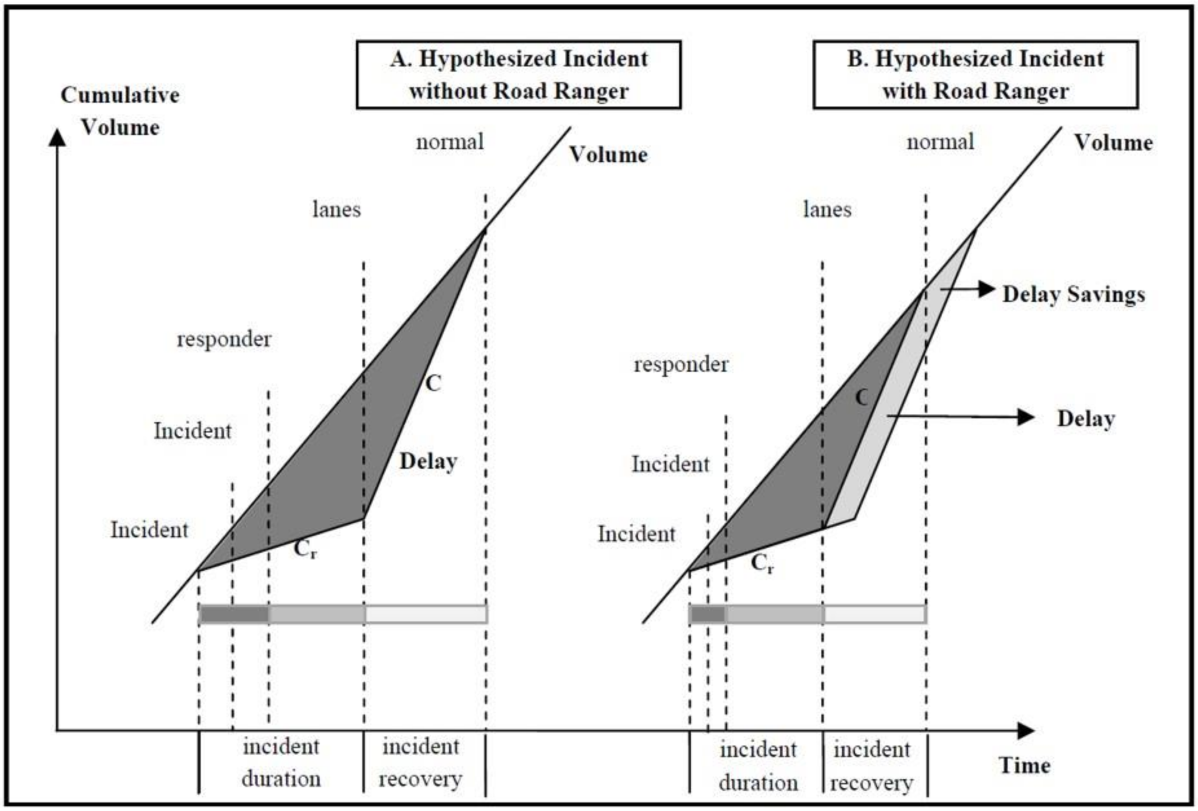


Figure 2-5: Delay Comparison with and without the Florida Road Ranger Program (Lin et al., 2012a)

Figure 2-5 assumes that the freeway is working at or near full capacity. When an incident occurs, the capacity is reduced to C_r, then recovers over time and returns to initial conditions (C) after the incident is cleared. When Road Rangers are patrolling the freeway, the detection and arrival times in Figure 2-5(b) are less than times shown in Figure 2-5(a), without Road Ranger assistance. Thus, the total delay savings, calculated as the total time in delay, with Road Ranger assistance is relatively shorter than the total delay savings experienced without Road Rangers. A similar methodology has also been used in previous studies (Chou et al., 2009; Dougald and Demetsky, 2008; Guin et al., 2007).

2.3.3.2 Incident Duration

Previous studies have focused on the effects of FSP programs on incident duration. Normally, FSPs are closer to incidents to which they are dispatched and may also detect incidents independently. This reduces the detection time significantly. Additionally, a recently completed FDOT study found that incidents detected by Road Rangers have relatively shorter durations

(Haule et al., 2018). In the San Francisco-Oakland area, the number of incidents detected by FSPs accounted for 92% of all incidents (Farradyne, 2000). Another study by Nee and Hallenbeck (2001) showed that for lane-blocking incidents in the Puget Sound region of Washington State, the average response time without an FSP was 7.5 minutes and response time was reduced to 3.5 minutes with an FSP. According to the study, FSPs reduced incident response times by 19% to 77%.

Although the majority of the literature has shown that implementation of FSPs leads to reduced incident duration, one study in Florida (Laman et al., 2018) reported conflicting results. According to the study, if the incident is detected by a police officer, the notification time reduced significantly; however, when detected by a Road Ranger, incident clearance time increased. The study concluded that Road Rangers are associated with longer reporting times which results in increased incident clearance time. There is a need to examine factors that might have caused these conflicting results.

2.3.4 Quantitative Benefits

Several studies conducted an economic appraisal of FSP programs. A case study in Florida (Lin et al., 2012a) quantified the benefits derived from the Florida Road Ranger program by developing a Freeway Service Patrol Evaluation (FSPE) model to calculate the benefit-cost (B/C) ratio using a variety of data from the Florida SunGuide database for the year 2010. The benefits (in terms of delay and fuel savings) of the Road Ranger program were about $135.3 Million in total, and the contractual costs were about $19.9 Million. Overall, the program achieved a B/C ratio of 6.78 in 2010. The study used delay savings (reduction in incident duration) and fuel consumption savings (reduction in fuel consumption) as performance measures.

A study by Dougald and Demetsky (2008) in Virginia showed that incident duration reductions attributable to Safety Service Patrol (SSP) operations in Northern Virginia and Hampton Roads, Virginia resulted in B/Cs of 5.4:1 and 4.7:1, respectively. The study quantified the benefits by considering the reductions in motorist delay, fuel consumption, and emissions attributable to SSP operations.

Guin et al. (2007) developed a methodology that computes the benefits derived from a motorist assistance service, reduction in delay, fuel consumption, secondary crashes, and the improvement in air quality attributable to the incident management program. The study was done on the Georgia NaviGAtor, Georgia’s intelligent transportation system. The results indicated substantial annual savings to motorists of 7.2 million vehicle-hours of incident-related delay. The overall cost savings computed for a 12-month period during 2003 and 2004 was $187 Million. On the basis of the annualized infrastructure, operations, and maintenance cost of the NaviGAtor system, the annual B/C ratio was calculated to be 4.4:1. Table 2-1 summarizes the B/C findings from several recent studies.

Table 2-1: Freeway Service Patrol (FSP) Benefit-Cost Analysis Results

Study	Location	Name	Year	Results
Olmstead (2004)	Arizona, Phoenix Metropolitan Region	Freeway Service Patrol	2004	Varies
Hagen et al. (2005)	Florida (Statewide)	Road Ranger Program	2005	2.3:1 to 41.5:1
Guin et al. (2007)	Georgia NaviGAtor	Highway Emergency Response Operations (HERO)	2007	4.4:1.
Baird (2008)	AL (Statewide)	Service and Assistance Patrol	2009	1.7:1 to 23.4:1
	Charlotte, NC	Incident Management	1993	1993 3:1 to 7:1
	Chicago, IL	Emergency Traffic Patrol	1990	17:1
	Dallas, TX	Courtesy Patrol	1995	3.3:1 to 36.2:1
	Denver, CO	Mile High Courtesy Patrol	1996	20:1 to 23:1
	Detroit, MI	Freeway Courtesy Patrol	1995	14:1
	Fresno, CA	Freeway Service Patrol	1995	12.5:1
	FL (Statewide)	Road Ranger Program	2005	2.3:1 to 41.5:1
	Houston, TX	Motorist Assistance Program	1994	6.6:1 to 23.3:1
	Los Angeles, CA	Metro Freeway Service Patrol	1993	11:1
	Minneapolis, MN	Highway Helper	1995	5:1
	New York, NY	Highway Emergency Local	1995	23.5:1
	Norfolk, VA	Safety Service Patrol	1995	2:1 to 2.5:1
	Oakland, CA	Freeway Service Patrol	1991	3.5:1
	Orange Co., CA	Freeway Service Patrol	1995	3:1
	Riverside Co., CA	Freeway Service Patrol	1995	3:1
	Sacramento, CA	Freeway Service Patrol	1995	5.5:1
Dougald and Demetsky (2008)	Virginia, Hampton	Safety Service Patrol	2008	4.7:1
Dougald and Demetsky (2008)	Northern Virginia (NOVA) region	Safety Service Patrol	2008	5.4:1
Chou et al. (2009)	New York	Highway Emergency Local Patrol	2009	Varies
Lin et al. (2012a)	Florida (Statewide)	Road Ranger Program	2012	6.78

2.4 Express Lanes

Express lanes are a type of managed travel lanes physically separated from general use or general toll lanes within a roadway corridor. They use dynamic pricing through electronic tolling in which toll amounts are set based on traffic conditions (Neudorff, 2011). Express lanes provide a high degree of operational flexibility, which enable them to be actively managed to respond to changing traffic demands. Aspects of express lanes include congestion pricing, vehicle restrictions, and may be operated as reversible flow or bi-directional facilities to best meet peak demands. These adjustments allow transportation agencies to offer drivers new and reliable mobility choices, provide more predictable travel times, deliver long-term solutions for managing traffic flow, decrease air pollution, and support transit usage (Florida Department of Transportation [FDOT], 2015).

2.4.1 Current Deployments in Florida

FDOT has been deploying express lanes throughout the state to provide drivers with an option to bypass heavily congested areas. Currently, FDOT has several express lane systems either in operation, under construction, or in the planning stages. Any two-axle vehicle equipped with SunPass can use Florida's express lanes. Trucks with three or more axles and passenger cars pulling trailers or boats are not permitted. Toll exemptions are applied to vehicles registered as public transit buses, school buses, over-the-road buses, and vanpools.

The express lane network covers major freeways and some arterial roads with congestion problems, especially during peak hours. The spatial distribution of the express lanes in Florida is divided into four groups, i.e., Northeast Florida, Central Florida, West Central Florida, and Southeast Florida. Figure 2-6 and Table 2-2 provide more details about the express lanes in the state.

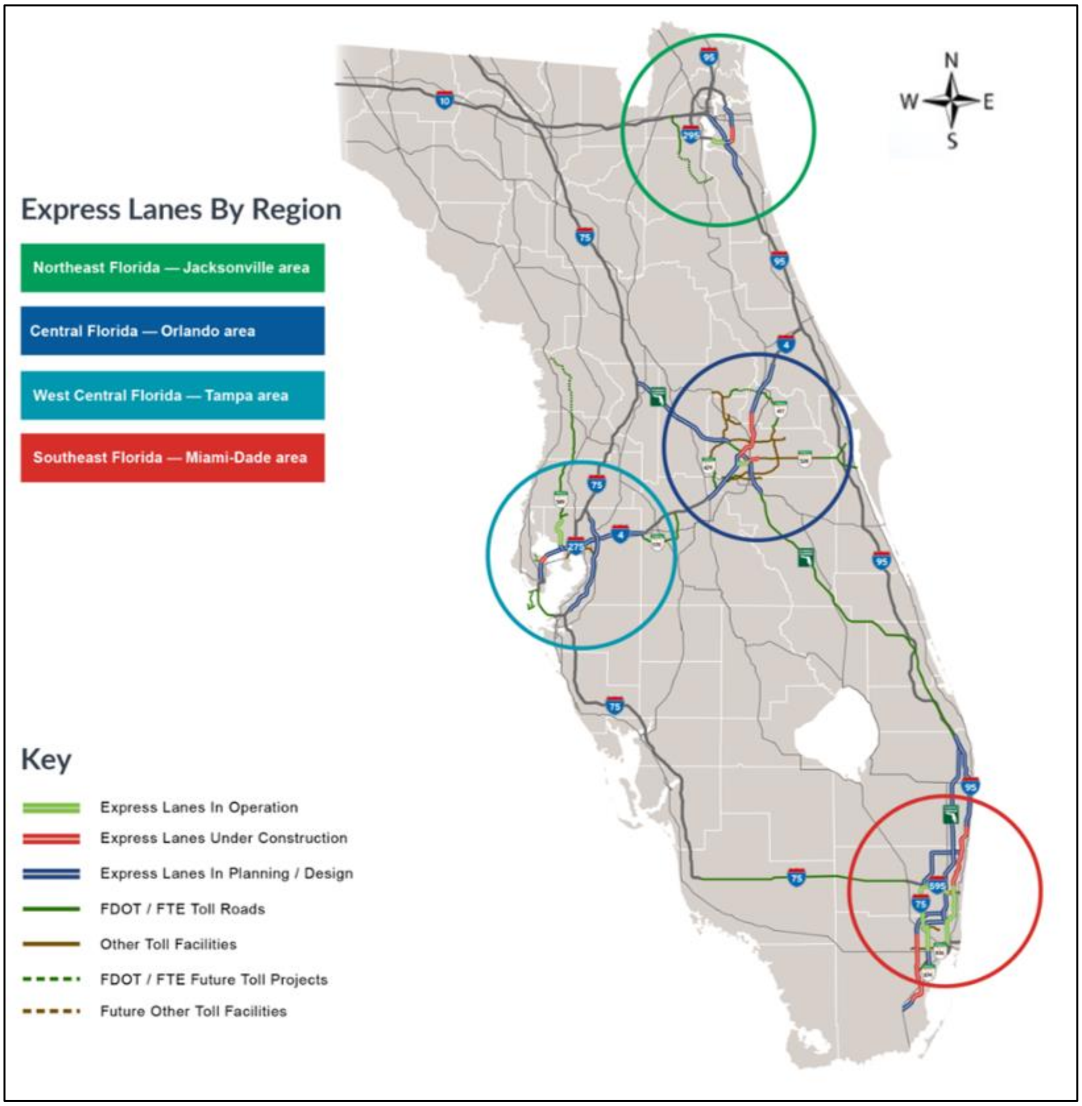


Figure 2-6: Express Lane Network in Florida

Table 2-2: Express Lane Network in Florida

Phase	Roadway	Description
Southeast Florida		
In operation	I-95	• Phase 1—Junction of I-95 and SR 836/I-395 in downtown Miami to Golden Glades interchange (7 miles): 2 express lanes/direction • Phase 2—Golden Glades interchange to Broward Boulevard (14 miles): 1 to 2 express lanes/direction
In operation	I-595	• I-75/Sawgrass Expressway to Turnpike Mainline (10 miles): 3 reversible lanes
In operation	I-75	• I-595 to the north of Griffin Road (5 miles): 2 express lanes per direction • North of Griffin Rd. to Sheridan St. (4 miles): 2 express lanes per direction • Sheridan St. to Miramar Pkwy (4 miles): 2 express lanes per direction • Miramar Pkwy to the north of NW 138th St. (6 miles): 2 express lanes/ direction • North of NW 138th St. to Palmetto Expressway (3 miles): 1 express lane/ direction
Under construction	Turnpike Extension (HEFT)	• Biscayne Drive to Killian Pkwy (14 miles): 1 express lane/direction • Killian Pkwy to SR 836 (7 miles): 2 express lanes/direction • Opens in sections starting in spring 2018 through spring 2020
Under construction	I-95	• Broward Boulevard to Commercial Blvd (10 miles): 2 express lanes/direction • Commercial Blvd to SW 10th St. (9 miles): 2 express lanes/direction • SW 10th St. to Glades Rd. (5 miles): 2 express lanes/direction • Broward Blvd to SW 10th St. - 2020, SW 10th St. to Glades Road • Expected Completion: - 2022
Under construction	Palmetto Expressway / SR 826	• West Flagler St. to NW 154th St. (10 miles): 2 express lanes/ direction Expected Completion: Early 2019
In planning/design	Turnpike Mainline	• Golden Glades to Turnpike Extension (3 miles): 1 express lane/direction • Turnpike Extension to the north of Johnson St. (4 miles): 2 express lanes/direction • North of Johnson St. to Griffin Rd. (3 miles): 2 express lanes/direction • I-595 to Atlantic Blvd (10 miles): 2 express lanes/direction • Atlantic Blvd to Wiles Rd. (5 miles): 2 express lanes/direction • North of Sawgrass Expressway / SR 869 to Glades Road (4 miles): 2 express lanes/direction • Glades Rd. to Atlantic Avenue (6 miles): 2 express lanes/direction • Atlantic Avenue to Boynton Beach Blvd (5 miles): 2 express lanes/direction • Boynton Beach Blvd to Lake Worth Rd. (7 miles): 2 express lanes/direction • West Palm Beach Service Plaza to SR 710 (12 miles): 2 express lanes/direction • SR 710 to Jupiter (10 miles): 2 express lanes/direction • Stuart to Fort Pierce (19 miles): 2 express lanes/direction
In planning/design	I-95	• Glades Rd. to the south of Linton Blvd (6 miles): 1 to 2 express lanes/direction • Stirling Rd. to Broward Blvd (8 miles): 1 additional express lane/direction • I-95 Express direct connect to I-595 (1 mile): 1 additional lane per direction to ramp flyover connection
In planning/design	Sawgrass Expressway / SR 869	• South of Sunrise Blvd to Atlantic Blvd (7 miles): 2 express lanes/direction • Atlantic Blvd to US-441 (10 miles): 2 express lanes/direction • US-441 to Powerline Rd. (4 miles): 2 express lanes/direction
In planning/design	Palmetto Expressway / SR 826	• The junction at I-75 to Golden Glades interchange (9 miles): 1 to 2 express lanes/direction • SR 836 to US 1 (6 miles): 1 to 2 express lanes/direction

Table 2-2: Express Lane Network in Florida (continued)

Phase	Roadway	Description
Northeast Florida		
Under construction	I-295	• I-95 to Buckman Bridge (5 miles): 2 express lanes/direction • SR 9B to J. Turner Butler Blvd (5 miles): 2 express lanes/direction Expected completion: I-95 to Buckman Bridge: fall 2018, SR 9B to J. Turner Butler Blvd: spring 2019
In planning/ design	I-295	• J. Turner Butler to the south of Dames Point Bridge (9 miles): 1 to 2 express lanes/direction
	I-95	• North of International Golf Pkwy to I-295 (14 miles): 2 express lanes/direction • I-295 to J. Turner Butler Blvd (6 miles): 2 to 3 express lanes/direction • J. Turner Butler Blvd to Atlantic Blvd (6 miles): 2 express lanes/direction
Central Florida		
Under construction	Beachline West Expressway / SR 528	• I-4 to Turnpike Mainline (4 miles): 2 express lanes/direction • Turnpike Mainline to McCoy Road (4 miles): 1 express lane/direction • Expected Completion: I-4 to McCoy Rd: Tentatively opening in Summer 2019
	Turnpike Mainline	• Osceola Pkwy to Beachline West Expressway/SR 528 (6 miles): 2 express lanes/direction • Expected Completion: 2021
	I-4	• SR 434 to Kirkman Rd. (21 miles): 2 express lanes/direction • Expected Completion: 2021
In planning/design	Turnpike Mainline	• Kissimmee / St. Cloud south to Osceola Pkwy (7 miles): 2 express lanes/direction • Beachline West Expressway / SR 528 to I-4 (4 miles): 1 express lane/direction • Clermont / SR 50 to Minneola (6 miles): 2 express lanes/direction • Minneola to Leesburg North / US 27 (10 miles): 2 express lanes/direction • Leesburg North / US 27 to CR 468 (12 miles): 2 express lanes/direction • CR 468 to I-75 (7 miles): 2 express lanes/direction
	I-4	• West of Kirkman Road / SR 435 to west of Beachline West Expressway / SR 528 (4 miles): 2 express lanes/direction • West of Beachline West Expressway / SR 528 to east of Osceola Pkwy / SR 522 (6 miles): 2 express lanes/direction • East of Osceola Pkwy / SR 522 to west of Champions Gate Blvd / CR 532 (8 miles): 2 express lanes/direction • West of Champions Gate Blvd / CR 532 to west of US 27 (4 miles): 2 express lanes/direction • East of SR 434 to east of US 17-92 (9 miles): 2 express lanes/direction • East of US 17-92 to east of SR 472 (10 miles): 2 express lanes/direction
	Seminole Expressway / SR 417	• Aloma Avenue to SR 434 (6 miles): 2 express lanes/direction • SR 434 to Lake Mary Blvd / CR 427 (5 miles): 2 express lanes/direction • Lake Mary Blvd / CR 427 to Rinehart Rd. (6 miles): 2 express lanes/direction

Table 2-2: Express Lane Network in Florida (continued)

Phase	Roadway	Description
West Central Florida		
In operation	Veterans Expressway / SR 589	• Hillsborough Ave. to Dale Mabry Hwy. (9 miles): 1 express lane/direction
Under construction	I-275	• Gandy Blvd to 4th St. N (4 miles): 1 express lane/direction Expected Completion: 2022
In planning/ design	I-275	• 4th St. N to east of Howard Frankland Bridge (6 miles): 2 express lane/direction
	I-4	• Downtown (east of 50th St.) to Polk Pkwy (22 miles): 1-2 express lanes/direction.

There has been an improvement in traffic flow in areas where express lanes are operational. For example, the opening of the express lanes on I-95, called I-95 Express, resulted in a 4.6% increase in person throughput (Goel and Burris, 2012). Some agencies expand public transport services to help people minimize their travel time using the express lanes. Miami-Dade Transit (MDT) and Broward County Transit (BCT) operate express buses on I-95 Express, providing service for passengers who travel to and from Downtown Miami on weekdays. Transit services help to minimize the impact on capacity on the express lanes.

2.4.2 Safety Performance Measures

Several studies have evaluated the safety performance of managed lanes, which include high-occupancy vehicle (HOV) lanes, high-occupancy toll (HOT) lanes, express toll lanes, reversible lanes, and bus lanes, by relating crash occurrence to the geometric configuration of a facility. Eisele et al. (2006) determined that the safety of managed-lane facilities has a strong correlation with the cross-section of the facility, type of lane separation (i.e., buffer or barrier), and the access design of the lanes.

2.4.3 Mobility Performance Measures

The mobility benefits of express lanes can be assessed based on the travel speed of vehicles using the facilities, overall travel time savings resulting from using express lanes, and the travel time reliability in using these facilities. Following the construction of I-95 Express in 2008, several studies have documented the performance measures for the traffic and transit as the volume, speed, occupancy, throughput, travel time, delay, user experience, and ridership (Cambridge Systematics, Inc., 2011). Note that FDOT defines express lane free-flow conditions as maintaining speeds of at least 45 mph. The goal is to achieve this speed 90% of the time while operational.

2.4.4 Quantitative Benefits

Buckeye (2014) evaluated the express lane performance on I-35W in Minnesota and concluded that travel speeds of 50 to 55 mph (i.e., 1,500-1,600 vph) had been maintained for 95% of the time in the I-35W MnPASS lanes, assuring users a consistently high level of service. Vehicle throughput on the express lanes had increased by 77%, and person throughput increased by 39% since the base year, 2008.

The safety performance of expressway ramps and weaving sections has also been studied using real-time data. Wang et al. (2015) conducted a study on real-time crash prediction for expressway weaving segments on a 22-mile section of SR-408 in Central Florida. The results indicated that speed differences play an important role in estimating crash risks. A one-mph increase in speed difference increased the crash ratio by 6.6%, and a 10-mph increase in speed difference increased the crash ratio by 89.6%. Wet pavement surface condition was also found to increase the crash ratio by 77%. Xu et al. (2019) conducted a study to leverage the use of the floating car data to capture the speed variance in the morning rush hour on urban elevated expressways and examine its effect on safety. The results showed that a larger spatial and temporal speed variance increases the probability of crashes on urban expressways. Segment length and traffic volume were found to be significantly related to PDO crash frequency.

Crash analysis was performed along a 9.65-mile section of I-290 expressway from I-294 to Kostner Avenue in Chicago, Illinois. The section experienced a total of 6,066 crashes over a 3-year period from 2006-2008. The data showed that approximately 75% of the crashes occurred on I-290, 15% on the crossroads, and the remaining 10% occurred on the ramps and frontage roads. Analysis results indicated that congestion was the principal contributing factor of crashes, with rear-end crashes being the predominant type. In addition, Cao et al. (2012) found that the conversion from HOV to HOT lanes along I-394 reduced the number of crashes by approximately 9.8%.

2.5 Transit Signal Priority

Transit Signal Priority (TSP) modifies the signal timing at intersections to better accommodate transit vehicles. Typically, a bus approaching a traffic signal will request priority. This request for transit priority is often transmitted directly from an approaching bus to a traffic signal or originated by a centralized transit priority management system (FHWA, 2018). When a request is received, the traffic signal controller applies logical rules to decide whether or not to allow priority to the bus (FHWA, 2018). These rules typically include consideration of whether the bus is behind schedule, the length of time since the last priority was awarded to a bus, the state of the traffic signals along the route, and the time of day (FHWA, 2018). In most cases, the form of priority given is to extend an existing green phase to serve the bus or to shorten other phases to cycle to the next green phase earlier for the bus (FHWA, 2018).

In simple TSP systems operations, each signal controller operates independently. It detects the bus directly and does not receive priority requests from any external source. It makes a decision about providing priority without reference to any external system or consideration of the state of any other signal controller (FHWA, 2018). In more complex systems, a central priority management system may determine when to request priority at various intersections and employ more complex rules that include feedback from the traffic signal system (FHWA, 2018). This type of system could potentially be integrated into the larger integrated corridor management (ICM) system.

TSP promotes reduced transit travel times, better schedule adherence, better transit efficiency, increased road network efficiency, and increased safety. TSP may be applied across numerous intersections depending on (Smith et al., 2005):

- the level of service of the parallel, crossing roadway and intersection traffic operations,
- lane configuration characteristics of the signalized intersections along a corridor and can be combined in the same signal operation for each approach serving transit,
- TSP and non-TSP transit service characteristics (i.e., the frequency and ridership of the transit service),
- the vehicle and roadway TSP technologies, and
- other factors not examined within these conceptual analyses.

2.5.1 Current Deployment Locations in Florida

TSP is increasingly being deployed across the nation, and Florida is no exception. TSP is currently deployed at the following locations in Florida:

- Fletcher Avenue, Tampa
- Nebraska Ave, Tampa
- International Drive, Orlando
- Palm Tran 42, Palm Beach County
- Palm Tran 63, Palm Beach County
- Sunrise Blvd., Broward County
- NW 6th St to NW 159th St, Miami-Dade County

2.5.2 Safety Performance Measures

The safety performance of TSP can be evaluated using the following performance measures: total crashes, number of crashes (involving buses and signal priority), pedestrian crashes, average reduction in pedestrian walk cycle, pedestrian crossing time, pedestrian-transit conflicts, and secondary crashes. In the existing TSP studies, more attention has been given to the operational effectiveness; studies on the safety effectiveness of TSP have been sparse.

Goh et al. (2013) explored the road safety impacts of several bus priority treatments including TSP. An empirical Bayes (EB) before-after study was used for an aggregate level analysis to determine the changes in expected crash frequency at intersections and roadway segments where TSP was deployed. Results showed an 11.1% reduction in expected crash frequency after the TSP deployment. Goh et al. (2014) conducted another study on crashes involving buses under situations with and without bus priority treatments, including signal priority and right-of-way priority (Goh et al., 2014). Mixed effects negative binomial (MENB) and back propagation neural network (BPNN) modeling methods were used to analyze segment level crashes, Average Annual Daily Traffic (AADT), stop density, bus route lengths, bus service frequency, and presence of bus priority. The MENB model results showed 53.5% in reducing bus crash frequency along the analysis corridor and the BPNN model showed a reduction of 53.4%.

Naznin et al. (2016) studied the safety effects of streetcar priority along a corridor with 29 intersections with signal priority and 23 arterials with tram lane priority. Statistical results showed a 16.4% crash reduction rate with tram priority, 13.9% crash reduction rate with signal priority, and 19.4% with lane priority. Song and Noyce (2018) assessed the effects of TSP on traffic safety using EB before-after analysis along a study corridor in King County, Washington. The study results showed a 13% reduction in total corridor-level crashes, a 16% reduction in PDO crashes, and a 5% reduction in fatal and injury crashes.

2.5.3 Mobility Performance Measures

TSP reduces transit travel times, provides better schedule adherence, better transit efficiency, and increases road network efficiency. The mobility performance of TSP can be evaluated using travel time for transit and all other vehicles in the network, travel speed of transit vehicles, transit schedule deviation, bus on-time, person delay, vehicle delay, reliability, and bus on-time arrival percentage.

Consoli et al. (2015) evaluated the effectiveness of TSP on a test corridor along I-Drive in Orlando, FL. Several methods were used to determine whether TSP was effective in reducing bus travel time. Multiple runs were performed in VISSIM models for the following four scenarios: *No TSP*, *Unconditional TSP*, *Conditional TSP 3 minutes behind*, and *Conditional TSP 5 minutes behind* (Consoli et al., 2015). Conditional priority is given to a detected transit vehicle when conditions are met, such as the number of passengers, the schedule adherence of the route, or the time since the last priority was awarded (Ova and Smadi, 2001). Unconditional priority refers to when transit vehicles receive signal priority regardless to cross-street queue lengths or the time since priority was last awarded (Ova and Smadi, 2001). Automatic passenger counts from LYNX were used to determine the peak hours for the passenger demand that occurred between 4:00 PM and 5:00 PM on weekdays (Consoli et al., 2015). This information was very important and useful in considering delays to the bus that were not related to signals (e.g. increased volumes or delays caused by passenger boarding and alighting). This research study concluded that *Conditional TSP 3 minutes behind* was the most effective TSP scenario since it reduced travel times and delays for I-Drive more than the *Conditional TSP 5 minutes behind* without significantly increasing side street delays (Consoli et al., 2015).

Zlatkovic et al. (2013a) evaluated the individual and combined effects of queue jumpers (QJ) and TSP for the Bus Rapid Transit (BRT) system and vehicular traffic along 3500 S in West Valley City, Utah. Queue Jumper is a special lane with a leading transit signal phase interval to allow buses to bypass a waiting traffic queue (Zlatkovic et al., 2013a). The bus utilizes a right-turn bay (if available) to advance ‘jump’ in front of the queue by getting a leading green interval. These bays usually consist of a nearside right-turn-only lane, and a far-side open bus bay. The nearside right-turn lane enables buses to circumvent traffic queues, whereas, the far-side bus bays serve to avoid blockage of through traffic by a stopped bus. The authors developed and evaluated four VISSIM microsimulation models: the existing scenario without special treatments for transit, the QJ-only scenario, the TSP-only scenario, and a combination of QJ and TSP scenario (Zlatkovic et al., 2013a). The implementation of any transit strategy resulted in significant improvements in BRT operations. The study also stated that the transit treatments did not affect private traffic along the corridor, however, these strategies had certain impacts on the side street traffic (Zlatkovic et al., 2013a). In addition, QJ and TSP scenarios increased average delays for cross-street traffic by 15%. This study concluded that, with small improvements in QJ and TSP settings, the combination of the two strategies can be most beneficial and highly desirable for implementation.

2.5.4 Quantitative Benefits

Deploying TSP has several mobility and safety benefits. It improves bus travel time, bus travel speed, bus schedule deviation, bus on-time, person-delay, vehicle-delay, reliability, bus on-time arrival percentage, etc. By deploying TSP, bus travel time reduced by about 13-22%, the progression of the bus significantly improved, intersection delays and waiting times reduced, travel speeds increased (22%), and the travel time reliability and headway adherence improved (Zlatkovic et al., 2013b). Implementation of *conditional TSP 3 minutes behind schedule* along the I-Drive, Orlando, with a B/C ratio of 7.92, was determined to be the most beneficial and practical TSP scenario for real-world implementation at both corridor and regional levels (Consoli et al., 2015).

A case study in Washington D.C. showed that allowing TSP during an urban evacuation showed to have a little to no interference with evacuation clearance time (Parr et al., 2011). In addition, after TSP was deployed, it showed that the level of service increased for transit evacuees, and TSP resulted in a 26% reduction in travel time (Parr et al., 2011). This travel time saved translated into additional trips being made by transit units. A study on TSP in Okeechobee Blvd, West Palm Beach, Florida, showed travel time improvement for both transit and other vehicles when TSP was deployed. This study selected intersections that possessed a volume-to-capacity (v/c) ratio of 0.50-0.85 (Ali et al., 2017). The authors concluded that TSP was not required when the v/c is below 0.50, while TSP would not be efficient when the v/c of an intersection is ≥ 0.85 (Ali et al., 2017). In addition, the analysis of TSP showed that side street traffic will not have many negative impacts.

Hillsborough Area Regional Transit (HART) BRT project identified the use of TSP on the BRT route along the Fletcher Avenue and Nebraska Avenue corridors in Tampa, Florida (Kittelson & Associates, Inc., 2014). The key TSP strategies included a bus lateness threshold of one minute and a green extension of 5 to 10 seconds for buses. When TSP was deployed at these study corridors, the potential for noticeable impact on the side street and left-turn traffic operations were found to be minimal. With calls being granted to approximately 10% of the time, even if 5 to 10 seconds caused an impact on a specific signal phase, it was able to recover during the next cycle (Kittelson & Associates, Inc., 2014). Moreover, when a call is granted, the 5 to 10 seconds can be used by traffic on complementary signal phases, thus reducing delay for those traffic movements (Kittelson & Associates, Inc., 2014). When TSP was deployed, the bus travel times improved slightly, while the overall signal operations were not significantly impacted. Analysis of the bus on-time performance data also found that there may be opportunities to enhance the bus schedules and improve bus performance.

Cesme et al. (2015) concluded that the greatest benefit from TSP comes from when a near side stop is relocated to a far side stop, in which the far side stops reduced delay up to 30 seconds per intersection. Moreover, as the number of right-turn lanes increased along with the number of conflicting pedestrians, the benefit of a queue jump lane was found to disappear. TSP with 15 seconds of green extension and red truncation offered up to 19 seconds of reduction in delay, the benefit became more pronounced with high v/c ratio (Cesme et al., 2015). With a low v/c ratio; 10 seconds of green extension without red truncation provided very marginal benefits; only a delay reduction of 2 seconds per intersection was gained (Cesme et al., 2015). Overall, travel time along the corridor improved and delay time reduced after the deployment of TSP.

2.6 Adaptive Signal Control Technology

The Adaptive Signal Control Technology System (ASCT) is an Intelligent Transportation Systems (ITS) technology that optimizes signal timing in real-time to improve corridor flow. This strategy continuously monitors arterial traffic conditions and the queuing at intersections and dynamically adjusts the signal timing to optimize operational objectives (FHWA, 2017). ASCT works by collecting current traffic demand through sensors, evaluating performance using system specific algorithms and implementing modifications based on the outcome of those evaluations. The process is repeated every few minutes to keep traffic flowing smoothly (FHWA, 2017).
In the past few decades, several types of ASCT have been deployed (Hunt et al., 1981; Gartner et al., 2002; Zhao and Tian, 2012). Each ASCT utilizes a unique algorithm to optimize signal timing based on real-time traffic demand. Some systems provide an entire system solution evaluated on a second-by-second basis, other systems evaluate and optimize each individual signal on a cyclic basis. Each approach produces similar benefits and requires a varying level of detection, communications and processing capability that should be selected to be consistent with the agency's needs, operations and maintenance capabilities (Stevanovic, 2010; Radin et al., 2018). Various ASCT are described below;

Sydney Coordinated Adaptive Traffic System (SCATS)

SCATS is an intelligent transportation system and innovative computerized traffic management system developed in Sydney and other Australian cities. It matches traffic patterns to a library of signal timing plans and scales split plans over a range of cycle times. As of June 2012, SCATS has been distributed to 263 cities in 27 countries worldwide controlling more than 35,531 intersections (Radin et al., 2018). SCATS adjust the cycle time, splits and offsets in response to real-time traffic demand to minimize overall stops and delays. SCATS it's not a model based but has a library of plans that it selects from and therefore relies extensively on available traffic data. It can be described as a feedback control system (Lowrie, 1982).

SCATS have a hierarchical control architecture consisting of two levels, strategic and tactical (Lowrie, 1982). At the strategic level, a subsystem or a network of up to 10 intersections, is controlled by a regional computer to coordinate signal timings (Radin et al., 2018). These subsystems can link together to form a larger system operating on common cycle time. At the tactical level, optimization occurs at the intersection level within the constraints imposed by the regional computer's strategic control. Tactical control allows early termination of green phases when the demand is less than average and for phases to be omitted entirely when there is no demand. All the extra green time is added to the main phase or can be used by subsequent phases.

Split Cycle Offset Optimization Technique (SCOOT)

SCOOT is the most widely deployed adaptive system in existence. It was first developed in the U.K Transport Research Laboratory. SCOOT is a model-based system that enables it to generate a Cyclic Flow Profile (CFP) based on the actual field demand. The fundamental unit of demand in SCOOT is a Link Profile Unit, which is a hybrid measure of the flow and occupancy data received from the detectors. Based on the generated CFP, SCOOT can project platoon movement and dispersion at the downstream intersection. This helps it to model queue formation and queue discharge (Radin et al., 2018).

SCOOT is installed on a central computer and houses three optimizers: one for cycle time, one for green splits, and one for offsets. The cycle time optimizer computes an optimum cycle length for the critical intersection in the network. The split optimizer then assigns green splits for each intersection based on computed cycle length and the offset optimizer calculates offsets. These parameters are recalculated and implemented every second and change are made if required (Robertson, 1986).

InSync ASCT

InSync ASCT is an intelligent transportation system that enables traffic signals to adapt to actual traffic demand. The system was first developed in 2005 by Rythem Engineering and it uses real-time traffic data collected through four video detection cameras at each intersection to select signalization parameters such as state, sequence and amount of green time to optimize the prevailing conditions second by second. Optimization is based on minimizing the overall delay and reducing the number of stops (Rythem Engineering, 2017). As of March 2012, traffic agencies in 18 U.S states have selected InSync for use at more than 650 intersections (Radin et al., 2018).

SynchroGreen ASCT

SynchroGreen ASCT is an intelligent transportation system that optimizes signal timing for arterials, side-streets, and pedestrians through real-time adaptive traffic control. The system was developed in 2012 by Trafficware and Naztec. It uses an algorithm that optimizes signal timing based on real-time traffic demand. The optimization is based on minimizing total network delay while providing reasonable mainline progression bandwidth. These algorithms utilize the detection data obtained from non-proprietary technology such as inductive loops, video, wireless and radar. These algorithms require stop-bar detection and advanced detection, and the detection data are sent to the signal system master through local controllers (Trafficware, 2012).

Real Time Hierarchical Optimized Distributed Effective System (RHODES)

RHODES is an ASCT that responds to the natural stochastic behavior of traffic, which refers to spatial and temporal variations and tries to optimize a given performance measure by setting timing plans in terms of phase durations for any given phase sequence. It uses a peer-to-peer communications (no central supervisor) approach to communicating traffic volumes from one intersection to another in real-time (Gartner, 1983).

2.6.1 Safety Performance Measures

Previous studies have shown that ASCT can improve operational performance over conventional signal control in terms of frequently used mobility performance measures such as traffic delay, average stop delay, travel times, travel speeds, travel time reliability, etc. Such operational improvements translate into substantial safety improvements on the other hand. For example, reduced vehicle stops frequency reduces the chance of rear-end crashes (Stevanovic, 2010). Similarly, previous studies have shown that operational improvement as a result of ASCT installations can also create secondary safety benefits (Wilson et al., 2003; Khattak et al., 2018). Dutta and McAvoy (2010) evaluated the safety effectiveness of the Sydney Coordinated Adaptive Traffic System (SCATS) over the time-of-day (TOD) signal plan. This study compared a section of M-59 (with SCATS) with a section on Dixie Highway (with a TOD system) to assess the safety effectiveness of the SCATS. The results revealed a shift in crash severity from A (incapacitating injury) and B (visible injury) to C (possible injury). However, the improvements were not statistically significant at 95% confidence level.

2.6.2 Mobility Performance Measures

Several previous studies have evaluated the mobility benefits of the ASCT. In general, most of the studies observed that ASCT improves travel speeds, travel time, travel time reliability and reduces delays especially when the traffic flows are unpredicted and variable. Several studies have analyzed the mobility impact of ASCT using the travel time, travel speed, number of stops, delays and travel time reliability as the performance metrics (Martin, 2018; DKS Associates, 2010; Dutta and McAvoy, 2010; Hutton et al., 2010; Tian et al., 2011; Fontaine et al., 2015). A before and after study was conducted on an arterial segment with 10 adaptive signalized intersections in Las Vegas, to evaluate the performance of Sydney Coordinated Adaptive Traffic System (SCATS) (Tian et al., 2011). The analysis was based on field data collected using a probe vehicle. The study adopted descriptive statistics to estimate the operational benefits of the SCATS. The study found no significant improvement on arterial progression with SCATS.

2.6.3 Quantitative Benefits

Adaptive Signal Control Technology (ASCT) was found to improve safety by reducing the number of crashes. A study by Khattak et al. (2018) conducted in Pennsylvania observed a reduction of 13% for total crashes and 36% FI crashes at a 95% confidence level. Moreover, another study conducted in Virginia revealed a reduction in both total crashes and FI crashes by 17% (CMF = 0.83) and 8% (CMF = 0.92), respectively (Ma et al., 2016).

A study by Dutta and McAvoy (2010) evaluated the performance of SCATS over TOD along M-79 in Oakland County, Michigan. Descriptive statistics and hypothesis tests (ANOVA) were used to determine if there is any significant difference in the operational performance between SCATS and TOD. The results at 95% confidence level showed that SCATS reduce the number of stops and side-street delays compared to TOD. In South Lyon Michigan's field evaluation, SCATS was compared to fixed time control by switching the system ON and OFF (Martin, 2018). Descriptive statistics indicated that the use of the SCATS reduced travel time by 7.6%, stopped delay by 13% on the weekend and 20% on a weekday.

Other studies have also summarized the mobility benefits observed from the ASCT. The InSync ASCT was found to improve travel time by 9% and average speed by 11% and reduced stopped delays by 13% on weekdays. Fuel consumption and emissions were reduced by 3% to 9%, and stops were reduced by 37% to 52%. InSync ASCT deployment was associated with an annual benefit of about $1.3 million, which translated to the project benefit-to-cost ratio (BCR) of approximately 1.58 (Sprague, 2012).

Another study on the safety benefits of the SCATS system was done in Oakland County, Michigan, using a cross-sectional analysis and Multinomial logit models of injury severity (Fink et al., 2016). The findings revealed that SCATS reduced angle crashes by 19.3%, with a statistically significant increase in non-serious injuries and no significant reduction in incapacitating injury or fatal crashes. More recently, an observational before-after EB approach was conducted at 47 urban intersections deployed with InSync ASCT in Virginia, and the results revealed a reduction in both total crashes and FI crashes by 17% (CMF = 0.83) and 8% (CMF = 0.92), respectively. Note that only the reduction in total crashes was found to be statistically significant at 95% CI (Ma et al., 2016)

Furthermore, a before and after study was conducted to evaluate the effectiveness of InSync ASCT in San Ramon, California (DKS Associates, 2010). Based on the descriptive statistics on the field data, the authors concluded that InSync ASCT resulted in an improvement. Although the average vehicle delays along the major road decreased, the average vehicle delay along the minor streets increased by 3 sec per vehicle. Since this difference was relatively small, researchers concluded that the benefits of decreased delay along the mainline outweighed the costs of increased delay along the side-streets. Another study was conducted at 11 intersections with InSync ASCT along 10th Street in Greeley, Colorado (Sprague, 2012).

2.7 Summary

Congestion is a growing concern, especially in urban areas. Traffic congestion resulting from a high volume of vehicles and numerous outdated signal timings at signalized intersections is one of the primary causes of travel time unreliability and other mobility issues (Ali et al., 2017). ITS technologies and TSM&O strategies have been deployed to improve the mobility and safety of roadways by active management of transportation demand. In addition, these approaches strive to maximize the efficiency, safety, and utility of the existing and/or planned transportation infrastructure.

This chapter focused on identifying and reviewing the TSM&O strategies that are currently deployed in Florida. The strategies reviewed for freeways include Ramp Metering System, Dynamic Message Signs, Road Rangers, and Express Lanes. For arterial facilities, Transit Signal Priority and Advanced Traffic Management Systems were reviewed. An in-depth literature review was also conducted on the safety and mobility benefits of the aforementioned strategies.

CHAPTER 3
DATA SOURCES

This chapter presents the main data sources used in this study to quantify the safety and mobility benefits of the following TSM&O strategies:

Freeways

- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers (RRs)
- Express Lanes (ELs)

Arterials

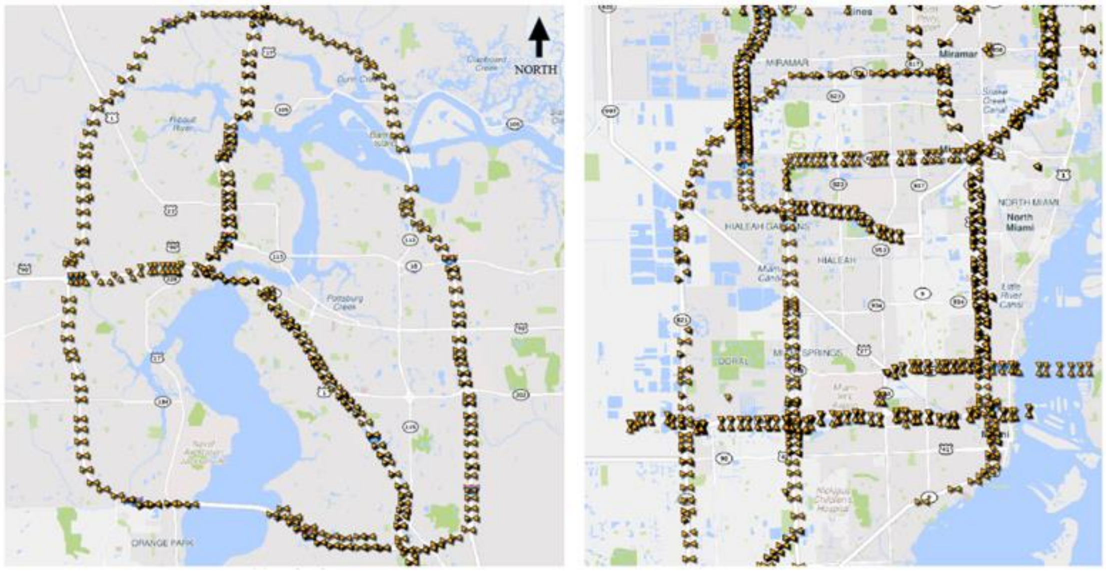
- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

Various types of data were used to quantify the safety and mobility benefits of the TSM&O strategies, with data requirements dependent on the strategy being analyzed, the study areas, and the analysis periods. Analyses utilized data collected and archived by various agencies and vendors, including crash data, traffic incident data, roadway geometric characteristics data, and traffic flow data. This chapter discusses the following databases:

- Regional Integrated Transportation Information System (RITIS)
- BlueToad®
- SunGuide™
- SignalFour Analytics
- Roadway Characteristics Inventory (RCI)
- Other data sources:
    - DMS locations and logs
    - TSP study corridors and signal plans
    - Express lane operational times
    - Ramp meter operational times

3.1 Regional Integrated Transportation Information System (RITIS)

The Regional Integrated Transportation Information System (RITIS) is an automated data sharing, dissemination, and archiving system that includes real-time data feeds and data analysis tools such as a probe, detector, and transit data analytics. These tools assist agencies in gaining situational awareness, measuring performance, and communicating information between agencies and to the public. RITIS archives a vast amount of traffic flow information, such as volume, speed, and occupancy, collected from nearly 11,647 detectors along the Florida roadway network. Figure 3-1 shows a network of RITIS detectors for several of the study corridors in FDOT Districts 2 and 6. Depending on the TSM&O strategy being analyzed, the extracted traffic flow data from RITIS varied by study corridor, study period, and data interval (e.g., 5-minute interval versus 15-minute interval data collection). Additional pertinent information regarding the detectors used to collect traffic data, such as detector location (i.e., latitude and longitude), was also extracted and used in the analysis.



(a) District 2 (b) District 6

Figure 3-1: RITIS Device Sample Network for FDOT Districts 2 and 6

3.2 SunGuide™

SunGuide™ is an Advanced Traffic Management System (ATMS) software used to process and archive incident data on Florida's transportation system. The scope of the incident data collected and utilized in this study depended on the analysis period, the study corridors, and the TSM&O strategy being analyzed. The SunGuide™ incident database contains most of the relevant information related to incidents, including the following:

- Event ID
- Roadway, e.g., I-95, I-295, I-10, etc.
- Latitude and longitude of the event location
- Incident notification time
- Incident clearance duration
- Event type, i.e., crash, flooding, disabled vehicle, debris on the roadway, etc.
- Time of event
- Number and categories of responding agencies
- Lane closure information
- Incident severity
- Incident detection method

All the above-listed variables are self-explanatory except for the event type and detection method; these two variables are discussed below. The SunGuide™ database has numerous categories describing the type of incident that occurred on a roadway network. These categories include crash, disabled vehicle, debris on the roadway, emergency vehicle, police activity, vehicle fire, flooding, pedestrian, abandoned vehicle, construction, and others. The database also identifies how an incident was detected, i.e., by Road Rangers, Florida Highway Patrol (FHP), FL511 Probe vehicle, closed-circuit television (CCTV), County Police, Jacksonville Sheriff's Office (JSO), Waze, or by a motorist.

3.3 BlueToad®

The BlueToad® database contains real-time traffic data that is collected using Bluetooth signal receivers which read the media access control (MAC) addresses of active Bluetooth devices in vehicles passing through their area of influence. BlueToad® devices act in pairs, or as a network (i.e., BlueToad® pairs), by recording the time when a vehicle passes both devices. This information is used to deduce the travel time of the vehicle between a pair of devices. The speed is calculated from the obtained travel time and a known path distance (not Euclidean distance) between the devices. Figure 3-2 shows a sample network of BlueToad® devices in Jacksonville, Florida. Similar to other databases, the scope of the data collected from BlueToad® depended on the study corridors, analysis periods, and the TSM&O strategy being analyzed.

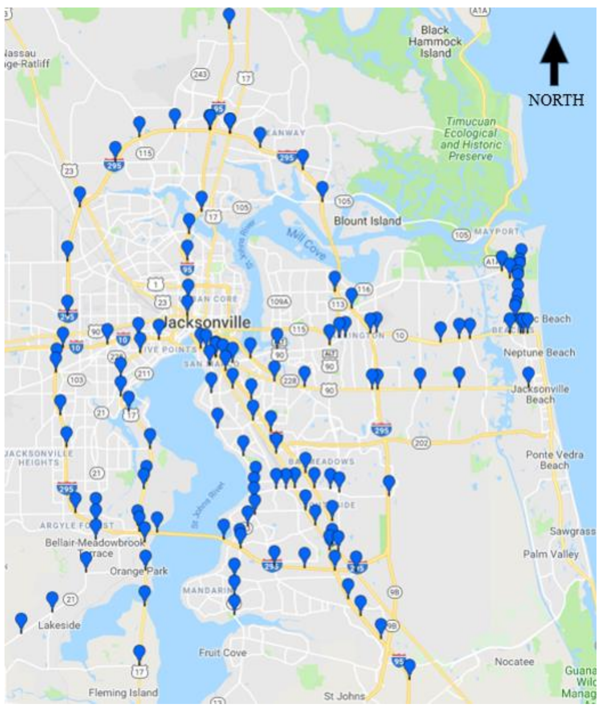


Figure 3-2: Network of BlueToad® Devices in Jacksonville, Florida

3.4 SignalFour Analytics

SignalFour Analytics is an interactive web-based geospatial analytical tool for the state of Florida that provides crash data with numerous crash attributes. The tool contains crash data provided by the Florida Department of Highway Safety and Motor Vehicles (DHSMV) from 2006 to present, and citation data provided by the FHP from 2011 to present. The following crash attributes can be obtained from the database: day of the crash, crash severity, lighting condition, crash type, and information about individuals involved in the crash, such as driver gender and age. For the majority of TSM&O strategies analyzed, SignalFour Analytics data served as the central source for crash data used in the safety analyses. Data extracted varied based on the TSM&O strategy being analyzed, the study corridors, and the analysis periods.

3.5 Roadway Characteristics Inventory (RCI)

The Roadway Characteristics Inventory (RCI) contains data describing the features and characteristics of Florida's roadway network. Maintained by FDOT, over 200 variables are available in the database. The information provided in the RCI database was essential in selecting the specific study corridors for analysis. A small sample of variables that are available in the RCI database and relevant to this study include:

- Average Annual Daily Traffic (AADT),
- number of lanes,
- median type,
- median width,
- shoulder type,
- speed limit,
- horizontal curvature,
- vertical curvature, and
- surface width.

Relevant roadway characteristics data were extracted from the most recent RCI database for each study corridor and TSM&O strategy analyzed.

3.6 Other Data Sources

In addition to the aforementioned databases, the following data were also required to evaluate the safety and operational performance of TSM&O strategies. These data elements are discussed in subsequent chapters, as applicable.

- DMS locations and logs
- TSP study corridors and signal plans
- Express lane operational times
- Ramp meter operational times

CHAPTER 4
MOBILITY BENEFITS

This chapter discusses the methodology and the mobility benefits of the following TSM&O strategies that are currently deployed in Florida:

Freeways

- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers
- Express Lanes

Arterials

- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

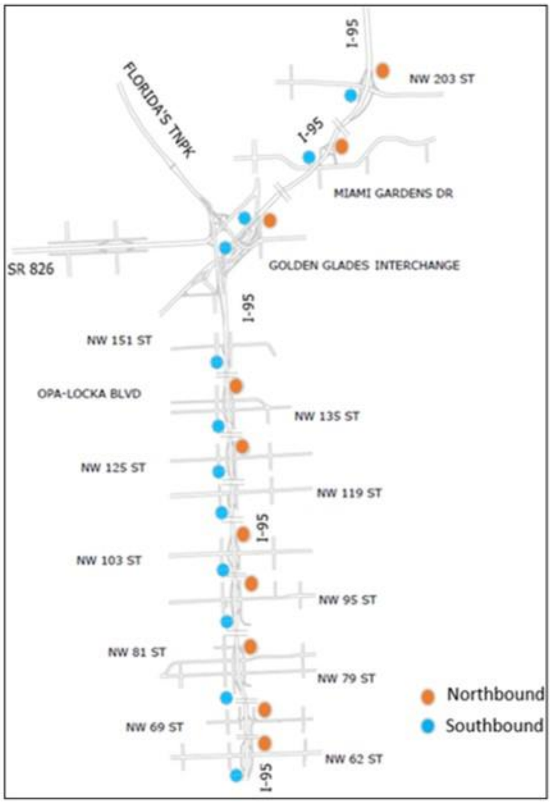
4.1 Ramp Metering System

Ramp metering or signaling is a traffic management strategy that employs traffic signals installed at freeway on-ramps to control and regulate the frequency at which vehicles join the flow of traffic on the freeway mainline (Gan et al., 2011; Mizuta et al., 2014). The following subsections discuss the study corridor, the data used in the analysis, the methodology, and the mobility benefits of ramp metering operations.

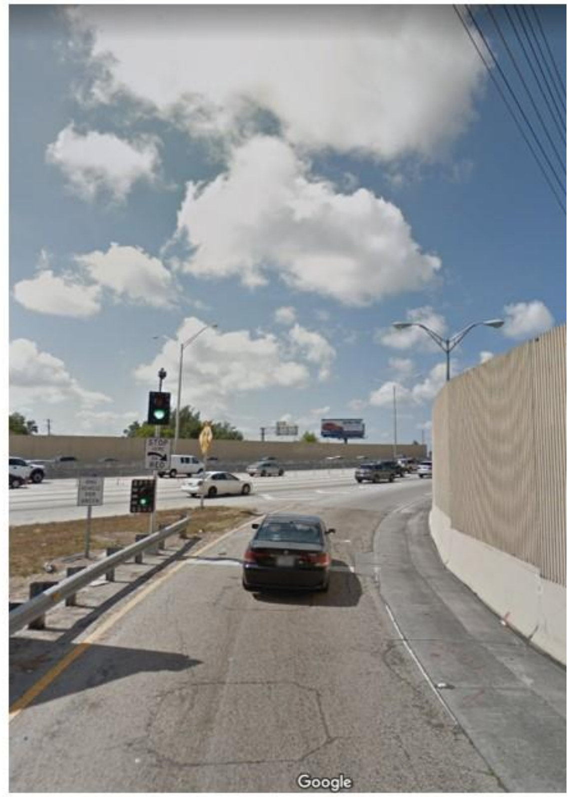
4.1.1 Study Corridor

A section along I-95 in Miami-Dade County, Florida was selected as the study corridor to evaluate the mobility benefits of the ramp metering strategy. This approximately 10-mile section of I-95 has a ramp metering system stretching between Ives Dairy Road and NW 62nd Street in both travel directions. Ramp Metering Signals (RMSs) started operating in 2009 and are located at each of the 10 ramps along I-95 NB and 12 ramps along I-95 SB (Zhu et al., 2010). The FDOT District 6 operates and manages the system. Figure 4-1(a) shows the locations of the existing RMSs in the study corridor and Figure 4-1(b) shows the ramp metering signal at the NW 69th when merging with I-95 NB.

The number of ramp vehicles joining the freeway per given time for each ramp (i.e., ramp metering rates) on the corridor is estimated using the Washington Fuzzy Logic algorithm. The Washington Fuzzy Logic algorithm is a system-wide control that is responsive to both local and corridor-wide real-time traffic conditions (Mizuta et al., 2014). The algorithm utilizes the traffic conditions upstream and downstream, and ramp queues in managing and controlling traffic on the freeway network. The Fuzzy Logic algorithm establishes the metering rates through a three-step procedure: fuzzification, activation of rules, and generation of numerical rates (i.e., defuzzification). Fuzzification involves translating the numerical inputs of the segment traffic conditions, such as occupancy, into the fuzzy classes. The developed fuzzy states are then associated with weighted rules to develop the metering rate and the degree of activation of each rule outcome. Finally, at the defuzzification stage, the developed metering rates that are represented by a set of linguistic fuzzy classes are converted to a single metering rate.



(a) On-ramps with RMSs in Miami-Dade County (adapted from Zhu et al., 2010)



(b) RMS at NW 69th Street along I-95 NB

Figure 4-1: Ramp Metering Performance Evaluation Study Corridors

4.1.2 Data

Three datasets were used to evaluate the mobility benefits of the ramp metering strategy: traffic flow data, RMS operations data, and contextual data.

4.1.2.1 Traffic Flow Data

Traffic flow data were collected from the Regional Integrated Transportation Information System (RITIS), a comprehensive database containing data from different original sources. The travel time data originated from HERE Technologies, while the traffic volume, speed, and occupancy data originated from traffic sensors managed by the FDOT District 6. All the traffic flow data were collected for a period of three years, from 2016 - 2018.

The HERE system records the travel time for freeway segments. The start and end of the segments in the HERE data are defined by the location of the off-ramps and on-ramps. To maintain consistency between the HERE data, traffic sensors used for the volume, speed and occupancy data extraction were selected to correspond with the start- and end-points of the HERE system segments. In addition, on-ramp traffic flow data were collected from on-ramp loop detectors categorized as passage loops, demand loops, or ramp-queue loops, depending on the location along the ramp.

4.1.2.2 RMS Operations Data

RMS operations data for the study period (2016 - 2018) were obtained from the FDOT District 6 Regional Transportation Management Center (RTMC). Data collected included: turn-On/Off time, turn-On reason, and event identification if the turn-On reason was an incident. The turn-On reason consisted of six categories: recurrent congestion, non-recurrent congestion, incident, weather, central time of day (CTOD), and local time of day (LTOD).

4.1.2.3 Contextual Data

To supplement the traffic flow and RMS operations data, the number of points along the mainline where vehicles entered the freeway (on-ramps) and vehicles exited the freeway (off-ramps) were determined using Google Maps.

4.1.3 Methodology

This study used travel time reliability to measure the effectiveness of the RMS operations on the study corridor. The most effective methods of measuring travel time reliability include the 90th or 95th percentile travel times, the buffer index, and the planning time index. Buffer index (BI) was selected to analyze the effectiveness of RMSs based on its popularity and ability to capture the true variation of the travel time at any time of day. The study compared the BI values of the study corridor when the RMSs were operational and when they were not operational. The following sections discuss the process adopted to estimate the mobility benefits of ramp metering systems using the BI.

4.1.3.1 Study Segments

Since the RMSs along the corridor were not turned on at the same time, the consecutive RMSs that were turned on at the same time were grouped together. The entire corridor was therefore divided into three segments for each direction of travel. Table 4-1 shows the most common turn-On/Off times for each study segment, length of the segment, number of on-ramps and off-ramps, number of days when at least one of the RMS was off during the most common turn-On/Off period, and number of days when all RMSs were on during the most common turn-On/Off period.

Table 4-1: Descriptive Statistics of RMS Study Segments

Segment	Direction	Length (miles)	No. of On-ramps	No. of Off-ramps	Turn-On Time	Turn-Off Time	No. of days at least one RMS was turned off	No. of days all RMSs were turned on
1	NB	2.6	4	3	2:45 pm	8:00 pm	296	74
2	NB	2.5	3	3	3:30 pm	8:00 pm	20	130
3	NB	5.3	3	3	*	*	*	*
4	SB	4.0	4	3	7:45 am	8:00 am	135	136
5	SB	3.0	4	2	6:30 am	9:00 am	52	108
6	SB	3.6	4	5	6:30 am	10:00 am	36	126

Note: * indicates no pattern for most common turn-On/Off times.

The days when RMSs were operational and the days when RMSs were not operational during the study period, and the most frequent turn-On/Off time for each segment were identified from the RMS operations data. The days when at least one of the RMSs was not operational were included in the analysis since all RMSs in a segment were turned off for a very few days, if any. Therefore, the analysis results provided the most conservative mobility benefits estimates. Holidays and the days affected by Hurricane Irma in 2017 and Hurricane Michael in 2018 were excluded from the analysis, as well as the days when RMSs were operational due to incidents or adverse weather. Segment 3 was excluded from the analysis due to lack of turn-On/Off time pattern while segment 4 was excluded because of having a short operational duration. Segment 2 was also excluded from the analysis due to few RMS non-operational days (< 30 days). The remaining segments, Segments 1, 5, and 6, as shown in Figure 4-2, were used in the analysis of ramp metering benefits.

4.1.3.2 Estimation of the Buffer Index (BI)

The BI represents the *extra* time (in minutes) that travelers must add to their average time when planning trips to ensure on-time arrival at a given confidence level. As shown in Equation 4-1, the BI is calculated as the ratio of the difference between 95th percentile travel time and average travel time to the average travel time. Travel time data for the study segments, collected from HERE, for the identified RMS operational and non-operational days were used to estimate the BIs.

$$BI = \frac{95th\ percentile\ travel\ time - Average\ travel\ time}{Average\ travel\ time} \tag{4-1}$$

The BIs were calculated for each 5-minute interval when the RMSs were operational. There were a different number of observations for each segment because of dissimilar durations between the turn-On and turn-Off times. As discussed earlier, segments 1, 5, and 6 were used to analyze the travel time reliability along the study corridor, while segments 2, 3, and 4 were excluded from the analysis.

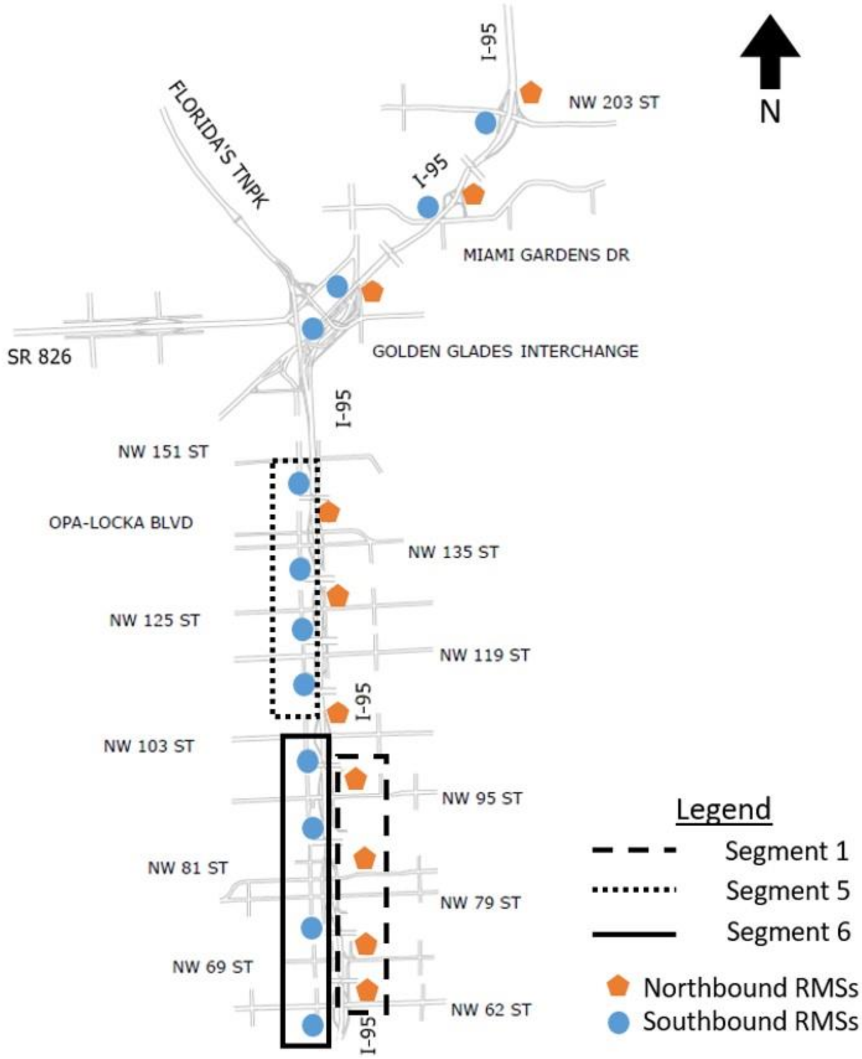


Figure 4-2: Study Segments Selected for Analysis of Ramp Metering Benefits

4.1.3.3 Penalized Regression Methods

Penalized regression methods were used to develop a model that can predict BIs of the freeway mainline segment when RMSs were operational and not operational. Penalized regression methods regularize (constrain) regression coefficients to enhance prediction accuracy and interpretability of a model (James et al., 2013). The imposed regularization allows the less contributive variables to have a coefficient close to or equal to zero (Kassambara, 2017) thus identifying the most influential variables. Two of the most common penalized regression methods are the ridge regression and the Least Absolute Shrinkage and Selection Operator (LASSO) regression (Kassambara, 2017). Two models were developed using both penalized regression methods (i.e., ridge regression and LASSO regression) and a model with better prediction accuracy was selected for prediction of the BIs on the freeway.

Given that the BIs are on a continuous scale, the relationship in Equation 4-2 between BIs and the predictor variables was established using linear regression. In Equation 4-3, y_i is the response for observation i, β_o is the constant term, β_j are the estimated model coefficients, x_{ij} is a vector of predictors j for observation i, and ε_i is the error term. The penalized methods (ridge regression and LASSO regression) were introduced in the estimation of the coefficients β_j of the linear regression. Ridge regression coefficient estimates are the values that minimize Equation 4-3 where $\lambda \geq 0$ is a tuning parameter, RSS is the residual sum of squares. Ridge regression shrinks close to zero the coefficients of variables with a minor contribution to the response variable (Kassambara, 2017). Although ridge regression shrinks coefficients towards zero it does not set the coefficients exactly to zero.

The LASSO regression is an alternative that achieves variable selection by setting coefficients exactly to zero and account for the existing multicollinearity between variables. The LASSO regression coefficients estimates are values that minimize Equation 4-4. As λ increases, the elements of β_j are continuously reduced towards zero, such that some elements will be reduced to zero and automatically deleted. Both models were developed using the 5-minute interval BI values of the study segment as the response variable. The penalized regression models were developed using the GLMNET package in *R*.

$$y_i = \beta_0 + \beta_j x_{ij} + \varepsilon_i \tag{4-2}$$

$$\sum_i^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^p \beta_j^2 = RSS + \lambda \sum_{j=1}^p \beta_j^2 \tag{4-3}$$

$$\sum_i^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^p |\beta_j| = RSS + \lambda \sum_{j=1}^p |\beta_j| \tag{4-4}$$

The penalized regression models were developed using the 5-minute interval BI values of the study segment as the response variable. The following predictor variables were used in the models: RMS operational status (i.e., On or Off), mainline Level of Service (LOS), mainline average traffic speed, ramp volume, on-ramp density, and off-ramp density. The status of the RMS variable had two categories, i.e., On and Off. The On category corresponded to the 5-minute interval BI values when all RMSs were On, while the Off category corresponded to the 5-minute intervals when at least one of the RMSs along the segment was Off.

The mainline LOS was estimated from the traffic occupancy data extracted from RITIS. The traffic occupancy represented the average traffic occupancy of the sections defined by the traffic sensors in each study segment. The relationship between traffic occupancy and LOS was established based on previous work by Bertini et al. (2004). Table 4-2 shows the relationship between the traffic occupancy and LOS used to estimate the mainline LOS variable for the model.

Table 4-2: Traffic Occupancy for Different Levels of Service (LOS)

LOS	Occupancy (%)
A	0 ≤ Occupancy < 5
B	5 ≤ Occupancy < 8
C	8 ≤ Occupancy < 12
D	12 ≤ Occupancy < 17
E	17 ≤ Occupancy < 28
F	Occupancy ≥ 28

The mainline traffic speed represented the average traffic speed of the study segment at the 5-minute interval data extracted from RITIS. The on-ramp density referred to the number of on-ramps per the segment length, while the off-ramp density was estimated from the number of off-ramps per the segment length.

4.1.3.4 Prediction Accuracy

Cross-validation was used to test the prediction accuracy of the fitted models. Data were divided into training and testing datasets. Data contained 276 observations where each observation represented a 5-minute interval within the ramp metering operational timeframe of the selected study segments (Segment 1, 5 and 6). Also, data included the same number of observations when all RMSs in a segment were turned on and when at least one RMS was turned off. About 80% of the data was used as the training dataset to fit the models and 20% was used as the testing dataset. The training and testing dataset observations were selected randomly. The Root Mean-Squared Error (RMSE) between the predicted and the observed BI values from the testing dataset were used to measure the prediction accuracy of the model.

4.1.3.5 Mobility Enhancement Factors

A Mobility Enhancement Factor (MEF) is a multiplicative factor used to describe the mobility benefits of a TSM&O strategy on a specific infrastructure element, i.e., intersection, corridor, etc. The observed infrastructure mobility level which is measured by a selected performance measure is multiplied by the MEF to determine the expected mobility benefits of the TSM&O strategy. For example, since the BI was selected as a performance measure for ramp metering, the expected BIs due to ramp metering are estimated by applying the MEF on the BIs of the freeway segment without RMSs. A MEF of 1.0 is considered a reference, such that a value below or above 1.0 represents a decrease or increase of the BIs due to ramp metering.

MEF for ramp metering was calculated using Equation 4-5, where $\hat{y}_{o,i}$ is the predicted BI of *i*th 5-minute time interval in dataset assuming the RMS was On, and $\hat{y}_i$ is the predicted BI of the *i*th 5-minute interval in dataset assuming that RMS was Off.

$$MEF_i = \frac{\hat{y}_{o,i}}{\hat{y}_i} \tag{4-5}$$

The overall MEF of the RMSs was calculated using Equation 4-6, where MEF is the mobility enhancement factor for each 5-minute interval from the *i*th 5-minute interval to the *n*th 5-minute interval.

$$MEF_{BI}^{RMS} = \frac{\sum_i^n MEF}{n} \tag{4-6}$$

4.1.4 Results

4.1.4.1 Descriptive Statistics

Table 4-3 shows the descriptive statistics of the variables used in the analysis. The mean, minimum, and maximum BIs were 0.446, 0.149, and 0.885, respectively. The average on-ramp volume was 32 vehicles/5-minutes, the minimum on-ramp volume was 18 vehicles/5-minutes, and the maximum on-ramp volume was 55 vehicles/5-minutes. The minimum and maximum on-ramp density was 1.11 ramps/mile and 1.54 ramps/mile, respectively. The minimum off-ramps density was 0.67 ramps/mile, and the maximum was 1.39 ramps/mile.

Table 4-3: Descriptive Statistics of the Continuous Variables for the RMS Study Segments

Variable	Mean	Standard Deviation	Minimum	Maximum
Buffer Index	0.446	0.164	0.149	0.885
Mainline Speed (mph)	29	8.794	15	49
Ramp Volume (vehicles/5-min)	32	9.936	18	55
On-ramp Density (ramps/mile)	1.359	0.187	1.11	1.54
Off-ramp Density (ramps/mile)	1.117	0.262	0.67	1.39

Figure 4-3(a) shows the distributions of the BI values when the RMSs were operational and not operational. The mean BI was 0.38 when the RMSs were operational and 0.51 when not operational. Figure 4-3(a) indicates that the BIs during RMS operations were less than BIs when not operational. For example, approximately 58% of the BIs were less than 0.4 during RMS operations while only 23% of the BIs were less than 0.4 when the RMSs were not operational. A Welch two-sample *t*-test was performed to test the hypothesis that the BIs during RMS operations were less than BIs when the RMSs were not operational. Results of the *t*-test indicated that the BIs during RMS operations were significantly less than BIs when the RMSs were not operational at the 95% confidence level. These findings indicate that travelers experience more reliable travel times when the RMSs are operational.

Figure 4-3(b) shows the distributions of the average traffic speed on the freeway mainline when the RMSs were operational and not operational. The distributions suggest that when the RMSs were operational, the average mainline speeds were higher than when RMSs were not operational. Traffic speeds during RMS operations ranged from 10 mph to 50 mph, and 10 mph and 40 mph when RMSs were not operational.

Figure 4-3(c) shows the distributions of the on-ramp traffic volume when the RMSs were operational and not operational. As illustrated in Figure 4-3(c), on-ramp volumes during RMS operations were slightly less than volumes observed when RMSs were not operational. On average, when RMSs were operational, on-ramp volumes ranged from 20 vehicles/5 minutes to almost 50 vehicle/5 minutes. When RMSs were not operational, average ramp volumes ranged from 20 vehicle/5 minutes to 60 vehicles/ 5 minutes.

Figure 4-3(d) shows the freeway LOS distributions when the RMSs were operational and not operational, according to the BIs. Low BI values were observed at LOS E&F, and high BIs were observed at LOS C&D. Also, the variability in the BI at LOS E&F was greater than at LOS C&D. Figure 4-3(d) suggests that the BI values for the study corridor were lower during RMS operations than when RMSs were not operational for both LOS C&D and LOS E&F.

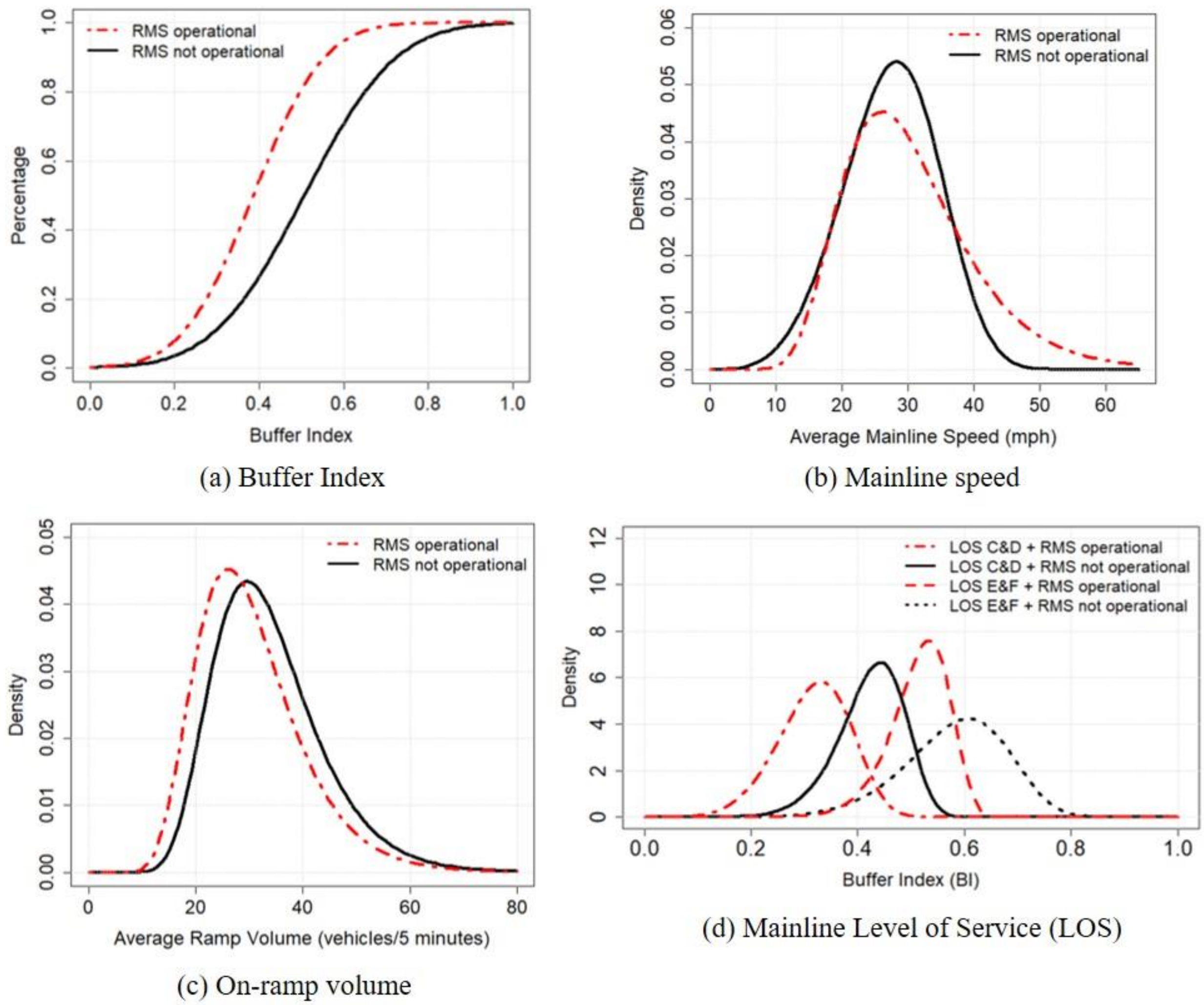


Figure 4-3: Distribution of Variables When RMSs Were Operational or Not Operational

4.1.4.2 Model Results

Table 4-4 shows the estimated parameters of the penalized regression models. The magnitude and sign of the estimated parameters indicate the influence of the variables on the BI values. Results from both the models are consistent in terms of the relationship between the independent variables and the BIs. Both models indicate that operations of the RMS have a positive impact on the travel time reliability of the segment. The coefficients of the RMS operations variable indicate a decrease in the BIs when the RMSs are operational. Similar to Bertini et al. (2004) this result suggests that RMS operations increase the travel time reliability on the freeway mainline.

Table 4-4 also shows the impact of LOS on travel time reliability of the freeway mainline. The estimates of the LOS variable suggest that LOS E&F is associated with lower BIs as compared to LOS C&D. There is a minor difference between the 95th percentile travel times and the average travel time on the freeway mainline when it is congested at LOS E&F than at LOS C&D. This indicates that traffic uses relatively similar travel time when traversing a segment during the congested periods (LOS E&F) on different days.

Table 4-4: Results of the LASSO Model

Variable	Category	Estimate	
		Ridge	LASSO
Intercept		-0.508	-0.096
RMS operations	No		
	Yes	-0.116	-0.130
LOS	C&D		
	E&F	-0.104	-0.008
Mainline Speed		0.008	0.013
Ramp Volume		0.004	0.010
Off-ramp Density		0.196	0.422
On-ramp Density		0.364	0.843
Root Mean Squared Error (RMSE)		0.108	0.107

High traffic speeds are associated with unreliable travel times. High speeds on the freeway mainline can be observed during uncongested periods; traffic speeds during these periods have more variability since drivers are able to acquire a greater range of speeds compared to congested conditions. During congested times, vehicles travel with lower speeds, and travel times are more consistent such that only minor variations exist between the 95th percentile travel times and the average travel time.

Similarly, high ramp volumes are associated with unreliable travel times on the freeway mainline. High ramp volumes indicate that more traffic enters the freeway mainline from the arterials. Traffic is easily allowed to enter the mainline during the uncongested times compared to congested times. Therefore, higher ramp traffic volumes are associated with periods where mainline traffic can acquire a greater range of speeds and, hence, high variance in the travel time.

High off-ramp density is associated with increased travel time unreliability. Off-ramp exits have a tendency to affect the mainline traffic when the downstream arterials receiving the traffic are congested. Therefore, the presence of many off-ramp exits in a short segment may result in higher variability in travel times along the mainline segment compared to the segment with few off-ramp exits.

The model results show that high on-ramp density is associated with increased travel time unreliability. Segments with high on-ramp density are subjected to many vehicles entering the freeway and increased turbulence at the merging locations. On-ramp merging locations are associated with increased traffic turbulence and variation of traffic conditions between locations upstream and downstream of the exit. Therefore, varying conditions at the exits negatively affect the travel time reliability of the freeway mainline.

4.1.4.3 Prediction Accuracy

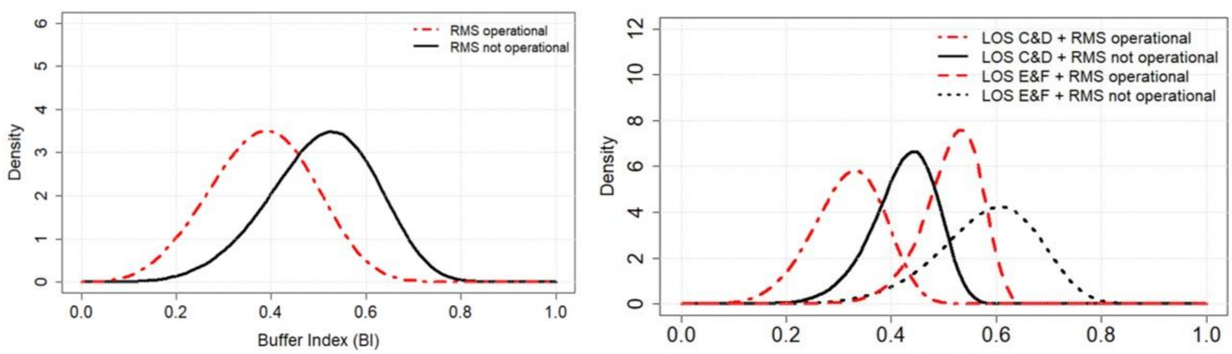
Results in Table 4-4 show that the RMSE of the ridge regression model and the LASSO model were 0.108 and 0.107, respectively. This indicates that the prediction accuracy of the LASSO model was slightly better than the prediction accuracy of the ridge regression. Therefore, the LASSO model was used to estimate the predicted BIs for calculating the MEFs.

4.1.4.4 Mobility Benefits of Ramp Metering System

MEFs for RMSs were estimated using the predicted BI values from the fitted LASSO model. MEFs of less than one (1.0) indicated improvement in travel time reliability due to RMS operations, and MEFs greater than one (1.0) indicated a worsening in travel time reliability due to RMS operations.

The predicted values of the travel time reliability measure (BI) when RMSs were operational and not operational were estimated using the fitted LASSO model. Figure 4-4(a) shows the distributions of the predicted BIs for both RMS scenarios. The distribution of the BIs when the RMSs were operational is more to the right of the distribution of BIs when RMSs were not operational. This indicates that the predicted BI values when the RMSs were operational are lower than when the RMSs were not operational. Thus, RMS operations improve the travel time reliability of the freeway mainline segments.

The predicted BIs were categorized according to the observed LOSs to evaluate the expected benefits when the RMSs were operational during LOS C&D and LOS E&F. Figure 4-4(b) shows the distribution of BIs for specific LOSs. All distributions of the BIs when the RMSs were operational are on the right of the corresponding distributions when the RMSs were not operational. This indicates that the RMS operations improve the travel time reliability of freeway segments during both LOS C&D and LOS E&F.



(a) Overall

(b) Specific LOS

Figure 4-4: Distribution of the Predicted BIs When RMSs Were Operational or Not Operational

The predicted values for the two LOS groups were averaged to estimate the MEFs of the RMS as described in Section 4.1.3.4. The MEFs were estimated using the predicted BIs at LOS E&F and LOS C&D. Table 4-5 shows the MEFs during both LOS C&D and LOS E&F. From Table 4-5, the MEF of RMS operations for LOS C&D is 0.784, indicating that RMS operations increase the travel time reliability along a segment by approximately 22%. The MEF of RMS operations for

LOS E&F is 0.701, indicating that RMS operations increase the travel time reliability along the segment by 30%.

Table 4-5: MEFs for Ramp Metering System

LOS	MEF
C & D	0.784
E & F	0.701

4.1.5 Conclusions

Ramp metering is a TSM&O strategy that utilizes signals installed at freeway on-ramps to improve mobility, travel time reliability, and safety on freeways. The analysis focused on calculating MEFs to quantifying the mobility performance of ramp meters. MEFs are numerical values that indicate the percent increase or decrease in a defined mobility performance measure. For this study, travel time reliability was selected as the mobility performance measure for estimating the MEFs of ramp meters. The MEFs were developed based on the operational performance of ramp meters along a 10-mile section on I-95 in Miami-Dade County, Florida. BI, estimated using the 95th percentile travel time and average travel time, was adopted as the travel time reliability measure for the analysis.

BIs were estimated for study segments when RMSs were operational and not operational using travel time data extracted from HERE. The MEFs were calculated as the ratio of the predicted BIs when ramp metering was operational to when not operational. Two penalized regression methods, ridge and LASSO regressions, were used to identify factors that can predict the BIs of a freeway segment with ramp metering. The regression models investigated various factors, including ramp metering operations, freeway mainline LOS, freeway mainline traffic speed, ramp volume, on-ramp density, and off-ramp density. The models indicated that all factors were significant in predicting the BIs of the segments with RMSs. The LASSO regression model was selected to predict the BIs of the study segment based on better prediction accuracy compared to the ridge regression.

The LASSO regression model predicted the BIs when RMSs were operational and not operational, and the predicted values were used to show the overall benefit of ramp metering. In addition, the predicted BI values were categorized based on freeway LOS and used to estimate the MEFs of ramp metering for different levels of service. The MEF for ramp metering at LOS C&D was 0.784, indicating a 22% reduction in the BI values. The MEF for ramp metering operations during LOS E&F was 0.701, indicating a 30% reduction in the BI values. In summary, the results showed mobility improvements in freeway traffic resulting from ramp metering operations, regardless of the LOS on the freeway mainline. Note that the improvements evaluated in this study are applicable when RMSs are operational during peak hours.

4.2 Dynamic Message Signs

Dynamic Message Signs (DMSs) are programmable electronic signs used for disseminating information to road users. Generally installed along freeways, DMS messages may consist of real-time alerts regarding unusual traffic conditions, roadway incidents, adverse weather conditions, construction activities, travel times, road closures or detours, advisory phone numbers, etc. The information displayed on DMSs enables fast and appropriate responses to changing traffic conditions and incidents, thus, assisting motorists in making informed decisions (Montes et al. 2008). Much of the literature on DMSs used surveys to evaluate the effectiveness (Cheng and Firmin, 2004; Peng et al., 2004; Chen et al., 2008). Surveys are effective in obtaining user perception on how drivers respond to different messages displayed on DMSs, especially pertaining to a driver's decision for route diversions, such as purpose of travel, schedule flexibility, travel distance, cause of congestion on current route, familiarity with alternative routes, information available on alternative routes, and previous experiences with traveler information. However, the responses that drivers provide may not necessarily be the same as how they would react when faced with actual situations. Therefore, this research used real-time traffic data to assess the reaction of drivers to the messages displayed on the DMSs.

4.2.1 Study Corridor

In Florida, DMSs have been deployed statewide on all major freeways and some arterials. For this study, the analysis focused on permanently mounted DMSs along I-75. Figure 4-5 shows the 470.7-mile I-75 corridor that runs across the entire state of Florida and passes through FDOT Districts 1, 2, 4, 5, and 7. This study corridor was selected primarily for two reasons: the presence of DMSs between on- and off-ramps and the availability of DMS message data from 2016 through 2018. As of June 2019, a total of 140 DMSs are operational along the study corridor.

Figure 4-5: DMS Performance Evaluation Study Corridor

4.2.2 Data

The data collection process involved contacting the TMCs in each District to acquire information on the locations of DMSs (i.e., longitudes and latitudes/ Mileposts), the direction of traffic that the permanent-mounted DMSs are facing (i.e., southbound or northbound), the logs of all messages displayed, and the begin and end timestamps for each message for a period of three years, from 2016 through 2018. Data from 43 DMSs were collected from the TMCs in FDOT Districts 1, 2, 4, 5, and 7. Entry logs for most DMSs consisted of more than 4,000 entries of messages throughout the 3-year analysis period. The messages involved travel time information, silver and amber alerts, congestion and safety warning messages, weather information, advisory messages, such as Driving under the Influence (DUI), seatbelt law, crashes and incidents information, roadworks, etc. Each message was associated with the time it was displayed and the time it was removed. Some messages were displayed for longer periods of time while others lasted for shorter durations. Traffic flow data used for analysis included real-time traffic volume, speed, and occupancy. These data were retrieved from RITIS for three years, from 2016 through 2018, and collected only for the detectors within the influence area of the DMSs. The following subsections discuss the data collection process.

4.2.2.1 DMS Influence area

An impact area upstream was identified for each DMS based on the average size of electronic sign characters and maximum visibility distance of the signs, as recommended in the Manual on Uniform Traffic Control Devices (MUTCD) (USDOT, 2009). The distance of 1,000 feet upstream was measured from the DMSs locations to consider factors that may limit the drivers' ability to see the message, such as the presence of horizontal or vertical curves, overpasses, or environmental factors. The influence area downstream was identified as the distance from the DMS location where the messages are being displayed to the next downstream exit point where drivers may consider exiting the freeway. The study corridor was divided into several segments; each segment contained the DMS influence area upstream of the DMSs where drivers are expected to be able to read the sign, and downstream between the DMS and the location of the next exit. After identifying the influence areas for DMSs, a total of 23 segments were selected for the analysis.

The DMSs were associated with the position of detectors defined in RITIS. For each DMS, an upstream detector within 1,000 ft, and at least one and up to two downstream detectors between the DMS location and the next exit were identified, as illustrated in Figure 4-6. Each detector zone ID consisted of detectors for each lane along the DMS influence segments. The number of lanes ranged from three to six lanes per direction based on the location of the DMS along the study corridor.

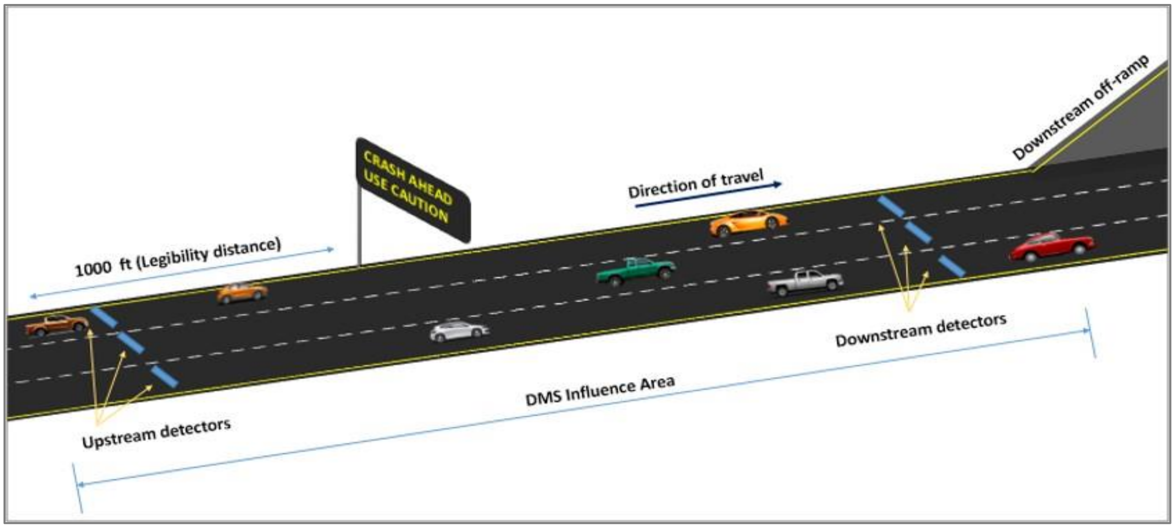


Figure 4-6: DMS Influence Area

4.2.2.2 DMS Log Messages

DMS messages listed in the logs included a variety of warning messages to drivers regarding their own safety, the safety of other drivers, stalled vehicles, and emergency responders. The data reduction process involved sorting the messages that reported information requiring driver action. Although there were several messages identified that reported critical roadway conditions that required drivers' attention, the analysis was focused on messages that displayed incidents or *crash* information. These messages informed drivers of the presence of a crash downstream along the corridor and gave information about possible impacts of the crash, such as lane closures. Some of the messages indicated the location of the crash in terms of distance from the DMS, such as the mileposts of the crash locations and names of the downstream intersecting roadways. Examples of such messages include "CRASH 1 MI AHEAD USE CAUTION", "CRASH I-75 AT SR-222/NW 39TH AVE RT LANE BLOCKED", CRASH I-75 BEYOND CR-234 ALL LANES BLOCKED", etc.

4.2.3 Methodology

4.2.3.1 Average Speed Adjustments

After identifying the messages conveying information about crashes, termed as *crash* messages in this study, the analysis focused on observing the changes in traffic patterns, particularly speed adjustments, in order to assess the reaction of drivers to the displayed messages. Traffic speeds observed 30 minutes prior to the display of the *crash* messages were compared with the observed speeds 30 minutes during the display of the *crash* messages. During the 30-minute "before" period, the DMSs displayed messages that did not require drivers to change their driving behaviors, e.g., travel time information, amber alerts, and advisory messages, such as "BUCKLE UP", "DO NOT DRIVE UNDER INFLUENCE", etc. These types of messages are termed *clear* messages in this study. The analysis was performed to observe if drivers reacted to the messages by comparing the average speeds while the *clear* message was being displayed with the average speeds while the *crash* message was being displayed.

The analysis started with identifying the *clear* (i.e., non-crash related) and *crash* DMS messages among other messages and merging them with real-time traffic data from RITIS. For every *crash* message that had been displayed for at least 30 minutes, the message that was displayed 30 minutes prior was checked. For example, if a crash occurred at 8:00 AM, and the DMS upstream displayed a *crash* message from 8:05 AM – 9:35 AM, the displayed message in the prior 30-minute period (7:35 AM – 8:05 AM) was checked to determine if it fits the criteria of a *clear* message, such as "CLICK IT OR TICKET". If the prior message was a *clear* message that also lasted for at least 30 minutes, then (i) the average speed 30 minutes during the *clear* message, and (ii) the average speeds during the first 30 minutes of the *crash* message were calculated. The two sets of speed data were then compared using a paired *t*-test to determine if the drivers changed their speeds after seeing the *crash* messages displayed on the DMSs. The speed ratio of the two sets of speed data was used in the analysis to determine the mobility impacts of the DMSs.

The *crash* messages were analyzed based on lane blockage information. This was based on secondary information displayed on the DMSs describing the impact of a crash and or advising drivers *en route* of the possible actions required. To observe the impact of the displayed messages on speed adjustments, the information was categorized into five groups: (i) use caution, (ii) all lanes blocked, (iii) right lane blocked, (iv) left lane blocked, and (v) others.

4.2.3.2 Welch's *t*-test

Welch's *t*-test (unequal variance *t*-test) is a modification of a Student's *t*-test to determine if two sample means are significantly different. This test is recommended over the student's *t*-test because it does not assume equal variances between the two datasets. It modifies the degree of freedom used for the Student's *t*-test and hence increases the test power for samples with unequal variances. Equation 4-7 shows Welch's *t*-test statistic, and Equation 4-8 denotes the degree of freedom for the Welch's *t*-test.

$$t = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{s_1{}^2/n_1 - s_2{}^2/n_2}} \tag{4-7}$$

$$\text{Degree of freedom} \approx \frac{\left(\frac{s_1{}^2}{n_1} - \frac{s_2{}^2}{n_2}\right)^2}{\left(\frac{s_1{}^4}{n_1{}^2 v_1} - \frac{s_2{}^4}{n_2{}^2 v_2}\right)} \tag{4-8}$$

where $\bar{X}_1$ and $\bar{X}_2$ are sample means, s_1 and s_2 are sample variances, n_1 and, n_2 represent the sample size for the first and the second samples, and v_1 and v_2 are the degrees of freedom associated with the first and the second variance estimate.

4.2.3.3 Multiple Linear Regression

To estimate the influence of other factors in speed adjustments, a multiple linear regression model was developed with the speed ratio as the response variable. Speed ratio was calculated as the ratio of the average speeds during the *crash* message to the average speeds during a *clear* message, as shown in Equation 4-9. Multiple linear regression was performed to model the relationship between two or more predictor variables and the response variable by fitting a linear equation to observed data. Equation 4-10 gives the model formula with the speed ratio (R_s) as the response variable.

$$R_s = \frac{Average\ speeds_{crash}}{Average\ speeds_{clear}} \tag{4-9}$$

$$y_i = \beta_0 - \sum_{i=1}^{n} \beta_i x_i \tag{4-10}$$

where, R_s = the speed ratio,
y_i = R_s for the *i*th observation,
β_0 = the estimated intercept,
β_i = the estimated regression coefficient of independent variable *I*, and
x_i = value of independent variable i.

The predictor variables in the model included temporal, traffic flow, and content of message variables described in Table 4-6. Prior to modeling, the variables were checked for association using Pearson's Correlation method and multicollinearity by ensuring the variance inflation factor was less than 10.

Table 4-6: Descriptive Statistics of the Categorical Variables for Calculating the Speed Ratio

Categorical Variable	Factor	Frequency	Share (%)
Lane Blocked	None-Use Caution	462	11
	All	393	9
	Left	1,236	29
	Right	1,732	41
	Other	372	9
Day of the week	Weekdays	2,960	71
	Weekends	1,235	29
Time of day	Off-peak hours	2,534	60
	AM peak	624	15
	PM peak	1,037	25

4.2.4 Results

4.2.4.1 Descriptive Statistics

The analysis was based on 23 DMSs along I-75 and focused on messages that informed drivers of crashes ahead from 2016 through 2018. The timestamps of the displayed messages were matched with the real-time traffic flow data collected from detectors upstream and downstream of each DMS. Table 4-7 provides the descriptive statistics of the averages of traffic variables collected from the detectors for the duration of *clear* and *crash* messages.

Table 4-7: Descriptive Statistics of the Traffic Data for Calculating the Speed Ratio

	$Speed_b$ (mph)	$Speed_a$ (mph)	$Volume_b$ (veh/5min)	$Volume_a$ (veh/5min)	$Occupancy_b$ (%)	$Occupancy_a$ (%)
Mean	68.75	64.70	51.32	48.11	5.07	6.28
Standard Deviation	10.79	16.48	45.49	42.87	4.43	7.64
Minimum	5.44	3.00	0.00	0.07	0.00	0.00
Maximum	107.17	111.00	344.83	305.71	33.87	59.17
Count	4,195					

Note: $_b$ – during a *clear* message, $_a$ – during the *crash* message.

The two sets of speed data (i.e., the average speed during *clear* messages and average speed during *crash* messages) were compared. As can be observed from Figure 4-7, once the messages pertaining to a crash were displayed, average speeds reduced 57% of the time, increased 41% of the time, and remained the same 2% of the time. Figure 4-8 provides the distributions of the two sets of speed data.

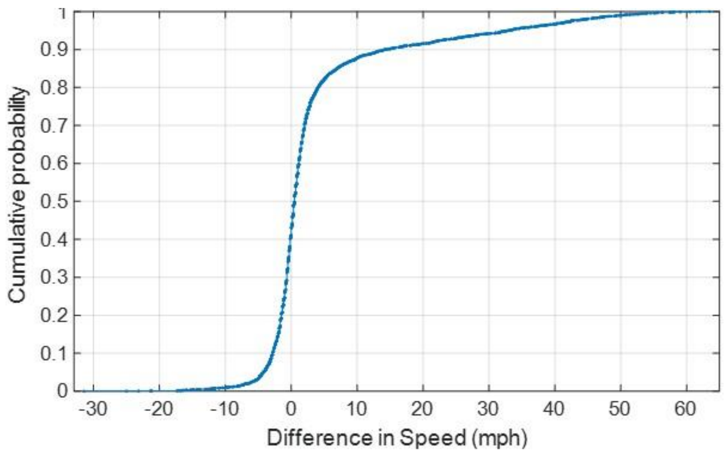
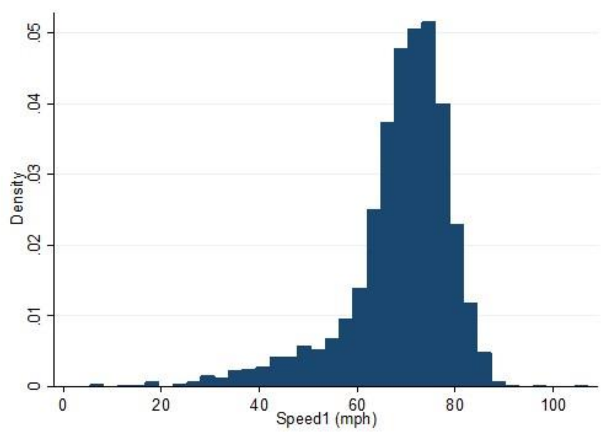
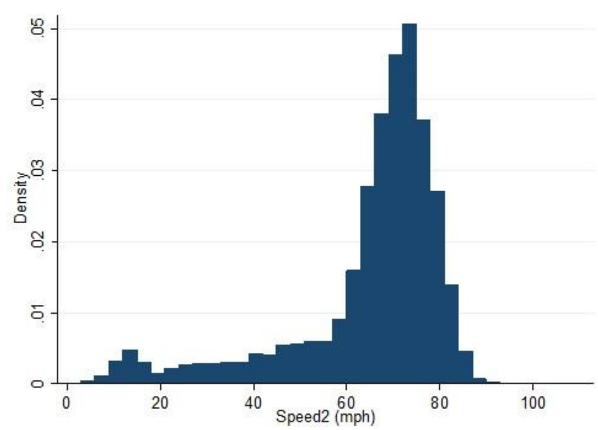


Figure 4-7: Difference in Speeds When *Clear* and *Crash* Messages Are Displayed on DMSs



(a) Average Speeds During *Clear* Messages



(b) Average Speeds During *Crash* Messages

Figure 4-8: Average Speeds When *Clear* and *Crash* Messages Are Displayed on DMSs

4.2.4.2 Paired *t*-test

A paired *t*-test analysis was performed for the two sets of average speed data. The null hypothesis was that the difference in the means of average speeds when *clear* messages were displayed and when *crash* messages were displayed is zero (i.e., H_o: $\bar{X}_{clear} = \bar{X}_{crash}$). The alternative hypothesis was that the average speeds when *clear* messages were displayed are greater than the average speeds when *crash* messages were displayed at a 95% confidence level (i.e., H_a: $\bar{X}_{clear} > \bar{X}_{crash}$). Table 4-8 presents the *t*-test results.

The t-statistic value was found to be greater than the critical t-values at a 95% confidence level. The results imply that the null hypothesis can be rejected. The average speeds during the *clear* messages were found to be significantly higher than the average speeds during the *crash* messages. The mean difference in speeds was 3.75 mph indicating that the average speeds decreased when the *crash* messages were displayed.

Table 4-8: Paired *t*-test Results

	*Clear*_Speed	*Crash*_Speed
Mean	68.750	64.996
Variance	116.411	271.693
Observations	4195	4195
Pearson Correlation	0.739	
Hypothesized Mean Difference	0	
df	4194	
t Stat	**21.726**	
P(T<=t) one-tail	**0.000**	
t Critical one-tail	**1.645**	

4.2.4.3 Model Results

Table 4-9 presents the multiple linear regression model results. The results indicated that all variables were statistically significant at the 95% confidence level except when all lanes are closed. The fourth column shows the model coefficients, whereby negative coefficients imply a reduction of speed during *crash* messages with respect to *clear* messages. The overall average speed reduction when all variables are at their mean is 0.94, implying that there were lower average speeds when *crash* messages were displayed compared to when the DMSs displayed *clear* messages with no crash indicated downstream.

Traffic Factors: The real-time traffic volume had a positive regression coefficient in the model indicating that a unit increase in traffic volume (i.e. the number of vehicles passing through a point in a given time) results in an increase in speed ratio. In other words, when the DMSs are displaying messages about crashes, the higher the traffic volume, the more drivers increased their speeds. Occupancy had an inverse relationship since vehicle speeds were lower when detectors recorded high percentage occupancy.

Temporal Factors: Day of the week was grouped into weekdays and weekends. The results show that the average speeds reduced when the DMSs were displaying *crash* information on weekends compared to weekdays. This may be attributed to drivers being less in a rush on weekends, so they are more willing to comply with the displayed messages. Similarly, during peak hours, average speeds were observed to increase compared to off-peak hours.

Table 4-9: MLR Model Coefficients

Variable	Category	Mean (X)	Coeff (β)	β *X	Std. Err.	P>t	[95% Conf. Level]	
Volume	Continuous	47.844	0.0007	0.0344	0.0001	0.000*	0.0006	0.0008
Occupancy	Continuous	6.2809	-0.0202	-0.1269	0.0003	0.000*	-0.0207	-0.0196
Day of week	Weekday	0.7053						
	Weekend	0.2947	-0.0132	-0.0039	0.0044	0.003*	-0.0220	-0.0045
Time of Day	Off-Peak	0.6036						
	1-AM Peak	0.1489	0.0235	0.0035	0.0059	0.000*	0.0119	0.0351
	2-PM Peak	0.2475	0.0366	0.0091	0.0049	0.000*	0.0269	0.0463
Lane blocked	Use Caution	0.1103						
	1-All lanes	0.0928	-0.0125	-0.0012	0.0089	0.159	-0.0299	0.0049
	2-Left	0.2947	-0.0193	-0.0057	0.0070	0.006*	-0.0331	-0.0055
	3-Right	0.4131	-0.0255	-0.0106	0.0068	0.000*	-0.0388	-0.0123
	4-Other	0.0890	-0.0540	-0.0048	0.0089	0.000*	-0.0715	-0.0364
Constant				1.0461	0.0070	0.000*	1.0324	1.0598
Average				**0.94**				

R-squared = 0.5679, *Significant at a 95% confidence level

Message Text Contents: Messages displayed on the DMS contained roadway condition information and additional information that directs drivers on how they should react to the condition. For messages displaying *crash* information, secondary information advising road users on lane blockages depends on the severity of the crash. For analysis, this secondary information was classified as: use caution, all lanes blocked, right lane blocked, left lane blocked, and others (e.g., exit ramps closed, shoulders blocked, etc.). Model results indicate that compared to a "use caution" message, lane blockage information resulted in lower average speeds when the DMS was displaying additional information with *crash* messages. The observation of right/left lane closure having more impact than all lane closure could partially be the result of lane change maneuvers. Drivers may tend to move away from the lanes that are said to be closed as opposed to situations when the message suggests that all lanes are closed.

4.2.4.4 Mobility Enhancement Factors

To examine the performance of the DMSs, MEFs were calculated based on speed adjustments. The ratios of average speeds during the *crash* messages to average speeds during a *clear* message were determined for each *crash* message. Other factors that could affect the speed of vehicles, such as volume, occupancy, temporal factors, and the content of the message, were used to perform a multiple linear regression analysis with the speed ratio as the response variable. Ratio values below 1 indicate a reduction in speed after displaying the message, whereas a value above 1 indicates an increase in speed. The predicted speed ratios from the multiple linear regression model were used to estimate the overall MEF using Equation 4-11, where n is the number of observations. As seen in Table 4-10, displaying *crash* messages on DMSs is expected to reduce average vehicle speed overall by 6.0%, compared to DMSs displaying *clear* messages.

$$MEF_{Speed\ adjustment}^{DMS} = \frac{\sum_{i=1}^{n} MEF}{n} \tag{4-11}$$

Table 4-10: MEFs for DMSs

Variable	Category	MEF	% Reduction in Speed
Volume	Volume	0.91	9.4
Occupancy	Occupancy	1.05	-4.7
Day of week	Weekday	0.94	6.0
	Weekend	0.93	6.9
Time of Day	Off-Peak	0.94	6.0
	1-AM Peak	0.96	4.0
	2-PM Peak	0.97	3.2
Lane blocked	Use caution	0.94	6.0
	1-All lanes	0.93	7.1
	2-Left	0.93	7.4
	3-Right	0.93	7.5
	4-Other	0.89	10.9
Average		0.94	5.8

4.2.5 Conclusions

The analysis focused on calculating the MEFs for DMSs by considering the reactions of drivers when the displayed messages on DMSs did not require any action (clear condition/information) versus when the DMSs displayed messages about crashes. Real-time traffic data, including speed, volume, and occupancy retrieved from RITIS and information on DMS locations and displayed messages collected from TMCs were used in the analysis.

The methodology involved assessing the reaction of drivers to crash messages by looking at their speed adjustments between the *clear* and *crash* message display durations. For every *crash* message that had been displayed for at least 30 minutes, the message that was displayed 30 minutes prior was checked. If the prior message was a *clear* message that also lasted for at least 30 minutes, then average speeds were determined for the 30-minute period during the *clear* message and the first 30 minutes after the *crash* message was displayed. The average speed ratio (average speed during *clear* messages to average speed during *crash* messages) was then used as a performance measure to estimate the MEFs of DMSs.

The *t*-test results comparing the average speeds during *clear* message periods and *crash* message periods showed that the average vehicle speeds along DMS influence areas decreased by 3.75 mph when messages of crashes downstream were displayed compared to when the messages indicating clear conditions or general information that did not require drivers to change their driving patterns were displayed. The overall MEF with speed ratios as a performance measure was found to be 0.94, implying that there was a 6% reduction in average speeds when the DMSs displayed *crash* information. Results also revealed that among messages displaying *crash* information, if secondary information required drivers to "use caution", there were fewer speed reductions compared to lane blockage information (all lanes blocked, left lane, blocked, and right lane blocked). This implies that the drivers were more willing to reduce speeds if there were blocked lanes downstream as a result of a crash.

With a better understanding of drivers' speed adjustments as a response to different message types displayed on DMSs, agencies can better plan potential sign locations, the wording of the messages, and predict the resulting impact on traffic management operations. It should be noted that there is a complex relationship between the messages displayed and the resulting reaction of drivers; thus, displaying a certain type of message will not automatically lead to an improvement in all circumstances.

4.3 Road Rangers

The Road Rangers Service Patrol (simply known as Road Rangers) is a Freeway Service Patrol (FSP) program provided by FDOT that offers free highway assistance services to motorists. Road Rangers provide a direct service to motorists by providing a limited amount of fuel, assisting with tire changing and other types of minor repairs, and by quickly clearing travel lanes affected by incidents, as well as supporting other responders at crash sites. Florida's Road Rangers provide free highway assistance services during incidents on state roadways to reduce delays and improve safety for the motorists and incident responders. The following sections discuss the selected study corridors, data collected, and the methodology used to quantify the mobility benefits of the Road Ranger program.

4.3.1 Study Corridors

The following freeway corridors in Jacksonville, Florida were included in the analysis of the mobility benefits of Road Rangers: Butler Boulevard/State Road 202 (SR-202), Interstate 10 (I-10), I-95, and I-295. As shown in Figure 4-9, the study corridors include a 35-mile section of I-95, a 21-mile section of I-10, a 61-mile section of I-295, and a 13-mile section of SR-202 (Butler Blvd.), for a total of 130 miles.

Figure 4-9: Road Rangers Performance Evaluation Study Corridors

4.3.2 Data

Incident data were obtained for the years 2014 – 2017 from the SunGuide® database, an FDOT repository of incident information, for freeway sections along Butler Blvd./SR-202, I-10, I-95, and I-295 in Jacksonville, Florida. Data collected included incident detection times, response times, clearance times, and geographic locations to identify both the temporal and spatial information of incidents. Other information obtained included the incident type, detection method, severity, and the agencies that responded. A total of 28,000 valid observations (N) were included in the analyses, and observations with missing information were removed from the dataset. Prior to developing the model, a preliminary analysis of the compiled incident data was conducted to identify the statistical characteristics of the different variables analyzed.

In this study, the response variable is the incident clearance duration, as illustrated in Figure 4-10. Incident clearance duration is defined as the time elapsed (minutes) from the time an incident is reported (i.e., first notified) until all evidence of the incident has been removed from the incident scene, i.e., when the last responder leaves the scene, as shown in Figure 4-10. Incident clearance duration consists of three stages: incident verification time, incident response time, and incident clearance time.

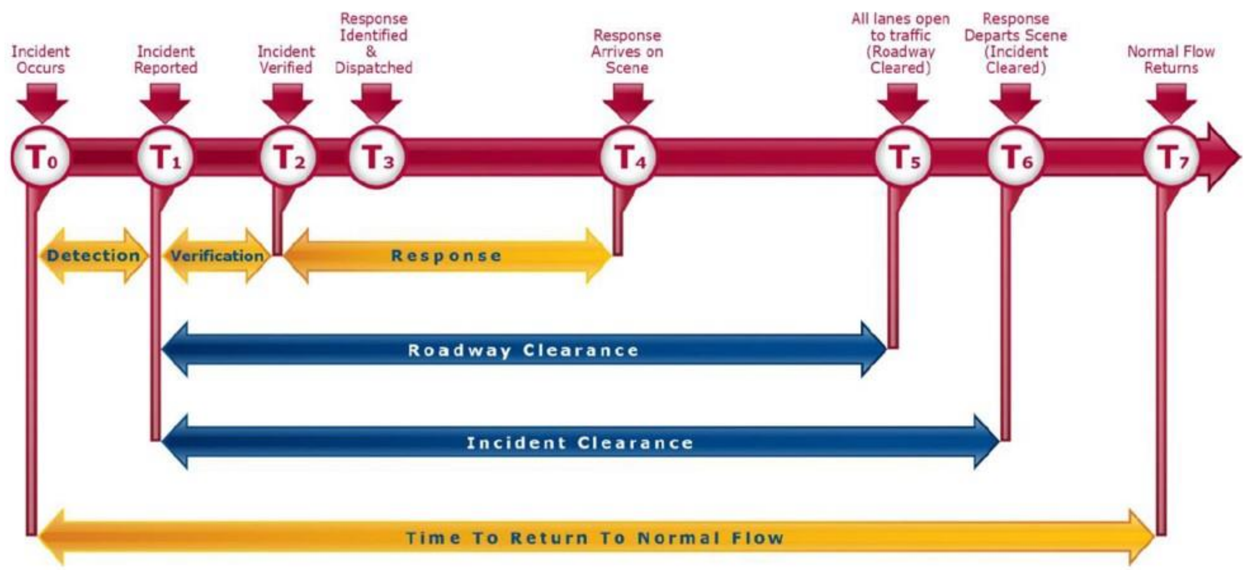


Figure 4-10: Traffic Incident Duration Timeline (Amer et al., 2015)

Table 4-11 lists the eleven explanatory variables included in the analysis. As shown in Table 4-11, the number of responding agencies variable was considered continuous, while the remaining ten variables, generally associated with freeway incidents, were considered categorical. *Event type* (or, *incident type*) was categorized into crashes, vehicle problems (disabled or abandoned vehicles, emergency vehicles, vehicle fires, and police activity), and traffic hazards (debris, flooding, and spillage). Two temporal variables, *time of day* and *lighting condition*, were included in the analysis. Peak hours included morning peak (0600 to 1000 hours) and evening peak (1530 to 1830 hours), and lighting condition was categorized as day or night based on sunrise and sunset times on the day of the incident. *The detection methods* were divided into three categories: Road Rangers, Intelligent Transportation System (ITS) services, and on-road services (e.g., police, Florida

Highway Patrol (FHP), and motorists). ITS services included the use of closed-circuit televisions (CCTV), the Florida 511 travel information system (FL511), FL511 probe vehicles, Waze, and TMCs.

The variable *lane closure* refers to whether an incident resulted in lane(s) closure. The percent of lanes closed is usually considered an indicator of the severity of an incident, as severe incidents tend to result in an increased number of lanes closed. In the current study, a 25% lane closure implies one lane out of four lanes of a roadway section is closed. A closure of one of three lanes will eventually mean 33.3% lane closure and 100% means all lanes are closed. This variable was considered discrete as 0 - 25 and 25%. *Shoulder blockage* was divided into two categories: No (no any shoulder is blocked) and Yes (at least one shoulder is blocked). In the same token, *towing* was divided into either no towing was involved, or towing was involved.

Table 4-11: Descriptive Statistics of Incident Data

Categorical Variables	Factor	Code	Frequency	Share (%)
Event Type	Crash	0	8,974	32.05
	Vehicle problems	1	17,231	61.54
	Traffic hazards	2	1,795	6.41
Detection Method	Road Rangers	0	14,790	52.82
	ITS services	1	2,649	9.46
	On-road services	2	10,561	37.72
Incident Severity	Minor	0	26,235	93.70
	Moderate	1	1,328	4.74
	Severe	2	437	1.56
Shoulder Blocked	No	0	17,106	61.09
	Yes	1	10,894	38.91

Valid N = 28,000, [a] response variable

Table 4-11: Descriptive Statistics of Incident Data (continued)

Categorical Variables	Factor	Code	Frequency	Share (%)
Lane Closure (%)	0 – 25	0	24,216	86.49
	> 25	1	3,784	13.51
Time of Day	Peak hours	0	15,475	55.27
	Off-peak hours	1	12,525	44.73
Day of the Week	Weekdays	0	26,066	93.09
	Weekends	1	1,934	6.91
Lighting Condition	Day	0	24,610	87.89
	Night	1	3,390	12.11
Towing Involved	No	0	24,580	87.79
	Yes	1	3,420	12.21
Responding Agencies	Road Rangers	0	23,680	84.57
	Other Agencies	2	4,320	15.43
Continuous Variables	**Min**	**Mean**	**Median**	**Max**
Number of Responding Agencies	1	1.7	1	10
Incident Clearance Duration[a] (min)	1	36.71	20	325

Valid N = 28,000, [a] response variable

4.3.3 Methodology

4.3.3.1 Quantile Regression

Previous studies have demonstrated the application of various modeling techniques to predict incident clearance durations, oftentimes resulting in skewed distributions. Such models include hazard-based models (Haule et al., 2018; Li and Shang, 2014; Sando et al., 2018), and nested models (Ghosh et al., 2012). The current study used quantile regression, a good methodology for outliers, to fit the incident clearance distribution. Other models may not accurately predict incidents that have a much shorter or longer than average duration. Theoretically, quantile regression provides better prediction accuracy since it can account for dispersed and skewed distributions of incident clearance durations. Quantile regression is a statistical technique that can relate quantiles of the incident clearance duration distribution to explanatory variables (Khattak et al., 2016), and a more complete picture of incident clearance duration distribution can be obtained through quantile regression analysis. Rather than modeling only the average incident clearance duration, as in Ordinary Least Square (OLS) regression, quantile regression can model the relationship of any quantile with a set of explanatory variables (Khattak et al., 2016). In quantile regression, a sum that gives asymmetric penalties for over-prediction, $(1-q)|\varepsilon_i|$, and under-prediction, $q|\varepsilon_i|$, is minimized (Koenker, 2005). The prediction errors in quantile regression are given by Equation 4-12.

$$\varepsilon_i^q = y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \tag{4-12}$$

where q is the quantile point of the outcomes, $0 < q < 1$,

y_i = observed duration for *i*th incident in data set (min),

$\hat{\beta}_0^q$ is the estimated intercept at quantile point q,

$\hat{\beta}_j^q$ is the estimated coefficient of independent variable *j* at quantile point q, and

x_{ij} = value of independent variable *j* in *i*th incident.

The coefficients $\hat{\beta}_0^q$ and $\hat{\beta}_j^q$ are estimated by minimizing the following objective function (Koenker, 2005) shown in Equation 4-13.

$$\sum_{i: y_i \geq \hat{\beta}_0^q + \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij}}^{n} q \left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \right| + \sum_{i: y_i \geq \hat{\beta}_0^q + \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij}}^{n} (1-q) \left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \right| \tag{4-13}$$

In this study, quantile regression was applied to predict incident clearance duration at the 5th, 15th, 25th, …, 95th percentiles. Table 4-12 provides the regression model results for the 25th, 50th (median), 75th, and 95th percentiles.

Incident Clearance Duration Prediction: From the perspective of modeling outcomes, OLS models provide intuitive results, giving a single value that is the predicted mean. Quantile regression provides estimates for any quantile q, where q can be any number between 0 and 1. Thus, the estimates incorporate the entire (conditional) distribution of incident clearance durations, given certain conditions, and do not provide just a single value of how long an incident may last.

Location-based Prediction: This study applied a location-based prediction method to predict incident clearance durations with quantile regressions at the 5th, 15th, 25th, …, 95th percentiles in increments of 10, with the assumption that traffic safety outcomes do not change dramatically in a short period (Khattak et al., 2016). Therefore, the predicted duration could be obtained at the 5th percentile regression if the observed value was less than the 10th percentile, or at the 15th percentile regression if the observed value was between the 10th and the 20th percentile, and so forth. Using the location-based prediction method, the incident clearance duration was predicted using Equation 4-14.

$$\hat{y} = \left\{ \hat{y}_m \left| \begin{array}{c} m = 5, if \;\; q_0 < \bar{y} \leq q_{10} \\ m = 15, if \; q_{10} < \bar{y} \leq q_{20} \\ \vdots \\ \vdots \\ m = 95, if \; q_{90} < \bar{y} \leq q_{100} \end{array} \right. \right\} \tag{4-14}$$

where,

$\hat{y}$ = predicted incident clearance duration using location-based prediction method,
$\hat{y}_m$ = predicted incident clearance duration at center of interval *m* (i.e., percentile location),
$\bar{y}$ = average of historical incident clearance duration at a particular location (e.g., bottleneck),
q_p = *p*th percentile value of durations of incidents in the region.

Using the coefficients from quantile regression, the probability that an incident with a given duration will occur, resulting in a change in values of the independent variables, can be quantified using Equations 4-15 and 4-16. Equations 4-15 and 4-16 estimate incident clearance durations when an incident is not related and related to a particular independent variable (category in case of discrete variable), respectively. This allows the prediction of the incident clearance duration given a certain value of the independent variable while holding other variables at their means.

$$y_i = \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} - \hat{\beta}_j^q x_{ij} \tag{4-15}$$

$$y_i = \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} - \hat{\beta}_j^q x_{ij} + \hat{\beta}_j^q \tag{4-16}$$

where y_i is the estimated duration (min) of *i*th incident for independent variable *j*. All other notations are defined earlier.

Model Accuracy

To investigate the accuracy of model predictions, the resulting Root Mean Square Error (RMSE) from the incident clearance duration predictions was calculated using the Equation 4-17. A smaller RMSE indicates a better prediction.

$$\text{RMSE} = \sqrt{\frac{\sum_i^n (y_i - \hat{y}_i)^2}{n}} \tag{4-17}$$

where,

n = number of observations,
y_i = observed duration (min) for *i*th incident in data set, and
$\hat{y}_i$ = predicted duration (min) for *i*th incident in data set.

4.3.3.2 Mobility Enhancement Factors

As defined earlier, a Mobility Enhancement Factor (MEF) is a multiplicative factor used to estimate the expected mobility level after implementing a given strategy, such as Road Rangers, at a specific site. The MEF is multiplied by the expected facility mobility level without the strategy. An MEF of 1.0 serves as a reference, where below or above indicates an expected increase or decrease in mobility, respectively, after implementation of a given strategy and depending on the performance metric. For example, in this study, an MEF of 0.8 for the incident clearance duration, the response variable (i.e., performance measure), indicates an expected mobility benefit; more specifically, a 20 percent expected reduction in incident clearance duration after treatment, and therefore, an increase in mobility. MEFs were calculated using Equation 4-18, as follows:

$$\mathrm{MEF}_i = \frac{\hat{y}_{r,i}}{\hat{y}_i} \tag{4-18}$$

where $\hat{y}_{r,i}$ is the predicted incident clearance duration for *i*th incident in dataset assuming Road Rangers were involved, and $\hat{y}_i$ is the predicted incident clearance duration for *i*th incident in dataset assuming Road Rangers were not involved. The overall MEF for Road Rangers was calculated using Equation 4-19.

$$MEF_{Incident\ clearance\ duration}^{Road\ Rangers} = \frac{\sum_{i=1}^{n} MEF}{n} \tag{4-19}$$

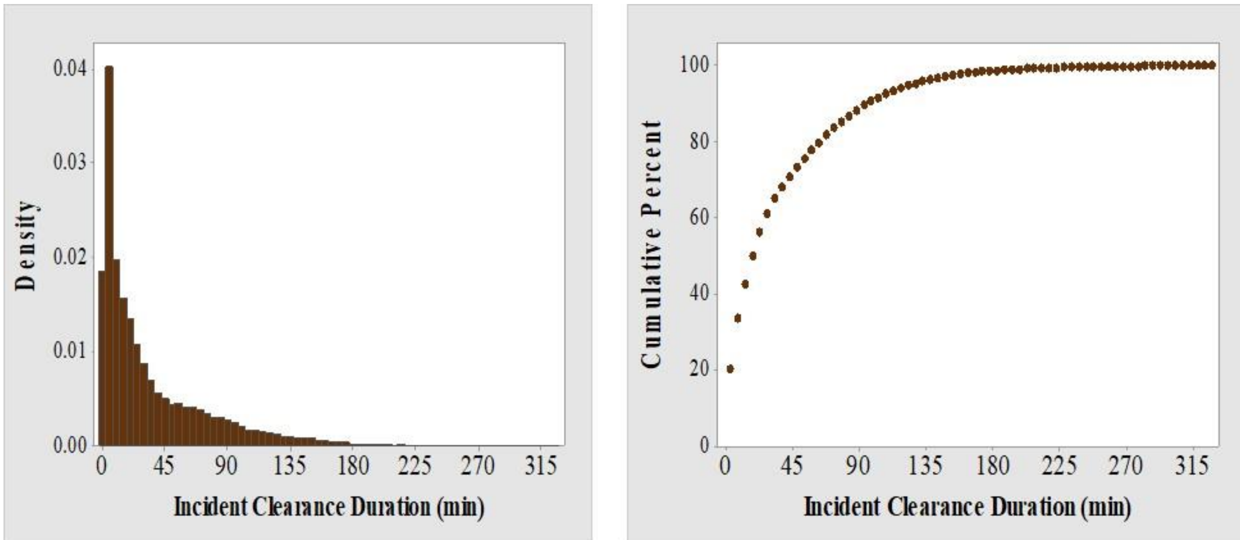
4.3.4 Results

4.3.4.1 Descriptive Statistics

The analysis was based on a total of 28,000 incidents that occurred from 2015-2017 along SR-202, I-10, I-95, and I-295 in Jacksonville, Florida. Table 4-11 provides the descriptive statistics of all variables included in the analysis. Incidents associated with vehicle problems accounted for 61.54% of incidents, while 32.05% and 6.41% were crashes and traffic hazards, respectively. Overall, statistics showed that the mean incident clearance duration for crashes, vehicle problems, and traffic hazards was 74.18, 19.30, and 16.55 minutes (min), respectively. Nearly half (49.05%) of the incidents analyzed were responded to by only Road Rangers. Road Rangers combined with other collaborating agencies responded to 35.52% of the incidents, while other rescue services (other agencies) responded to only 15.43%. Collectively, Road Rangers were involved in responding to nearly 85% of incidents.

Figure 4-11 shows the incident clearance duration distribution of the dataset. Nearly one-fourth (23.79%) of the incidents were cleared within 5 min. Cumulatively 35.58% of incidents lasted 10 min or less, and 51.24% lasted 20 min or less. Overall, the vast majority of incidents (95%) lasted 125 min or less, and the maximum incident clearance duration was 325 min. Nearly 86% of incidents were cleared within the 90 minutes, a target goal stipulated in Florida's Open Road Policy

(FDOT, 2014a). The mean and median incident clearance durations were 36.71 min and 20 min, respectively, and the standard deviation was 43.33 min. This dispersed distribution of incident clearance duration implies that the mean duration does not appropriately represent all incidents.



(a) Frequency distribution

(b) Relative frequency distribution

Figure 4-11: Incident Clearance Duration Distribution of the Analyzed Incidents (*N* = *28,000*)

As shown in Figure 4-12, the average incident clearance duration was considerably less for all three incident types (crashes, vehicle problems, and traffic hazards) when the responding agencies included Road Rangers. The average incident clearance duration for crashes was 66.3 min with Road Ranger involvement, 22.4% less than the average duration with other responding agencies. Similar results were also observed for vehicle problems and traffic hazard incident types. On average, Road Rangers resulted in shorter average incident clearance durations compared to other responding agencies by 58.0% and 69.0% for incidents involving vehicle problems and traffic hazards, respectively. Overall, the average incident clearance duration with Road Ranger assistance was 28.9 min, compared to 79.3 min without Road Ranger involvement, a 63.6% reduction. These reductions in incident clearance duration translate into substantial travel time and fuel consumption savings for motorists.

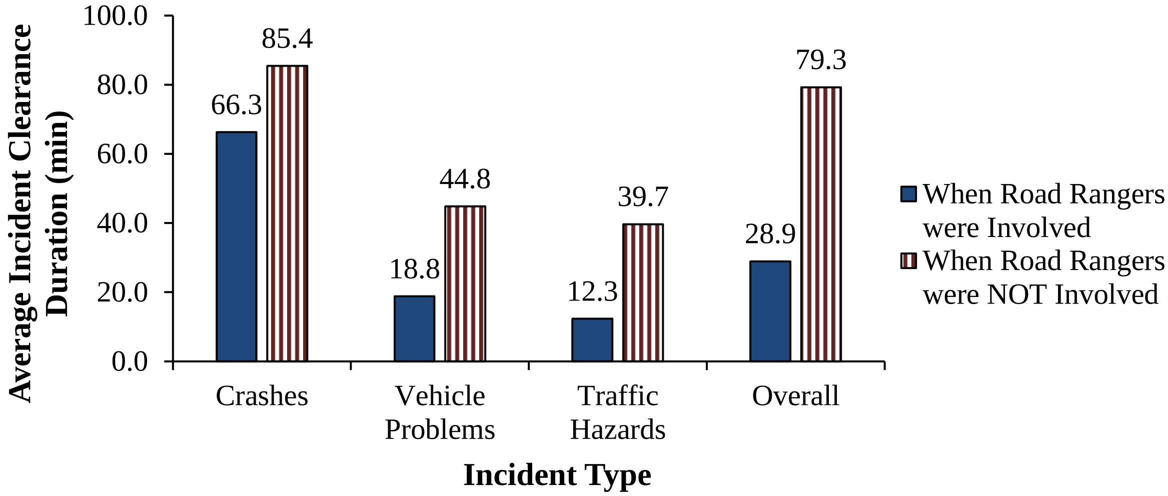


Figure 4-12: Average Incident Clearance Duration with and without Road Ranger Involvement

4.3.4.2 Model Results

Results from the quantile regression models estimated at the 25th, 50th, 75th, and 95th percentiles are presented in Table 4-12, and most variables are statistically significant at the 95% confidence level. Coefficients for each quantile regression model indicate the amount of increase or decrease in the average incident clearance duration for each unit increase in the independent variable when other variables are held constant. For a given quantile (percentile), the interpretation of the coefficients is like other regression models, i.e., the coefficients represent the change in the dependent variable (i.e., incident clearance duration) for a given quantile category, for each unit increase in the continuous independent variable, and a categorical change of a discrete variable. Figure 4-13 graphically illustrates the coefficients from Table 4-12 for key factors analyzed, with all quantiles combined. Note that the quantile regression coefficients vary among the different quantiles.

Table 4-13 provides the estimation of incident clearance duration by holding all variables at their mean values. The mean incident clearance duration is estimated as 17.46 min at the 25th percentile, 29.83 min at the 50th percentile, 48.65 min at the 75th percentile, and 87.15 min at the 95th percentile. From Table 4-13, the incident clearance duration can be predicted, given a specific independent variable value while keeping other variables at their means. Changes in the probability that an incident with a given duration will occur, based on the change in values of independent variables, can be quantified.

For example, if all other factors are set to their mean values, and only the incident type can vary, the incident clearance duration at the 75th percentile can be estimated to be 48.65 + 3.14 = 51.29 min for an incident that is not related to a traffic hazard. Hence, for incidents other than traffic hazards, there is a 25% chance that the incident will last at least 51.29 min. If the incident is related to a traffic hazard, the incident clearance duration at the 75th percentile can be calculated to be 48.65 + 3.14 – 49.00 = 2.79 min, indicating a 25% chance that a traffic hazard incident will last 2.79 min or longer. Incident clearance durations with other associated factors can be interpreted in the same manner. The exact increase or decrease in probability can also be obtained by comparing estimations among the different percentiles using Equations 4-12 and 4-13.

The quantile regression results reveal that all variables except time of day are statistically significant at a 95% confidence level, and the coefficients vary across different percentiles. The following sections discuss the results in more detail.

Incident Attributes

Incident Type: Analysis results reveal that crashes generally have longer incident clearance durations than the incidents involving vehicle problems and traffic hazards. As shown in Table 4-13 (25^{th} percentile), incident clearance durations resulting from vehicle problems and traffic hazards averaged 11 min and 15 min shorter than crashes, respectively. This trend is consistent for each quantile (percentile), and consistent with previous studies by Haule et al. (2018), Hojati et al. (2013), Khattak et al. (2012), Khattak et al. (2009), and Zhang and Khattak (2010).

Detection Method: The model coefficients for the variable Detection Method indicate that incidents first detected by methods other than by Road Rangers resulted in longer incident clearance durations. For example, for the 50^{th} percentile shown in Table 4-13, incident clearance duration for incidents first reported by Road Rangers were 12 min and 14 min shorter than for incidents first reported by ITS services and on-road services, respectively. Note also that incidents reported by on-road services, such as the FHP, law enforcement officials, and motorists, resulted in slightly longer durations (2 min) compared to incidents reported by ITS-services. These findings reveal the benefits of mobile-based incident identification measures.

Incident Severity: Incident severity was positively correlated with incident clearance duration. Relative to minor incidents (in the 25^{th} percentile, relative to their duration), the incident clearance durations for moderately severe and severe incidents were found to be 20 min and 35 min longer, respectively. However, the correlation between severe incidents and incident clearance durations varied significantly. The quantile regression analysis revealed a higher positive correlation at higher quantiles, compared to lower quantiles. This result was expected since severe incidents often result in longer incident clearance durations.

Shoulder Blockage: Incidents resulting in blocked shoulders tended to last slightly longer compared to incidents that did not involve shoulder blockage. On average, incident clearance duration resulting from an incident that blocked a shoulder was 4 min longer (50^{th} percentile) than one with no shoulder blockage. Quantile regression results also reflect an increasing trend in incident clearance duration with quantiles for incidents associated with shoulder blockages, as shown in Table 4-13.

Lane Closure (%): The variable 'lane closure' refers to whether a lane closure resulted from an incident. Nearly 14% of incidents analyzed had at least 25% closure of a lane. Nearly 2% of analyzed incidents involved full lane closures (100 % lane closure / all lanes closed). Substantial lane closures generally increase incident clearance duration due to their resulting influence on traffic. Consequently, more time is required for responders and rescue vehicles to reach the incident scene (Khattak et al., 2009; Junhua et al., 2013; Jeihani et al., 2015). Surprisingly, quantile regression analysis produced unexpected coefficients for lane closure, indicating that lane closures of less than 25% resulted in longer incident clearance durations than lane closures of greater than 25%. Although counterintuitive, these findings are, however, consistent with previous studies (Chimba et al., 2014; Ding et al., 2015; Haule et al., 2018).

There are several potential scenarios that may account for shorter incident clearance durations associated with lane closures. One scenario is that partial or complete lane closures can quickly result in considerable non-recurring congestion, prompting an urgent and prioritized response. Another scenario involves road debris from trucks or vehicles that can be easily removed by responders, thus clearing the lane for traffic. Road debris can also be secondary to a crash, where the vehicles involved reside in the median or along the shoulder, and the debris can be quickly removed by responders to clear the blockage. Nevertheless, more research is needed to examine the effects of lane closures on incident clearance duration.

Temporal Attributes

Time of Day: Analysis results revealed that the time of day was insignificant at a 95% confidence level, indicating that there is relatively no difference in the clearance duration of incidents which occurred during peak and off-peak hours. However, on average, incidents that occurred during peak hours exhibited a slightly longer clearance duration of one minute at the 95^{th} percentile, compared to incidents that occurred during off-peak hours. Although these findings are consistent with several previous studies (Lee and Fazio, 2005; Junhua et al., 2013), findings from other studies contradict these results (Ghosh et al., 2012; Haule et al., 2018).

Day of the Week: Model coefficients for weekday incidents are significant for shorter and longer incident clearance durations (25^{th} percentile or lower and 95^{th} or higher percentiles), yet insignificant for relatively medium incident clearance durations (50^{th}, and 75^{th} percentiles). However, compared to weekend incidents, incidents that occurred on weekend days resulted in longer clearance durations. Haule et al. (2018) suggested that longer incident clearance durations on weekends may be attributed to fewer responders on duty. These findings suggest that the day of the week on which a freeway incident occurs has little influence on incident clearance duration. Similar findings were reported by Lee and Fazio (2005), Chimba et al. (2014), and Khattak et al. (2016).

Lighting Condition: Results show that incident clearance times during nighttime hours were, on average, nearly five minutes longer than the clearance times during daytime hours (50^{th} percentile). This finding is consistent with studies by Haule et al. (2018) and Khattak et al. (2016). One possible explanation for the longer incident clearance durations at night may be the result of fewer services or responders available during nighttime hours. Additionally, less available light may also impede first responders.

Table 4-12: Results of the Quantile Regression Models

Variable	Factor	25th percentile			Median (50th percentile)			75th percentile			95th percentile		
		Estimate β	Std. Error	P-Value Pr(>|t|)	Estimate β	Std. Error	P-Value Pr(>|t|)	Estimate β	Std. Error	P-Value Pr(>|t|)	Estimate β	Std. Error	P-Value Pr(>|t|)
Intercept		23.000	1.309	0.000	51.000	1.539	0.000	89.000	2.055	0.000	158.000	5.166	0.000
Event Type	Crash												
	Vehicle problems	-11.000	0.554	0.000	-25.000	0.711	0.000	-39.000	1.008	0.000	-65.000	2.365	0.000
	Traffic hazards	-15.000	0.607	0.000	-29.000	0.984	0.000	-49.000	1.016	0.000	-87.000	2.408	0.000
Detection Method	Road Rangers	-9.000	0.3611	0.000	-12.000	0.704	0.000	-15.000	0.756	0.000	-24.000	3.019	0.000
	ITS services												
	On-road services	*1.000*	*0.518*	*0.054*	*2.000*	*0.813*	*0.014*	*4.500*	*0.970*	*0.000*	*1.500*	*3.399*	*0.659*
Incident Severity	Minor												
	Moderate	20.000	1.051	0.000	11.000	1.186	0.000	7.000	1.422	0.000	12.000	4.380	0.006
	Severe	35.000	2.580	0.000	43.000	4.312	0.000	57.000	4.210	0.000	85.000	10.795	0.000
Shoulder blocked	No												
	Yes	2.000	0.190	0.000	4.000	0.179	0.000	5.000	0.356	0.000	8.000	0.866	0.000
Lane Closure (%)	0 - 25	2.000	0.557	0.000	*1.000*	*0.707*	*0.157*	*1.000*	*0.786*	*0.203*	*4.000*	*2.591*	*0.123*
	> 25												
Time of day	Peak hours	*0.000*	*0.185*	*1.000*	*0.000*	*0.173*	*1.000*	*0.000*	*0.335*	*1.000*	*1.000*	*0.808*	*0.216*
	Off-peak hours												
Day of the week	Weekdays												
	Weekends	3.000	1.422	0.035	*2.000*	*1.351*	*0.139*	*0.000*	*2.078*	*1.000*	-6.000	2.959	0.043
Lighting Condition	Day												
	Night	2.000	0.461	0.000	5.000	0.685	0.000	6.000	0.859	0.000	12.000	2.314	0.000
Number of Responding Agencies	Continuous	4.000	0.282	0.000	4.000	0.357	0.000	3.500	0.431	0.000	6.500	1.481	0.000
Towing involved	No												
	Yes	10.000	0.801	0.000	19.000	0.945	0.000	31.500	1.200	0.000	37.500	2.426	0.000
Responding agencies	Road Rangers	-7.000	1.176	0.000	-14.000	1.265	0.000	-25.500	1.806	0.000	-46.000	3.742	0.000
	Other Agencies												
Pseudo R^2			*0.471*			*0.503*			*0.504*			*0.499*	

Insignificant estimates at 95% level of confidence are in italics, RMSE = 48.18 min. The goodness-of-fit measure is calculated as pseudo-R^2

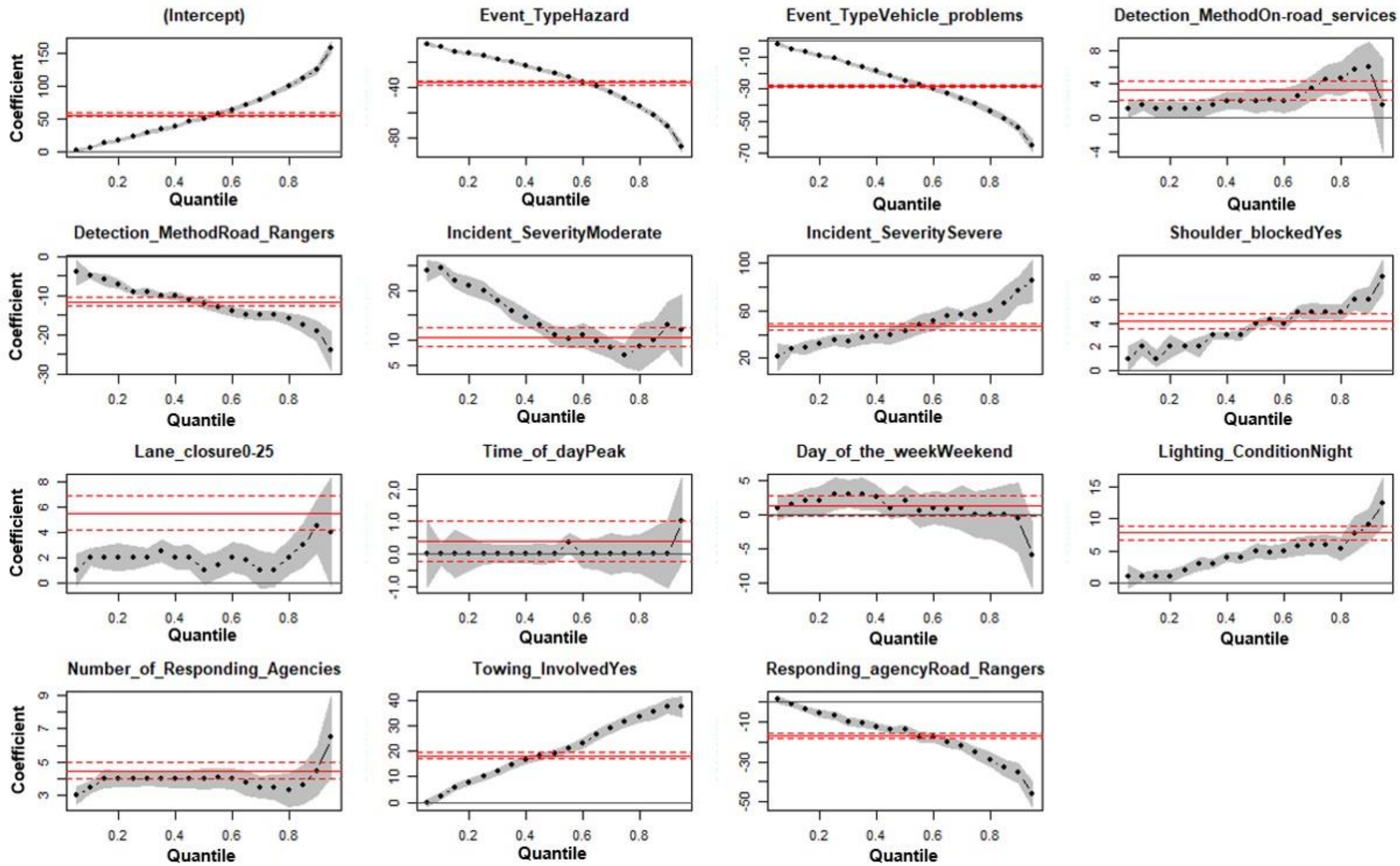


Figure 4-13: Quantile Regression Coefficients for the Incident Clearance Duration Model

Note: red solid lines show estimates from OLS regression; red broken lines show the OLS 95% confidence intervals; the black line shows estimates from quantile regression; the shaded region shows the 95% confidence intervals.

Table 4-13: Estimation of Incident Clearance Duration at Means of Independent Variables

			25th percentile		50th percentile		75th percentile		95th percentile	
Variable	**Categories**	**Mean X**	**Estimate β**	$\beta * X$	**Estimate β**	$\beta * X$	**Estimate β**	$\beta * X$	**Estimate β**	$\beta * X$
Intercept			23.000	23.00	51.000	51.00	89.000	89.00	158.000	158.00
Event Type	Crash	0.321								0.00
	Vehicle problems	0.615	-11.000	-6.77	-25.000	-15.38	-39.000	-23.99	-65.000	-39.98
	Traffic hazards	0.064	-15.000	-0.96	-29.000	-1.86	-49.000	-3.14	-87.000	-5.57
Detection Method	Road Rangers	0.528	-9.000	-4.75	-12.000	-6.34	-15.000	-7.92	-24.000	-12.67
	ITS services	0.095								0.00
	On-road services	0.377	1.000	0.38	2.000	0.75	4.500	1.70	1.500	0.57
Incident Severity	Minor	0.937								0.00
	Moderate	0.047	20.000	0.94	11.000	0.52	7.000	0.33	12.000	0.56
	Severe	0.016	35.000	0.56	43.000	0.69	57.000	0.91	85.000	1.36
Shoulder blocked	No	0.611								0.00
	Yes	0.389	2.000	0.78	4.000	1.56	5.000	1.95	8.000	3.11
Lane Closure (%)	0 – 25	0.865	2.000	1.73	1.000	0.87	1.000	0.87	4.000	3.46
	> 25	0.135								0.00
Time of day	Peak hours	0.553	0.000	0.00	0.000	0.00	0.000	0.00	1.000	0.55
	Off-peak hours	0.447								0.00
Day of the week	Weekdays	0.931								0.00
	Weekends	0.069	3.000	0.21	2.000	0.14	0.000	0.00	-6.000	-0.41
Lighting Condition	Day	0.879								0.00
	Night	0.121	2.000	0.24	5.000	0.61	6.000	0.73	12.000	1.45
Number of Responding agencies		1.700	4.000	6.80	4.000	6.80	3.500	5.95	6.500	11.05
Towing involved	No	0.878								0.00
	Yes	0.122	10.000	1.22	19.000	2.32	31.500	3.84	37.500	4.58
Responding agencies	Road Rangers	0.846	-7.000	-5.92	-14.000	-11.84	-25.500	-21.57	-46.000	-38.92
	Other Agencies	0.154								0.00
Estimation at means (min)	$\sum(\beta * X)$			17.46		29.83		48.65		87.15

Operational Attributes

Number of Responding Agencies: Regression results show that the number of responding agencies was positively related to incident clearance duration, and significant (see Table 4-12). This may be attributed to clearance procedures, which are complex when many responding agencies are on the scene, hence, resulting in longer incident clearance durations. The minor difference in incident clearance duration for higher quantiles may be attributed to the random arrival of the responding agencies at an incident scene, which depends largely on the location of each responding agency when dispatched. Some responding agencies may reach the site immediately, while others may take longer. This situation favors the reduction of incident clearance duration for incidents expected to last longer.

Road Rangers: Quantile regression results for Road Rangers indicate a considerable decrease in incident clearance duration for all four quantiles (see Table 4-12). As shown in Table 4-14 (50th percentile), incidents responded to by Road Rangers are estimated to last an average of 14 min shorter than incidents responded to by only other agencies. As shown in Table 4-14, incident clearance duration with Road Ranger involvement decreases to an estimated 46 min shorter at the 95th percentile, indicating a more pronounced benefit of mobile-based incident identification measures.

Table 4-14: Incident Clearance Duration Reduction Rate: Road Rangers vs. Other Agencies

Quantile (Percentile), *q*th	Observed *q*th incident clearance duration responded by other agencies (min)	Reduced incident clearance duration by Road Rangers	Percent reduction (%)
0.25	37	7	18.9
0.50	70	14	20.0
0.75	110	25.5	23.2
0.95	185	46	24.9

From Table 4-13, when all other factors are at their means and only the "responding agencies" variable can vary, the incident clearance duration at the 25th percentile is estimated to be 17.46 + 5.92 = 23.38 min for an incident not responded to by Road Rangers. This implies a 75% chance that an incident will last at least 23.38 min, and a 25% chance that it will last at most 23.38 min, if Road Rangers are not involved. If Road Rangers respond to the incident, the incident clearance duration at the 25th percentile can be calculated to be 17.46 + 5.92 – 7.00 = 16.38 min, indicating a 75% chance that an incident will last 16.38 min or longer. There is a 7 min (at 25th percentile) potential reduction of incident clearance duration when Road Rangers are involved. Previous studies present similar findings with FSPs (Zhang and Khattak, 2010; Lin et al. 2012a; Chimba et al., 2014; Haule et al., 2018).

Towing: Regression results show that towing operations lead to significantly longer incident clearance durations. For instance, at the median (50th percentile, Table 4-12), if an incident involves towing, the incident clearance duration will last up to 19 min longer, compared to if towing operations are not involved. Similar results were observed by Chimba et al. (2014), Khattak et al. (1995), and Li et al. (2017).

4.3.4.3 Mobility Benefits of Road Rangers Program

From the quantile regression analyses, MEFs were developed to evaluate the operational performance of the Road Ranger program, using incident clearance duration as a performance measure. As defined earlier, MEFs are multiplicative factors used to compute the expected mobility level after implementing a given strategy at a specific site. A factor of one (MEF = 1.0) is used as a reference, where below or above indicates an expected increase or decrease in mobility, respectively. Table 4-15 presents the MEFs developed to compute the operational effectiveness of Road Rangers in responding to incidents. Overall, the Road Ranger program offers a 25.3% reduction in incident clearance duration.

As shown in Table 4-15, Road Ranger involvement is expected to reduce the incident clearance duration of crashes, vehicle problems, and traffic hazards by 23.2%, 32.1% and 43.9%, respectively. Comparably, incident clearance duration reduction for crashes is less than that of other incidents. This result may be attributed to additional incident clearance procedures for crashes, which in many cases may involve multiple responding agencies.

For incidents categorized as minor, moderate, and severe, Road Ranger response is expected to reduce incident clearance durations by 26.1%, 22.4%, and 15.8%, respectively. Since most freeway incidents are generally minor in severity (nearly 94% in this study), reducing the incident clearance duration of such incidents can greatly enhance efforts to mitigate non-recurring congestion. Although severe incidents are more demanding, incident clearance durations are also shorter with Road Ranger involvement as well.

Table 4-15: MEFs for Road Rangers

Incident Attributes	Categories	MEF	95% CI		Std. Error	% Reduction in Incident Clearance Duration
Incident Type	Crash	0.768	0.766	0.770	0.001	23.2
	Vehicle Problems	0.679	0.665	0.693	0.007	32.1
	Traffic Hazards	0.561	0.547	0.575	0.007	43.9
Incident Severity	Minor	0.739	0.737	0.741	0.001	26.1
	Moderate	0.776	0.770	0.782	0.003	22.4
	Severe	0.842	0.838	0.846	0.002	15.8
Time of day	Off peak	0.752	0.750	0.754	0.001	24.8
	Peak	0.738	0.734	0.742	0.002	26.2
Day of the week	Weekday	0.752	0.750	0.754	0.001	24.8
	Weekend	0.740	0.736	0.744	0.002	26
Lighting Condition	Daylight	0.734	0.730	0.738	0.002	26.6
	Night	0.765	0.763	0.767	0.001	23.5
Towing Involved	No	0.734	0.732	0.736	0.001	26.6
	Yes	0.812	0.808	0.816	0.002	18.8
Overall		**0.747**	**0.745**	**0.749**	**0.001**	**25.3**

Performance metric: Incident Clearance Duration

4.3.5 Conclusions

Road Ranger Service Patrol is a mobile-based program provided by FDOT to assist motorists and minimize the impacts of freeway incidents on non-recurring traffic congestion. MEFs were developed, using incident clearance duration as a performance measure. The evaluation examined the benefits of the Road Ranger program in terms of reduced incident clearance duration, with a specific emphasis on the impact of the program. A statistical modeling approach was used to evaluate incident management and traffic operational improvement.

Quantile regression was applied to predict incident clearance duration at the 5th, 15th, 25th, 95th percentiles to provide a broader range of information for incident clearance duration predictions. Regression model results were presented for the 25th, 50th, 75th, and 95th percentiles. Factors analyzed that affect incident clearance duration included incident attributes (event type, detection method, incident severity, shoulder blockage, and % lane closure), temporal attributes (time of day, day of the week, and lighting condition), and operational attributes (number and type of responding agencies, and towing). The following seven factors were found to be significantly associated with longer incident clearance duration: crashes, severe incidents, shoulder blockage, peak hours, weekends, nighttime, number of responding agencies, and towing involvement.

Analysis results reveal that crashes generally have longer incident clearance durations than the incidents involving vehicle problems and traffic hazards. Incident clearance durations resulting from vehicle problems and traffic hazards averaged 25 min and 29 min shorter than crash events, respectively, in the 50th percentile. Incidents first detected by responding agencies other than Road Rangers were associated with longer incident clearance durations. Incident clearance duration for moderately severe and severe incidents was found to be 11 min and 43 min longer than minor incidents, respectively (in the 50th percentile).

Time of day was insignificant at a 95% confidence level, indicating that there is relatively no difference in the duration of incidents between the peak hours and the off-peak hours. However, weekend incidents were associated with longer durations, relative to weekday incidents. Results for responding agencies that include Road Ranger involvement, indicate a considerable decrease in incident clearance duration. Incidents responded to by Road Rangers are estimated to last an average of 14 min shorter than incidents responded to other agencies alone (50th percentile).

From the quantile regression analyses, the developed MEFs indicate the Road Ranger program offers a 25.3% reduction in incident clearance duration, overall. Road Ranger involvement is expected to reduce the incident clearance duration of crashes, vehicle problems, and traffic hazards by 23.2%, 32.1% and 43.9%, respectively. Road Ranger response is also expected to reduce incident clearance durations by 26.1%, 22.4%, and 15.8% for minor, moderate, and severe incidents, respectively. It is anticipated that the MEFs developed in this study may provide researchers and practitioners with an effective method for analyzing the economic benefits of the Road Ranger program.

4.4 Express Lanes

Express lanes are managed toll lanes, separated from general-purpose lanes or general toll lanes within a freeway facility. Dynamic pricing is used through electronic tolling where toll amounts are set based on traffic conditions (Neudorff et al., 2011). Express lanes provide a high degree of operational flexibility, which enables them to be actively managed to respond to changing traffic demands. They include congestion pricing, have vehicle restrictions, and may be operated as reversible flow or bi-directional facilities to best meet peak demands. These adjustments allow FDOT to offer drivers new and reliable mobility choices, with more predictable travel times and deliver long-term solutions for managing traffic flow, decreasing air pollution, and supporting transit usage (FDOT, 2015).

4.4.1 Study Corridor

The corridor selected for analyzing the mobility benefits of express lanes was 95Express, a limited-access express lane facility that runs adjacent to the I-95 general-purpose lanes in Miami, Florida. The express lanes along this corridor were constructed in two phases. Phase 1 extends approximately seven miles from SR 112 to the Golden Glades Interchange. Phase 2 extends the express lanes to the north another 14 miles from the Golden Glades Interchange to Broward Boulevard. Phase 1 northbound became operational in December 2008, while Phase 1 southbound became operational in January 2010. Phase 2 started operating in October 2016.

As part of the efforts to mitigate traffic congestion, ramp meters were installed on on-ramps along a section of 95Express from Ives Dairy Road to NW 62nd Street. This study focused on the 95Express corridor from Hallandale Beach Boulevard to Broward Boulevard, the corridor with no ramp meters, to avoid combining the benefits of express lanes with the existing ramp meters. The study corridor extends about 10 miles and consists of two express lanes and four general-purpose lanes in each direction (see Figure 4-14). The average hourly toll amounts along the study corridor remain at approximately $0.50 throughout the day, including the peak periods (FDOT, 2017b).

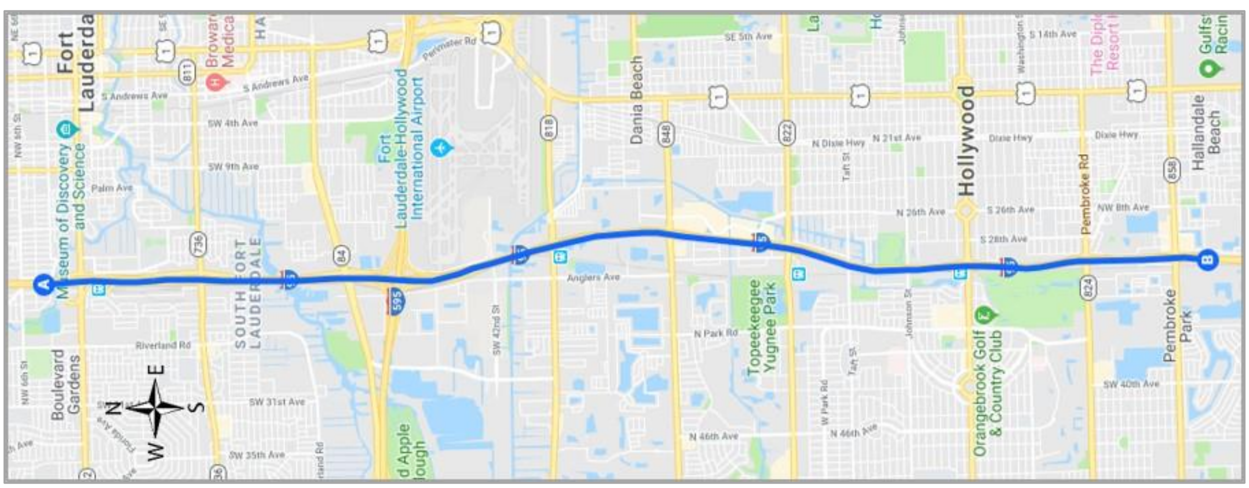


Figure 4-14: Express Lane Performance Evaluation Study Corridor

4.4.2 Data

In this research, travel time reliability was estimated using BI during typical weekdays for both northbound and southbound directions along the study corridor. Two years of data (2017-2018) were used in the analysis. The archived real-time traffic data were retrieved from RITIS. In the RITIS platform, the HERE data from detectors on express lanes are collected separately from the general-purpose lanes for both northbound and southbound sections. For the northbound express lanes, there were a total of 12 detectors on the 8-mile segment while the 9.3-mile southbound section also had 12 detectors. Similarly, for the northbound general-purpose lanes, there were a total of 14 detectors along the 7.8-mile segment while the 7.3-mile southbound section also had 14 detectors.

The dataset consisted of spot speed and travel time data aggregated at 5-min time intervals from January 1, 2017 through December 31, 2018. Since express lanes are not open every hour of every day throughout the year, extensive data processing steps had to be undertaken to match the historical real-time traffic data from RITIS with the time periods when the express lanes were operational. The specific times when the express lanes were operational were obtained from FDOT District 6 TMC. The data for the express lane operational mode changes had mode change request times associated with five mode IDs: 1 - Time of day, 2 - Dynamic, 3 - Closed, 4 - Zero toll, and 5 -Manual. The express lanes were operational during all the modes except during mode ID - 3 (closed). Hence, the durations when the express lanes were in mode 3 were omitted from the analysis to reflect only the durations when the express lanes were operational. For the general-purpose lanes, travel time data were separated for the periods when the express lanes were operational and for the periods when the express lanes were closed, i.e., when all traffic was using only the general-purpose lanes. Moreover, South Florida had witnessed two hurricanes during the analysis period (2017-2018). Traffic was affected from September 5, 2017 to September 20, 2017 during Hurricane Irma, and from October 7, 2018 to October 20, 2018 during Hurricane Michael. These days were omitted from the analysis.

Furthermore, because travel time patterns during weekends are significantly different from weekdays, the analysis only focused on travel time reliability measures during typical weekdays. In addition, federal holidays were excluded from the analysis because traffic patterns during holidays are considered to be atypical on most roadway facilities (Lomax et al., 2003; Eisele et al., 2005).

After data reduction, the 5-min travel data from each detector were summed to determine the total travel time along the study corridor, aggregated to 5-min intervals for each date in the two-year study period. The 5-min data for about 240 weekdays per year were averaged to obtain the hourly variation in travel time for a typical weekday. A total of 288 data points were obtained for 24 hours. Correspondingly, the 95th average travel times were calculated for every 5-min interval of a typical weekday. The BI values were calculated for each 5-min interval for the general-purpose lanes when the express lanes were open and when they were closed, and for the express lanes when they were operational for both northbound and southbound directions and for AM peak, PM peak, and off-peak hours.

4.4.3 Methodology

The methodology was divided into two sections: (a) comparing the performance of express lanes with that of their adjacent general-purpose lanes, and (b) assessing the operational performance of the general-purpose lanes when the express lanes were operational versus when they were closed. BIs were used to measure the operational performance of both the express lanes and the general-purpose lanes. The BIs for each 5-min intervals in a typical weekday were calculated and included in the analysis. The Welch's *t*-test was used to determine if there was a statistically significant difference in the BIs between the two periods (i.e., when express lanes were open and when they were closed) and the facilities (i.e., express lanes and general-purpose lanes) that are being compared. The MEFs were estimated for the express lanes and the general-purpose lanes, aggregated to different times of the day (i.e., AM peak, PM peak and off-peak hours) to meet the study objectives.

4.4.3.1 MEFs for Express Lanes

The BIs for the express lanes were compared to the BIs for the general-purpose lanes when the express lanes were operational. This was done to compare the performance of the express lanes with that of their adjacent general-purpose lanes. The MEF was calculated using the formula given in Equation 4-20. $MEF_{EL} < 1$ implies that the performance of the express lanes is better compared to the performance of the adjacent general-purpose lanes. Similarly, $MEF_{EL} > 1$ implies that the express lanes are performing worse than their adjacent general-purpose lanes. In other words, the lower the MEF_{EL}, the better is the operational performance of the express lanes.

$$MEF_{EL} = \left(\frac{\sum_{i=1}^{n} (EL\_BI_i)}{\sum_{i=1}^{n} (GPL\_BI_i)} \right) \tag{4-20}$$

where EL_BI_i is the buffer index of the ith 5-min interval in the express lanes, GPL_BI_i is the buffer index of the ith 5-min interval in the general-purpose lanes when the express lanes are open, and *i* is 1, 2, 3….*n*, where *n* is the number of 5-min intervals on a typical weekday.

4.4.3.2 MEFs for General-purpose Lanes

The BIs for the general-purpose lanes when the express lanes were operational were compared to the BIs for the general-purpose lanes during the periods when the express lanes were closed. This was done to assess the performance of the general-purpose lanes with and without the express lanes. The MEFs were calculated using the formula given in Equation 4-21. $MEF_{GPL} < 1$ implies that the general-purpose lanes perform better when the express lanes are operational. $MEF_{GPL} > 1$ implies that the general-purpose lanes perform worse when the express lanes are operational. In other words, the lower the MEF_{GPL}, the better is the operational performance of the general-purpose lanes when the express lanes are operational.

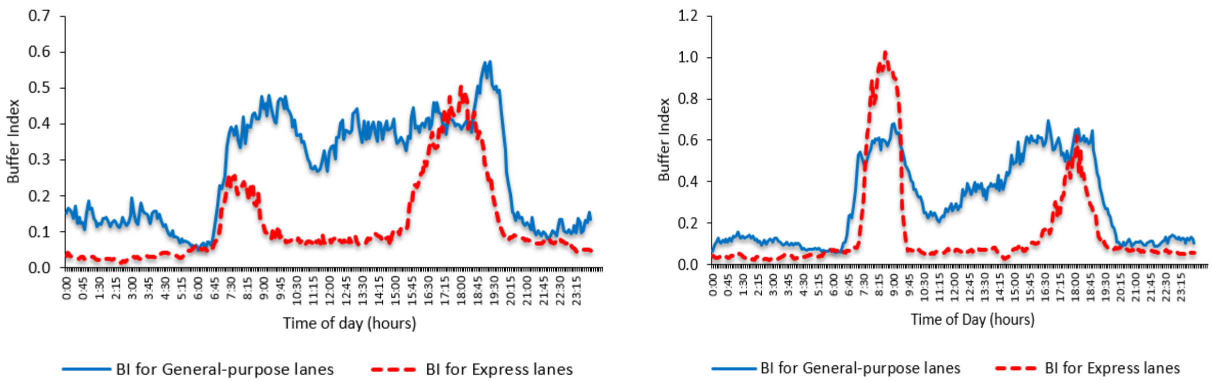
$$MEF_{GPL} = \left(\frac{\sum_{i=1}^{n} (GPL\_BI_i)}{\sum_{i=1}^{n} (GPL'\_BI_i)} \right) \tag{4-21}$$

where GPL_BI_i is the buffer index of the ith 5-min interval in the general-purpose lanes when the express lanes are open, GPL'_BI_i is the buffer index of the ith 5-min interval in the general-purpose lanes when the express lanes are closed, and *i* is 1, 2, 3….*n*, where *n* is the number of 5-min intervals on a typical weekday.

4.4.4 Results

4.4.4.1 Performance of Express Lanes

The performance of the express lanes was evaluated by comparing the BIs for the express lanes with the BIs for the general-purpose lanes when the express lanes were operational. Figure 4-15 shows the BI variations for both the express lanes and the general-purpose lanes. In general, the BIs for the express lanes were lower compared to the BIs for the general-purpose lanes, implying that the express lanes performed better compared to the general-purpose lanes. However, the AM peak period on northbound lanes was an exception to this observation. The BIs for the express lanes in the northbound direction were higher during the AM peak periods than the BIs for the adjacent general-purpose lanes. A similar trend, although not to this extent, was also observed during the PM peak hours in the southbound direction.



(a) Southbound (b) Northbound

Figure 4-15: BIs for Express Lanes and General-purpose Lanes

The Welch's *t*-test was performed to compare the performance of the express lanes with the general-purpose lanes when the express lanes were operational. The null hypothesis was that there was no difference between the mean BIs for the express lanes and mean BIs the general-purpose lanes when the express lanes are open (i.e., H_o: $\overline{BI}_{EL} = \overline{BI}_{GPL}$). The alternative hypothesis was that the mean BIs for the express lanes are less than the mean BIs for the general-purpose lanes when the express lanes are open (i.e., H_a: $\overline{BI}_{EL} < \overline{BI}_{GPL}$) at a 95% confidence level.

The t-statistic values provided in Table 4-16 for both the southbound and northbound sections are less than the critical t values. Thus, the null hypothesis is rejected. It can, therefore, be concluded that the mean BIs for the general-purpose lanes are significantly greater than the mean BIs for the express lanes at a 95% confidence level. Figure 4-16 summarizes the average BIs for the general-purpose lanes and the express lanes on the northbound and the southbound sections.

Table 4-16: Welch's *t*-test Results for the BI for the Express Lanes vs. General-purpose Lanes

	Estimates	BI_{EL}	$BI_{GPL\ when\ EL\ is\ open}$
Southbound	Mean	0.121	0.269
	Variance	0.014	0.021
	Observations	288	288
	Hypothesized Mean Difference	0	
	df	547	
	t Stat	**-13.494**	
	P(T<=t) one-tail	**0.000**	
	t Critical one-tail	**1.648**	
Northbound	Mean	0.155	0.296
	Variance	0.051	0.041
	Observations	288	288
	Hypothesized Mean Difference	0	
	df	566	
	t Stat	**-7.881**	
	P(T<=t) one-tail	**0.000**	
	t Critical one-tail	**1.648**	

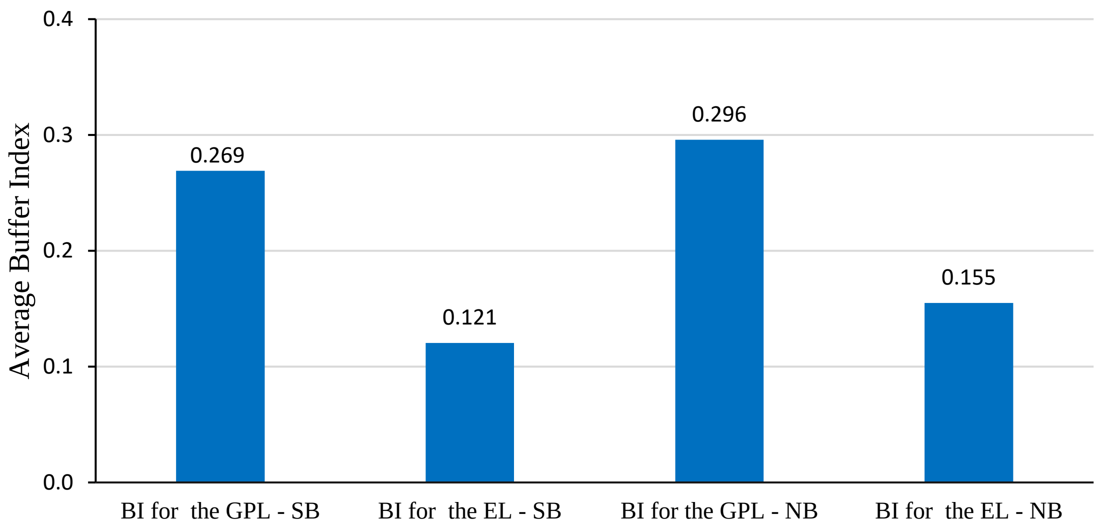


Figure 4-16: Average BIs for the Express Lanes vs. General-purpose Lanes

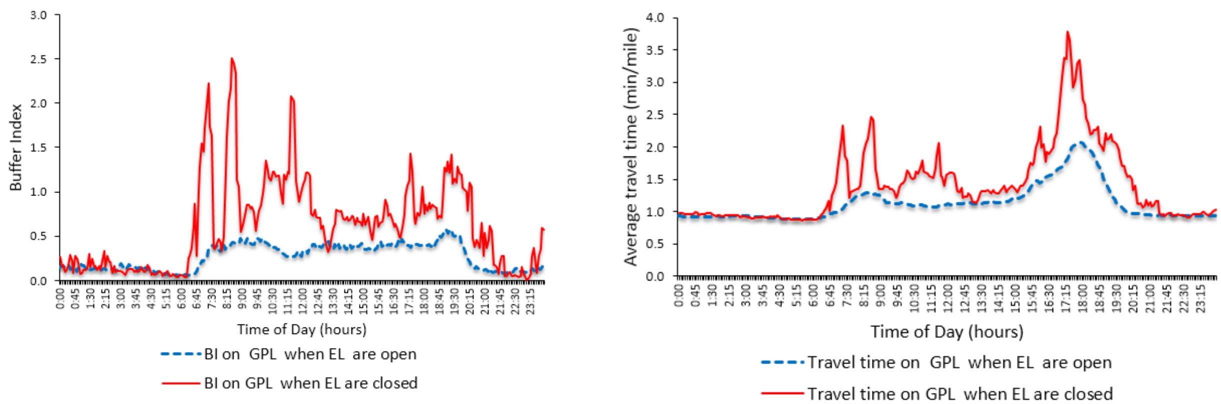
4.4.4.2 Performance of General-purpose Lanes

Figure 4-17 presents the hourly variations in the BIs and the average travel times for the general-purpose lanes for the southbound and the northbound directions. Travel times were found to be higher during peak hours (6 to 10 AM and 4 to 7 PM). In the southbound direction, PM peak hours were more congested than the AM peak hours, while the northbound direction experienced similar traffic conditions during both the AM and the PM peak hours. In general, travel times on the general-purpose lanes were better when the express lanes were operational (i.e., open) compared to the times when the express lanes were closed. From the graphs, it can also be deduced that the variations in travel times on the general-purpose lanes were more (i.e., traffic is more volatile) when the express lanes were closed. The BIs for the general-purpose lanes were generally lower and less variable when the express lanes were operational.

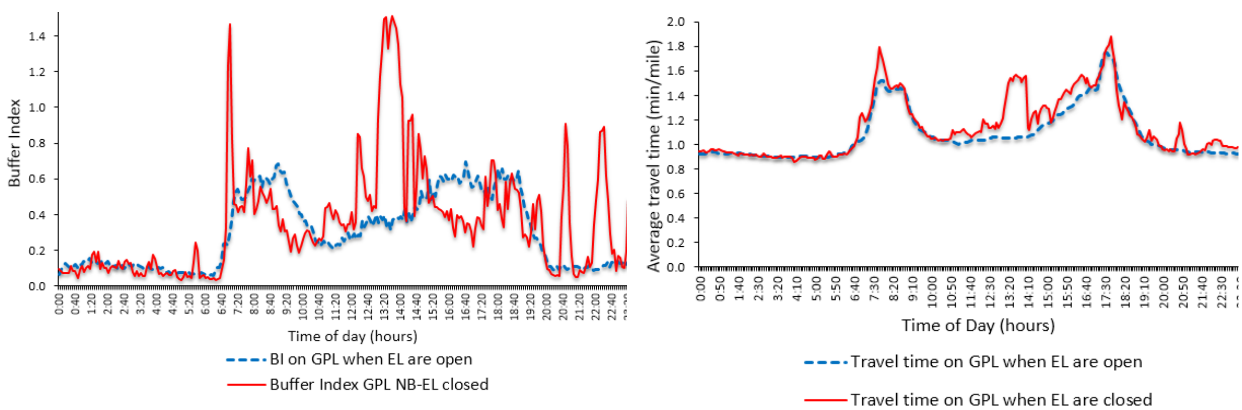
The Welch's *t*-test was performed to determine if the BIs for the general-purpose lanes were statistically different between the periods when the express lanes were operational and the periods when the express lanes were closed. The null hypothesis was that there was no difference between the mean BIs for the general-purpose lanes when the express lanes are open and mean BIs for the general-purpose lanes when express lanes are closed. The alternative hypothesis was that the mean BIs for the general-purpose lanes when the express lanes are open is greater than or equal to the mean BIs when the express lanes are closed at a 95% confidence level.

Null hypothesis (H_o): $\overline{BI}_{GPL\ when\ EL\ are\ open} = \overline{BI}_{GPL\ when\ EL\ are\ closed}$
Alternative hypothesis (H_a): $\overline{BI}_{GPL\ when\ EL\ are\ open} < \overline{BI}_{GPL\ when\ EL\ are\ closed}$

Table 4-17 shows the results of the Welch's *t*-test. Since the t-statistic values for both the southbound and the northbound approaches are less than the critical t values, the null hypothesis is rejected. Therefore, the mean BIs for the general-purpose lanes when the express lanes are open are significantly less than the mean BIs for the general-purpose lanes when the express lanes are closed at a 95% confidence level. Figure 4-18 summarizes the average BIs for the general-purpose lanes when the express lanes are open and when they are closed.



(a) Southbound General-purpose Lanes



(a) Northbound General-purpose Lanes

Figure 4-17: Hourly Variations in BIs and Travel Times for General-purpose Lanes

Table 4-17: Welch's *t*-test Results for BI for the General-purpose Lanes

	Estimates	$BI_{GPL\ when\ EL\ is\ open}$	$BI_{GPL\ when\ EL\ is\ closed}$
Southbound	Mean	0.269	0.618
	Variance	0.021	0.261
	Observations	288	288
	Hypothesized Mean Difference	0	
	df	334	
	t Stat	-11.128	
	P(T ≤ t) one-tail	0.000	
	t Critical one-tail	1.649	
Northbound	Mean	0.296	0.357
	Variance	0.041	0.099
	Observations	288	288
	Hypothesized Mean Difference	0	
	df	489	
	t Stat	-2.756	
	P(T ≤ t) one-tail	0.003	
	t Critical one-tail	1.648	

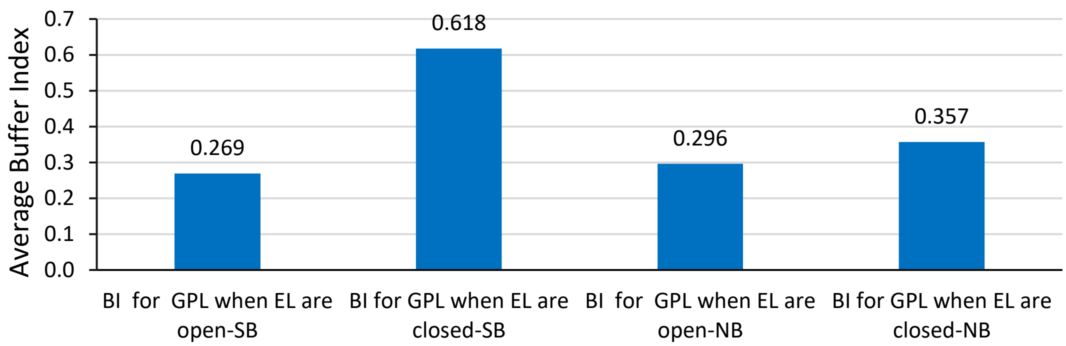


Figure 4-18: Average BIs for the General-Purpose Lanes

4.4.4.3 Mobility Enhancement Factors

Table 4-18 presents the MEFs estimated for the express lanes and the general-purpose lanes during peak and off-peak periods. The express lanes were found to be more reliable during off-peak hours compared to peak hours (MEF = 0.3, i.e., 70% more reliable). During AM peak hours, the express lanes and the general-purpose lanes were found to be equally reliable (MEF = 1) for the northbound direction, while the express lanes were found to be 60% more reliable than the general-purpose lanes in the southbound direction. During PM peak hours, the express lanes were found to be 50% and 20% more reliable than the general-purpose lanes in the northbound and the southbound directions, respectively.

Overall, the general-purpose lanes were found to perform better when the express lanes are open compared to when the express lanes are closed. The corresponding MEFs for the northbound and the southbound directions were found to be 0.8 and 0.4, respectively. That means the BIs for the general-purpose lanes improved by 20% and 60%, respectively, for the northbound and the southbound directions, when the express lanes were operational compared to when they were closed. In general, there was a slightly deteriorated performance on the general-purpose lanes during both AM and PM peak hours on the northbound approach presumably because of high demands during these periods. While on the southbound approach, the express lanes resulted in improved operational performance of the general-purpose lanes during all times of the day (i.e., AM peak, PM peak, and off-peak periods).

Table 4-18: MEFs for Express Lanes and General-purpose Lanes

	Performance of ELs compared to their adjacent GPLs		Performance of GPLs when ELs are operational	
Time	MEF_{EL} NB	MEF_{EL} SB	MEF_{GPL} NB	MEF_{GPL} SB
AM Peak	1.0	0.4	1.1	0.3
PM Peak	0.5	0.8	1.3	0.5
Off Peak	0.3	0.3	0.6	0.5
Overall	**0.5**	**0.4**	**0.8**	**0.4**

Note: EL is express lanes, GPL is general-purpose lanes.

4.4.5 Conclusions

Express lanes are one of the strategies deployed to increase the throughput of vehicles along freeways as an effort to manage traffic congestion within a limited right of way. Express lanes provide a high degree of operational flexibility, which enables them to be actively managed to respond to the changing traffic demands. This study quantified the mobility benefits of express lanes by comparing the performance of express lanes with that of their adjacent general-purpose lanes, and by assessing the performance of the general-purpose lanes when the express lanes were open versus when they were closed. The study site was 95Express in Miami, Florida. The corridor consists of two express lanes in each direction operating adjacent to the general-purpose lanes along I-95.

The mobility benefits of express lanes were assessed using archived real-time traffic data on the 95Express corridor. Travel time Buffer index (BI) was used as the performance measure for estimating the operational benefits of the express lanes. BI was estimated using the 95th percentile travel time and average travel time to express the average extra time a traveler should allow above the average travel time along the corridor. The Welch's *t*-test was performed to determine if the BIs for the general-purpose lanes were statistically different during the periods when the express lanes were operating and the periods when the express lanes were closed. Test results indicated that the BI values for the general-purpose lanes were less when the express lanes were operating compared to the periods when the express lanes were closed at a 95% confidence level.

For this study, the MEFs were estimated by considering BI as a performance measure. Overall, on 95Express northbound lanes, the express lanes resulted in a 50% reduction in BI (MEF = 0.5) compared to their adjacent general-purpose lanes, while the reduction was 60% (MEF = 0.4) for southbound lanes. When the express lanes were operational, the performance of the adjacent general-purpose lanes improved. The BIs for the general-purpose lanes improved by 20% (MEF = 0.8) and 60% (MEF = 0.4), respectively, for the northbound and the southbound directions, when the express lanes were operational compared to when they were closed. Overall, both the express

lanes and the general-purpose lanes were found to perform better when the express lanes were operational.
In summary, the study results showed mobility improvements on both the express lanes and the general-purpose lanes, although the extent of the improvement varied by direction and the time-of-day (i.e., AM peak, PM peak, off-peak). Transportation agencies may use MEFs estimated in this study to quantify the mobility benefits of express lanes and general-purpose lanes on express lane facilities. Moreover, the study methodology and the mobility performance measure employed in this study could also be used to analyze other TSM&O strategies that lack a consistent method for quantifying potential deployment benefits.

4.5 Transit Signal Priority

Transit Signal Priority (TSP) is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections (Smith et al., 2005). It is a tool that can be used to help make transit service more reliable, faster, and more cost-effective (Smith et al., 2005). TSP is relatively inexpensive and easy to implement to improve transit reliability and bus travel speed (Feng et al., 2015).

TSP improves transit operations and addresses capacity constraints by prioritizing the movement of buses over passenger vehicles. As a significant TSM&O strategy, TSP systems use detectors to detect approaching transit vehicles and alter signal timings when necessary to prioritize transit vehicle passage and improve their performance. For example, during peak hour periods where queuing is high, TSP can allocate more green time for transit vehicles to traverse through an intersection and remain on time. TSP reduces waiting times of transit vehicles at intersections, thereby reducing transit delay and travel time, and increasing reliability and quality of service.

In the stochastic setting of a transportation network, TSP prioritizes the movement of transit vehicles over other vehicles at a signalized intersection to adhere to a predetermined transit schedule. Signal control and prioritization scenarios for TSP can be categorized as (Li et al., 2008):

- Centralized TSP Architecture
- Distributed TSP Architecture

A centralized priority system utilizes the Transit Management Center and/or the TMC in the decision-making process. Here the Priority Request Generator (PRG), Priority Request Server (PRS), or both, are located in one of the management centers. The advantage of centralized TSP architecture is that a local agency can have its signal controllers connected to a centralized system and managed by a TMC in real-time. Whereas, a distributed priority system does not involve either a Transit Management Center or a TMC in the decision-making process. All requests to grant transit priority are made at the local intersection level itself. The advantage of distributed TSP architecture is when there is no communication to a Transit Management Center and/or TMC or where the communication to a center does not occur in real-time. In this study, the distributed TSP architecture was followed.

A TSP system constitutes 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) traffic control system software 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; (4) software to manage the system, collect data, and generate a report of TSP operations, after a priority decision is made (Smith et al., 2005).

This study describes the effectiveness of TSP integration along an arterial corridor in Florida. The following subsections discuss the study corridor, the data used in the analysis, the methodology, analysis results, discussions, and the mobility benefits of TSP. Mobility benefits of the TSP strategy were quantified, and MEFs were developed.

4.5.1 Study Corridors

The analysis was based on a 10-mile corridor along SR 7 (US-441) between SW 8th Street and the Golden Glades Interchange in Miami, Florida. The study corridor is parallel to I-95, and serves Bus route #77, a major transit route along both the NB and SB directions. Figure 4-19 shows the study corridor with the 25 signalized intersections that were enabled with TSP. The NB approach has a total of 6 nearside and 18 far-side bus stops, while the SB approach has 11 nearside and 11 far-side bus stops. Route 77 Bus circulates between Stephen P Clark Center on the SB approach and NW 183rd Street on the NB approach.

4.5.2 Data

The following data were used to quantify the mobility benefits of TSP:

- *Traffic Flow:* Travel time data, along with volume and speed data, were extracted from RITIS. RITIS is an automated data sharing, dissemination, and archiving system that includes real-time data feeds.

- *Geometric:* Geometric variables considered while developing the VISSIM simulation models include: number of lanes, median type, lane width, etc. These variables were extracted from the Roadway Characteristics Inventory (RCI) database maintained by the Florida Department of Transportation (FDOT). Google Maps was also used to verify certain roadway geometric characteristics of the study site.

- *Transit Vehicle:* Transit information considered while developing the VISSIM simulation models include: bus route, bus stops, and bus schedule. This information was obtained from the Miami-Dade County Transportation and Public Works official website.

- *Signal Timing:* To replicate the real-world conditions in the VISSIM model, 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 and turning movement counts were requested and obtained from the Miami-Dade County Traffic Signals and Signs Division and FDOT District 6, respectively.

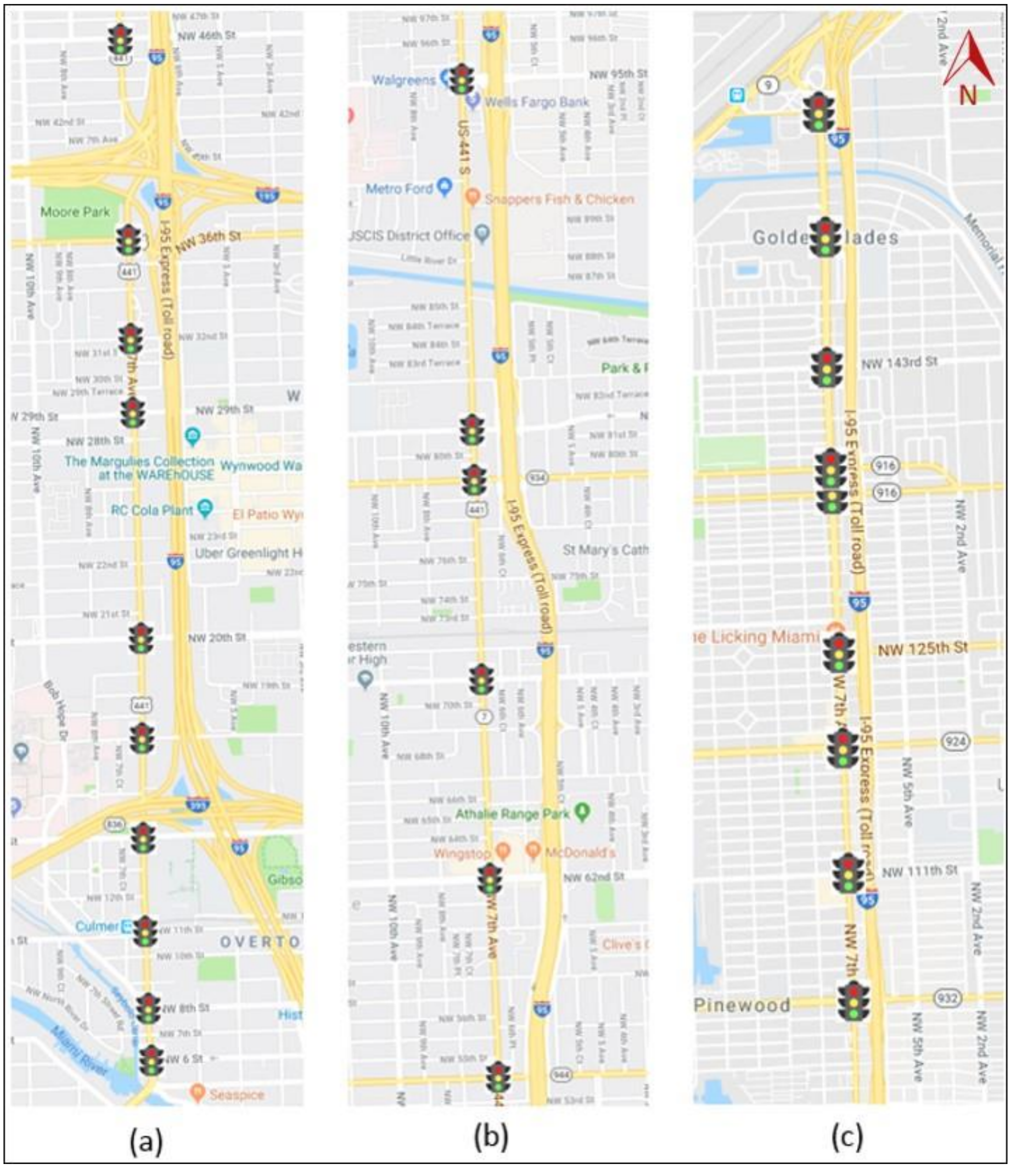


Figure 4-19: TSP Performance Evaluation Study Corridor along US-441 (a) Segments from NW 6th Street to NW 46th Street, (b) Segments from NW 54th Street to NW 95th Street, and (c) Segments from NW 103rd Street to NW 15900 Block (Source: Google Maps)

4.5.3 Methodology

The methodology for this research study was primarily divided into the following five steps:

1. Develop a VISSIM microsimulation model with no TSP scenario to realistically represent the existing field conditions (i.e., Base Scenario).

2. Integrate TSP scenario within the Base VISSIM microsimulation model.
3. Calibrate and validate the Base VISSIM model to present the model's ability to replicate field conditions.
4. Analyze data and conduct statistical tests of the network performance to document and evaluate the performance of the corridor with and without TSP integration.
5. Develop Florida-specific Mobility Enhancement Factors (MEFs) for the TSP strategy.

4.5.3.1 Base VISSIM Model

A Base model with no TSP integration was developed in VISSIM for the SR 7 (US-441) corridor between the SW 8th Street signalized intersection and the Golden Glades Interchange in Miami, Florida. The analysis was conducted for the evening peak period (4:00 PM - 6:00 PM) and was based on the existing network geometry, traffic, and transit operations. In this model, one transit line in each travel direction was added. Bus stops along the corridor in both travel directions were also included in this model. All the traffic signals along the study corridor were actuated. The analysis period was 2.5 hours, with the first 30 minutes used as the warm-up period. The Base model included transit vehicles operating in mixed traffic and did not consider any special transit treatment for TSP scenarios.

4.5.3.2 TSP Integrated VISSIM Model

For the inclusion of TSP operations along the same study corridor, the Base model was duplicated to create another simulation model where TSP parameters were integrated into the signal groups of the ring barrier controller (RBC) in VISSIM. The RBC emulator is integrated into the VISSIM modeling software. This interface provides users with a seamless way of simulating actuated control in a VISSIM model. Programmable transit priority options for each transit signal group are present in the signal controller. For 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.

TSP was implemented at 25 signalized intersections along the study corridor. Figure 4-20 shows all the 25 signalized intersections and the positions of the bus stops at each intersection. The model examined the scenario of transit vehicles operating in mixed traffic conditions using the TSP application. Early green signal (early start or red truncation of priority phase) and extended green (or phase extension of priority phase) TSP strategies were 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 is 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 is 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 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 a TSP-enabled signalized intersection. Travel time of transit buses and all other vehicles in the network along the study corridor was extracted from the VISSIM models along each travel direction. The average vehicle delay and the average stopped delay for buses and all other vehicles were also extracted from the models for each direction of travel.

4.5.3.3 VISSIM Model Calibration and Validation

Signal timing data, turning movement counts, and travel time data along the study corridor were used in the development of the VISSIM model. For each of the 25 signalized intersections along the study corridor, the signal timing data and the turning movement counts data were collected from the Miami-Dade County Traffic Signals and Signs Division and FDOT District 6, respectively. Signal timing data included the local time-of-day plans along with signal phasing information. Travel time along the corridor was collected from the RITIS database. In addition, travel time data were also collected using the floating car technique.

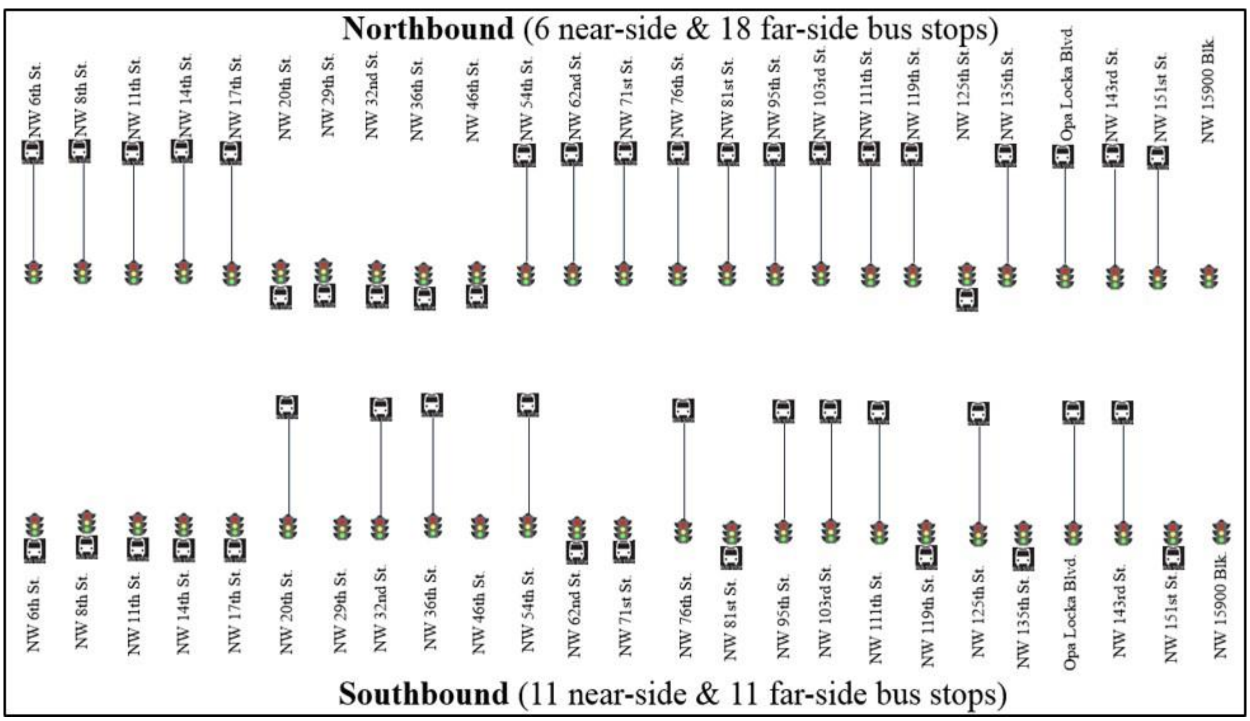


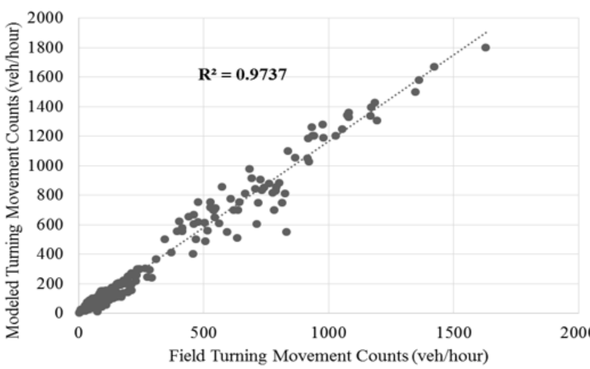
Figure 4-20: TSP-enabled Signalized Intersections and Bus Stop Locations

The Base VISSIM model was calibrated using the turning movement counts data at each signalized intersection. Figure 4-21(a) illustrates the comparison of turning movement traffic counts of the simulation model and the collected field data for a simulation period of 2.5 hours during the evening peak hour. 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 0.97 indicating high similarity between the field and the simulated data. The Geoffrey E. Havers (GEH) empirical formula, shown in Equation 4-22, was also used as the acceptance criteria for the model (FDOT, 2014b):

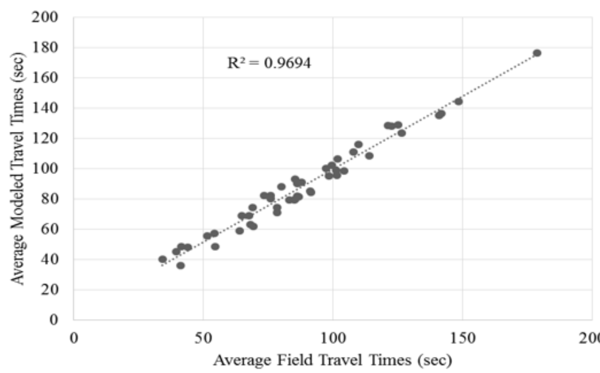
$$\text{GEH}=\sqrt{\frac{2(M-C)^2}{M+C}} \tag{4-22}$$

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, 2014b). The simulation model had a GEH < 5.0 for 89% of the intersections.

To validate the travel times along the study corridor, the US-441 corridor from NW 6th Street to NW 15900 Block was split into 48 segments between the signalized intersections (24 in each travel direction) where the measurement points in VISSIM were set. Validation was performed using the travel times collected from field observations. Figure 4-21(b) shows the comparison of the travel time data from the two sources. The R^2 value was found to be 0.96.



(a) Calibration Results



(b) Validation Results

Figure 4-21: Calibration and Validation Results of VISSIM Base Model

4.5.4 Results

The objective of this study was to evaluate the operational performance of TSP and develop MEFs to quantify the mobility benefits of TSP. Two VISSIM models, one with no TSP strategy (i.e., Base model) and the other with TSP strategy (i.e., TSP-integrated model), were developed for the 10-mile study corridor in Miami, Florida. The mobility benefits were quantified based on travel times, average vehicle delay, average stopped delay time and overall network performance of all vehicles and buses in the network. The base model and the TSP-integrated model were run for 10 differently seeded simulations. Each model was run for 2.5 hours, where the first 30 minutes period was used as the warm-up time. The following subsections discuss the simulation results.

4.5.4.1 Travel Time

Travel times were measured for segments between each pair of signalized intersections along the study corridor in both directions of travel. The travel times obtained from the Base model and the TSP-integrated model were obtained and compared. Tables 4-19 and 4-20 show the travel time results for northbound and southbound segments for all vehicles and buses, respectively. The tables also include total travel time along the study corridor. It can be inferred from the tables that the TSP-integrated scenario resulted in lower travel times for all vehicles and for buses, and for both the northbound and the southbound approaches. These results are statistically significant at a 90% confidence level.

Table 4-19: Corridor Travel Time for All Vehicles and Buses along Northbound Approach

Travel Time (seconds)				
Segments	Base Scenario		TSP-integrated Scenario	
Northbound Approach	All Vehicles	Buses	All Vehicles	Buses
NW 6th St.-NW 8th St.	34.11	31.85	25.12	27.12
NW 8th St.-NW 11th St.	39.48	39.77	29.12	30.51
NW 11th St.-NW 14th St.	51.47	92.57	48.26	81.71
NW 14th St.-NW 17th St.	54.23	93.5	53.14	85.23
NW 17th St.-NW 20th St.	79.98	179.38	76.15	183.59
NW 20th St.-NW 29th St.	122.62	219.87	121.3	198.51
NW 29th St.-NW 32nd St.	43.83	88.46	43.13	85.51
NW 32nd St.-NW 36th St.	73.43	116.92	78.15	122.12
NW 36th St.-NW 46th St.	109.94	150.29	115.15	155.12
NW 46th St.-NW 54th St.	101.73	100	90.15	89.15
NW 54th St.-NW 62nd St.	107.78	157.43	106.91	145.21
NW 62nd St.-NW 71st St.	98.33	146.67	97.75	140.78
NW 71st St.-NW 79th St.	104.36	133.84	104.52	125.12
NW 79th St.-NW 81st St.	41.51	91.07	41.24	62.15
NW 81st St.-NW 95th St.	178.62	186.2	170.31	172.15
NW 95th St.-NW 103rd St.	126.35	177.91	124.18	164.38
NW 103rd St.-NW 111th St.	97.42	139.64	96.41	132.15
NW 111th St.-NW 119th St.	101.55	92.48	97.99	85.12
NW 119th St.-NW 125th St.	87.76	183.94	85.17	167.51
NW 125th St.-NW 135th St.	121.31	178.36	119.12	163.04
NW 135th St.-Opa Locka Blvd.	124.96	169.08	122.12	155.12
Opa locka Blvd.-NW 143rd St.	76.04	86.55	74.25	75.12
NW 143rd St.-NW 151st St.	86.24	84.97	83.5	78.15
NW 151st St.-NW 15900 Blk.	85.34	121.59	83.61	116.12
Total	**2,148.39**	**3,062.34**	**2,086.75***	**2,840.69***
Compared to Base	**N/A**	**N/A**	**-2.87%**	**-7.24%**

* Value is statistically lower than the corresponding Base value.

Table 4-20: Corridor Travel Time for All Vehicles and Buses along Southbound Approach

Travel Time (seconds)				
Segments	Base Scenario		TSP-integrated Scenario	
Southbound Approach	All Vehicles	Buses	All Vehicles	Buses
NW 15900 Blk.-NW 151st St.	68.86	105.12	65.13	88.15
NW 151st St.-NW 143rd St.	75.79	115.77	72.11	80.12
NW 143rd St.-Opa locka Blvd.	64.78	61.44	65.09	64.78
Opa Locka Blvd.-NW 135th St.	67.58	124.73	68.05	126.09
NW 135th St.-NW 125th St.	99.63	145.84	95.15	143.93
NW 125th St.-NW 119th St.	78.51	160.06	75.32	155.8
NW 119th St.-NW 111th St.	83.25	87.18	79.85	82.99
NW 111th St.-NW 103rd St.	91.09	93.08	78.12	83.18
NW 103rd St.-NW 95th St.	113.95	161.68	110.13	125.12
NW 95th St.-NW 81st St.	148.48	180.82	145.12	182.94
NW 81st St.-NW 79th St.	140.82	182.58	85.55	168.15
NW 79th St.-NW 71st St.	85.11	182.35	80.11	168.45
NW 71st St.-NW 62nd St.	86.24	179.56	79.67	184.43
NW 62nd St.-NW 54th St.	85.45	140.42	80.51	125.54
NW 54th St.-NW 46th St.	86.75	139.05	84.12	115.65
NW 46th St.-NW 36th St.	101.12	105.26	104.88	118.02
NW 36th St.-NW 32nd St.	68.04	110.45	71.85	103.21
NW 32nd St.-NW 29th St.	54.63	97.16	49.12	90.91
NW 29th St.-NW 20th St.	141.89	182.21	138.11	165.23
NW 20th St.-NW 17th St.	78.32	118.33	74.23	101.23
NW 17th St.-NW 14th St.	69.19	104.57	67.65	87.12
NW 14th St.-NW 11th St.	63.98	102.22	62.81	89.12
NW 11th St.-NW 8th St.	91.4	133.41	90.97	120.12
NW 8th St.-NW 6th St.	41.26	43.68	38.12	40.31
Total	**2,034.45**	**3,056.97**	**1,961.77***	**2,810.59***
Compared to Base	**N/A**	**N/A**	**-3.57%**	**-8.06%**

* Value is statistically lower than the corresponding Base value.

4.5.4.2 Delay

Average vehicle delay time and average stopped delay time were also considered as the performance measures to quantify the mobility benefits of TSP operations. Vehicle delay is measured by subtracting the theoretical (i.e., ideal) travel time from the actual travel time. The theoretical travel time is the travel time which could be achieved if there were no other vehicles and/or no signal controls, or other reasons for stops. Reduced speed areas were also considered. The actual travel time does not include any passenger service times of public transportation vehicles (i.e. buses) at stops. Delay due to braking before a bus stop and/or the subsequent acceleration after a bus stop were included in the average vehicle delay time. Average stopped delay is measured per vehicle in seconds without stops at bus stops and in parking lots. Tables 4-21 and 4-22 provide the average vehicle delay times and the average stopped delay times for all vehicles and buses on northbound and southbound directions, respectively. The table also includes the total average vehicle delay time and the total average stopped delay time along the corridor. It can be inferred from the tables that the TSP-integrated scenario resulted in lower average vehicle delay time and average stopped delay time for all vehicles and for buses, and for both the northbound and the southbound approaches. However, only the results for average vehicle delay time are statistically significant at a 90% confidence level.

Table 4-21: Delay Time Measurement along Northbound Approach

Delay Measurement (seconds)								
	Average Vehicle Delay Time				Average Stopped Delay Time			
Segments	Base Scenario		TSP-integrated Scenario		Base Scenario		TSP-integrated Scenario	
Northbound Approach	All Vehicles	Bus	All Vehicles	Bus	All Vehicles	Bus	All Vehicles	Bus
NW 6th St.-NW 8th St.	9.63	8.51	6.5	7.12	5.3	2.99	5.13	1.73
NW 8th St.-NW 11th St.	7.8	8.18	5.8	6.74	4.52	3.18	4.46	1.67
NW 11th St.-NW 14th St.	12.74	24.12	11.9	18.3	6.88	5.98	6.26	3.83
NW 14th St.-NW 17th St.	13.93	23.61	12.82	20.93	7.89	5.9	7.12	4.84
NW 17th St.-NW 20th St.	39.51	79.43	41.94	79.15	24.13	39.44	24.11	38.5
NW 20th St.-NW 29th St.	36.1	74.22	34.64	67.24	18.97	39.49	18.62	38.05
NW 29th St.-NW 32nd St.	12.12	27.15	11.4	21.19	5.5	10.96	5.04	9.37
NW 32nd St.-NW 36th St.	32.62	46.52	41.99	55.51	20.56	24.07	28.42	40.79
NW 36th St.-NW 46th St.	25.69	36.69	26.61	45.12	12.61	17.53	12.58	25.95
NW 46th St.-NW 54th St.	22.96	21.07	21.71	16.54	10.7	8.78	10.38	7.93
NW 54th St.-NW 62nd St.	29.38	49.86	28.51	42.52	16.97	22.8	16.05	18.32
NW 62nd St.-NW 71st St.	19.55	39.3	18.81	33.12	10.19	17.03	9.72	12.87
NW 71st St.-NW 79th St.	27.42	28.27	20.23	26.3	15.95	8	16.06	7.45
NW 79th St.-NW 81st St.	19.24	39.12	18.94	37.1	14.03	13.31	13.84	12.93
NW 81st St.-NW 95th St.	50.21	58.62	42.23	47.93	29.57	31.17	27.74	22.67
NW 95th St.-NW 103rd St.	51.71	74.18	45.12	60.8	32.81	39.14	31.06	28.83
NW 103rd St.-NW 111th St.	24.67	37.92	21.1	34.12	15.3	15.02	14.58	14.87
NW 111th St.-NW 119th St.	29.71	21.11	21.21	19.21	20.34	6.99	17.14	6.5
NW 119th St.-NW 125th St.	31.32	68.55	28.64	51.89	22.44	32.12	19.77	18.98
NW 125th St.-NW 135th St.	31.82	60.54	27.1	45.13	18.39	31.36	17.34	20.24
NW 135th St.-Opa Locka Blvd.	28.3	44.26	24.51	41.68	14.49	12.36	14.16	14.82
Opa Locka Blvd.-NW 143rd St.	15.64	27.34	12.13	26.21	7.35	7.78	7.27	7.3
NW 143rd St.-NW 151st St.	13.32	13.32	10.23	11.58	6.81	2.76	6.85	2.41
NW 151st St.-NW 15900 Blk.	13.37	20.99	11.12	18.21	4.82	1.88	4.8	1.86
Total	**598.76**	**932.90**	**545.19[a]**	**833.60[a]**	**346.52**	**400**	**338.50[b]**	**362.70[b]**

[a] Value is statistically lower than the corresponding Base value; [b] Value is not statistically lower than the corresponding Base value.

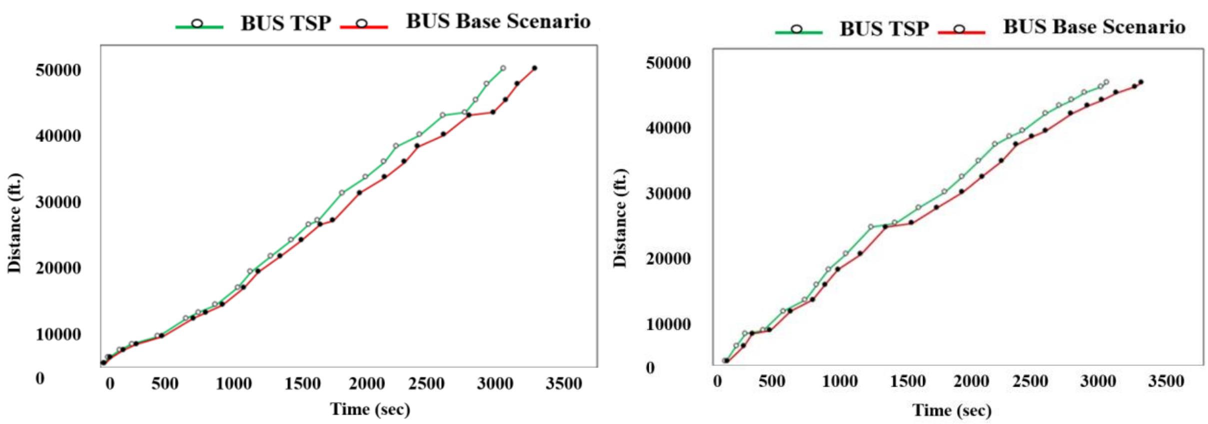
Table 4-22: Delay Time Measurement along Southbound Approach

Delay Measurement (seconds)								
	Average Vehicle Delay Time				Average Stopped Delay Time			
Segments	Base Scenario		TSP-integrated Scenario		Base Scenario		TSP-integrated Scenario	
Southbound Approach	All Vehicles	Bus	All Vehicles	Bus	All Vehicles	Bus	All Vehicles	Bus
NW 15900th Blk.-NW 151st St.	5.98	13.51	6.16	9.51	2.99	3.56	3.08	3.12
NW 151st St.-NW 143rd St.	10.76	20.01	8.16	17.31	5.35	3.83	5.12	3.21
NW 143rd St.-Opa Locka Blvd.	13.78	9.64	11.15	9.1	7.98	4.8	7.91	4.5
Opa Locka Blvd.-NW 135th St.	9.29	35.83	9.87	34.21	4.74	16.5	5.16	17.27
NW 135th St.-NW 125th St.	19.61	34.49	16.21	29.1	11.35	14.07	11.07	12.71
NW 125th St.-NW 119th St.	29.27	50.28	26.18	46.17	17.97	11.56	16.72	12.61
NW 119th St.-NW 111th St.	19.91	22.24	15.23	17.33	13.24	9.89	12.01	9.8
NW 111th St.-NW 103rd St.	28.09	28.43	20.15	18.73	20.17	18.14	17.97	10.51
NW 103rd St.-NW 95th St.	48.81	65.51	43.21	54.23	34.05	36.83	32.86	31.55
NW 95th St.-NW 81st St.	37.42	37.76	37.15	38.12	22.12	16.86	22.04	19.46
NW 81st St.-NW 79th St.	20.77	30	16.89	24.82	9.68	12.92	9.71	8.6
NW 79th St.-NW 71st St.	16.66	53.39	16.48	49.5	7.8	18.87	7.93	15.55
NW 71st St.-NW 62nd St.	13.45	46.67	13.86	51.42	5.84	15.21	6.31	17.65
NW 62nd St.-NW 54th St.	14.55	39.28	12.51	34.23	8.12	20.81	7.34	18.89
NW 54th St.-NW 46th St.	14.85	37.1	11.1	28.12	8.76	15.65	8.26	10.95
NW 46th St.-NW 36th St.	25.87	28.12	20.12	31.12	17.97	16	21.56	26.72
NW 36th St.-NW 32nd St.	25.11	37.35	22.58	35.23	17.34	16.28	20.88	26.72
NW 32nd St.-NW 29th St.	13.89	25.9	11.24	19.61	7.9	10.28	5.71	5.01
NW 29th St.-NW 20th St.	35.52	44.23	31.2	33.39	23.1	24.79	21.78	16.35
NW 20th St.-NW 17th St.	26.7	36	25.2	29.3	17.77	18.48	16.57	13.88
NW 17th St.-NW 14th St.	18.18	22.93	14.26	17.9	10.66	6.46	9.31	4.73
NW 14th St.-NW 11th St.	15.89	23.91	14.66	20.57	9.23	7.56	8.09	6.65
NW 11th St.-NW 8th St.	16.39	27.81	12.1	24.31	7.5	7.46	7.18	6.82
NW 8th St.-NW 6th St.	12.45	14.04	12.07	14.68	7.05	4.47	6.82	4.43
Total	**493.2**	**784.40**	**427.74[a]**	**688[a]**	**298.68**	**331.30**	**291.39[b]**	**307.70[b]**

[a] Value is statistically lower than the corresponding Base value; [b] Value is not statistically lower than the corresponding Base value

4.5.4.3 Bus Progression and Corridor Performance

Bus positions in the TSP environment were recorded in VISSIM for every simulation step. These records were used to plot and compare bus trajectories for the two scenarios, i.e., the Base scenario and the TSP-integrated scenario. There were eleven buses in the northbound approach and nine buses in the southbound approach that started and finished their trips during the evaluation interval in each simulation. For example, Figure 4-22 shows one randomly seeded simulation. The figure shows the progression of one northbound bus and one southbound bus along the study corridor for the Base and the TSP scenarios. Note that the stopped time of buses at an intersection is not shown in the figure.



(a) Northbound Bus Trajectories

(b) Southbound Bus Trajectories

Figure 4-22: Example of Bus Trajectories in the Base and the TSP-integrated Scenarios

It can be inferred from Figure 4-22 that bus progression in the TSP-integrated scenario is relatively quicker than with the Base scenario for both directions. Table 4-23 summarizes the performance results of the entire corridor, and shows the travel time, average vehicle delay time and average stopped delay in seconds for both directions. The results are shown for the Base scenario and the TSP-integrated scenario separately.

Table 4-23: Performance Results of the Entire Corridor with TSP

	Network Performance	Northbound		Southbound	
		Base Scenario	TSP-integrated Scenario	Base Scenario	TSP-integrated Scenario
All vehicles	Travel time (s)	2148.39	2086.75	2034.45	1961.77
	Average Vehicle Delay Time (s)	598.76	545.19	493.2	427.74
	Average Stopped Delay Time (s)	346.52	338.50	298.68	291.39
Buses	Travel time (s)	3062.34	2840.69	3056.97	2810.59
	Average Vehicle Delay Time (s)	932.90	833.60	784.40	688
	Average Stopped Delay Time (s)	400	362.70	331.30	307.70

4.5.5 Discussion

4.5.5.1 Corridor Travel Times

Compared to the Base scenario, implementation of TSP was found to improve travel times for all vehicles and buses in both the northbound and the southbound approaches. For the northbound approach, TSP resulted in a reduction of 7.24% in travel time for buses compared to the Base scenario with no TSP. A similar trend, although not to this extent, was observed for all vehicles in the northbound direction. On average, all vehicles on the northbound lanes experienced a 2.87% reduction in travel time compared to the Base scenario with no TSP.

Travel times along the southbound approach showed similar trends for both buses and all vehicles. For the southbound approach, TSP implementation resulted in a reduction of 8.06% of travel time for buses compared to the Base scenario. For all vehicles, the reduction in travel time was 3.57%. Figures 4-23 and 4-24 provide the travel time results for the northbound and the southbound approaches, respectively.

Statistical *t*-tests were performed on the raw output data from the 10 simulation runs for each scenario. One-tail *t*-tests for paired samples with α=0.1 were performed to test the null hypothesis that the travel time in the TSP-integrates scenario is equal to the travel time in the Base scenario with no TSP integration. The alternative hypothesis for the tests was that travel time in the TSP-integrated scenario was less than the travel time in the Base scenario with no TSP integration. The analysis was performed for all vehicles and buses. The *t*-tests results revealed that travel time for all vehicles and buses in the TSP-integrated scenario were significantly lower than the travel times for all vehicles and buses in the Base scenario with no TSP integration. This result is applicable for both the northbound and the southbound directions of travel. From the study results, it could be concluded that TSP implementation could improve the operational performance of not only transit vehicles but also all vehicles.

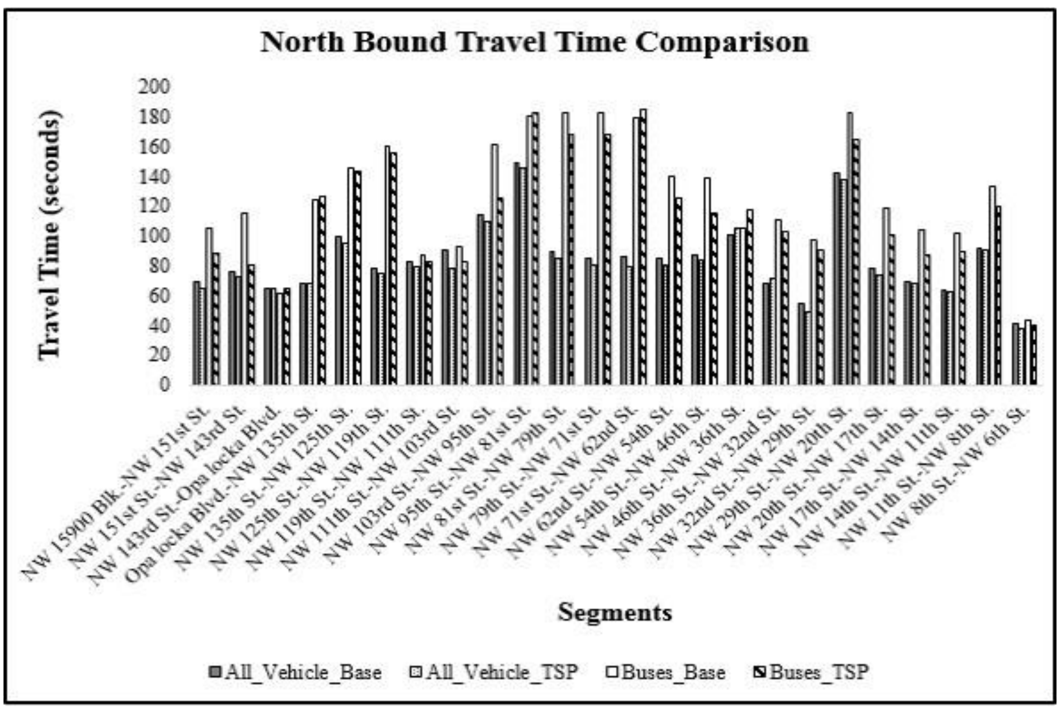


Figure 4-23: Travel Time along US-441-NB Direction

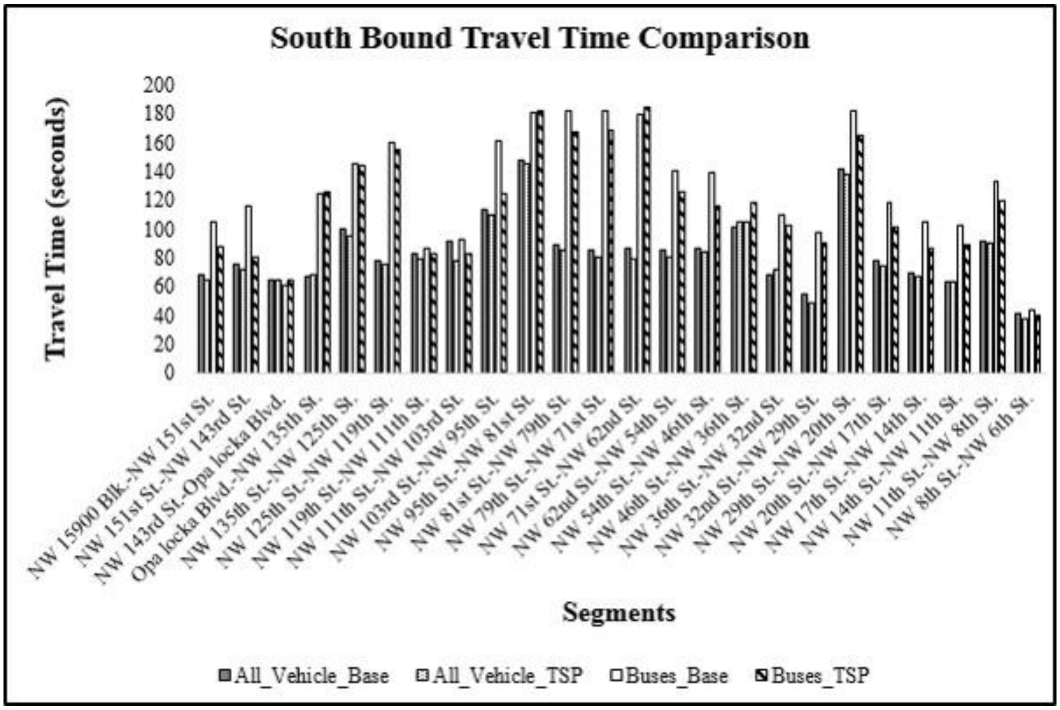


Figure 4-24: Travel Time along US-441-SB Direction

4.5.5.2 Delay

In addition to travel times, average vehicle delay and average stopped delay for all vehicles and for buses were also estimated to quantify the mobility benefits of the TSP strategy. A one-tail *t*-test for paired samples with $\alpha=0.1$ was performed to test the null hypothesis that the average vehicle delay time in the TSP-integrated scenario is equal to the average vehicle delay time in the Base scenario with no TSP integration. The alternative hypothesis for the test was that the average vehicle delay time in the TSP-integrated scenario is lower than the average vehicle delay time in the Base scenario with no TSP integration. The paired *t*-test was conducted for both the average vehicle delay time and the average stopped delay time, and for all vehicles and for buses along the corridor. In general, the TSP strategy resulted in a statistically significant reduction in the average vehicle delay for all vehicles and for buses. However, the average stopped delay in the TSP-integrated scenario did not result in a statistically significant improvement over the Base scenario with no TSP integration. This discussion, therefore, focuses only on average vehicle delay.

For the northbound travel direction, the average vehicle delay time for buses in the Base scenario with no TSP integration was found to be 932.90 seconds, which is 12% higher than the average vehicle delay for buses in the scenario with TSP-integration. For the same direction of travel, the average vehicle delay for all vehicles in the Base scenario and the TSP-integrated scenario were 598.76 seconds and 545.19 seconds, respectively. There was a 9% improvement in the average vehicle delay for all vehicles in the TSP-integrated scenario.

Similar results, although with a slightly different magnitude, were observed for the southbound travel direction. The average vehicle delay time for buses in the Base scenario with no TSP integration and in the TSP-integrated scenario were found to be 784.40 seconds and 688.0 seconds, respectively. It can be inferred that the TSP-integrated scenario resulted in a 14% improvement in the average vehicle delay for buses compared to the Base scenario with no TSP integration. Again, the average vehicle delay for all vehicles in the Base scenario and the TSP-integrated scenario were found to be 493.2 seconds and 427.74 seconds, respectively, resulting in a 15.3% improvement in the TSP-integrated scenario. From the analysis results, it is evident that the TSP-integrated scenario resulted in a statistically significant reduction in average vehicle delay time compared to the Base scenario with no TSP integration.

4.5.5.3 Network Performance

The implementation of any transit preferential treatment, such as TSP, can impact vehicular traffic at the network level, including the cross-street traffic and the through traffic. When compared to the Base scenario with no TSP integration, the corridor-level travel time reduced significantly for buses and all vehicles in both directions of travel. For buses, the total travel time in the TSP-integrated scenario reduced by 7.24% and 8.06% for the northbound and the southbound directions, respectively. Similarly, the total travel time for all vehicles in the TSP-integrated scenario reduced by 2.87% and 3.57% for the northbound and the southbound directions, respectively. It is evident from the analysis results that implementing TSP decreased travel time along the main street. However, it reduced the available green time for the turning vehicles and cross-street traffic. Increased delays were therefore observed for the side-street movements, especially where side-streets had volumes that exceed capacity. The percentage increase in average delay for all other movements except the through and right turn movements on the northbound and southbound approaches of the study corridor was found to be 5.8% for all vehicles. Although the average travel delay increased for all other movements, the reduction in delay for the through traffic on the main street is significantly higher.

4.5.5.4 MEFs

Florida-specific 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, such as TSP in this study, at a specific site. The MEF is multiplied by the expected facility mobility level without the strategy. A MEF of 1.0 serves as a reference, where below or above indicates an expected increase or decrease in mobility, respectively, after implementation of a given TSM&O strategy and depending on the performance metric. These MEFs will assist agencies and professionals in evaluating the effectiveness of the TSP strategy. In this study, MEFs for implementing TSP were estimated based on travel time and delay measurements.

The MEFs based on the total travel time and average vehicle delay were estimated using Equations 4-23 to 4-25.

$$MEF_{travel-time,i} = \frac{ttt_{i,TSP}}{ttt_{i,NOTSP}} \tag{4-23}$$

$$MEF_{delay,i} = \frac{avdt_{i,TSP}}{avdt_{i,NOTSP}} \tag{4-24}$$

$$MEF = \frac{\sum_{i=1}^{n} MEF_i}{n} \tag{4-25}$$

where,

$MEF_{travel\text{-}time,i}$	=	the mobility enhancement factor based on travel time for a particular i^{th} corridor,
$MEF_{delay,i}$	=	the mobility enhancement factor based on average vehicle delay for a particular i^{th} corridor,
$ttt_{i,TSP}$	=	the total travel time along a TSP-enabled corridor,
$ttt_{i,NOTSP}$	=	the total travel time along a corridor with no TSP,
$avdt_{i,TSP}$	=	the average vehicle delay time along a TSP-enabled corridor, and
$avdt_{i,NOTSP}$	=	the average vehicle delay time along a corridor with no TSP.

Table 4-24 presents the estimated MEFs for travel time for all vehicles and buses. The MEFs for TSP in terms of travel time for all vehicles and buses were estimated to be 0.96 and 0.91, respectively. It implies that deploying TSP along a corridor would result in a 4% decrease in travel time for all vehicles and a 9% decrease in travel time for buses along the corridor. The MEFs in terms of average vehicle delay was estimated to be 0.87 for all vehicles and for buses. It implies that deploying TSP along a corridor would result in a 13% decrease in average vehicle delay along the corridor. The study results show that TSP improves the operational performance of the corridor.

Table 4-24: MEFs for TSP

Performance Measure	All Vehicles	Buses
Travel Time	0.96	0.91
Average Vehicle Delay Time	0.87	0.87

4.5.6 Conclusions

Transit Signal Priority (TSP) is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections. The analysis was based on a 10-mile corridor along US-441 between SW 8th Street and the Golden Glades Interchange in Miami, Florida. Two microsimulation VISSIM models, the Base model with no TSP integration and the TSP-integrated model, were developed.

One of the key findings observed from the evaluation is that the TSP transit preferential treatment offers significant mobility benefits for transit buses and all vehicles. TSP was found to provide significant savings in travel time and travel delay along the corridor. For transit buses, TSP resulted in a 7.24% reduction in travel time for the northbound section, and an 8.06% reduction in travel time for the southbound section. Also, for all vehicles in the network, a 2.87% reduction in travel time for the northbound section, and a 3.57% reduction in travel time for the southbound section was observed as a result of TSP deployment. Implementation of TSP also provided significant reductions in average vehicle delay. For transit buses, TSP deployment resulted in a reduction in average vehicle delay of 10.64% and 12.30% for northbound and southbound directions, respectively. For all vehicles in the network, a reduction in the average vehicle delay time of 9% and 13.3% for northbound and southbound directions was observed.

The MEFs based on travel time were 0.96 for all vehicles and 0.91 for buses, and the MEF based on average vehicle delay time was 0.87 for all vehicles and buses. Based on the MEF results for travel time and average vehicle delay time, it can be concluded that TSP improves the operational performance of the corridor. MEF results could provide researchers and practitioners with an effective method for analyzing the economic and other benefits of the TSP strategy.

The performance of TSP was affected by the location of the bus stops along the corridor (i.e., near-side and far-side). The benefits of the TSP were found to decrease for near-side bus stops. Moreover, predicting the travel time from an upstream transit vehicle detector to the stop bar of a signalized intersection after stopping in a near-side bus stop proved to be challenging. It was observed that intersections with far-side bus stop locations improved the performance of TSP. However, at major intersections where the side-street volume exceeds capacity, TSP implementation produced similar results to the Base scenario with no TSP integration; thus, deploying TSP at intersections where side-street volume exceeds capacity is not beneficial. While TSP, in general, provided major benefits for all vehicles and buses along the main street, side streets with traffic volumes greater than capacity observed a 5.8% increase in average delay. Although the average delay for side-street traffic and left-turning vehicles increased, the reduction in delay in the main street is significantly higher. Overall, mobility benefits were observed with TSP implementation.

4.6 Adaptive Signal Control Technology

The following sections examine the mobility benefits of a TSM&O strategy involving adaptive signal control technology (ASCT) systems.

4.6.1 Study Corridor

The Mayport Road (Hwy A1A) corridor was selected to analyze the mobility benefits of ASCT. As shown in Figure 4-25, the study segment spans from the Atlantic Boulevard (SR-10) to Wonderwood Drive (SR-116), along Mayport Road for a total of 3.3 miles. This segment of the corridor has 10 adaptive (SynchroGreen) signalized intersections, and a posted speed of 45 mph. The corridor has 8.5 and 11.5 driveways per mile along the northbound and southbound directions, respectively. The ASCT was activated at all 10 intersections on June 25, 2018.

4.6.2 Data

Real-time traffic flow data (i.e., travel time and travel speed) with and without ASCT were retrieved from the BlueToad® database for the periods July 08, 2018 through February 10, 2019. Data were collected for the same days of the week for both with and without ASCT and the same sample size of the data for each group (with and without ASCT) were considered in the analysis.

Traffic data for the first two weeks with ASCT was excluded from the analysis to account for the activation period. Thus, the traffic data with ASCT for the analysis were collected from July 08, 2018 to October 23, 2018. The traffic data without ASCT were collected from October 24, 2018 to February 02, 2019. To reduce variations in the data, only typical days of the week, i.e., Tuesday, Wednesday, and Thursday, were considered in the analysis. Time blocks used in the analysis consisted of AM peak (0600-1000), PM peak (1500-1900) and off-peak hours (1000-1200) and during the night.

Table 4-25 presents travel speed descriptive statistics for the typical days of the week. As indicated in Table 4-25, the average speeds in the northbound direction are slightly higher than the average speeds in the southbound direction. These average speeds were used in the transformation of the standardized speeds coefficient from the model in this study.

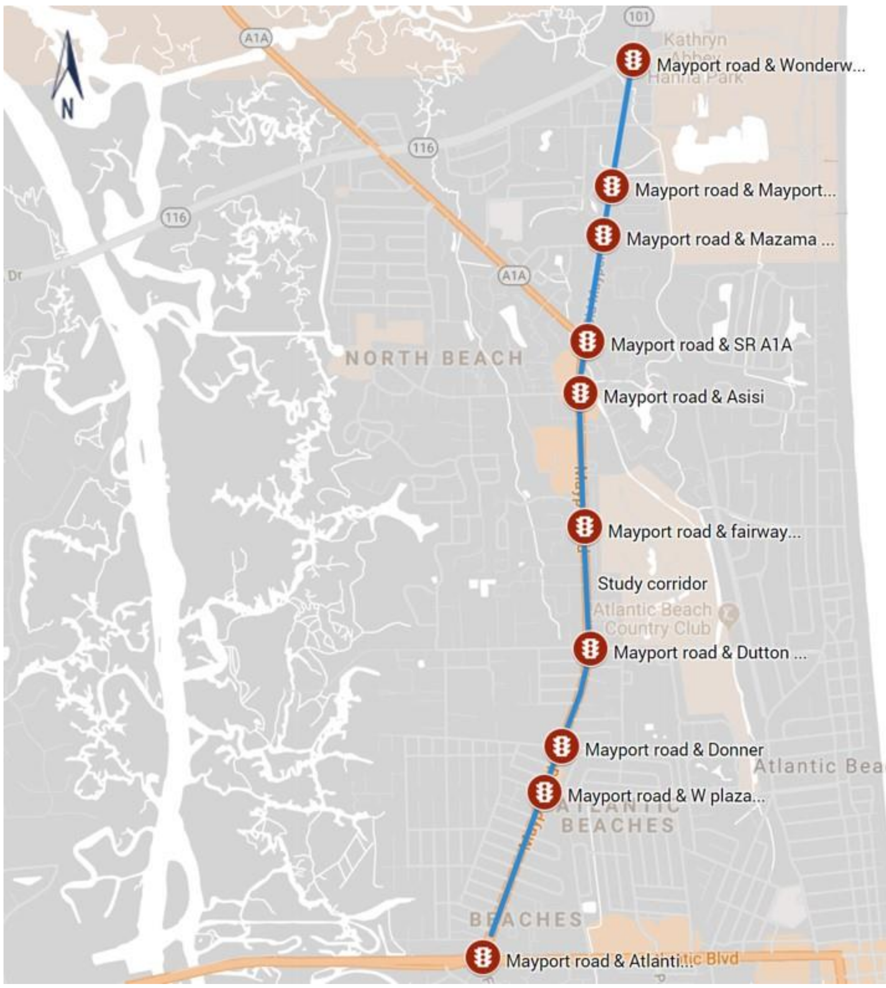


Figure 4-25: ASCT Performance Evaluation Study Corridor

Table 4-25: Descriptive Statistics of the Speed Data for ASCT Evaluation

	Northbound				Southbound			
Day of Week	**Mean (mph)**	**Max. (mph)**	**Min. (mph)**	**S.Dev (mph)**	**Mean (mph)**	**Max. (mph)**	**Min. (mph)**	**S.Dev (mph)**
Tuesday	36.54	45.03	11.55	3.41	32.22	40.18	10.59	3.48
Wednesday	36.53	44.58	14.15	3.25	32.45	39.61	16.69	2.93
Thursday	36.41	44.88	11.19	3.69	32.34	40.68	11.94	3.46

Note: Max. = Maximum, Min. = Minimum, and S.Dev = Standard Deviation.

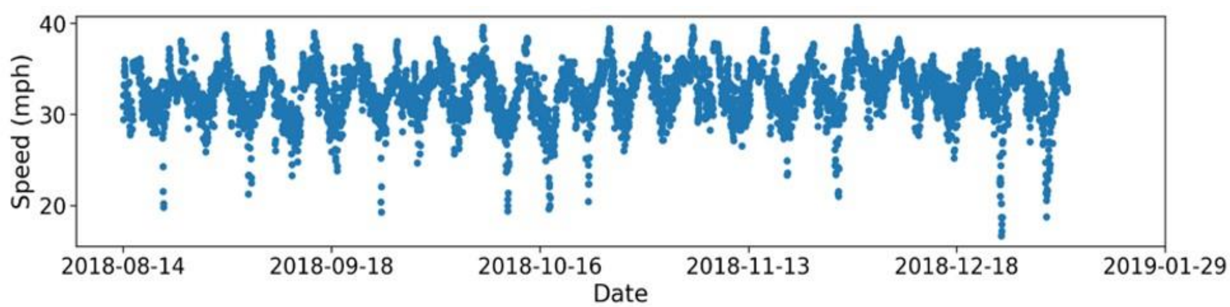
4.6.3 Methodology

4.6.3.1 Theoretical Concept of a Bayesian Switch-Point Regression (BSR) Model

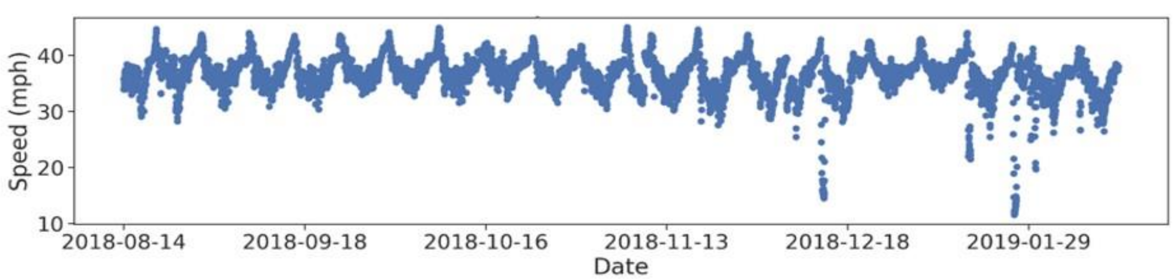
The BSR is a common model in calibrating time-series data (Kidando et al., 2019a), particularly, when identifying the unknown location in which patterns change is one of the primary goals (Lin et al., 2012b). The pattern change in data characteristics could be due to change in sequence, data variations or shift in the mean between before and after the threshold (Bhagat et al., 2017; Kidando et al., 2017; Kruschke and Liddell, 2018). Even though this model has been used for a while in fitting different data characteristics, such as stock prices and DNA sequences, it has not been used extensively in the field of transportation (Kidando et al., 2017, 2019a).

As it was expected, the general trend of the speed time series reveals that there are fluctuations in daily data (Figure 4-26). To fit this pattern, the BSR is integrated with a sinusoidal function to accurately approximate the data characteristics. Furthermore, the developed model was set to be flexible as the average speeds and variances for data with and without ASCT are allowed to be different (see Equation 4-26).

Suppose that the average speed with ASCT μ_1 is linearly added to the daily data fluctuation (sinusoidal), $\beta_{11}sin(2\pi\emptyset x) + \beta_{12}cos(2\pi\emptyset x)$. Similarly, the pattern without ASCT is formulated with the average speed parameter μ_2 and the sinusoidal function, $\beta_{21}sin(2\pi\theta x) + \beta_{22}cos(2\pi\theta x)$. The switch-point parameter τ is unknown, which is estimated by the model. This parameter separates the two patterns such that there is a different data characteristic between the two patterns. The proposed model also assumes that the errors, (ε_{i1} and ε_{i2}) are randomly and normally distributed in the regression. Note that other types of distributions such as Student-t distribution could be implemented in the analysis.



(a) Tuesday-Northbound traffic



(b) Tuesday- Southbound traffic

Figure 4-26: Time Series of Travel Speeds Collected at 5-min Intervals

$$Y_i \sim \begin{cases} N(\alpha_{1i}, \sigma_1), & if\ \ x_i\ \leq\ \tau \\ N(\alpha_{2i}, \sigma_2), & otherwise \end{cases} \tag{36}$$

where,

$\alpha_{1i} =\ \mu_1 + \beta_{11} sin(2\pi\emptyset x_i) + \beta_{12} cos(2\pi\emptyset x_i) + \varepsilon_{i1}$
$\alpha_{2i} =\ \mu_2 + \beta_{21} sin(2\pi\theta x_i) + \beta_{22} cos(2\pi\theta x_i) + \varepsilon_{i2}$
$\varepsilon_{i1} \sim N(0, \sigma_1)$
$\varepsilon_{i2} \sim N(0, \sigma_2)$
$\mu_1\ and\ \mu_2$ is the predicted average travel speed with and without ASCT respectively,
x represents index of the data point,
$\emptyset,\ \theta,\ \beta_{11},\ \beta_{12},\ \beta_{21}, and\ \beta_{22}$, are the regression coefficients of the sinusoidal functions,
Y represents speed variable,
σ_1 and σ_2 are the standard deviation of the data with and without ASCT respectively, and
N means a univariate Gaussian (normal) distribution.

Prior Specification and Parameter Posterior Distribution Estimation: For the Bayesian analysis, the prior distribution, likelihood function, number samples, and sampling algorithm must be assigned in estimating the posterior distributions of the model parameters. In this aspect, the prior distribution for the switch-point τ in Figure 4-27 was assigned to be non-informative prior with a uniform distribution ($\tau \sim DiscreteUniform(\min_s, \max_s)$). The lower and upper boundaries were assigned to be the minimum and maximum data index to allow equal probability of τ to be at any index. For the regression parameters, $\mu_1,\ \mu_2,\ \beta_{11},\ \beta_{12},\ \beta_{21},$ and β_{22}, the prior distributions were assumed to follow the normal distribution with zero mean and variance of 100. Moreover, the standard deviations of data σ_1 and σ_2 in the model were taken as the half normal distribution with parameter 5. The sampling algorithm adopted to estimate these parameters' posterior distributions is the MCMC simulations with the No-U-Turn Sampler (NUTS) sampling step. This algorithm is one of the commonly applied approaches to approximate the posterior distributions without directly computing the marginal distribution (Kruschke, 2013). A PyMC3 version 3.6, an open-source Python package through MCMC simulations was used to estimate the posterior distributions (Salvatier et al., 2016).

Model Evaluation: The proposed model was evaluated its goodness of fit by comparing to the null model. In this instance, the present study used the Widely Applicable Information Criterion (WAIC). The WAIC provides a way of measuring the fit of Bayesian models by trading in the model simplicity and prediction accuracy to reduce the possibility of the fitted model failing to generalize on the new data (overfitting) (Watanabe, 2010). It is conceptually similar to Akaike and Bayesian Information criteria, the commonly used performance indicators in the maximum likelihood estimation. Like these indicators, lower values of WAIC indicate a better model fit than others. The WAIC can be expressed using Equation 4-27.

$$WAIC = -2 * lppd + 2 * p\_wic \tag{4-27}$$

where,

p_waic is the effective number of parameters,
$lppd$ is the log point-wise posterior predictive density

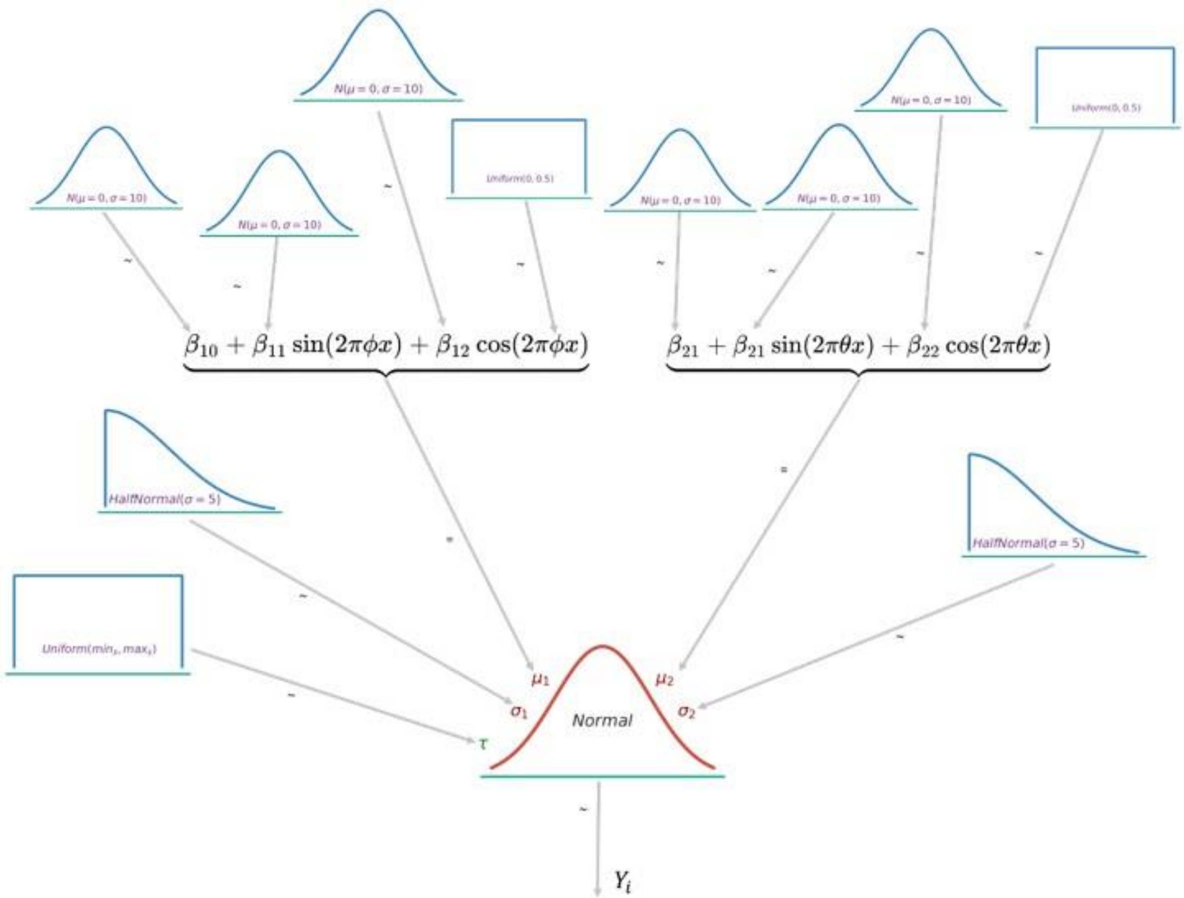


Figure 4-27: Prior Distribution of the Bayesian Switch-Point Regression (Kidando et al., 2019a)

Bayesian Hypothesis Testing (BHT): In order to understand if there is a credible difference in operating characteristics with and without ASCT, BHT was conducted. The estimated posterior distributions for the difference in average speed and the standard deviation of speed with and without ASCT were used. The 95% highest posterior density interval (HDI) is the criterion that was used for making a discrete decision to reject or fail to reject the null hypothesis. A similar criterion has been adopted by the previous studies to decide about the null value from the estimated posterior distribution (Kruschke, 2010, 2013; Kidando et al., 2019a). The null hypothesis (H_0) was formulated that there is no difference between the two patterns (i.e., the two patterns are the same) while the alternative hypothesis (H_1) was expressed that the patterns with and without ASCT are credibly different. The formulated hypothesis test can be summarized as follows:

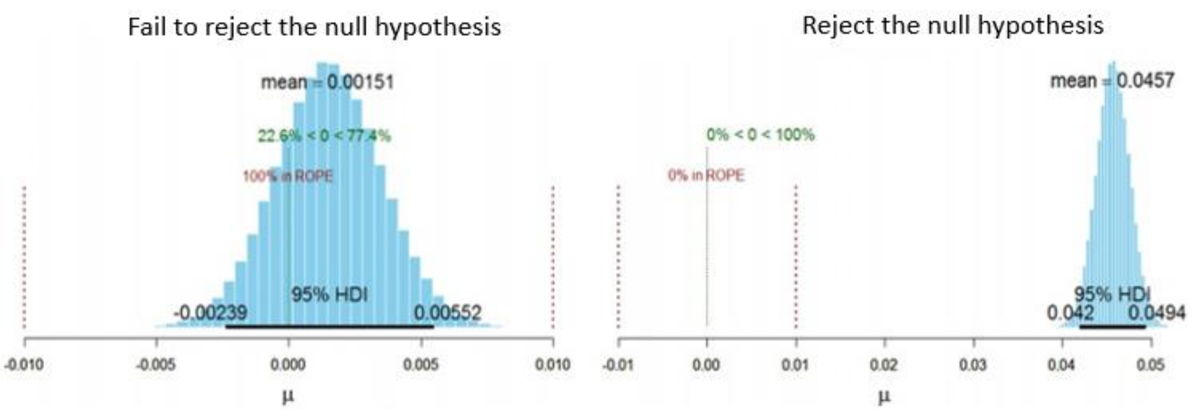
Hypothesis on the average travel speeds:

Null hypothesis (H_0): $\mu_1 - \mu_2 = 0$
Alternative hypothesis (H_1): $\mu_1 - \mu_2 \neq 0$

For the standard deviation of speeds:

Null hypothesis (H_0): $\sigma_1 - \sigma_2 = 0$
Alternative hypothesis (H_1): $\sigma_1 - \sigma_2 \neq 0$

In the Bayesian context, rejecting or not rejecting the null value is done by looking at the difference of the posterior distribution densities (i.e. $\mu_1 - \mu_2$). When the resulting density include zero as one of the credible values in the 95% HDI, the null hypothesis is not rejected (Kruschke, 2010) as illustrated in Figure 4-28. This suggests that there is no credible difference between the operating speed with and without ASCT. A similar interpretation can be made when the standard deviation of speed parameters are used $(\sigma_1 - \sigma_2)$.



(a) Posterior distribution of μ with the 95% HDI inside the ROPE (b) Posterior distribution of μ with the 95% HDI outside the ROPE

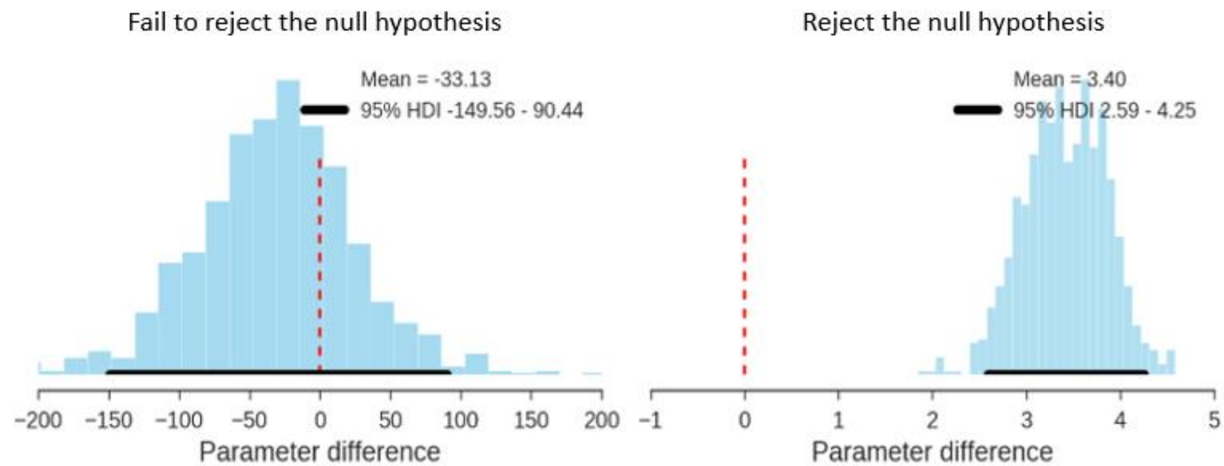


Figure 4-28: Decision Criteria for the Bayesian Hypothesis Testing (BHT) (Kidando et al., 2019a)

4.6.3.2 MEF Definition

A Mobility Enhancement Factor (MEF) is a multiplicative factor used to estimate the expected mobility level after implementing a given strategy (in this case, ASCT) at a specific site. The MEF is multiplied by the expected facility mobility level without the strategy. An MEF of 1.0 serves as a reference, where below or above indicates an expected decrease or increase in mobility, respectively, after implementation of a given strategy. For the ASCT strategy, an MEF value less than one (MEF <1.0) indicates an expected mobility benefit. MEFs were calculated using Equation 4-28.

$$\text{MEF} = \frac{\mu_2}{\mu_1} \quad (4\text{-}28)$$

The overall MEF for the ASCT was calculated using Equation 4-29.

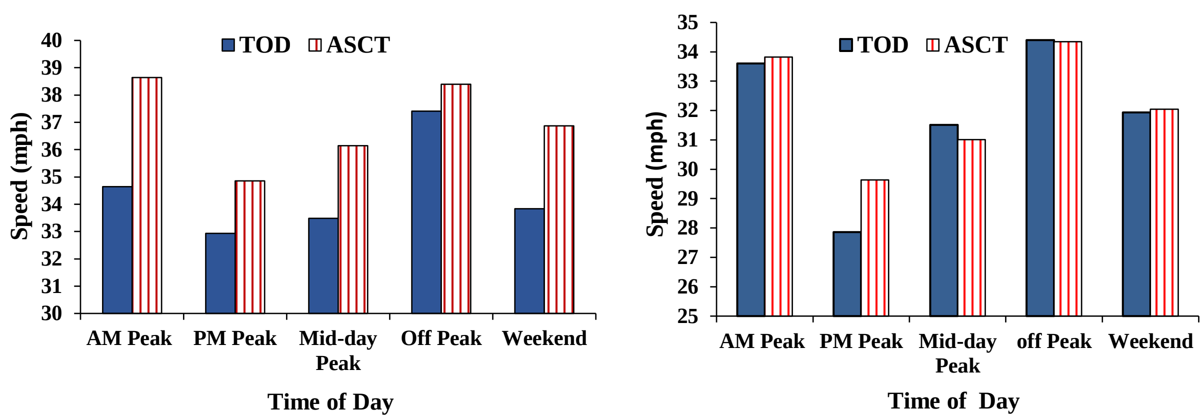
$$MEF_{overall} = \frac{\sum_{i=1}^{n} MEF}{n} \quad (4\text{-}29)$$

where, *n* represents number of days analyzed in the study.

4.6.4 Results

4.6.4.1 Descriptive Statistics

Descriptive statistics of travel speed as the performance measure is presented in Figure 4-29. As shown the figure, average travel speeds are considerably higher with ASCT in the northbound direction, especially during AM peak hours, with an average increase of 11.5% in travel speed (4 mph) compared to time of a day (TOD) signal plans. Similarly, travel speeds increased for other periods of the day following ASCT deployment, with an increase of 5.8%, 7.9%, 2.6%, and 9% in the travel speeds for the PM peak, mid-day peak, off-peak, and weekend hours, respectively. Travel speed results varied for the southbound direction. ASCT showed positive benefits during PM peak hours, with an increase of 7.3% in average travel speed, equivalent to 2 mph. Slight increases in travel speeds were observed during AM peak hours (0.7% increase) and weekend hours (0.3% increase). However, average travel speeds decreased following ASCT installation during mid-day hours (-1.6% decrease) and off-peak hours (-0.2% decrease).



(a) Travel speed NB

(b) Travel speed SB

Figure 4-29: Travel Speeds with and without ASCT

4.6.4.2 Model Results and Discussions

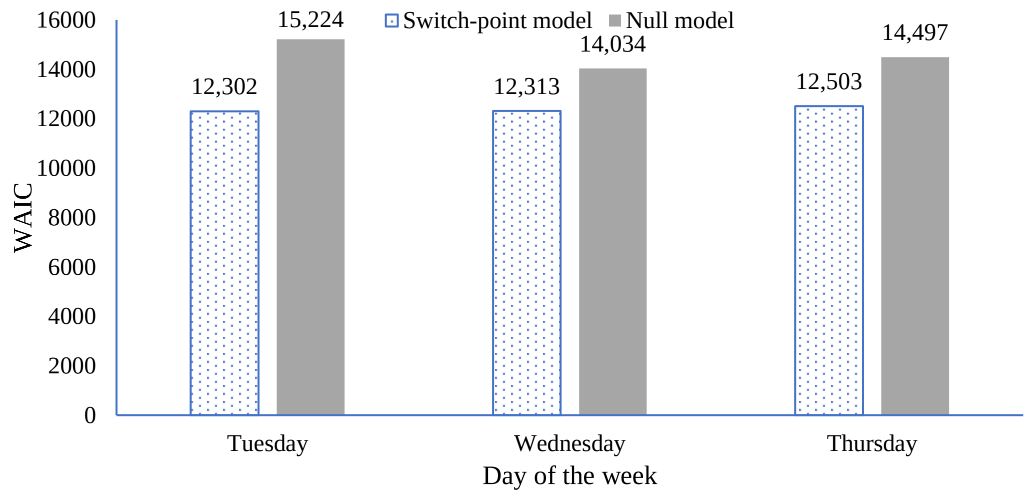
The posterior distributions of the BSR and the null model were estimated using 20,000 iterations as initial burn-in and tune samples while the subsequent 10,000 iterations were used for inference. The convergence of the two fitted models were assessed using the Gelman-Rubin Diagnostic statistic. Moreover, visual diagnostics approach using the trace, density, and autocorrelation plots of each parameter were used to evaluate chains convergence. Model comparison, BSR, BHT and MEFs results are presented in this section.

Model Goodness-of-fit Evaluation: Fitting the BSR can be viewed as a hypothesis test (Liu & Qian, 2010). The comparison with the null model, a model without a switch-point, is important to justify the use of the BSR. This study used the WAIC to asses the goodness of fit (GOF) of the BSR and the null model. The WAIC provides a trade-off between the model complexity and prediction accuracy to account for the overfitting problem (Watanabe, 2010). The model is considered to better fit the observed data when it has the lowest WAIC value when compared with the other models generated using the same dataset (McElreath, 2016). Figure 4-30 provides the results of the GOF statistics for the three days analyzed in both directions. As stipulated in this figure, the switch-point model has a WAIC value of 12,302 versus 15,224 of the null model for the Tuesday in the northbound direction. As observed in Figure 4-30 the WAIC value of the switch-point model is smaller compared to the WAIC value of the null model for other days in both directions. According to GOF measured by WAIC values, the switch-point mode had better fit compared to null model, with the observed smaller WAIC difference of 1,721 and 549 in northbound and southbound directions, respectively.

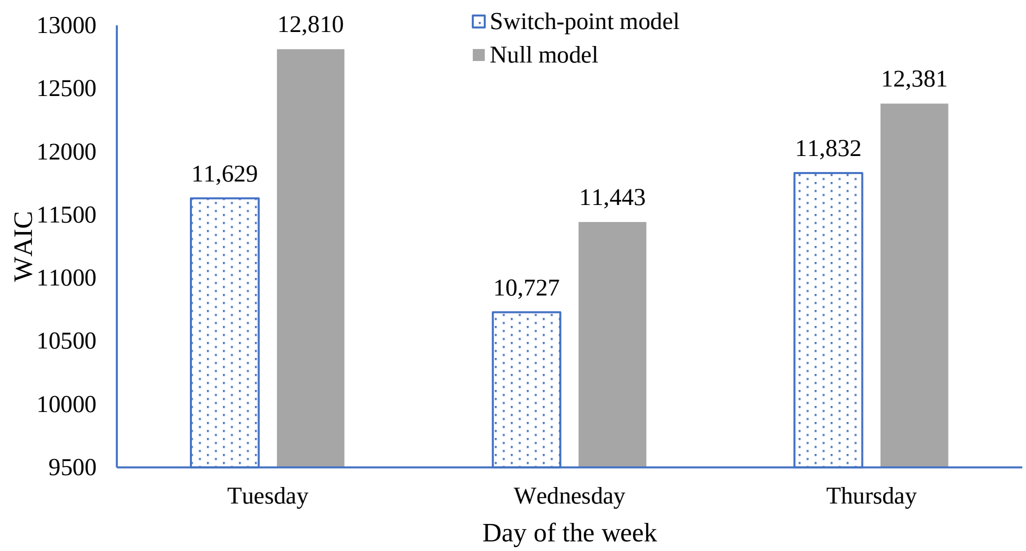
The estimated switch-points, τ, were compared to the date that the ASCT was turned-off to check the accuracy of the model in calibrating this parameter. As presented in Table 4-26, the average estimated switch-point date for southbound and northbound traffic on Tuesday by the BSR is November 06, 2018. For the northbound and southbound traffic on Wednesday, the average estimated switch-point date is November 07, 2018. On the other hand, November 01, 2018 and October 27, 2018 are the average etimated switch-point dates for Thursday northbound and southbound directions, respectively. Comparing to the actual date that the ASTCS was turned-off, on October 24, 2018, the estimated switch-point dates by the BSR model are not too far from the date the system was turned-off. Thus, the proposed model demonstrates that it can be useful to identify the dates at which there is a difference in operating characteristics in the study corridor.

Figure 4-31 shows the histogram of observed field data with and without ASCT as well as the predicted posterior estimates from the BSR. As indicated in the figure the lines of the posterior predicted data densities are too close and superimpose the histograms for the observed data densities indicating that the BSR can be used to fit the data. This suggests that the BSR model can calibrate the data trend with a reasonable accuracy including the switch-point dates. Note that the field observed data with and without ASCT were extracted using the actual date that the ASCT was turned-off. On the other hand, the posterior predicted densities with and without ASCT are based on the estimated switch-point dates calibrated by the BSR model.

Figure 4-32 shows how the model performed in predicting the time series data. As seen in this figure, the proposed model estimates and the actual data trend are close. More specifically, the predicted posterior lines follow daily data fluctuations. Moreover, Figure 4-32 clearly portrays that there is a large speed variation without ASCT than with ASCT for all days except Wednesday southbound direction. Nevertheless, the average travel speed difference with and without ASCT are not visible.



(a) Northbound traffic

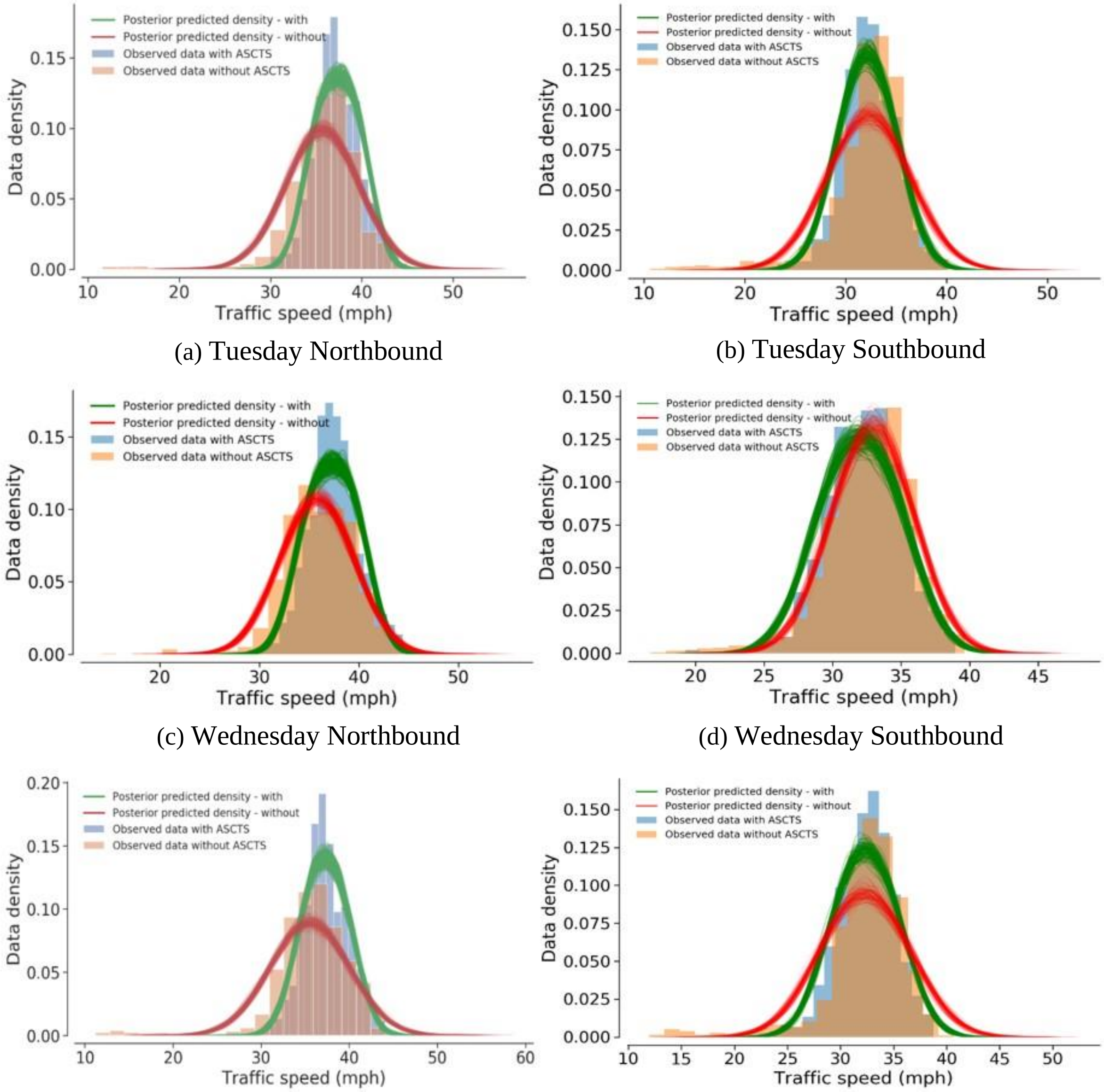


(b) Southbound traffic

Figure 4-30: Goodness-of-fit of the Switch-Point and Null Models

Table 4-26: Posterior Summary Results of the BSR Model

	Tuesday Northbound				Tuesday Southbound			
Parameter	**Mean**	**Sd**	**95% BCI**		**Mean**	**Sd**	**95% BCI**	
β_{11}	-0.54	0.02	-0.58	-0.50	-0.65	0.02	-0.69	-0.61
β_{12}	-0.56	0.02	-0.61	-0.52	0.02	0.05	-0.08	0.10
β_{21}	-0.25	0.12	-0.47	-0.02	0.63	0.04	0.55	0.71
β_{22}	-0.42	0.08	-0.54	-0.25	-0.06	0.15	-0.35	0.23
μ_1	0.23	0.01	0.21	0.25	-0.01	0.01	-0.03	0.02
μ_2	-0.24	0.02	-0.28	-0.20	0.00	0.02	-0.04	0.04
τ	11/06/2018	1.32	11/06/2018	11/06/2018	11/06/2018	2.54	11/06/2018	11/06/2018
$\emptyset$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
θ	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01
σ_1	0.50	0.01	0.49	0.52	0.67	0.01	0.65	0.69
σ_2	1.10	0.01	1.07	1.13	1.06	0.02	1.03	1.09
	Wednesday Northbound				**Wednesday Southbound**			
Parameter	**Mean**	**Sd**	**95% BCI**		**Mean**	**Sd**	**95% BCI**	
β_{11}	0.75	0.02	0.71	0.79	0.67	0.04	0.59	0.74
β_{12}	-0.46	0.03	-0.51	-0.41	-0.66	0.04	-0.73	-0.58
β_{21}	-0.09	0.13	-0.34	0.18	0.45	0.09	0.28	0.63
β_{22}	-0.72	0.04	-0.78	-0.65	-0.53	0.08	-0.68	-0.37
μ_1	0.22	0.01	0.20	0.25	-0.16	0.02	-0.19	-0.12
μ_2	-0.23	0.02	-0.26	-0.19	0.14	0.02	0.10	0.17
τ	11/07/2018	0.82	11/07/2018	11/07/2018	11/07/2018	6.11	11/07/2018	11/07/2018
$\emptyset$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
θ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
σ_1	0.54	0.01	0.53	0.56	0.73	0.01	0.71	0.75
σ_2	0.97	0.01	0.95	1.00	0.85	0.01	0.83	0.88
	Thursday Northbound				**Thursday Southbound**			
Parameter	**Mean**	**Sd**	**95% BCI**		**Mean**	**Sd**	**95% BCI**	
β_{11}	0.02	0.03	-0.03	0.07	0.08	0.04	0.01	0.15
β_{12}	-0.68	0.01	-0.71	-0.65	-0.77	0.02	-0.80	-0.73
β_{21}	0.49	0.11	0.28	0.69	-0.38	0.18	-0.73	-0.03
β_{22}	0.52	0.11	0.31	0.71	-0.75	0.11	-0.91	-0.51
μ_1	0.24	0.01	0.22	0.26	0.00	0.01	-0.03	0.02
μ_2	-0.25	0.02	-0.29	-0.21	-0.02	0.02	-0.07	0.02
τ	11/01/2018	1.79	11/01/2018	11/01/2018	10/27/2018	3.63	10/27/2018	10/27/2018
$\emptyset$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
θ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
σ_1	0.52	0.01	0.51	0.54	0.69	0.01	0.67	0.70
σ_2	1.06	0.01	1.03	1.09	1.00	0.02	0.97	1.03



(a) Tuesday Northbound

(b) Tuesday Southbound

(c) Wednesday Northbound

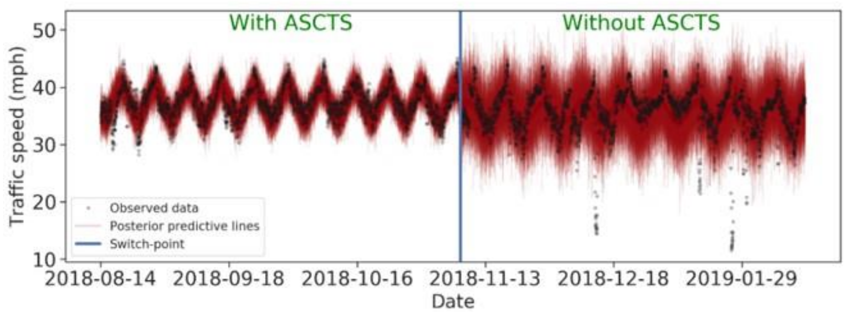
(d) Wednesday Southbound

(e) Thursday Northbound

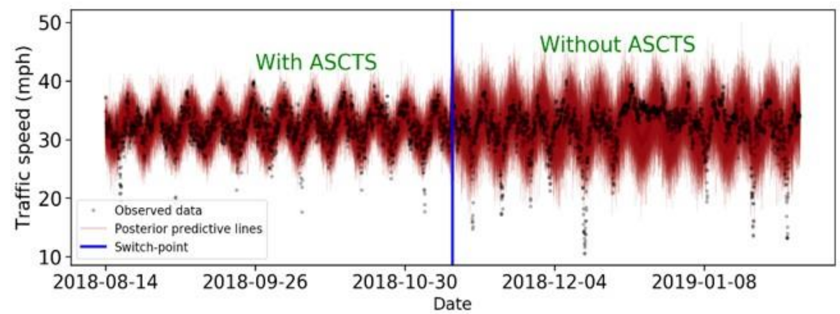
(f) Thursday Southbound

Figure 4-31: Posterior Predicted and Observed Data Densities

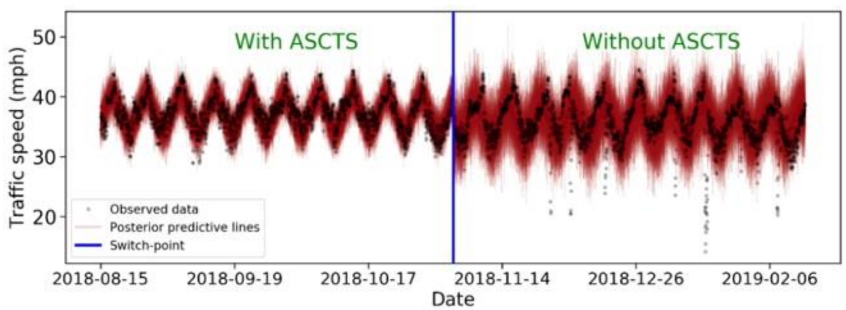
Note: "Posterior predicted densities – with" represents estimated density by the BSR before the switch-point, i.e., predicted data with ASCT; "Posterior predicted density – without" represents the estimated density after the switch-point in the BSR model, i.e., predicted data without ASCT.



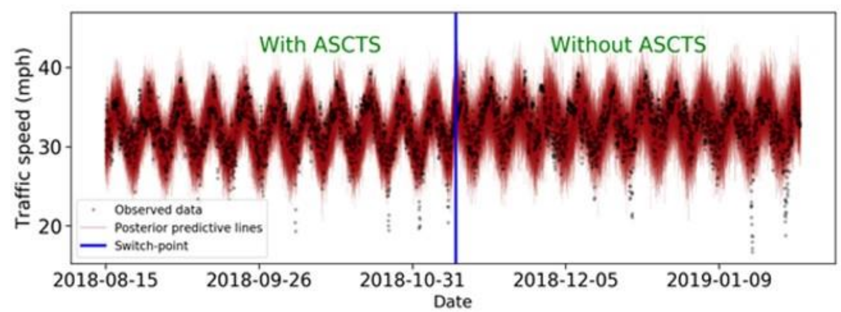
(a) Tuesday Northbound



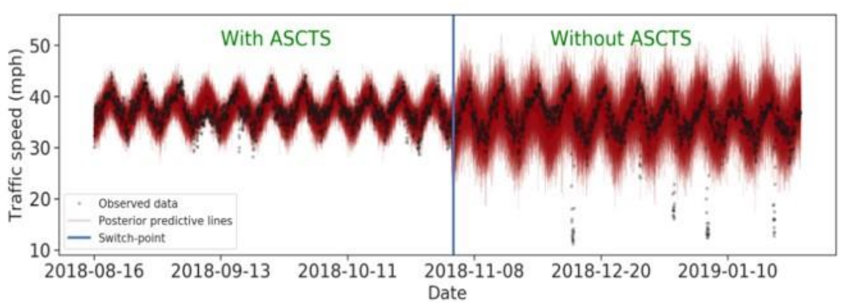
(b) Tuesday Southbound



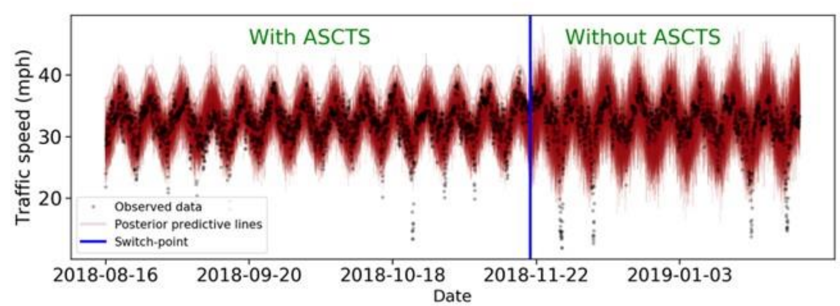
(c) Wednesday Northbound



(d) Wednesday Southbound



(e) Thursday Northbound



(f) Thursday Southbound

Figure 4-32: Time Series Plot of Actual Traffic Speed with Posterior Predictive Estimates

BSR Model Results: Results from the BSR are presented in Table 4-26. Note that in estimating the parameters' posterior distributions of the model, travel speed data were standardized following a z-score approach to allow the model to easily converge in the analysis. Equations 4-30 and 4-31 were used to transform the estimated coefficients to speed posterior distributions using the average speed and standard deviation of the observed data presented in Table 4-25. For instance, for Tuesday northbound traffic, with a mean speed and standard deviation of 3.41 mph and 36.54 mph, respectively (see Table 4-25), and μ_1 = 0.23 (see Table 4-26), the average estimated speed with ASCT ($speed_{with}$) $= 0.23 \times 3.41 + 36.54 = 37.32$ mph (95%BCI = [37.26, 37.39]). Using Equation 4-31, the estimated average speed without ASCT ($speed_{without}$) $= 35.72$ mph (95%BCI = [35.59, 35.86]). According to these estimates, ASCT improved the operating speed from 35.72 mph to 37.32 mph.

$$speed_{with} = \mu_1 \times s + \bar{x} \tag{4-30}$$

$$speed_{without} = \mu_2 \times s + \bar{x} \tag{4-31}$$

where,

$\bar{x}$ represents the average speed of the observed data,

s is the standard deviation of the observed speed data, and

$speed_{with}$ and $speed_{without}$ denotes the average speed (mph) with and without ASCT respectively.

For the southbound traffic, the estimated average speeds with and without ASCT were 32.21 mph (95%BCI = [32.08, 32.36]) and 32.18 mph (95%BCI = [32.12, 32.29]), respectively. Note that the average travel speeds with and without ASCT are approximately equal for the southbound traffic, indicating that there is no significant improvement following ASCT installation.

For Wednesday northbound traffic, the estimated average speeds with and without ASCT are 37.25 mph (95%BCI = [37.18, 37.34]) and 35.78 mph (95%BCI = [35.69, 35.91]), respectively. Furthermore, in southbound traffic the estimated average speeds values are 31.98 mph (95%BCI = [31.89, 32.10]) and 32.86 mph (95%BCI = [32.74, 32.95]) with and without ASCT respectively. Values of the estimated average speeds are higher with ASCT in the northbound direction, indicating a significant improvement in travel speed following ASCT installation. However, in the southbound direction estimated average speed without ASCT is higher, compared to with ASCT, indicating a slight decrease in travel speed following the ASCT deployment.

For Thursday, the estimated average speeds with and without ASCT are 37.29 mph (95%BCI = [37.22, 37.37]) and 35.49 mph (95%BCI = [35.34, 35.64]), respectively, in the northbound direction. In southbound direction, estimated average speeds are 32.34 mph (95%BCI = [32.24, 32.41]) and 32.27 mph (95%BCI = [32.10, 32.41]) with and without ASCT respectively. The values of the estimated average speeds are higher with ASCT in the northbound direction, indicating a significant improvement in travel speed following ASCT installation. However, the southbound estimated average speeds with and without ASCT are approximately equal, indicating that there is no significant change following ASCT installation. Parameters β_{11}, β_{12}, $\beta_{21}, \beta_{22}, \emptyset,$ and θ listed in Table 4-26, are sinusoidal parameters for the sine and cosine function, which in this study were considered to calibrate daily speed due to demand variations.

Bayesian Hypothesis Testing (BHT) Results: Table 4-27 shows the difference between the credible values of the model parameters for the typical days analyzed in both directions of travel. This table shows the summary statistics that facilitate decision to reject or fail to reject the null hypothesis at 95% HDI.

As shown in Table 4-27, the mean difference in average speeds with and without ASCT ($Speed_{with} - Speed_{without}$) and the mean difference in the standard deviation of speeds with and without ASCT ($Std_{with} - Std_{without}$) was 1.60 (95%HDI = [1.45, 1.76]) and -2.03 (95%HDI = [-2.14, -1.93]), respectively for Tuesday in the northbound direction. The null value zero is far from the 95% HDI estimated difference for all parameters' posterior distribution indicating that there is a credible difference between with and without ASCT. For the southbound direction on Tuesday, the mean difference in average speed and standard deviation of speed was -0.02 (95%HDI = [-0.2, -0.16]) and -1.34 (95%HDI= [-1.46, -1.21]) respectively. The null value zero is far from the 95% HDI estimated difference for the standard deviation of speed only and is within zero for the average speed differences indicating that the is no credible difference between with and without ASCT.

Similarly, the mean difference in average speeds and standard deviation of speeds for Wednesday northbound was 1.47 (95%HDI = [1.33, 1.60]) and -1.41 (95%HDI = [-1.51, -1.31]), respectively. The mean difference in average speed and standard deviation of speed was -0.87 (95%HDI = [-1.0, -0.74]) and -0.35 (95%HDI = [-0.44, -0.25]), respectively for the southbound direction. The null value zero is far from the 95% HDI estimated difference for all parameters' posterior distribution in both directions indicating that there is a credible difference between with and without ASCT.

For the northbound direction on Thursday, the mean difference in average speed and standard deviation of speed was 1.80 (95%HDI = [1.64, 1.97]) and -2.0 (95%HDI = [-2.12, -1.89]), respectively. In the southbound direction, the mean difference in average speed and standard deviation of speed was 0.06 (95%HDI = [-0.12, -0.23]) and -1.08 (95%HDI = [-1.20, -0.95]), respectively. In the northbound direction, the null value zero is far from the 95% HDI estimated difference for all parameters' posterior distribution. This suggests that there is credible difference between with and without ASCT. In the southbound direction, the null value zero is far from the 95% HDI estimated difference for standard deviation of speed only and is within zero for the average speed difference. This indicates that there is no credible difference between with and without ASCT.

Table 4-27: Results of the Bayesian Hypothesis Testing

	Northbound					Southbound			
			95% HDI				95% HDI		
Day of week	**Parameter**	**Mean (mph)**	**Upper limit (mph)**	**Lower limit (mph)**	**Decision**	**Mean (mph)**	**Upper limit (mph)**	**Lower limit (mph)**	**Decision**
Tuesday	Ave. speed	1.60	1.76	1.45	Reject	-0.02	0.16	-0.20	Fail to Reject
	Speed std.	-2.03	-1.93	-2.14	Reject	-1.34	-1.21	-1.46	Reject
Wednesday	Ave. speed	1.47	1.60	1.33	Reject	-0.87	-0.74	-1.00	Reject
	Speed std.	-1.41	-1.31	-1.51	Reject	-0.35	-0.25	-0.44	Reject
Thursday	Ave. speed	1.80	1.6	1.33	Reject	0.06	0.23	-0.12	Fail to Reject
	Speed std.	-2.0	-1.89	-2.12	Reject	-1.08	-0.95	-1.20	Reject

Note: Ave. speed represents estimated average speed difference between with and without ASCT and Speed std. is the difference in estimated standard deviation of speed between with and without ASCT.

4.6.4.3 Mobility Benefits of ASCT

From the BSR model's posterior distributions, the MEFs were computed to quantify the operational benefits of the ASCT. Table 4-28 presents the estimated MEFs for the typical days, PM peak, AM peak, and off-peak hours for both directions of travel.

Findings from MEFs revealed that ASCT improved travel speed by 7%, 2%, and 5% in the AM peak, PM peak, and off-peak hours, respectively. This finding is consistent with previous studies (Hutton et al., 2010; Sprague, 2012) which suggested that ASCT improves speed by 11%. However, during the PM peak hour, ASCT showed less improvement in travel speed. This may be attributed to congestion resulting from an increase in traffic demand during this specific period. It has been observed that ASCT cannot perform well in congested or oversaturated conditions because green time cannot be reallocated effectively (Fontaine et al., 2015). However, in the southbound direction, ASCT was found to increase the travel speed by 3% and 2% during AM peak and off-peak hours, respectively. In contrast, during the PM peak hour, the ASCT was found to reduce the travel speed by 5%.

For the typical days analyzed, ASCT improved travel speed by 4% in the northbound direction. However, there is no improvement in the southbound direction with ASCT. This observation is supported by other studies (Hutton et al., 2010) in which ASCT showed improvement in one direction of travel. The presence of a large number of high-volume unsignalized access points in the southbound direction may also contribute to the lower performance of ASCT (Fontaine et al., 2015; Zheng et al., 2017).

Table 4-28: MEFs for ASCT

		Northbound				Southbound			
		MEF	**95% HDI**		**% Speed increase**	**MEF**	**95% HDI**		**% Speed increase**
			Lower Limit	**Upper Limit**			**Lower Limit**	**Upper Limit**	
Day	Tuesday	0.96	0.95	0.96	4%	1.00	1.00	1.01	0%
	Wednesday	0.96	0.95	0.97	4%	1.02	1.031	1.02	-2%
	Thursday	0.96	0.96	0.96	4%	1.00	0.99	1.00	0%
Time	AM peak	0.934	0.932	0.951	7%	0.967	0.964	0.971	3%
	PM peak	0.978	0.976	0.981	2%	1.048	1.013	1.053	-5%
	Off-peak	0.953	0.951	0.955	5%	0.979	0.976	0.982	2%

Performance metric: Average Travel Speed

4.6.5 Conclusions

ASCT is an ITS technology that optimizes signal timing in real-time to improve corridor flow. This study introduced a new approach to evaluate the operational benefits of the ASCT. The proposed BSR model was used to (i) estimate the possible dates that define the boundary between two different operating characteristics, (ii) conduct the Bayesian hypothesis test (BHT), and (iii) estimate MEFs. The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida.

The findings indicate that the BSR can estimate the dates that the ASCT was switched-off in the study corridor. This is important in the analysis especially when the possible switched-off dates of the system are unknown. An important contribution of using the BSR is its ability to objectively incorporate the uncertainty surrounding the estimate including the location of switch-point dates, a significant advantage over the previous applied approach that has been used to quantify the benefit of the ASCT.

Furthermore, the BHT formulated using the BSR posterior distributions revealed that there is a difference, at 95% HDI, in the estimated average speeds with and without ASCT in the northbound direction. More specifically, the ASCT was found to increase the travel speed while reducing the speed variation. On the other hand, the analyses on the southbound direction revealed mixed results. Wednesday and Thursday indicated no difference, at 95% HDI, on the average travel speed between with and without ASCT. The BHT suggests that installation of ASCT reduces the data variations at 95% HDI. This observation was consistent across the three evaluated days.

Moreover, the computed MEFs were consistent with the BHT findings. The ASCT was found to improve the travel speeds by 4% during typical days of the week, 7% during AM peak hours, 5% during off-peak hours, and 2% during PM peak hours, in the northbound direction. Nevertheless, southbound traffic MEFs show no improvement with ASCT on Tuesday and Thursday while a slight decrease in travel speed by 2% was observed on Wednesday. Moreover, the analysis based on peak and off-peak hours revealed that ASCT increased the travel speed by 3% and 2% during AM peak and off-peak hours, respectively. In contrast, during PM peak hours, ASCT showed a 5% reduction in travel speeds in the southbound direction. A small improvement in the southbound direction may be attributed to congestion and the presence of a large number of unsignalized access point.

4.7 Summary

This chapter discussed in detail the study locations, research methodology, data, and the analysis results to quantify the mobility benefits of the following TSM&O strategies that are currently deployed in Florida:

Freeways

- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers
- Express Lanes

Arterials

- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

For each of these strategies, an index called Mobility Enhancement Factor (MEF) was developed. The analysis utilized specific performance measures for each strategy to develop the MEFs. Table 4-29 shows the MEFs for each of the TSM&O strategies evaluated in this study. As can be observed from the Table 4-29, all the TSM&O strategies resulted in mobility improvements with the exception of the impact of ASCT in the southbound direction of the study corridor on Tuesday, Wednesday, Thursday and during PM peak.

Table 4-29: Summary of MEFs for TSM&O Strategies

	TSM&O Strategy	Performance Measure	MEF*	MEF Interpretation
Freeways	Ramp Metering	Buffer Index	0.784 (LOS C&D)	Ramp metering is expected to reduce BI by ~ 22% when LOS is C or D
			0.701 (LOS E&F)	Ramp metering is expected to reduce BI by ~ 30% when LOS is E or F
	Dynamic Message Signs	Average Speed Adjustment	0.94	A 6% reduction in average speeds will be observed when the messages displayed crash-related information, compared to when the DMSs display advisory information.
	Road Rangers	Incident Clearance Duration	0.747	Overall, Road Ranger response is expected to reduce incident clearance duration by 25.3%
	Express Lanes	Buffer Index	0.5 (NB) Performance of ELs compared to their adjacent GPLs	ELs are expected to reduce BI by 50% compared to their adjacent GPLs on 95Express NB direction.
			0.4 (SB) Performance of ELs compared to their adjacent GPLs	ELs are expected to reduce BI by 60% compared to their adjacent GPLs on 95Express SB direction.
			0.8 (NB) Performance of GPLs when ELs are operational	BIs for the GPLs are expected to improve by 20% on 95Express NB when the ELs were operational compared to when they were closed.
			0.4 (SB) Performance of GPLs when ELs are operational	BIs for the GPLs are expected to improve by 60% on 95Express SB when the ELs were operational compared to when they were closed.
Arterials	Transit Signal Priority	Travel Time	0.96 (for all vehicles) 0.91 (for buses)	TSP is expected to reduce travel time by up to 4% for all vehicles and by up to 9% for buses along the corridor
		Average Vehicle Delay Time	0.87 (for both buses and all vehicles)	TSP is expected to reduce average vehicle delay by up to 13% for both buses and all vehicles.
	Adaptive Signal Control Technology	Average Speed	NB 0.96 (on Weekdays); 0.934 (on AM Peak); 0.978 (on PM Peak); 0.953 (during off-peak) SB 1.00 (on Tuesday and Thursday); 1.02 (on Wednesday); 0.967 (on AM Peak); 1.048 (on PM Peak); 0.979 (during off-peak)	E.g.*: Adaptive Signal Control Technology is expected to increase average speed by 4% on weekdays on the NB approach.

Note: RMS = Ramp Metering Signals, LOS = Level of Service. EL = Express lanes, GPL = General-purpose lanes, NB = Northbound, SB = Southbound, BI = Buffer Index, DMS = Dynamic Message Signs, TSP = Transit Signal Priority.
*Only one MEF is explained as an example. The other MEFs could be interpreted in a similar manner.

CHAPTER 5
SAFETY BENEFITS

This chapter discusses the methodology and the safety benefits of the following TSM&O strategies deployed in Florida:

Freeways
- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers

Arterials
- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

5.1 Ramp Metering System

Ramp metering or signaling is a traffic management strategy that employs traffic signals installed at freeway on-ramps to control and regulate the frequency at which vehicles join the flow of traffic on the freeway mainline (Gan et al., 2011; Mizuta et al., 2014). The following subsections discuss the study corridor, data used in the analysis, methodology, and the safety benefits of ramp metering operations.

5.1.1 Study Corridor

A section along I-95 in Miami-Dade County, Florida was selected as the study corridor to quantify the safety benefits of the ramp metering strategy. This approximately 10-mile section of I-95 has a ramp metering system stretching between Ives Dairy Road and NW 62nd Street in both directions of travel. Ramp Metering Signals (RMSs) became operational in 2009 and are located at each of the 10 northbound ramps and 12 southbound ramps along the I-95 study corridor (Zhu et al., 2010). FDOT District 6 operates and manages the system. Figure 4-1(a) (see Section 4.1.1) shows the locations of the existing RMSs along the study corridor, and Figure 4-1(b) provides an example view of the RMS at the NW 69th Street on-ramp to I-95 NB.

5.1.2 Data

Four datasets were used to evaluate the safety benefits of the ramp metering strategy: traffic flow data, crash data, RMS operations data, and contextual data.

5.1.2.1 Traffic Flow Data

Traffic flow data were collected from the Regional Integrated Transportation Information System (RITIS), a comprehensive database containing data from different original sources. The traffic volume, speed, and occupancy data originated from traffic sensors managed by FDOT District 6. All the traffic flow data were collected at 5-minute intervals over a study period of three years, from 2016 to 2018.

5.1.2.2 Crash Data

Crash data were collected from the SunGuide® incident database for a three-years study period (2016 – 2018). The database contained detailed information about each crash, including the time of occurrence, crash location, and crash clearance timeline. Additional details on the SunGuide® database are discussed in Section 3.2.

5.1.2.3 RMS Operations Data

RMS operations data for the study period (2016 – 2018) were obtained from the FDOT District 6 Regional Transportation Management Center (RTMC). Data collected included: turn-On/Off time, turn-On reason, and event identification number from the incident data if the turn-On reason was an incident. The turn-On reason consisted of six categories: recurrent congestion, non-recurrent congestion, incident, weather, central time of day (CTOD), and local time of day (LTOD).

5.1.2.4 Contextual Data

To supplement the traffic flow, crash, and RMS operations data, the distance between traffic detectors, the number of points along the mainline where vehicles entered the freeway (on-ramps) and exited the freeway (off-ramps), were determined using Google Maps.

5.1.3 Methodology

A crash risk model was developed to measure the safety effectiveness of the RMS operations on the study corridor. The impacts of traffic flow characteristics and RMS operations on the risk of crashes on the segments with RMSs were analyzed. The following sections provide a detailed discussion on the research design, the applied statistical method, and the selection of model variables.

5.1.3.1 Crash and Non-Crash Cases Study Design

A *case-control* study design was applied by considering crash and non-crash cases. A matched crash and non-crash analysis enabled the exploration of the effects of traffic flow variables while controlling the impact of confounding factors through study design. For each crash case, the corresponding non-crash cases were determined using the spatial and temporal characteristics of the crash.

For each crash used in the analysis, the location, categorized as upstream or downstream of an on-ramp with RMS, the time of the crash, and the day of the week were determined. Non-crash cases were then identified as having occurred at a similar time and location to that of a corresponding crash and having occurred on any weekday. Note that weekends, holidays, and days during Hurricanes Irma or Michael were excluded from the analysis. For example, for a crash that occurred on a Monday at 8:00 AM on a segment downstream of the NW 119th Street RMS (see Figure 5-1), the corresponding non-crash cases were identified within the same week on a Tuesday, Wednesday, Thursday, and Friday at 8:00 AM on the same segment, given no other crashes occurred at the same location during these days. Therefore, the ratio of 1 crash to 4 non-crash cases was used in the analysis, similar to methods used in previous *case-control* safety studies (Xu, et al. 2012).

After identifying the cases, traffic flow data were collected for each crash case and its corresponding non-crash cases from the detectors upstream and downstream of the case location. Traffic flow data for each lane in the segment was collected for a period of 30 minutes, in 5-minute intervals, before the crash or non-crash case occurred. The traffic flow condition of the segment was estimated by calculating the average of the lanes' traffic flow parameters at each 5-minute interval. In addition, various traffic variables, established by previous studies, were calculated at 5-minute intervals, including the coefficient of variation of speed (CVS), the standard deviation of speed, volume, occupancy, and volume-to-occupancy ratio. Crashes and their corresponding non-crash cases with missing traffic detector data were removed from the analysis. Figure 5-1 shows the location of traffic detectors for the study segments related to the RMS at the NW 119th Street on-ramp and its related downstream segment for a hypothetical crash.

Figure 5-1: Example of Analysis Segments for RMSs

5.1.3.2 Logistic Regression with Random Parameter

A logistic regression with a random parameter was used to investigate the relationship between the traffic flow variables and other factors on the risk of crash occurrence. Logistic regression models are used to predict the choices between binary or two alternatives. However, the traditional logistic regression does not consider details of each specific observations or its associated heterogeneity. For this study, it was important to apply a methodology that allows for the possibility that the influence of variables on crash and non-crash cases may vary across the freeway segments. Since driver behavior and geometric characteristics vary, it was unrealistic to assume traffic volume, traffic speed, and occupancy were the same across all freeway segments. To account for such unobserved individual heterogeneity, an extension of logistic regression that considers a random parameter was used in the analysis.

A random parameter logistic regression was applied to the dependent categorical variable of the crash and non-crash cases to account for the effect of individual freeway segments downstream of on-ramps with RMSs. The modeling approach used for determining the crash or non-crash case for the freeway segment was defined as shown in Equation 5-1. In Equation 5-1, y_{in} is a case function determining the case category i (crash case, non-crash case) on freeway segment n; x_{in} is a vector of explanatory variables (traffic volume, speed, and occupancy); β_i is a vector of estimable parameters, and ε_{in} is the error term. To allow for the parameter variations across roadway segments (variations in β), a mixed distribution is introduced such that the crash and non-crash case proportions are calculated using Equation 5-2, where $f(\beta|\phi)$ is the density function of β while ϕ refers to a vector of parameters of the density function (mean and variance).

$$y_{in} = \beta_i x_{in} + \varepsilon_{in} \tag{5-1}$$

$$P_{in} = \int \frac{EXP[\beta_i X_{in}]}{EXP[\beta_i X_{in}]} f(\beta|\phi) d\beta \tag{5-2}$$

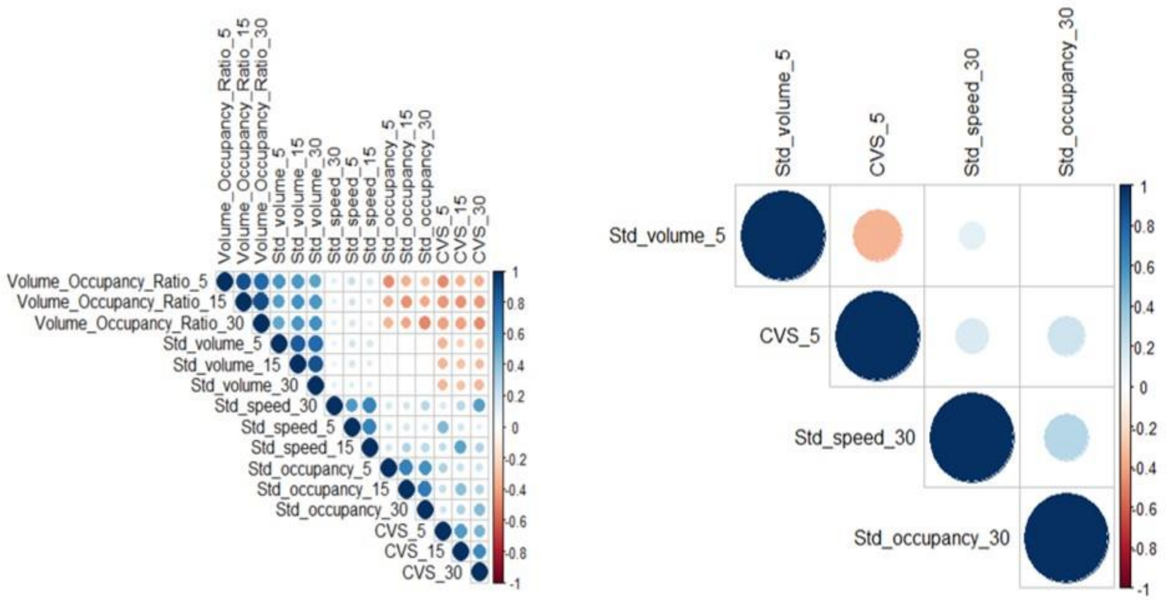
Therefore, β accounts for segment-specific variations of the effect of x on crash and non-crash case proportions, with the density function $f(\beta|\phi)$ used to determine β. The density function used in this study, $f(\beta|\phi)$, was selected by testing different distributions and selecting one with a better model fit. The estimation of the model variables was performed by a simulation-based maximum likelihood using Halton draws, and the analysis was performed in *R Studio*, an integrated development environment for *R*, a programming language for statistical computing and graphics.

5.1.3.3 Model Variables

Similar to previous studies, the following variables were considered in the model to examine the impact of traffic flow characteristics on crash risk: the coefficient of variation of speed (CVS), the standard deviation of speed, the standard deviation of traffic volume, and the standard deviation of traffic occupancy. These traffic flow measures were collected at 5-minute intervals; however, only the traffic flow characteristics at 5 minutes, 15 minutes, and 30 minutes before the crash were considered in the analysis. This approach was used to determine both the traffic flow risk near the time the crash occurred and well before the crash event so as to know the crash risk in advance and disseminate travel advice to drivers. Apart from the continuous variables, the RMS operations variable consisted of two categories: operational and non-operational.

5.1.3.4 Variables Correlation

A Pearson correlation test was performed to investigate the existing correlation between the variables related to traffic flow. Figure 5-2 shows the Pearson correlation test results for all variables selected as independent variables for the logistic regression. Other variables were not included in the model based on their high correlation values to the selected variables. A correlation value of +/-0.6 was used to determine variables with high or low correlation. Variables with values higher than +0.6 and those with values of less than -0.6 were considered to be highly correlated.



(a) All variables for downstream segments

(b) Selected variables for downstream segments

Figure 5-2: Correlation of Traffic Flow Variables Downstream of RMSs

5.1.4 Results

5.1.4.1 Descriptive Statistics

The dataset used in the analysis contained 1,516 cases for the downstream segments, whereby 33% were crash cases and 67% were non-crash cases, as shown in Table 5-1. Approximately 31% of cases associated with non-operational RMSs were crash cases, while 69% were non-crash cases. Table 5-1 summarizes the data used in the analysis based on RMS operations.

Table 5-1: Descriptive Statistics of the Dataset Based on RMS Operations

RMS status	Crash Cases		Non-Crash Cases		Total
	Number	**%**	**Number**	**%**	
Operational	366	33%	746	67%	1,112
Not operational	127	31%	277	69%	404
Total	493	33%	1,023	67%	1,516

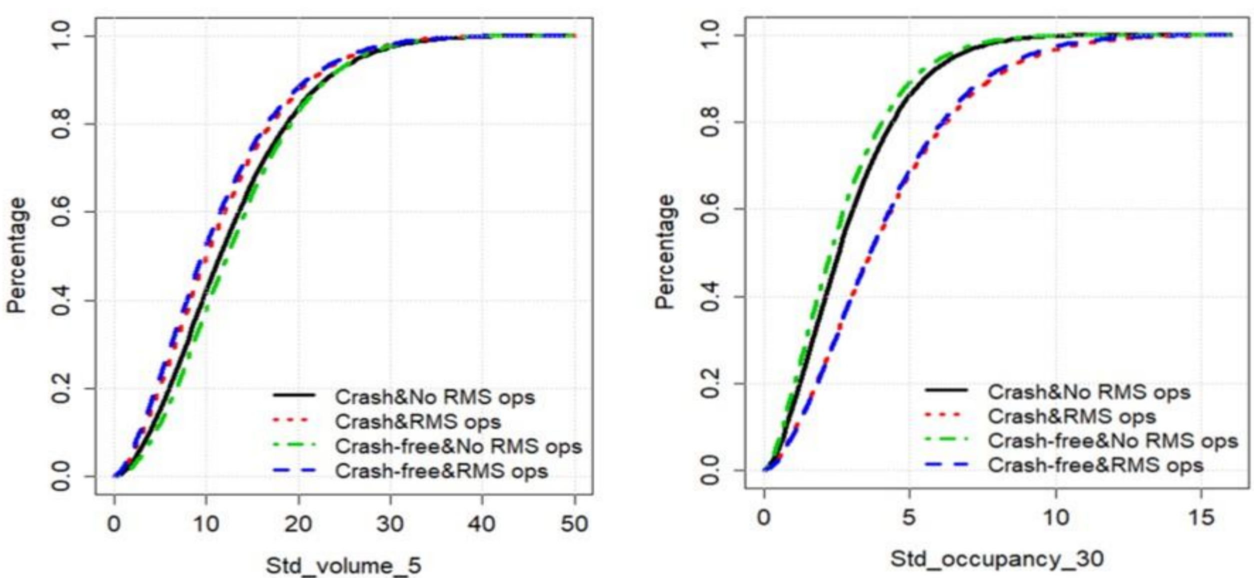
Table 5-2 provides the descriptive statistics for the continuous variables used in the model. The analysis revealed that a higher average CVS and standard deviation of volume were associated with crash cases when compared to non-crash cases that occurred five minutes later. Also, higher standard deviations of traffic occupancy were associated with crash cases compared to non-crash cases that occurred 30 minutes later. Lower standard deviations of traffic speed were associated with non-crash cases compared to crash cases that occurred 30 minutes later.

Table 5-2: Descriptive Statistics of Continuous Variables for Safety Evaluation of RMSs

Variable	Crash Cases				Non-crash Cases			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
CVS, 5 min before a particular time	0.11	0.07	0.01	0.30	0.10	0.06	0.01	0.36
S.D. of volume, 5 min before a particular time	12.39	8.20	0.58	37.40	12.34	8.48	1.00	49.60
S.D. of speed, 30 min before a particular time	3.04	2.30	0.07	16.87	3.07	2.25	0.10	15.44
S.D. of occupancy, 30 min before a particular time	3.79	2.71	0.16	15.38	3.71	2.58	0.23	14.59

Note: CVS = Coefficient of variation of speed, S.D. = Standard deviation, Min. = Minimum, Max. = Maximum, min = Minutes.

Figure 5-3(a) and 5-3(b) show the distribution of standard deviations of volumes and occupancy five and thirty minutes before the crash and non-crash cases according to RMS operations, respectively. As shown in Figure 5-3(a), both crash and non-crash cases that occurred when RMSs were operational are associated with lower standard deviations of volumes compared to cases when RMSs were not operational. Figure 5-3(b) shows more distinct distributions between cases. It suggests that cases associated with operational RMSs also had higher standard deviations of occupancy compared to cases when RMSs were not operational.



(a) Standard deviation of volume

(b) Standard deviation of occupancy

Figure 5-3: Distribution of Traffic Volume and Occupancy According to RMS Operations

5.1.4.2 Model Results

Table 5-3 summarizes the results of the logistic regression with a random parameter for segments downstream of the RMS. Results showed that the crash occurrence risk at a particular time was significantly affected by the standard deviation of speed 30 minutes before the time, standard deviation of occupancy 30 minutes before the time, and the ramp metering operations at that time.

Table 5-3: Logistic Regression with a Random Parameter Model Results

Variable	Estimate	Std. Error	Z-value	P-value	Odds Ratio
CVS, 5 min before a particular time	0.679	1.091	0.623	0.533	1.97
S.D. of volume, 5 min before a particular time	-0.006	0.008	-0.730	0.465	0.99
S.D. of speed, 30 min before a particular time	0.069	0.030	2.299	0.021	1.07
S.D. of occupancy, 30 min before a particular time	0.126	0.026	4.828	0.000	1.13
RMS operational	-0.533	0.151	-3.536	0.000	0.59
Mean of constant	-1.059	0.217	-4.892	0.000	
S.D. of constant	0.396	0.067	5.905	0.000	

Note: CVS = coefficient of variation of speed, S.D. = standard deviation, min = minutes.

The unit increase in the standard deviation between lane speeds indicates a 7% increase in the risk of a crash 30 minutes later. A higher standard deviation in traffic speeds between lanes may indicate turbulent traffic conditions. For segments downstream of an entry ramp with RMSs, a high standard deviation of lane speeds can be associated with higher speeds on inner lanes (left and center lanes) and lower speeds on the right lanes that are adjacent to the ramp acceleration lane. This is expected since drivers in the right lane may need to perform lane-changing maneuvers with small gaps in the high-speed lanes, thus increasing the risk of sideswipe or rear-end crashes.

Model results also indicate that a unit increase in the standard deviation of traffic occupancy corresponds to a 13% increase in the risk of a crash 30 minutes later. Similar to traffic speeds, high standard deviations in occupancy between lanes is associated with turbulent traffic flow in the downstream segment. However, the traffic occupancy impact on the risk of crashes was observed to be more than that of traffic speeds. The higher difference in the amount of time drivers spend at the same point on a segment, compared to adjacent lanes, may frustrate drivers to a point of accepting lane gaps that they would not have accepted in normal conditions and increase the risk of being involved in a crash.

The crash risk on the segments downstream of RMSs decreased when the RMSs were turned “on”. The model suggests a 41% decrease in crash risk when RMSs are operational compared to when RMSs are not operational. The RMS controls the movement of vehicles into the mainline, which harmonizes the traffic flow on the mainline by ensuring less disparity in traffic conditions between lanes. As such, less risk results from lane-change maneuvers and less hard-braking scenarios occur, thus, reducing the risk of sideswipe and rear-end crashes downstream of entry ramps.

The standard deviation of constant indicates that there exists a significant variation in the crash risk between the downstream segments. This means that although other factors influencing the crash risk are similar, there is disparity regarding the mean crash risk when the independent variables are not considered. In addition, the significance of the negative mean of constant indicates that the unobserved heterogeneity in the segments leads to a decrease in the risk of crashes.

5.1.5 Conclusions

Ramp metering is a TSM&O strategy that utilizes signals installed at freeway on-ramps to improve mobility, reliability, and safety on freeways. As congestion continues to become more problematic on roadway networks, transportation agencies are increasingly seeking to deploy ramp metering signals on freeway on-ramps. Although ramp metering is a mobility-based strategy, it can help improve safety along the segments downstream of the entry ramp. Currently, there is a scarcity of literature on the safety benefits of ramp metering signals. Therefore, the objective of this study was to develop a consistent and easily comparable safety benefit measure for ramp metering.

The study analyzed the benefits of ramp metering by analyzing the crash risk on the freeway mainline. The risk of traffic crashes was estimated using a *case-control* study design of crash and non-crash cases. The crash cases were identified using the crash data, while the non-crash cases were identified using the spatial and temporal criteria of each crash case. Traffic flow characteristics at 5 minutes, 15 minutes, and 30 minutes before both cases (crash and non-crash) were collected and used in the model to identify factors that influence the crash risk on the freeway mainline. Apart from the traffic flow characteristics, the operational status of RMSs (i.e., operational or non-operational) was used as a variable in the model for identifying the influencing factors using a logistic regression with a random parameter.

Results from the logistic regression model showed that the crash risk at a particular time was significantly affected by the standard deviation of speed 30 minutes before the time, the standard deviation of occupancy 30 minutes before the time, and ramp metering operations at that time. Moreover, results revealed a 41% decrease in the risk of crashes when RMSs were operational compared to when they were not operational.

Based on the study results, it can be concluded that ramp metering operations improve safety on the freeway mainline. However, the improvements evaluated in this study are applicable to the mainline traffic when ramp metering is operational during peak hours. Additional research is needed to evaluate the safety impacts of ramp metering during off-peak hours, as well as the safety implications of ramp metering on adjacent arterials.

5.2 Dynamic Message Signs

Dynamic Message Signs (DMSs) are programmable electronic signs used for disseminating information to road users. Generally installed along freeways, DMS messages may consist of real-time alerts regarding unusual traffic conditions, roadway incidents, adverse weather conditions, construction activities, travel times, road closures or detours, advisory phone numbers, etc. The information displayed on DMSs assist motorists in making informed decisions, thus, enabling fast and appropriate responses to changing traffic conditions and incidents (Montes et al., 2008). Much of the literature on DMSs used surveys to evaluate their effectiveness (Cheng and Firmin, 2004;

Peng et al., 2004; Chen et al., 2008). Surveys are effective in obtaining user perception on how drivers respond to different messages displayed on DMSs, especially pertaining to a driver's decision, such as purpose of travel, schedule flexibility, travel distance, cause of congestion on current route, familiarity with alternative routes, information available on alternative routes, and previous experiences with traveler information. However, the responses that drivers provide may not necessarily be the same as how they would react when faced with actual situations. Therefore, this research used real-time traffic data to assess the reaction of drivers to the messages displayed on the DMSs and the implication of those reactions on safety.

5.2.1 Study Corridor

In Florida, DMSs have been deployed statewide on all major freeways and some arterials. For this study, the analysis focused on permanently mounted DMSs along I-75. As shown in Figure 4-5 (see Section 4.2.1), the approximately 471-mile I-75 corridor that runs across the entire state of Florida and passes through FDOT Districts 1, 2, 4, 5, and 7. This study corridor was selected primarily for two reasons: the presence of DMSs between on- and off-ramps and the availability of DMS message data from 2016 through 2018. As of June 2019, about 140 DMSs were operational along the study corridor.

5.2.2 Data

5.2.2.1 DMS Log Messages

The data collection process involved contacting the Regional Transportation Management Centers (RTMCs) in each FDOT district to acquire information on the locations of DMSs (i.e., longitudes and latitudes/ mileposts), the direction of traffic that the permanent-mounted DMSs are facing (i.e., southbound or northbound), the logs of all messages displayed, and the begin and end timestamps for each message for a period of three years, from 2016 through 2018. Data from 43 DMSs were collected from the RTMCs in FDOT Districts 1, 2, 4, 5, and 7. Entry logs for most of the DMSs consisted of more than 4,000 entries of messages throughout the 3-year analysis period. The messages included travel time information, silver and amber alerts, congestion and safety warning messages, weather information, advisory messages, such as DUI, seatbelt law, crash and incident information, roadworks, etc. Each message was associated with the time it was displayed and the time it was removed. Some messages were displayed for longer periods of time while others lasted for shorter durations. Of the 43 DMSs, 20 did not have data for all three years of the analysis period, hence, only the 23 DMSs that had data for the full 3-year period were used in the analysis.

DMS messages listed in the logs included a variety of warning messages to drivers regarding their own safety, the safety of other drivers, stalled vehicles, and emergency responders. The data reduction process involved sorting the messages that reported information requiring driver action from messages that did not require drivers to change their driving pattern or behavior. Although there were several messages identified that reported critical roadway conditions that required the drivers' attention, the analysis was focused on messages that displayed crash information to compare with messages that did not require drivers to change their driving pattern or behavior. These crash messages informed drivers of the presence of a crash downstream along the corridor and gave information about possible impacts of the crash, such as lane closures or advisories to use caution. Some of the messages indicated the location of the crash in terms of distance from the DMS, such as the milepost of the crash location and/or the name of the downstream intersecting roadway. Examples of such messages include “CRASH 1 MI AHEAD USE CAUTION”, “CRASH I-75 AT SR-222/NW 39TH AVE RT LANE BLOCKED”, CRASH I-75 BEYOND CR-234 ALL LANES BLOCKED”, etc.

5.2.2.2 Traffic Flow Data

Traffic flow data used for analysis included real-time traffic volume, speed, and occupancy. These data were retrieved from RITIS for three years (2016 through 2018) and collected only for the detectors within the influence area of the DMSs (i.e. within 1000 feet upstream and downstream before the next ramp). Detectors upstream and downstream of DMS locations were identified based on location data (latitudes, longitudes, and mileposts), and 5-minute aggregated real-time data were extracted from each detector. The real-time data were merged with the identified DMS messages based on the times the messages were displayed. Due to the large amounts of both DMS message data and real-time traffic data, the merging process was performed using a code developed with the C# programming language. Further analysis focused only on the speeds of the vehicles to determine the safety implications of the DMS messages.

5.2.2.3 Crash Data

Crash data for the years 2016 to 2018 on I-75 were retrieved from the SignalFour Analytics database, a statewide interactive, web-based geospatial crash analytical tool hosted by the Geoplan Center at the University of Florida. The data included crash information and related attributes, such as location, dates and times of the crashes, severity, weather condition, lighting condition, etc. A total of 21,016 crashes were retrieved for the entire I-75 study corridor for the 3-year study period. The data were then reduced to obtain the crashes within the DMS study locations. Crash location information was used to associate the crashes with their respective DMSs to identify crashes that occurred downstream of the DMSs. The crashes were then matched with the specific messages that were being displayed during the reported time of the crash occurrence.

From the analysis of displayed crash messages that indicated the location of a crash (e.g., “CRASH 2 MI AHEAD USE CAUTION”), the distance between the DMS and the crash location ranged from less than one mile to 40 miles, with an average of 10 miles between the DMS and the crash location. Note that the downstream crashes referred to by the DMS messages could not be identified with certainty. The segments between the DMS positions to about 10 miles downstream were considered as potential segments for the occurrence of *secondary crashes* (crashes resulting from the impacts of the *primary crash* referred to by the DMS message), as shown in Figure 5-4. However, since variations in speeds were determined from detectors immediately downstream of the DMSs, the influence of the messages to drivers was not expected to extend 10 miles downstream.

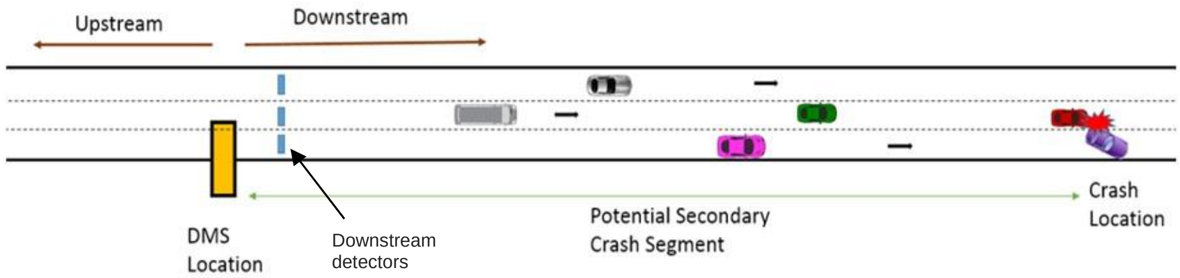


Figure 5-4: Segments for Crash Data Collection for Analyzing Benefits of DMSs

5.2.3 Methodology

Previous research suggests that the probability of a crash or potential crash is largely dependent upon the turbulence in the traffic flow (Lee et al., 2003). The use of real-time traffic flow data to predict crashes has been encouraged to improve crash prediction models, as opposed to using archived crash data typically used in traditional models (Shi and Abdel-Aty, 2015).

The real-time traffic data collected from detectors downstream of the 23 DMSs were analyzed using the CVS as a surrogate measure of safety. Speed variations observed 30 minutes prior to the display of the *crash* messages were compared with the speed variations observed for 30 minutes during the display of the *crash* messages (Golob and Recker, 2003). During the 30-minute "before" period, the DMSs displayed messages that did not require drivers to change their driving behaviors, e.g., travel time information, amber alerts, and advisory messages, such as "BUCKLE UP", "DO NOT DRIVE UNDER INFLUENCE", etc. These types of messages are referred to as *clear* messages in this study.

An analysis was conducted to determine the traffic behavior (variations in speeds) downstream of the DMS during the display of *clear* and *crash* messages, as illustrated in the flow chart shown in Figure 5-5. For each pair of *crash* and *clear* messages, the CVS was calculated. The goal was to compare the variations in traffic speeds during the first 30 minutes of a *crash* message display with the variations 30 minutes before, when a *clear* message was being displayed. The processed dataset, therefore, consisted of two sets of CVS data, i.e., one set for *clear* messages and another set for *crash* messages.

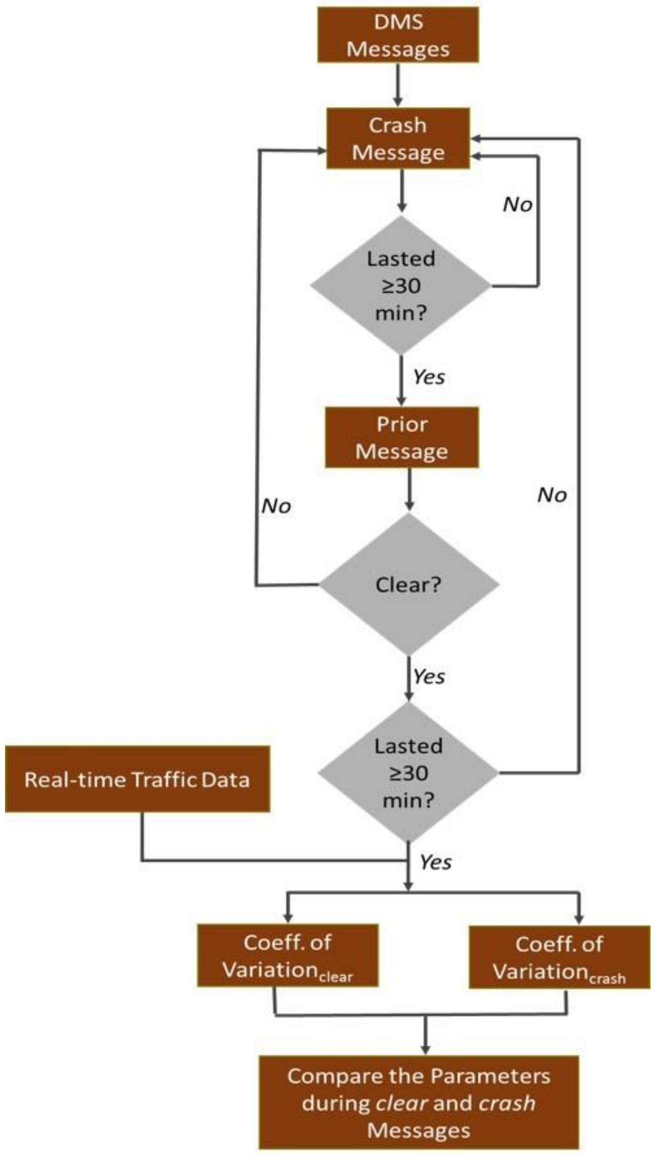


Figure 5-5: Data Processing Steps for Analyzing Safety Benefits of DMSs

5.2.4 Results

5.2.4.1 Paired *t*-test

A paired *t*-test was performed on the two sets of CVS data. The null hypothesis was set as the difference in the means of the CVS when *clear* messages were displayed and when *crash* messages were displayed is equal to zero (i.e., H_o: $\overline{CV}_{clear} = \overline{CV}_{crash}$). The alternative hypothesis was that the CVS when *crash* messages were displayed are higher than the average speeds when *clear* messages were displayed at a 95% confidence interval (H_a: $\overline{CV}_{crash} > \overline{CV}_{clear}$). Table 5-4 presents the *t*-test results.

Based on the *t*-test results, the null hypothesis was rejected. The t-statistic value was found to be greater than the critical t-value at a 95% confidence level. This signifies that the coefficient of variation of vehicle speeds during the *crash* messages were significantly higher than the CVS of speeds during the *clear* messages.

Table 5-4: *t*-Test Results for Coefficient of Variation of Speed

Estimates	Coefficient of Variation of Speed When DMS Displays *Crash* Message	Coefficient of Variation of Speed When DMS Displays *Clear* Message
Mean	0.10	0.09
Variance	0.03	0.02
Number of Observations	876	876
Hypothesized Mean Difference	0	
Degrees of Freedom	1,625	
t-Stat	1.7086	
P (T <= t) one-tail	0.0439	
t-Critical one-tail	1.6458	

The *crash* messages analyzed consisted of two parts. First, information about the crash was considered, and secondly, the expected downstream status or advisory information, such as “USE CAUTION”, “RT LANE BLOCKED”, “ALL LANES BLOCKED”, etc., was considered. Advisory information requires drivers to take action, such as changing their driving speed or changing lanes. From the mobility analysis (see Chapter 4), an average vehicle speed reduction of up to 6% during crash messages was observed. During crash message displays, the flow of traffic, particularly the speed of vehicles, was found to be less uniform, compared to conditions when *clear* messages were displayed. The higher variations in speed during *crash* messages may be attributed to the drivers’ responses to the posted messages.

5.2.4.2 Crashes during Clear and Crash Messages

Based on previous studies, variations in vehicle speeds are considered to promote the potential for crash occurrence (Golob et al., 2008; Shi and Abdel-Aty, 2015). Therefore, ‘*secondary crashes’* that occurred downstream of the DMSs, between the DMS location and the location of the ‘*primary*’ crash (the crash referred to by the DMS), and resulting from the ‘*primary crash*’ event, were identified. For this scenario, further analysis was conducted to investigate the crashes that occurred during the display of *clear* messages and *crash* messages. For both NB and SB directions, the crashes that occurred downstream of the DMSs 30 minutes during the *crash* message display and 30 minutes prior to the *crash* message (during the display of *clear* messages) were filtered.

Out of 21,016 recorded crashes on I-75 during the 3-year study period, 18 crashes occurred 10 miles downstream of the DMSs 30 minutes after the *crash* message started displaying, and 23 crashes occurred 30 minutes prior to the *crash* message (i.e., during the *clear* message display). Within two miles downstream, five crashes were observed during *crash* messages and eight crashes during *clear* messages. Due to the small sample size of those crashes, no further statistical analysis was performed. However, the total number of crashes during *crash* messages was relatively lower than the number of crashes during *clear* messages, even though higher speed variations were found during *crash* message displays.

The fewer number of crashes during the *crash* messages suggests that drivers complied with the DMS messages, and although they reduced their speed and changed lanes during *crash* messages, they proceeded more cautiously. As a result, the variations in speeds did not actually result in *secondary crashes*.

5.2.5 Conclusions

This section provided the safety analysis of DMSs by using the coefficient of variation of vehicle speeds (CVS) as a surrogate safety measure. The variations were determined when the displayed messages on DMSs did not require drivers to take action (clear condition/information messages) versus when the DMSs displayed messages about downstream crashes. Real-time speed data collected from RITIS, aggregated for 5-minute intervals, for a 3-year study period (2016 – 2018) were used to evaluate the coefficient of variation of speeds. The variations were determined downstream of the DMS locations where vehicles were assumed to have started reacting to the posted messages on the DMSs.

The *t*-test results comparing the CVS during *clear* message periods and *crash* message periods showed the CVS during *crash* messages were significantly higher than during *clear* messages at a 95% level of confidence. Based on the literature review, variations in vehicle speeds have translated into the potential for crash occurrences. The number of crashes downstream during crash messages was, however, relatively small. Out of 21,016 crashes that occurred on I-75 during the three years, 18 crashes occurred 10 miles downstream of the DMSs 30 minutes after the *crash* message started displaying, and 23 crashes occurred 30 minutes prior to the *crash* message (i.e., during the *clear* message displays). Within two miles downstream, five crashes were observed during *crash* messages and eight crashes during *clear* messages.

Overall, displaying crash messages on DMSs was found to result in fewer crashes despite the increase in speed variations. It is worth noting that the higher variations in vehicle speeds observed when the DMSs display *crash messages* may be attributed to other sources of information such as navigation maps, Highway Advisory Radio, etc. The analysis did not consider other potential factors such as incidents downstream which may result in speed reduction and variations. Although changes in the traffic speeds and the occurrence of *secondary crashes* provide insight into how drivers react, driver responses to the DMS messages are subjective and dependent upon driver behavior.

5.3 Road Rangers

The Road Rangers Service Patrol (simply known as Road Rangers) is a FSP program provided by FDOT that offers free highway assistance services to motorists. Road Rangers provide a direct service to motorists by providing a limited amount of fuel, assisting with tire changing and other types of minor repairs, and by quickly clearing travel lanes affected by incidents, as well as supporting other responders at crash sites. Florida’s Road Rangers provide assistance during incidents on state roadways to reduce delays and improve safety for the motorists and incident responders. The following sections discuss the selected study corridors, data collected, and the methodology used to quantify the safety benefits of the Road Ranger program.

5.3.1 Study Corridors

The following freeway corridors in Jacksonville, Florida were included in the analysis of the safety benefits of Road Rangers: Interstate 10 (I-10), I-95, and I-295. As shown in Figure 5-6, the study corridors include a 35-mile section of I-95, a 21-mile section of I-10, and a 61-mile section of I-295, for a total of 117 miles. The posted speed limits along the study corridors range between 55 mph and 70 mph.

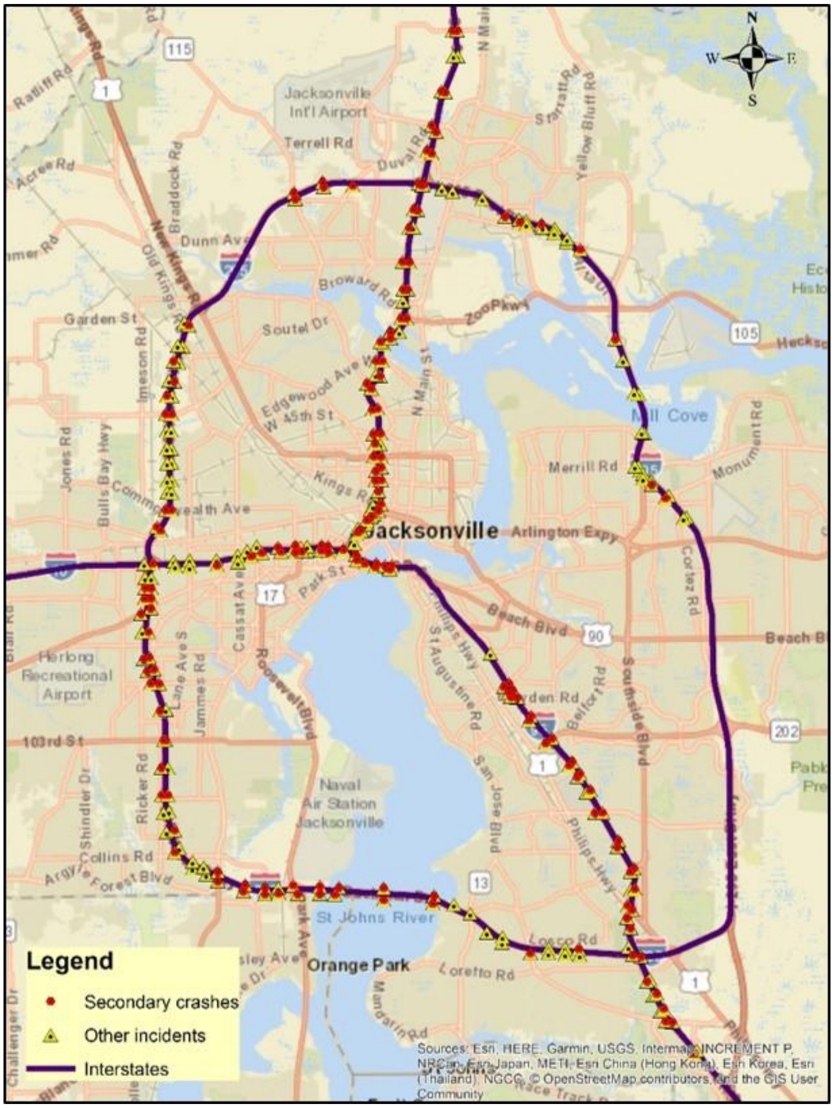


Figure 5-6: Road Rangers Program Study Corridor

5.3.2 Data

Data collected to evaluate the safety benefits of the Road Ranger program included speed data from BlueToad® devices, incident data from the SunGuide® database, and real-time traffic data from the RITIS for the years 2015 – 2017. A detailed discussion of these data sources is provided in Section 3.1.

5.3.3 Methodology

The objective of the analysis was to evaluate the safety benefits of Road Rangers based on real-time traffic flow conditions. This was achieved through the following steps: (1) identification of SCs; (2) identification of SC contributing factors; and finally, (3) prediction of the probability of SCs and estimation of the safety benefits of the Road Ranger program. Figure 5-7 provides a framework for the evaluation process adopted in this study.

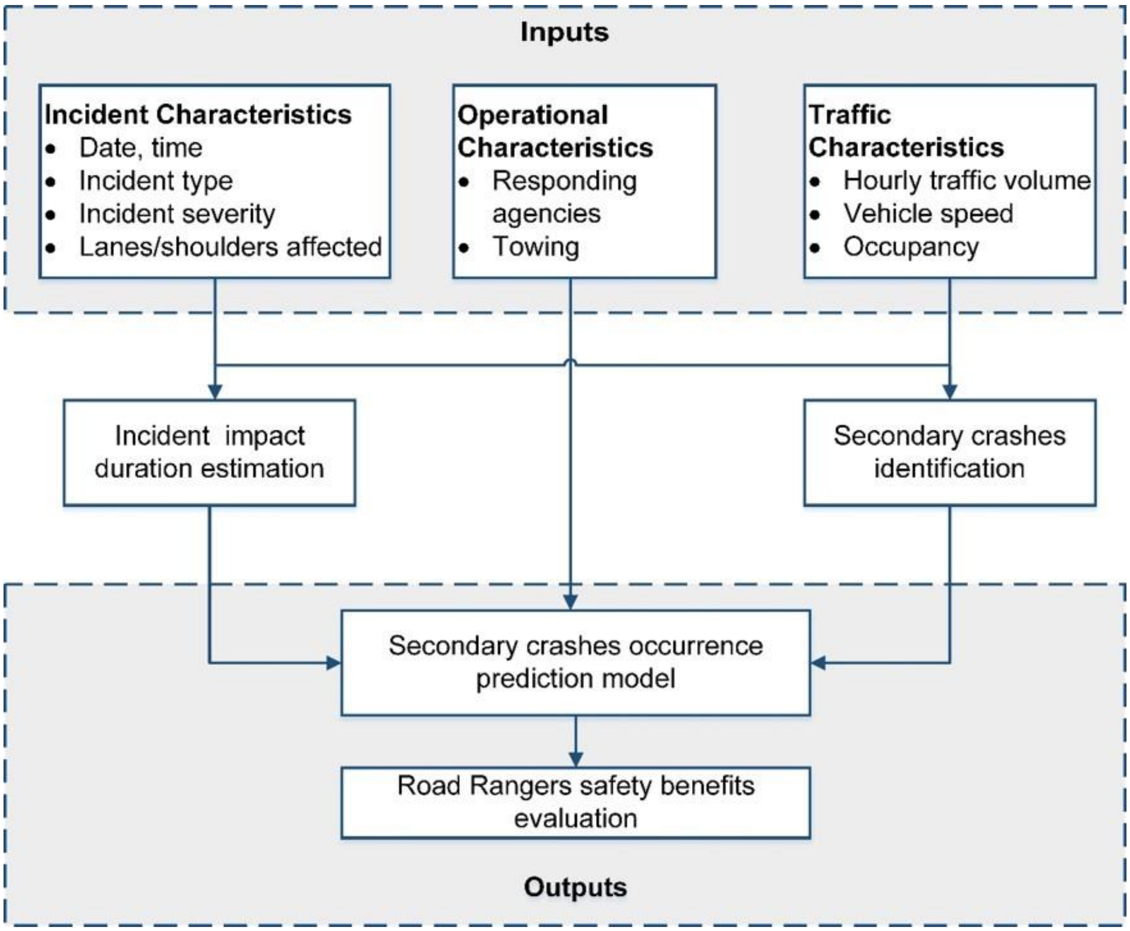


Figure 5-7: Framework for Road Ranger Safety Benefits Evaluation

5.3.3.1 Identification of Secondary Crashes

The first step in the safety evaluation process was to identify crashes that would be categorized as SCs. Secondary crashes result from a change in traffic characteristics caused by primary incidents (PIs). Researchers have traditionally used static and dynamic approaches to identify SCs. Previous studies (Zheng et al., 2014; Goodall, 2017; Kitali et al., 2018a; Kitali et al.,2019; Yang et al., 2018) provide more details about these methods. In this study, SCs were identified using the method developed by Kitali et al. (2018a) where the spatiotemporal impact ranges of the PIs were identified dynamically using archived BlueToad® speed data. This method captures the effects of traffic flow characteristics, such as speed, that change over space and time and affects the queue formation resulting from a PI. It overcomes the challenges of predefining the impact range thresholds or considering the deterministic queues of PIs that occur within observed queues from empirical measurements.

The developed SC identification algorithm was automated in the *R* programming language. As presented in Table 5-5, out of 6,865 reported incidents analyzed, 537 incidents were categorized as SCs resulting from 377 primary incidents. The remaining incidents (5,951) were not linked to SCs, and so were termed as ‘normal’ incidents.

Table 5-5: Secondary Crash Distribution by Freeway Corridors (2015 – 2017)

Freeway	Normal Incidents	Primary Incidents	Secondary Crashes	Total Incidents	Secondary Crashes Share (%)
I-10 E	133	16	20	169	11.83
I-10 W	105	9	15	129	11.63
I-95 N	1,581	110	174	1,865	9.33
I-95 S	1,387	95	133	1,615	8.24
I-295 E	555	13	15	583	2.57
I-295 W	2,190	134	180	2,504	7.19
Total	**5,951**	**377**	**537**	**6,865**	**7.82**

5.3.3.2 Complementary Log-Log Analysis

A complementary log-log analysis was performed where the response variable (SC likelihood) was binary, taking a value of 0 for normal incidents (incidents that did not result in SCs) and 1 for PIs (incidents that resulted in SCs). From the descriptive statistics provided in Table 5-6, PIs constitute 5.9% of all incidents. This means that the proportion of PIs was much less than the proportion of normal incidents, i.e., the PIs and the normal incidents were asymmetrically distributed. Thus, a complementary log-log model (cloglog) was applied to associate the relationship between the probability of SCs and predictors. The model analyzed the relationships between the PI characteristics and the possibility of SC. A complementary log-log model, being asymmetrical around the inflection point, provides a more reliable prediction of SCs likelihood (Kitali et al., 2018a). The cloglog model is asymmetrical with a fat tail as it departs from zero (0) and sharply approaches one (1) (Kitali et al., 2018a). The cloglog model can be presented using Equations 5-3 and 5-4.

$$y_i = Binomial(n_i, \pi_i) \tag{5-3}$$

$$cloglog(\pi_i) = \log(-\log(1-\pi_i)) = \beta X + \alpha \tag{5-4}$$

where,
π_i denotes the probability of a SC induced by a primary incident,
X denotes the vector of explanatory variables,
β is the coefficients vector for explanatory variables X, and
α is the specific constant term.

The likelihood function for the cloglog regression can be expressed using Equation 5-5.

$$Likelihood = \prod_{i=1}^{n} [\pi(x_i)^{y_i}(1 - \pi(x_i)^{(1-y_i)}] \tag{5-5}$$

where, $\pi(x_i)^{y_i}$ is the probability of the event for the *i*th incident, which has covariate vector *x*.

5.3.3.3 Potential Explanatory Variables

To predict the likelihood of SCs, this study examined a set of the incident, traffic, and operational characteristics having the potential for inclusion as independent variables in the cloglog regression model. The goal was to determine what factors increase the likelihood of SC. The following variables were considered:

Incident Characteristics

- *Incident impact duration*: This variable referred to the time taken for the traffic flow speed to return to normal. This was estimated using the approach developed by (Haule et al., 2018). It is generally assumed that the SC likelihood increases as incident impact duration increases (Karlaftis et al., 1999; Haule et al., 2018).

- *Incident type*: Since it is logical to anticipate that the probability of SC differs with incident type, this variable was considered categorical that included: crashes, vehicle problems (disabled or abandoned vehicles, emergency vehicles, vehicle fire, and police activity), and traffic hazards (debris, flooding, spillage, and pedestrian crossing).

- *Incident severity*: Incident severity may influence the clearance time of an incident resulting in a higher chance of SC. Therefore, this variable was considered as a bivariate variable categorized as minor, or moderate/severe.

- *Lane closure*: This variable referred to whether an incident blocked travel lane(s). The percent of lanes closed is usually considered an indicator of the severity of an incident, as severe incidents tend to result in an increased number of lanes closed. In this study, a 25% lane closure implied that one out of four lanes of a roadway section were closed. A closure of one out of three lanes is reported as a 33.3% lane closure, and 100% indicates that all lanes were closed. It can be anticipated that the probability of SC increases with an increase in the percent of lanes closed.

- *Shoulder blockage*: This variable referred to whether an incident blocked a shoulder. Similarly, it is logical to anticipate that the probability of SC increases when a shoulder is blocked. This variable was divided into two categories: No (no shoulder is blocked) and Yes (at least one shoulder is blocked).

- *Incident occurrence time*: This variable indicated whether the incident occurred during peak hours (0600 to 1000 or 1530 to 1830 hours) or off-peak hours (other times of day). Time factors are good indicators of traffic conditions, driver alertness, and familiarity with the route (Zhan et al., 2009).

- *Day of the week*: This variable was a proxy for activity variability and was coded as either weekday (Monday to Friday) or weekends (Saturdays and Sundays).

- *Lighting condition*: This variable was a proxy for lighting variability and was coded as daylight or night conditions, with respect to sunrise/sunset times.

Traffic Characteristics

- *Hourly traffic volume*: This variable reflected the 15-minute aggregated traffic volumes, collected five minutes before the incident's first notified time and within 1-mile upstream and downstream of the incident.

- *Vehicle speed*: This variable reflected the 15-minute aggregated vehicle speeds, collected five minutes before the incident's first notified time and within 1-mile upstream and downstream of the incident.

- *Occupancy*: This variable referred to the percent time that the sensor (detector) was occupied by a vehicle, usually at 30-sec intervals. The 15-minute aggregated detector occupancy was collected five minutes before the incident's first notified time and within 1-mile upstream and downstream of the incident.

Operational Characteristics

- *Responding agencies*: This variable was a bivariate, coded as Road Rangers involved or other agencies involved. Other agencies included, but not limited to, Florida Highway Patrol (FHP), Jacksonville Sherriff's Office (JSO), emergency medical, the Fire Department, and Safety Tow. Of the variables, this was a central variable.

- *Towing*: This variable indicated whether towing was involved or not involved in the incident.

5.3.4 Results

5.3.4.1 Descriptive Statistics

Table 5-6 provides the descriptive statistics of variables selected for analysis and modeling for 6,088 valid incidents (*N*) from the initial 6,865 incidents analyzed. The 537 SCs presented in Table 5-5 were excluded from the analysis, as well as 18 PIs, and 222 normal incidents (not linked to SCs) which had missing information. Of the valid 6,088 observations, normal incidents accounted for approximately 94.0%, and nearly 6.0% were primary incidents. Over half (53.07%) of the incidents involved vehicle problems, while 36.84% were categorized as crashes and 10.09% were associated with traffic hazards.

Overall, statistics showed that Road Rangers responded to over three-quarters (76.94%) of the 6,865 incidents analyzed. As shown in Table 5-7, despite Road Rangers responding to such a significant proportion of incidents, 270 (5.2%) were PIs, which resulted to 321 (6.2%) SCs compared to 107 (6.4%) PIs and 216 (12.9%) SCs responded to by other agencies. Table 5-7 also presents the incident impact duration distributions with respect to the responding agencies. In all cases, Road Rangers were associated with shorter average incident durations compared to other responding agencies. Since there exists a relationship between incident duration and SCs (Khattak et al., 2009), these reductions in incident impact duration can translate into substantial travel time and fuel consumption savings for motorists, as well as a potential reduction in SC occurrence.

Table 5-6: Descriptive Statistics of the Variables for SC Likelihood Model

Categorical Variable	Factor		Frequency		Share (%)
Incident	Normal incidents		5,729		94.10
	Primary incidents		359		5.90
Incident type	Crash		2,243		36.84
	Vehicle problems		3,231		53.07
	Traffic hazards		614		10.09
Incident severity	Minor		5,731		94.14
	Moderate/Severe		357		5.86
Day of the week	Weekday		5,702		93.66
	Weekend		386		6.34
Incident occurrence time	Peak		3,350		55.03
	Off-peak		2,738		44.97
Lighting condition	Daylight		5,419		89.01
	Night		669		10.99
Lane closure (%)	0 - 25		5,254		86.30
	> 25		834		13.70
Shoulder blocked	Yes		3,468		56.96
	No		2,620		43.04
Towing involved	Yes		826		13.57
	No		5,262		86.43
Responding agencies	Road Rangers		4,684		76.94
	Other agencies		1,404		23.06
Continuous variable	**Min**	**Mean**	**Median**	**Max**	**SD**
Hourly traffic volume (veh/hr.)	8	192	186	1564	93.47
Average vehicle speed (mph)	6.08	63.23	65.74	85.14	9.00
Average detector occupancy	0.24	7.69	6.88	48.29	4.37
Incident impact duration (min)	15	86.93	75	285	60.00

Valid N = 6,088

Table 5-7: Incident Impact Duration with Respect to Responding Agencies

Responding agencies/Incident level	Mean (min)	Median (min)	N	Min	Max	Std. Dev. (min)
Other Agencies	99.19	83.3	1672	15	285	64.45
Normal incidents	92.13	75	1349	15	285	62.51
Primary incidents	154.68	150	107	30	285	62.63
Secondary crashes	118.06	105	216	30	285	61.44
Road Rangers	83.04	66.4	5193	15	285	57.99
Normal incidents	77.67	60	4602	15	285	54.59
Primary incidents	143.87	135	270	30	285	62.29
Secondary crashes	112.25	105	321	30	285	65.54
All incidents	86.93	70.5	6865	15	285	60.00

Figure 5-8 presents the relative frequencies of Road Ranger responses versus other responding agencies. The four plots show that Road Rangers responded to vehicle problems and minor incidents more frequently than other agencies, and these responses were more evident on weekdays and during peak hours.

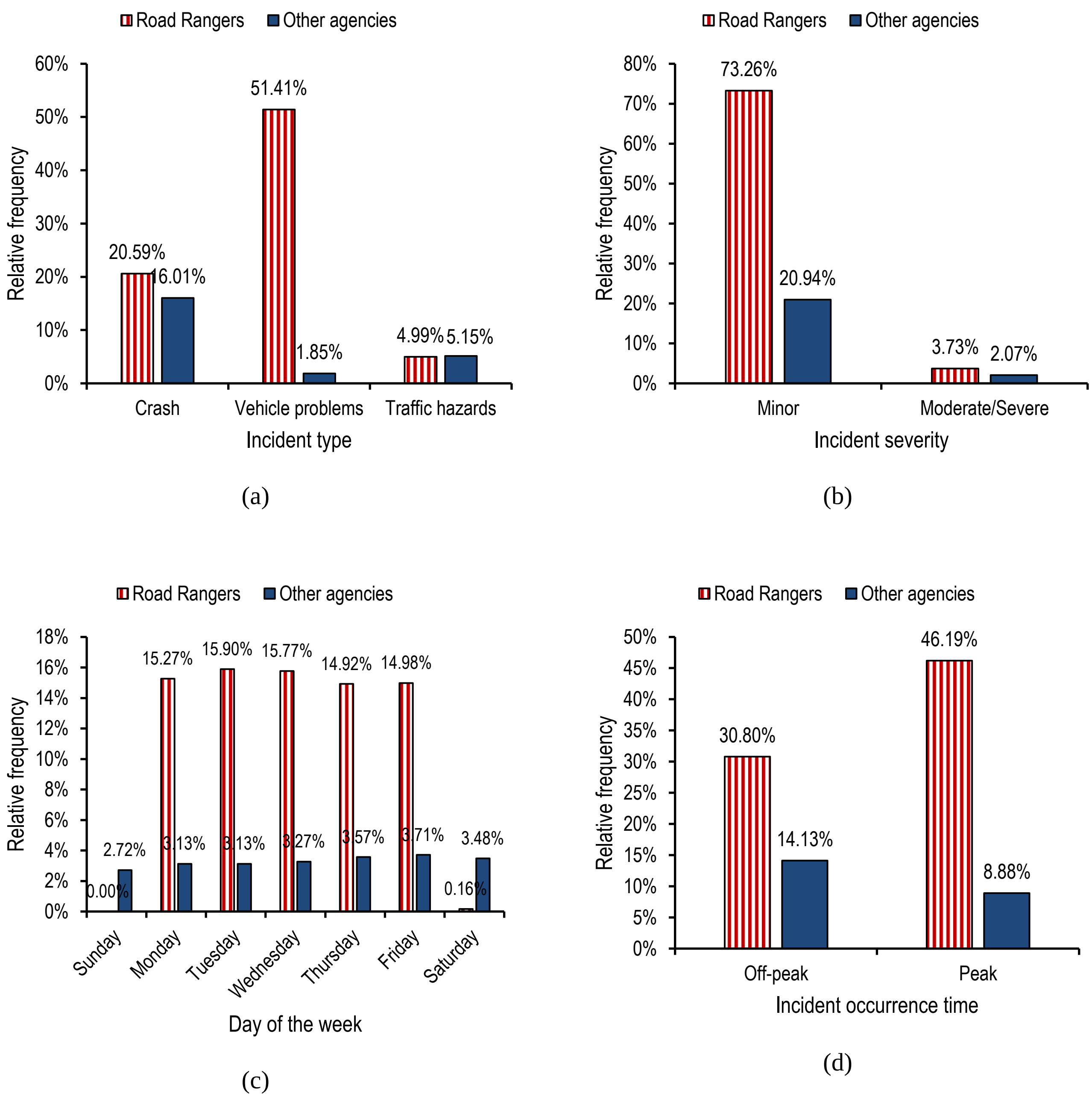


Figure 5-8: Road Ranger versus Other Agencies Relative Response Frequencies
(a) Incident type, (b) Incident severity, (c) Day of the week, and (d) Incident occurrence time

5.3.4.2 Secondary Crash Occurrence Likelihood Model

Results from the regression analysis are presented in Table 5-8, and most variables are statistically significant at the 95% confidence level ($\alpha = 0.05$). All of the variables discussed in Section 5.3.3 were included in the model. These results can be useful in explaining how various factors affect

SC occurrence. Estimated coefficients measure the change in the SC likelihood due to a change in the predictor variable while keeping the other predictor variables constant. A positive estimated coefficient implies an increase in SC likelihood, and a negative estimated coefficient indicates a less likelihood of SC occurrence. The p-values indicate whether a change in the predictor variable significantly changes the SC likelihood ($\alpha = 0.05$). The hazard ratio measures the instantaneous strength of as the association between predictors and the probability of SC occurrence. In this study, the emphasis was placed on Road Rangers.

The cloglog results in Table 5-8 indicate that a unit increase in traffic volume increases the likelihood of SCs by 0.1%. Alternatively, a unit increase in occupancy increases the risk of SCs by 0.9%. A study by Kitali et al. (2018a) suggested that congested traffic is characterized by smaller gaps between vehicles, which limits maneuverability, and an increase in average occupancy represents an increase in traffic density, traffic volatility, and queue formation. Thus, at higher traffic volumes and occupancy rates, the disturbances induced by a PI can easily propagate in queuing traffic conditions, leading to a higher risk of SCs. Similarly, when all other factors are held constant, the likelihood of SCs is higher during peak hours than during other time periods. The coefficient of the peak hours variable was positive, suggesting that the probability of SC is higher during peak hours.

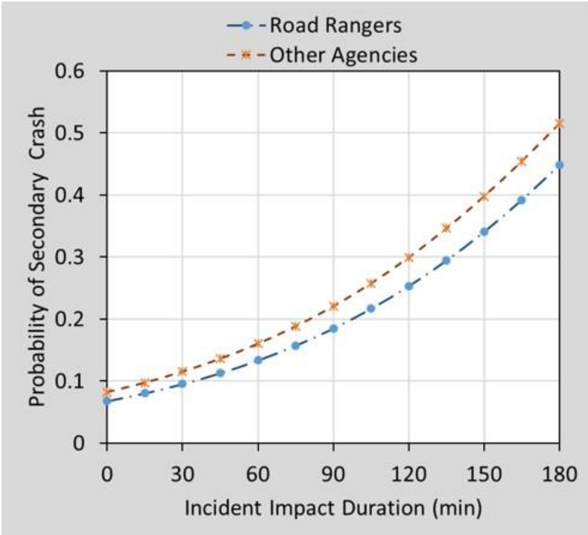
Incident type and severity also significantly contribute to the likelihood of SCs. Crashes have a higher likelihood of resulting in SCs compared to the incidents associated with vehicle problems and traffic hazards. The risk of moderate/severe incidents increases by 4.7% relative to minor incidents. One possible reason for the increase in SC risk is that the percent of lane closure is an indicator of the severity of an incident. Severe incidents tend to result in an increased number of lanes closed. Thus, lane closure will increase freeway congestion, and as traffic queue length increases, the possibility of SCs increase, as represented by its positive coefficient. Furthermore, additional procedures involved in clearing collisions increase the incident duration which in turn increases the probability of SCs.

For responding agencies, the negative coefficient of Road Rangers indicates a decrease in the likelihood of SC. Probabilities of SC are illustrated in Figure 5-9 for PIs consisting of (a) a crash, (b) a vehicle problem, and (c) a traffic hazard. For example, for a moderate/severe crash that occurred on a weekday during afternoon peak hours with moderate traffic (750 veh/h) conditions at a mean speed of 60 mi/h and occupancy of 7.68, blocked both the shoulder and a lane, and impacted traffic for 90 min, from Figure 5-9(a), the probability of a SC can be estimated as 18.5% when Road Rangers were involved compared to 21.2% when Road Rangers were not involved and other agencies responded. This indicates a 2.7% reduction in the risk of SC with Road Ranger involvement.

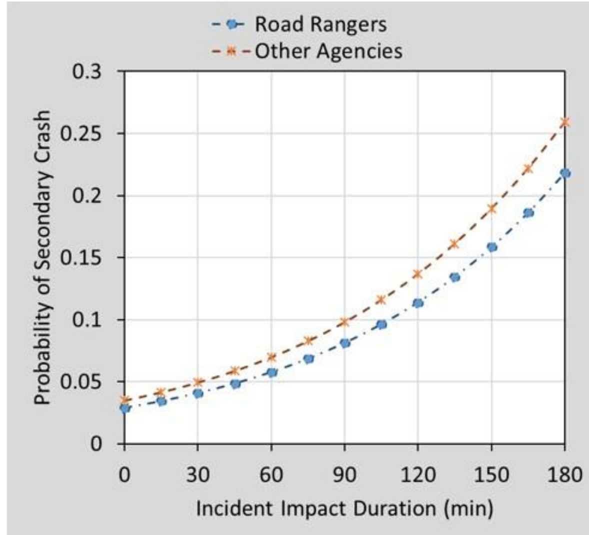
Table 5-8: Secondary Crash Occurrence Likelihood Model Results

	Variable	Factor	Coefficients	Std. Error	P-Value	95 % Confidence Interval Lower Bound	95 % Confidence Interval Upper Bound	Hazard Ratio	Change (%)
	Intercept		-3.4666	0.6249	< 0.0001	-3.4826	-3.4506	0.031	-96.9
Traffic characteristics	Hourly traffic volume (veh/h)		0.0015	0.0005	0.0024	0.0014	0.0015	1.001	0.1
	Average vehicle speed (mph)		*-0.0124*	*0.0081*	*0.1250*	*-0.0126*	*-0.0122*	*0.988*	*-1.2*
	Average detector occupancy		0.0090	0.0174	0.6042	0.0086	0.0094	1.009	0.9
Primary/normal incident characteristics	Incident impact duration (min)		0.0119	0.0008	< 0.0001	0.0118	0.0119	1.012	1.2
	Incident type	Crash							
		Vehicle problems	-0.8820	0.1378	< 0.0001	-0.8855	-0.8785	0.414	-58.6
		Traffic hazards	-0.9734	0.3212	0.0024	-0.9816	-0.9651	0.378	-62.2
	Incident severity	Minor							
		Moderate/Severe	0.0455	0.2052	0.0246	0.0402	0.0507	1.047	4.7
	Day of the week	Weekday							
		Weekend	-1.1217	0.3120	0.0003	-1.1297	-1.1137	0.326	-67.4
	Incident occurrence time	Off-peak hours							
		Peak hours	0.4470	0.1360	0.0010	0.4435	0.4505	1.564	56.4
	Lighting condition	*Daylight*							
		Night	*-0.0990*	*0.1967*	*0.6147*	*-0.1040*	*-0.0940*	*0.906*	*-9.4*
	Lane closure (%)	0 - 25							
		> 25	0.3550	0.1694	0.0361	0.3507	0.3594	1.426	42.6
	Shoulder blocked	Yes							
		No	-0.3085	0.1262	0.0145	-0.3118	-0.3053	0.735	-26.5
Operational characteristics	Towing involved	No							
		Yes	0.2888	0.1470	0.0495	0.2850	0.2925	1.335	33.5
	Responding agencies	Other agencies							
		Road Rangers	-0.1974	0.1559	0.0256	-0.2014	-0.1934	0.821	-17.9

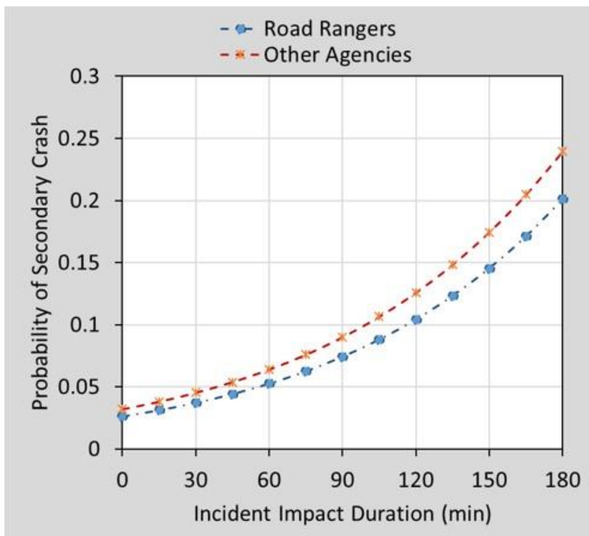
Note: AIC: 2364.9, Null deviance: 2729.4, Residual deviance: 1312.5, pseudo R2: 0.42, Italicized variables are not significant at 95% level.



(a) Probability of SC when PI is a crash



(b) Probability of SC when PI is related to a vehicle problem



(c) Probability of SC when PI is related to a traffic hazard

Figure 5-9: Probability of SC Occurrence against Incident Impact Duration

5.3.4.3 Safety Benefits of Road Rangers Program

As discussed earlier, the assumption exists that FSPs can help with reducing SCs since one of their duties is to provide traffic control at incident scenes, and the better the traffic control, the less likely a SC will occur. Additionally, since FSPs are mobile-based, they are often able to arrive at an incident scene quickly to enable early safety protection and traffic control measures which may help to prevent another related incident. In this study, two safety scenarios of Road Rangers are discussed. The first scenario considers the benefit delivered from reduced incident duration, and the second scenario considers safety benefits from traffic control, i.e., increased safety at incident scenes.

Incident Duration Reduction

The hazard ratios listed in Table 5-8 assist in quantifying the effect of predictors on the likelihood of SC, as they measure the instantaneous strength of association between predictors and the probability of SC occurrence. For example, the hazard ratio for incident impact duration listed in Table 5-8 is 1.012. This suggests that for each additional minute the incident impact duration increases, the likelihood of a SC increases by 1.2%. Figure 5-10 shows that the probability of a SC occurrence increases as incident impact duration increases, implying that reducing incident impact duration would translate into reduced SCs.

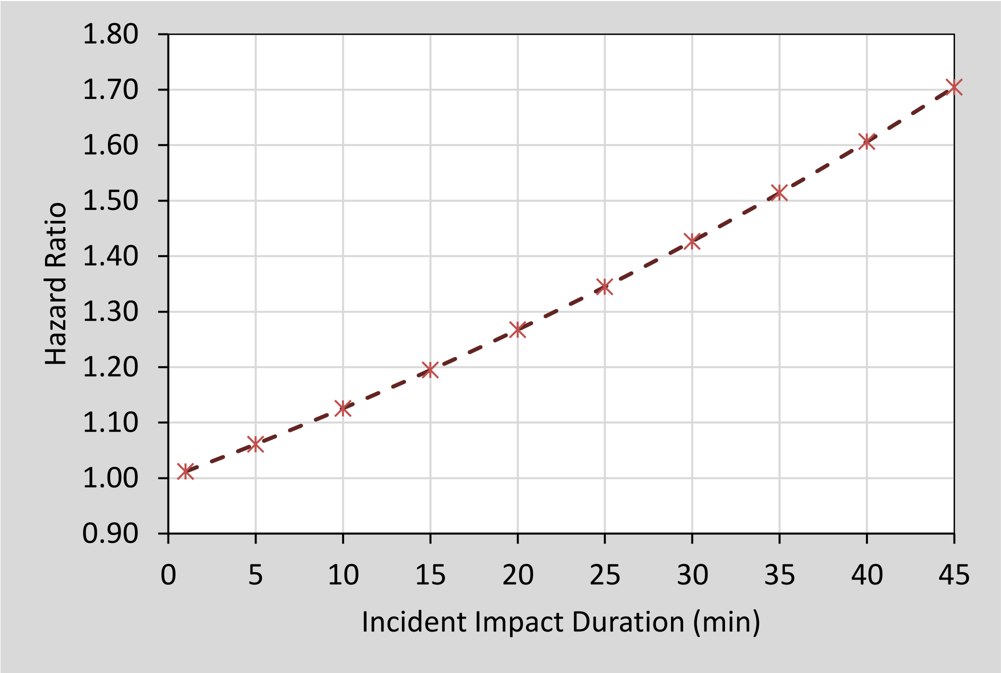


Figure 5-10: Probability of Secondary Crash Occurrence

Since the analysis showed that Road Ranger involvement reduces the incident duration by offering faster incident detection and response, a reduction in SCs was also expected. For example, if Road Rangers reduce the incident duration by an average of 10 min, based on Figure 5-10 (or Table 5-8), the likelihood of a SC decreases by 12.6%. From Table 5-6, the average incident impact duration is 83.04 minutes with Road Ranger involvement, which is 16 minutes less than the average duration with other responding agencies (99.19 min). According to Table 5-9, a 16-minute incident impact duration corresponds to a hazard ratio of 1.209, indicating that Road Rangers may help reduce the likelihood of SCs by 20.9%. Therefore, traffic management strategies, such as Road Rangers, that clear roadway blockage as quickly as possible have a significant impact on reducing the probability of SCs.

Table 5-9: Estimation of Reduction of Probability of Secondary Crash Occurrence

Incident Impact Duration Reduction (minutes)	Hazard Ratio	Safety Effectiveness	Probability of Secondary Crash Reduction (%)		
			Estimate	95% Confidence Interval	
				Lower Bound	Upper Bound
0	1.000	1.000	0.0	0.0	0.0
4	1.049	0.951	4.9	4.8	4.9
8	1.099	0.901	9.9	9.9	10.0
12	1.153	0.847	15.3	15.3	15.3
16	1.209	0.791	20.9	20.8	20.9
20	1.267	0.733	26.7	26.7	26.8
24	1.329	0.671	32.9	32.8	33.0
28	1.393	0.607	39.3	39.3	39.4
32	1.461	0.539	46.1	46.0	46.2
36	1.532	0.468	53.2	53.1	53.3
40	1.606	0.394	60.6	60.5	60.8
44	1.684	0.316	68.4	68.3	68.6

Traffic Control

Based on the model results presented in Table 5-7, Road Rangers reduce the probability of SCs by 17.9% (mean 17.9%; 95% confidence interval: 17.6 - 18.2). This reduction may be associated with how quickly Road Rangers respond to incidents. Also, safety features, such as the flashing lights on the patrol vehicles, warn motorists to exercise caution in the vicinity of assisted incidents.

5.3.5 Conclusions

This study evaluated the safety performance of the Road Ranger freeway service patrol, a mobile-based program administered by FDOT to assist motorists and minimize the impacts of freeway incidents on non-recurring traffic congestion. Specifically, this study examined the benefits of the Road Ranger program in reducing the risk of SC occurrence. A model was developed to predict SC probabilities using data from I-10, I-95, and I-295 corridors in Jacksonville, Florida. Data used in the analysis included: speed data from BlueToad® devices, incident data from the SunGuide® database, and real-time traffic data from RITIS for the years 2015 – 2017.

A Complimentary log-log regression model was developed to associate the probability of SC occurrence with potential contributing factors. Of the factors analyzed, traffic volume, incident impact duration, moderate/severe crashes, weekdays, peak periods, percentage of lane closure, shoulder blockage, and towing involving incidents were found to significantly increase the likelihood of SCs. Road Ranger involvement, weekend days, off-peak periods, minor incidents, vehicle problems, and traffic hazard related incidents were associated with relatively lower probabilities of SC occurrence.

Model results predicted that the probability of SC occurrence increased by approximately 1.2% for each additional minute of an incident. Practical inferences to the model's explanatory variables were drawn from the estimated model coefficients and hazard ratios. For instance, based on average incident duration reduction, the results suggest that the Road Ranger program may reduce SC likelihood by 20.9%. By controlling the traffic at an incident scene, Road Rangers reduce the probability of SCs by 17.9%. These findings provide researchers and practitioners with an effective means for conducting the economic appraisal of the Road Ranger program.

It is worth mentioning that in evaluating the safety benefits of the Road Ranger program, the evaluation did not account for the disaggregate-level operational details of Road Rangers, such as day-to-day or seasonal variations in Road Ranger activities, fleet sizes, patrol lengths, and probe vehicle types (e.g., pickup trucks, tow trucks, etc.). In addition, this study used speed data extracted from BlueToad® devices to determine the spatiotemporal impact range of primary incidents to identify SCs. The average spacing of the BlueToad® devices was 1.8 miles, which may not have precisely captured the speed changes over space. Therefore, future studies may seek to expand the analysis of Road Ranger operations (or other FSP program) to a microscopic level. Moreover, future analysis can incorporate virtual detectors that use crowdsourced traffic information to obtain additional traffic speed data.

5.4 Transit Signal Priority

Transit Signal Priority (TSP) is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections (Smith et al., 2005). Various types of transit priority initiatives have been proposed internationally, and types vary depending on road space, e.g., dedicated lanes, and time, or a combination of both space and time. TSP has been implemented for transit systems throughout the U.S.

TSP provides significant mobility benefits on transit corridors (Zlatkovic et al., 2013b; Feng et al., 2015; Ali et al., 2017; Shaaban and Ghanim, 2018). Regardless of the significant improvements in operational performance realized by TSP implementation, the safety benefits are usually overlooked by transit agencies during the project development process. Also, little in-depth research has been undertaken to measure the safety implications of TSP on roadways. Incorporating safety assessments into the transit project development process would be helpful for transportation agencies as a standard practice during decision making. The Highway Safety Manual (HSM) offers one analytical tool with rigorous and rational procedures for traffic safety assessments (Song and Noyce, 2018). However, safety assessments for transit preferential treatment, such as TSP, has rarely been performed by agencies and research entities. Despite the immense advances in research valuing the wider ridership, mode shift, and environmental benefits of TSP, the safety impacts of TSP has yet to be considered.

More support for the implementation of TSP may be realized if an assessment is conducted to quantify the road safety benefits. Moreover, a detailed evaluation may alleviate concerns agency officials have to traffic and road safety related to TSP implementation. Previous studies on the topic have shown mixed results of TSP pertaining to road safety. Several studies indicate that TSP deployment improves road safety, while others correlate it with worsening road safety. Therefore, a comprehensive study to quantify the safety impacts of TSP, as well as to develop crash modification factors (CMFs) is needed. The objective of this study was to quantify the safety benefits of TSP using CMFs. A Full Bayes (FB) before-after study was conducted to assess the safety effects of TSP along corridors in Florida with TSP systems deployed in the years of 2016 and 2017. A corridor level assessment was performed considering all traffic crashes, including property damage only (PDO) crashes and fatal/injury (FI) crashes.

5.4.1 Study Corridors

The analysis was based on 12 corridors as treatment corridors and 29 non-treatment corridor segments in Orange and Seminole Counties in Florida. The treatment corridors consisted of roadways with TSP systems deployed, while the non-treatment corridors were roadways without TSP. Treatment corridors were selected based on being existing TSP enabled transit corridors in the years of 2016 and 2017. Table 5-10 lists the treatment corridors analyzed and the year each TSP system was activated.

The 29 non-treatment corridors were identified either on the upstream or downstream of the treatment corridor or the adjacent corridor to the treatment corridor. Non-treatment corridors also had similar geometric design and traffic patterns as the selected treatment corridors.

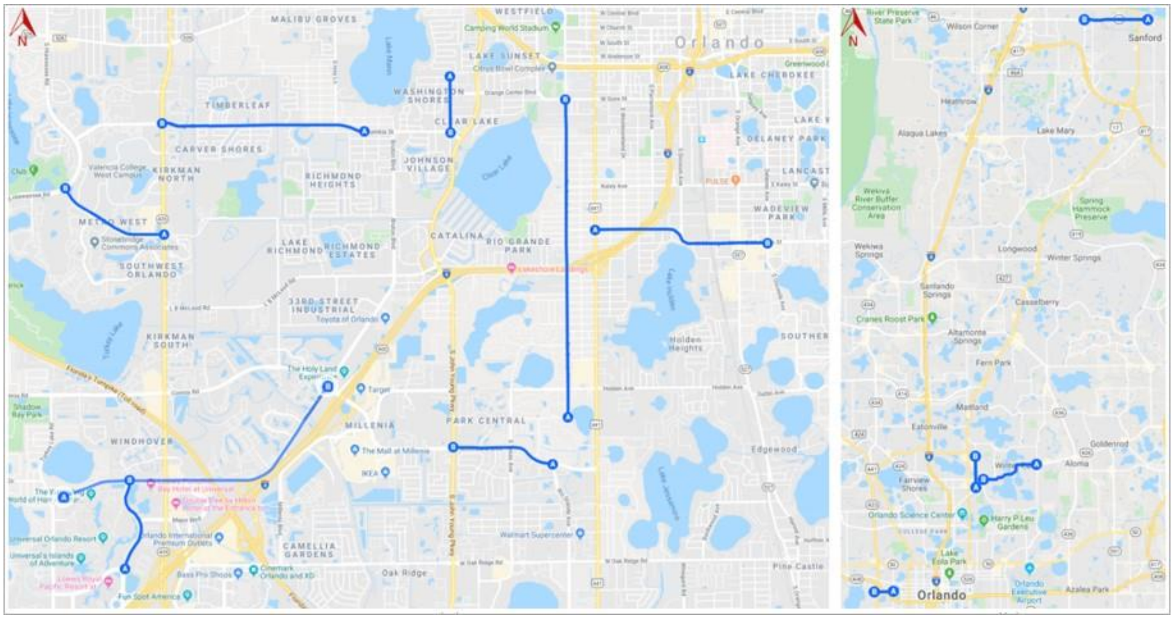
Table 5-10: TSP Enabled Corridors (Treatment Group)

County	ID	Treatment Corridors	TSP Activation Year
Orange	1	Americana Boulevard	2016
	2	Church Street	2017
	3	Denning Drive	2017
	4	Fairbanks Avenue	2017
	5	Goldwyn Avenue	2016
	6	Metrowest Boulevard	2016
	7	Michigan Street	2016
	8	Raleigh Street	2016
	9	Rio Grande Avenue	2016
	10	Universal Boulevard	2016
	11	Vineland Road	2016
Seminole	12	State Road 46	2017

Figure 5-11 maps the location of the 12 TSP treatment corridors in Florida. As noted in Table 5-9, 11 treatment corridors are located in Orange County, and one corridor is located in Seminole County. The south section of the analysis area (Figure 5-11(a)) contains eight of the treatment corridors, and four corridors are located in the north section (Figure 5-11(b)).

5.4.2 Data

Since the treatment corridors had TSP installed in the years of 2016 and 2017, crash data for both the treatment and the non-treatment corridors were collected for the years 2014 to 2018. Crash data were extracted from Florida's SignalFour Analytics database and aggregated for each street section by year as annual frequencies. Apart from the total crash frequency, which included crashes of all severity levels, separate analyses involving PDO and FI crash categories were also performed. Traffic volume data were obtained from Florida's Traffic Online database. Roadway information was collected from multiple sources, including Google Maps, Google earth-street view, and historical imagery tools, to retrieve geometric information for previous years before-and-after TSP installation. Functional classification information was extracted using the ArcGIS geoprocessing tool from FDOT's shapefiles website.



(a) South Section (b) North Section

Figure 5-11: TSP Treatment Corridors in Orange and Seminole Counties, Florida

5.4.3 Methodology

The respective year when TSP was installed on each study corridor was excluded from the analysis to allow enough buffer time for changes brought by this strategy. To form a reference group (non-treatment corridors) for the full Bayesian methodology, 29 corridors without TSP were selected. To ensure a good similarity between the non-treatment and the treatment corridors, with respect to the geometric design features and the traffic patterns, only non-treatment corridors consisting of urban streets with the same functional classification, the same number of lanes, the same posted speed limit, and in the same county as the treatment corridors, were considered. It should be noted that the pairing of treatment and non-treatment corridors is not necessarily one-to-one; hence, the number of treatment and non-treatment corridors do not have to be equal.

A full Bayesian before-after evaluation was adopted in lieu of other approaches, including the empirical Bayes approach. The FB method is a single step integrated procedure, where it integrates the process of estimating the safety performance function (SPF) and treatment effect in a single step, thus incorporates the uncertainties of the SPFs in the final estimates. This method is also independent of sample size, yielding robust results even when the sample size is small. Furthermore, this approach has the ability to account for most of the uncertainties in the dataset and model parameters (Park et al., 2010).

The safety effectiveness of countermeasures installed on roadways generally can be quantified using either a before-after or cross-sectional evaluation, depending on the study design and the nature of the data. However, a before-after evaluation is typically considered superior to cross-sectional data analysis in that before-after assessments also can manage site-to-site variability more efficiently. Figure 5-12 provides the steps involved to evaluate the safety benefits of TSP using a FB before-after method.

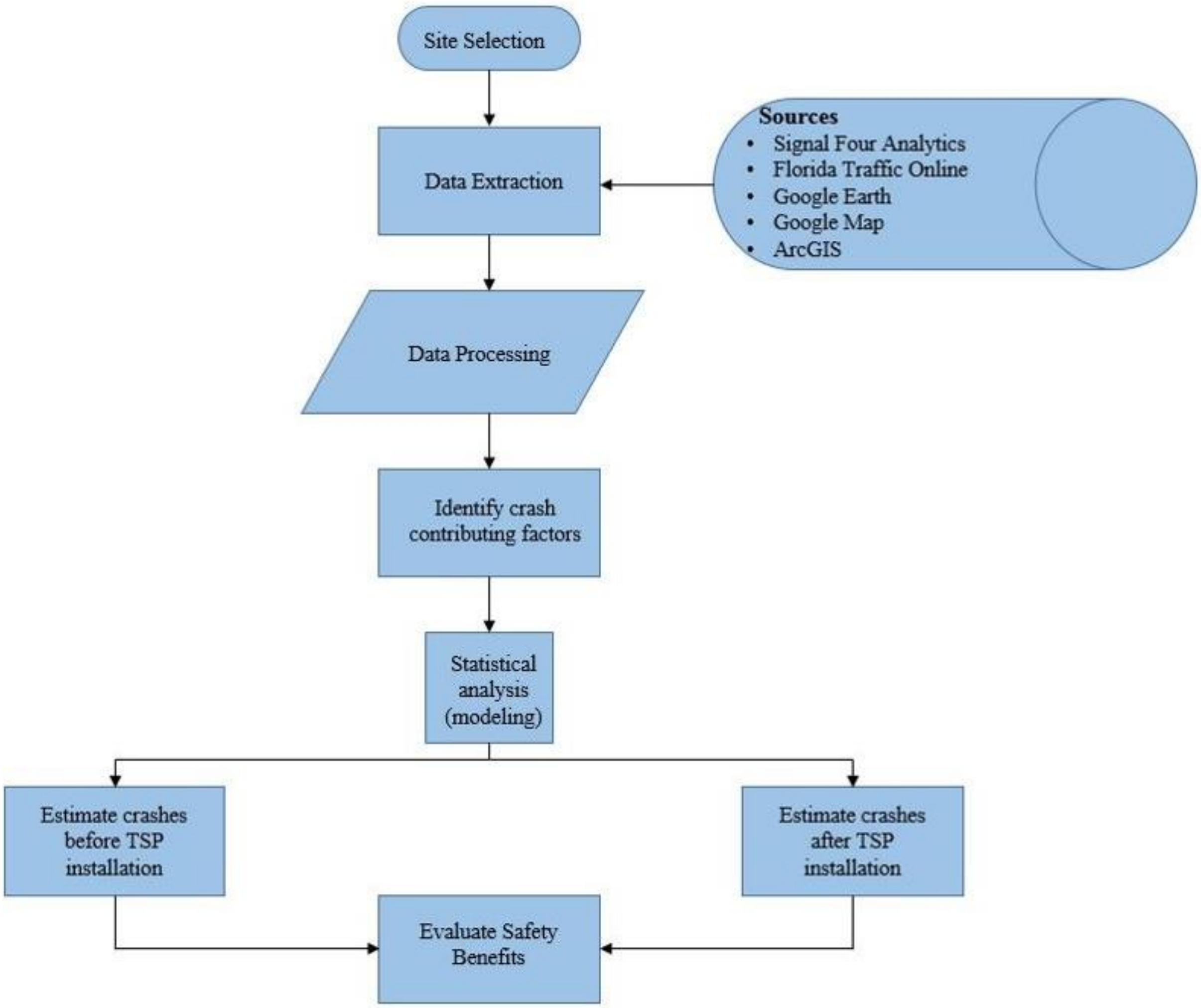


Figure 5-12: Approach to Evaluate Safety Benefits of TSP

5.4.3.1 Poisson Lognormal Model

The Poisson lognormal model, a statistical model to analyze crash counts of treatment corridors, was used to assess the effect of TSP on the safety performance of the corridors (Li et al., 2008). In all cases, Y_{it} in Equation 5-6 denotes the crash count observed at a TSP corridor *i* (*i*= 1, 2, 3,…,*n*) during year *t* (*t* = 1, 2,…,3) and can be modeled with a Poisson distribution with mean and variance equal to θ_{it}.

$$Y_{it}|\ \theta_{it} \sim \text{Poisson}\ (\Theta_{it}) \qquad (5\text{-}6)$$

The Poisson mean Θ_{it} can be written as shown in Equation 5-7.

$$ln\ (\theta_{it}) = ln\ (\mu_{it}) \qquad (5\text{-}7)$$

The before-and-after study employed collecting crash data before and after TSP was installed. A linear intervention model (Equation 5-8) was incorporated, such that T_i represents the treatment indicator (assigned 1 for a treatment corridor, and 0 for a comparison corridor), t_{oi} represents the intervention year for the i^{th} treatment corridor and its matching comparison corridors, and I_{it} represents the time indicator (assigned 1 in the after period, and 0 in the before period). For exposure variables, $X1_{it}$ denotes the Average Annual Daily Traffic (AADT) on the corridors. Additionally, $(X2_{i\,...,}\,X_{ji})$ symbolizes other explanatory variables, including geometric characteristics, such as the number of lanes, posted speed limit, etc.

The lognormal model for crash density is a piecewise linear function of the predictor variables, shown by Equation 5-8, such that the function is continuous at the change point, $t_{oi.}$ The piecewise linear function was defined by at least two equations, each of which applies to a different part of the domain (i.e., before and after installation of TSP).

$$ln(\mu_{it}) = \alpha_0 + \alpha_1 T_i + \alpha_2 t + \alpha_3 \mathrm{T_i I_{t>t_{0i}}} + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_n X_n \tag{5-8}$$

The linear intervention model allows for different slopes of crash frequency for times before and after the installation of TSP, and also across the treatment and comparison corridors.

5.4.3.2 Model Evaluation

The Widely Applicable Information Criterion (WAIC) was used to investigate the performance of the Poisson lognormal model in fitting the crash data. Similar to many other information criteria goodness-of-fit statistics, such as the Deviance Information Criterion, the WAIC considers model complexity and prediction accuracy to correct for overfitting (Gelman et al., 2014; Martin, 2018). A model with the excess effective number of parameters is penalized more than a model with fewer effective numbers of parameters (Kidando et al., 2019b). Alternatively, the WAIC is a full Bayesian measure of out-of-sample predictive accuracy, which is suitable for use in evaluating models that are fitted using the Bayesian approach. The WAIC estimate comes from the log pointwise posterior predictive density (Gelman et al., 2014; Kidando et al., 2019b). Equation 5-9 presents the expression used to calculate the WAIC from the estimated posterior distribution.

$$WAIC = -2 * (lppd + P_{waic}) \tag{5-9}$$

where, $lppd$ is the log pointwise posterior predictive density and P_{waic} is the effective number of parameters.

5.4.3.3 Measuring Treatment Effectiveness

Let μ_i^{TB} and μ_i^{TA} represent the predicted crash counts for the i^{th} treatment corridor averaged over the years before and the after periods, respectively. In addition, let μ_i^{CB} and μ_i^{CA} represent the corresponding counts for the paired comparison corridors. Superscripts *A* and *B* represent the after and the before periods, respectively, and superscripts *T* and *C* represent the treatment and the comparison corridors, respectively. The ratio $\mu_{it}^{CA}/\mu_{it}^{TB}$, conventionally known as the comparison ratio, is included during the evaluation of the safety effect of the countermeasure to account for other external factors that may influence the change in the crash frequency (Kitali and Sando, 2017). Potential external factors include improvements in vehicle safety technology, new traffic policies, traffic safety awareness education, etc., that cannot be attributed to the treatment (i.e., TSP deployment). Explicitly, the estimate of the comparison ratio $\mu_{it}^{CA}/\mu_{it}^{TB}$ 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(π_{it}^{TA}). Finally, the treatment effectiveness index, i.e., CMF, was estimated using Equation 5-10.

$$\mathrm{CMF}_{it} = \frac{\mu_{it}^{TA}}{\pi_{it}^{TB}}\text{, where } \pi_{it}^{TA}=\mu_{it}^{TB}\,\frac{\mu_{it}^{CA}}{\mu_{it}^{TB}} \tag{5-10}$$

5.4.3.4 Model Estimation Using the Hamiltonian Markov Chain Algorithm

The Bayesian approach implemented in this study employed the Hamiltonian Markov Chain (HMC) algorithm. The HMC algorithm is a Markov Chain Monte Carlo (MCMC) algorithm that uses the derivatives of the density function being sampled, Poisson lognormal in this case, to generate the posterior distributions of the parameters intended to be expected. HMC employs the principles of the Hamiltonian dynamics simulation that is based on numerical integration. The fact that this algorithm employs the use of physical system dynamics rather than a probability distribution to estimate future states in the Markov chain makes it more appealing than other MCMC algorithms (Brooks et al., 2011). The use of physical system dynamics allows the Markov chain to approach the target distribution more efficiently, thus resulting in faster convergence.

5.4.4 Results and Discussion

One additional model, a Poisson model, was compared to justify the use of the Poisson lognormal model. Specifically, the WAIC goodness-of-fit measure was used. Note that the model with the lowest WAIC best fits the data characteristics (Gelman et al., 2014). After fitting the two models, the Poisson lognormal model was observed to have the lowest WAIC value for total crashes (2257.1), PDO crashes (2439.2), and FI crashes (1589.4). Since the Poisson lognormal model was observed to best fit the data, further analysis was performed using this model.

The safety assessment of the 12 corridors with TSP in Orange and Seminole Counties was performed by following the steps of the FB before-after method. To obtain the FB estimates of the unknown parameters, prior distributions for the hyper-parameters must be specified. The most commonly used priors are vague normal distributions (with zero mean and large variance) for the regression parameters. The posterior distributions needed in the FB method were sampled using the HMC, and the posterior estimates of the model's parameters for the FB method were obtained using four independent chains with 50,000 iterations, whereby the first 20,000 were used as a burn-in sample. Descriptive statistics of variables used in the analysis are presented in Table 5-11.

Table 5-11: Descriptive Statistics of Treatment and Non-Treatment Corridors for TSP Evaluation

		Treatment Corridors				Non-Treatment Corridors			
Variable	Year	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
Total Crashes	2014	9	263	116.44	78.58	6	99	38.71	27.68
	2015	8	231	104.00	74.72	4	76	33.20	22.30
	2016	12	174	69.75	71.41	9	43	23.11	14.35
	2017	9	218	107.67	70.58	1	83	30.00	21.60
	2018	9	247	114.54	81.72	2	83	35.43	21.44
PDO Crashes	2014	6	184	77.78	53.08	2	73	26.62	20.61
	2015	5	162	72.08	54.13	2	54	23.30	15.72
	2016	9	130	49.50	54.53	7	32	17.22	9.40
	2017	4	143	9.64	47.71	1	60	20.43	15.36
	2018	6	183	79.92	58.22	0	58	23.63	15.33
FI Crashes	2014	2	79	38.67	27.08	6	30	12.10	8.12
	2015	3	70	31.92	21.78	4	28	9.90	7.93
	2016	3	44	20.25	17.33	9	14	5.89	5.23
	2017	5	75	35.22	23.81	1	29	9.57	7.38
	2018	3	74	34.62	25.20	2	26	11.80	7.55
AADT	2014	1500	35,500	16,878	10,340	1,500	35,500	16,338	9598
	2015	1500	38,500	17,977	12,366	1,500	38,500	17,090	11,707
	2016	4500	37,500	19,275	16,994	4,500	37,500	17,700	15,457
	2017	1600	40,000	21,000	12,879	1,600	40,000	20,695	12,179
	2018	1600	41,000	20,461	13,453	1,600	41,000	19,777	12,981
Length	All	0.5	2.8	1.47	0.74	0.2	1.1	33.42	0.23
No. of Lanes	All	2	6	3.42	1.23	2	6	3.59	1.12
Speed Limit	All	30	45	34.38	4.57	30	45	33.11	6.07

Note: SD = Standard Deviation

The posterior distributions for each crash category, along with the means and the 95th percentile Bayesian credible intervals (BCIs), are shown in Table 5-12. The predictor variable is considered to be significant at 95% BCI if the values of the 2.5% and 97.5% percentiles do not include zero, and they are both either negative or positive. Overall, the results of the posterior means indicate a decreasing trend in crashes for treatment sites over years and for corridors with a higher proportion of signalized intersections with TSP enabled. Moreover, jump parameters also show a sudden decrease in crashes after TSP was installed. However, for all crash categories, the resulting posterior means also indicate an increase in the tendency for crashes on corridors with higher AADT, posted speeds of 40 mph and over, and a higher number of lanes. With an increase in traffic volume, accompanied by an increase in heterogeneity in driving behavior, the probability of crash occurrence is expected to rise (Kitali and Sando, 2017). Higher posted speed limits on urban arterials are also associated with an increase in crashes (Wang et al., 2018).

Table 5-12: Posterior Distribution Summaries for Different Crash Categories

	Mean	2.5%	97.5%
Total Crashes			
Intercept	-4.814	-5.408	-4.234
Treatment indicator	4.103	3.846	4.358
Crash trend over years	-0.056	-0.073	-0.039
Jump parameter	-0.12	-0.159	-0.082
Posted speed > 40 mph	0.569	0.398	0.744
Ln AADT	0.799	0.751	0.848
Proportion of TSP intersections	-8.21	-8.684	-7.737
PDO Crashes			
Intercept	-4.935	-5.595	-4.291
Treatment indicator	3.94	3.639	4.253
Crash trend over years	-0.056	-0.077	-0.035
Jump parameter	-0.116	-0.163	-0.07
Posted speed > 40 mph	0.58	0.381	0.785
Ln AADT	0.773	0.717	0.83
Proportion of TSP intersections	-7.988	-8.564	-7.434
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	-0.13	-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 intersections	-8.183	-9.04	-7.347

As shown in Table 5-12, regression coefficients for the proportion of signalized intersections with TSP parameter (parameter accounting for a higher proportion of signalized intersections with TSP enabled) is significantly negative for all crash types. For the total crashes (Mean = -8.21, 95% BCI (-8.684, -7.737)), PDO crashes (Mean = -7.988, 95% BCI (-8.564, -7.434)), and FI crashes (Mean = -8.183, 95% BCI (-9.04, -7.347)). These results suggest a decrease for all crashes categories after TSP installation. Crash trend of the treatment sites over the years also showed significant decrease for total crashes (Mean = -0.056, 95% BCI (-0.073, -0.039)), PDO crashes (Mean = -0.056, 95% BCI (-0.077, -0.035)), and FI crashes (Mean = -0.055, 95% BCI (-0.087, -0.024)). The jump parameters for the total crashes (Mean = -0.12, 95% BCI (-0.159, -0.082)), PDO crashes (Mean = -0.116, 95% BCI (-0.163, -0.07)), and FI crashes (Mean = -0.13, 95% BCI (-0.202, -0.057)) indicate a sudden decrease in crashes for all crash categories in the after period.

Table 5-13 lists the evaluation results of the effectiveness of TSP, showing the CMFs and their related 95% credible intervals of the total, PDO, and FI crashes. The index of effectiveness was considered significant at the 95% BCI when the values of the 2.5% and 97.5% percentiles did not include one. As shown in Table 5-12, BCI values for all crash categories are less than one. The CMFs for total crashes (Mean = 0.8843, 95% BCI (0.8619, 0.9387)), PDO crashes (Mean = 0.9203, 95% BCI (0.8754, 0.9675)), and FI crashes (Mean = 0.8558, 95% BCI (0.7924, 0.9228)) crashes are significant at the 95% BCI. Analysis results indicate a significant reduction in total, PDO, and FI crashes after TSP installation. These findings were expected as drivers have more green time along TSP corridors to navigate through the signalized intersections, thereby reducing the queue formation at the intersection stop bar and avoiding crashes.

Table 5-13: CMFs for TSP

Crash Type	CMF for TSP		
	Mean	BCI	
		2.5%	97.5%
Total Crashes	0.88	0.86	0.94
PDO Crashes	0.92	0.88	0.97
FI Crashes	0.86	0.79	0.92

With the implementation of TSP, total crashes reduced by 12% along the treatment corridors. A similar pattern was also observed for PDO and FI crashes, revealing a reduction in crashes by 8% and 15%, respectively, along TSP, enabled corridors. Furthermore, these results are consistent with previous TSP safety studies by Goh et al. (2013), Goh et al. (2014), Naznin et al. (2016), and Song and Noyce (2018).

5.4.5 Conclusions

The objective of this study was to quantify the safety benefits of TSP. A full Bayesian before-after approach was used for the analysis of TSP enabled corridors (treatment corridors) with comparison groups (non-treatment corridors). The FB before-after study was performed using data on 12 transit corridors in Orange and Seminole Counties in Florida, which had TSP activated in the years of 2016 and 2017. A total of 29 street sections without the TSP treatment were selected as a reference group to compare with the treatment sites in each respective county. Findings from the FB before-after analysis include:

- The implementation of TSP correlates with the reduction of total corridor level crashes, with an index of effectiveness of 0.8843, i.e., about 12% reduction.

- Similarly, the implementation of TSP also correlates with the reduction of PDO and FI crashes at a corridor level, with indices of the effectiveness of 0.9203 (about 8% reduction) and 0.8558 (about 15% reduction), respectively.

From the results, it could be inferred that TSP not only provides mobility benefits to improve transit performance but also promotes safety to the driving public. A major implication of the research is that bus priority measures improve road safety overall, which is a strong rationale for implementing this TSM&O strategy.

5.5 Adaptive Signal Control Technology

Adaptive Signal Control Technology (ASCT) continuously monitors arterial traffic conditions and the queuing at intersections and dynamically adjusts the signal timing to optimize and improve operational objectives. ASCT has historically been deployed to reduce traffic congestion, particularly during highly variable traffic conditions. Signal timings and phasing scenarios are adjusted in real-time with ASCT, which allows the signal to better adjust the changes in demand created by incidents, special events, seasonal variation, or traffic growth over time (USDOT, 2017). The following sections discuss the evaluation of the safety benefits of this TSM&O strategy deployed in Florida.

5.5.1 Study Corridor

Recommended by the American Association of State Highway and Transportation Officials (AASHTO) HSM, an observational before-after empirical Bayes approach with comparison groups was used to evaluate the safety effectiveness of ASCT deployed in Florida (AASHTO, 2010). Also recommended in the HSM, study sites selected for ASCT evaluation must be homogenous, i.e., comparison sites (with and without ASCT) should have similar characteristics (AASHTO, 2010). Intersection characteristics considered in the initial identification of treatment sites with ASCT deployed consisted of intersections with four-legged geometry or three-legged geometry and maintained the same characteristics both before and after ASCT installations. A minimum of two years of crash data after ASCT deployment was also considered as a criterion for the selection of the treatment sites. Due to the limited number of three-legged signalized intersections with ASCT in the study area, only four-legged signalized intersections were analyzed in this study. Figure 5-13 shows the locations of the selected treatment intersections with ASCT in Orange and Seminole Counties, Florida.

The study area included five corridors containing 42 intersections with existing ASCT systems. Of the 42 intersections, 27 intersections were deployed with InSync ASCT, and the remaining 15 intersections were deployed with SynchroGreen ASCT. The two systems optimize signal timing using different algorithms. InSync uses real-time data collected through four video detection cameras at each intersection to select signalization parameters, such as state, sequence, and amount of green time, to optimize the prevailing conditions on a second-by-second basis. Optimization is based on minimizing the overall delay and reducing the number of stops (Rythem Engineering, 2017). Alternatively, SynchroGreen uses an algorithm that optimizes signal timing based on real-time traffic demand. With SynchroGreen, optimization is based on minimizing total network delay while providing reasonable mainline progression bandwidth. The algorithms of both systems utilize the detection data obtained from non-proprietary technology, such as inductive loops, video, wireless, and radar. Both algorithms also require stop-bar detection and advanced detection, and the detection data are sent to the signal system master through local controllers (Trafficware, 2012). Although the optimizations are different, the two systems are expected to have similar safety performance (Khattak et al., 2018).

A total of 47 comparison sites were selected for the evaluation of safety performance. These sites were located within the same jurisdiction as the treatment sites and had similar geometric characteristics and traffic volumes as to the treatment sites. Similar criteria have been used in previous studies (Fink et al., 2016; Kitali et al., 2018b). Figure 5-13 shows the locations of the selected comparison sites used in this study.

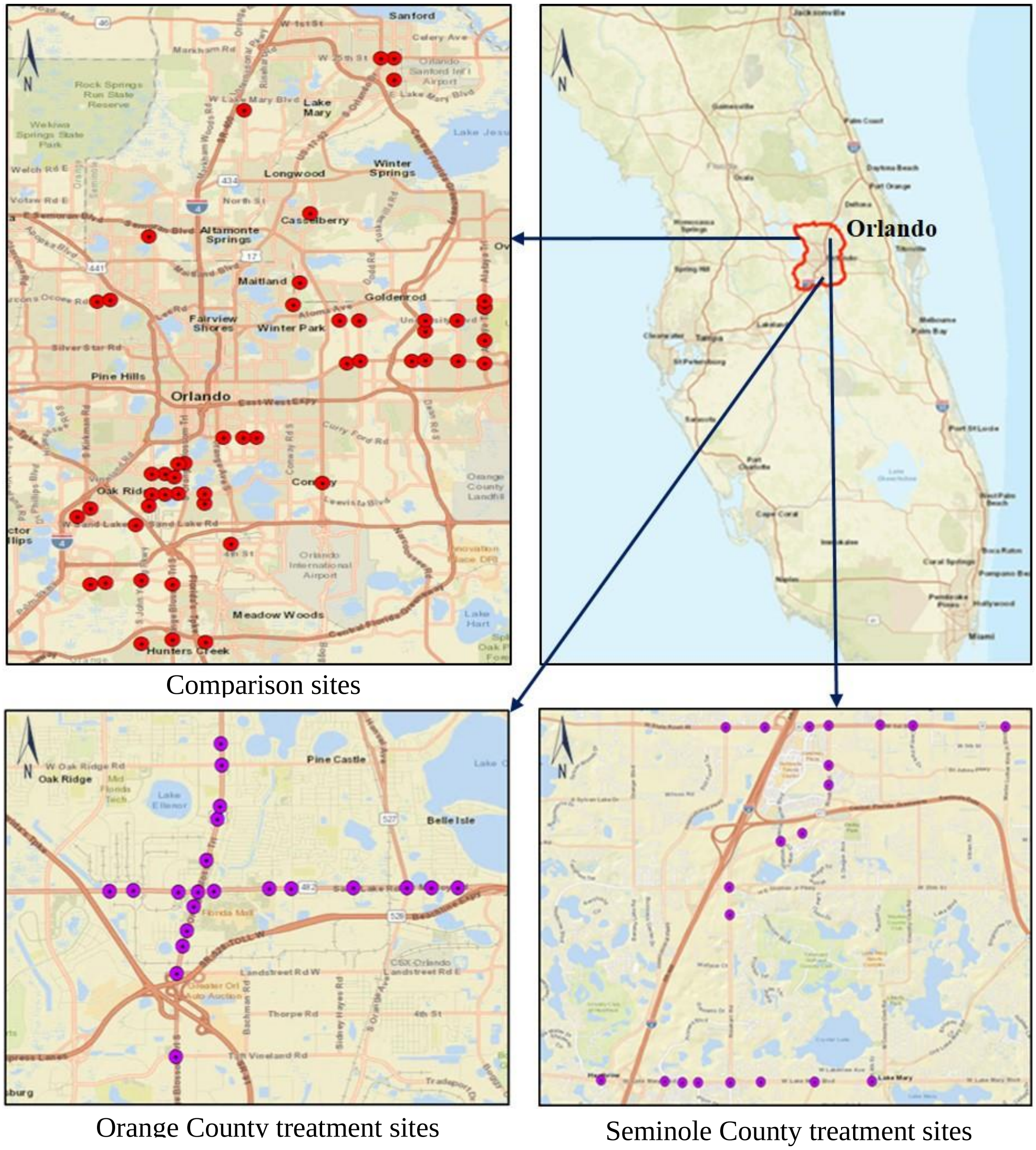


Figure 5-13: Treatment and Comparison Intersections for Analyzing ASCT Benefits

5.5.2 Data

The following data were needed to evaluate the safety performance of ASCT: crash data, geometric characteristics of major and minor intersection approaches, AADT for major and minor intersection approaches, land use information, and traffic control characteristics. These data were collected for both the treatment and comparison intersections. For each treatment intersection, at least two years of before and after data were retrieved, and at least two years of data were retrieved for each comparison intersection.

Historical AADT data for the major and minor intersection approaches were retrieved from the Florida Traffic Online and FDOT shapefiles. Since AADT is a vital variable, additional efforts were undertaken to estimate missing AADT data. If AADT data were available for only one year, a growth rate of 3% was used to estimate the AADT for the missing years. A similar approach was used in previous studies (Srinivasan and Bauer, 2013; Alluri et al., 2018). Additionally, if the AADT for the two major and minor approaches were different, the larger AADT was used for analysis.

Geometric characteristics data consisting of intersection geometry, number of lanes, and median width, and posted speed were retrieved from FDOT's Roadway Characteristics Inventory (RCI) and Geographic Information System (GIS) database, and Google Maps. Land use information was retrieved from the Florida Geographical Data Library (FGDL), metadata explorer. Google Earth Pro software was used to retrieve historical roadway geometric information. The Google Earth Pro historical imagery tool was used to verify that no major geometric changes occurred at the study intersections during the study period.

Crash attribute data were available for years 2011 – 2018 and were retrieved from the SignalFour Analytics database. Crash data were categorized as crash types (total and rear-end crashes) and crash severity (FI and PDO). Angle crashes were not included in the analysis due to the limited number of recorded angle crashes at the treatment and comparison intersections. All crashes that occurred within 250 ft of the intersections were considered as intersection-related crashes. The 250 ft radius conforms to the definition of intersection-related crashes in Florida (FDOT, 2012). Table 5-14 provides the descriptive statistics of annual crash data both before and after ASCT deployment at the selected treatment sites.

Table 5-14: Annual Crash Data Summary for ASCT Treatment Intersections

Crash Category	Before ASCT Deployment			After ASCT Deployment		
	Mean	Min	Max	Mean	Min	Max
Total crashes	32.73	1	98	20.07	2	103
Rear-end crashes	18.75	0	54	14.97	0	56
FI crashes	8.08	0	28	5.7	0	27
PDO crashes	25.29	0	70	17.02	0	84

Note: Units reflect crashes/year/intersection.

5.5.3 Methodology

5.5.3.1 Safety Performance Functions (SPFs)

Safety performance functions (SPFs) are crash prediction models that relate crash frequency to traffic volume, geometric characteristics, and other factors that influence a change in crash severity patterns and crash rates (Gross et al., 2010). SPFs are developed through statistical multiple regression techniques using observed crash data collected over a number of years at sites with similar characteristics referred to as comparison sites (Srinivasan and Bauer, 2013). These characteristics typically include traffic volume (historical AADT) for both major and minor intersection approaches, geometric characteristics (number of lanes, median characteristics, etc.), posted speed for both major and minor approaches, land use information, signal turning phase system, and number of bus stops within 1,000 ft of the intersection (AASHTO, 2010). There are two types of SPFs: simple SPFs and full SPFs. Simple SPFs include AADT as the only independent variable in predicting crash frequency. Full SPFs provide a mathematical relationship that relates all the possible attributes that may influence variation in crash frequency, including traffic volume, geometric characteristics, posted speed, signal phasing, and land use information, as predictor variables (Gross et al., 2010). Full SPFs were developed in this study to capture the influence of all attributes on the frequency and severity of crashes.

Florida-specific SPFs were developed in this study to be used in the before-after empirical Bayes analysis to estimate CMFs for the ASCT strategy. Therefore, SPFs were developed from the reference sites that are similar to the treated sites (Srinivasan and Bauer, 2013). A total of 47 comparison sites were selected for SPF development. These sites were located within the same jurisdiction as the treatment sites and had similar geometric characteristics and traffic volumes as to the treatment sites.

A negative binomial model is better suited for modeling crash data, rather than a Poisson regression model since a negative binomial model accounts for the over-dispersion of crash data (Srinivasan and Bauer, 2013). The degree of over-dispersion in the negative binomial model is represented by the over-dispersion parameter, which is then used to determine the value of a weight factor to be used in the empirical Bayes method (AASHTO, 2010). This study used the Bayesian Negative Binomial (BNB) approach to develop the SPFs. 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). Furthermore, the Bayesian inference technique can provide better results, even with a small sample size, since it can provide a distribution that includes prior information of the data (Xie et al., 2008). Utilization of prior probability distribution improves model fitting, prediction accuracy, and avoids overfitting (Genkin et al., 2007; Spiegelhalter and Rice, 2015). Several studies have reported the superiority of the Bayesian inference approach over the maximum likelihood approach in modeling crash data (Amer et al., 2012; Ahmed et al., 2013; Yu et al., 2013).

Bayesian Negative Binomial Model (BNB)

Modeling of crash frequency is performed using count models since crash count data are nonnegative, discrete, and generally random events in nature. This section presents an overview of the modeling technique used to develop the SPFs.

Consider crashes that occurred at intersection i, denoted by Y_i, are modeled with a negative binomial distribution with a mean and variance equal to λ_i, as presented in Equation 5-11.

$$Y_i \sim NegBinomial(\lambda_i, \alpha) \tag{5-11}$$

where,

$$ln(\lambda_i) = \beta_0 + \beta_1 X_i \tag{5-12}$$

where,

$NegBinomial$ represents the negative binomial distribution,
λ_i is a crash rate for the intersection i,
α is the over-dispersion parameter,
β_0 and β_1 are vectors of the regression coefficient, and
X_i is the vector of independent variables.

Model parameters of the negative binomial model presented in Equation 5-12 are estimated using a full Bayes approach through MCMC simulations. As such, it was necessary to assign the prior distributions to model parameters. Therefore, since informative priors from previous research with similar model set-ups were not available, vague priors were specified to the model. Normal distributions with a mean of zero and a standard deviation of 10 were assigned to the regression coefficients β_0, and β_1. For the dispersion parameters, Gamma distributions with shape 0.001 and rate 0.001, $\Gamma(0.01, 0.01)$, were assigned as prior distributions. The convergence of the MCMC simulations was assessed using the Gelman-Rubin Diagnostic statistic. This statistic assesses the difference between multiple chains and across steps within the chains. For the model to achieve convergence, the difference between variances, which is the Gelman-Rubin Diagnostic statistic, had to be equal to 1 (Huang et al., 2008). Moreover, a visual diagnostics approach was used to assess chain convergence, including the use of an autocorrelation plot and trace plot of each parameter.

5.5.3.2 Empirical Bayes Method

The empirical Bayes method with comparison groups prescribed in the HSM (AASHTO, 2010) was used to estimate the CMFs for the ASCT strategy. The empirical Bayes method accounts for the regression-to-the-mean effects, as well as changes in traffic volume and other roadway characteristics by combining SPFs with crash counts (Hauer, 1997). It is also considered more reliable and rigorous than other methods since it takes observed crash frequency into account and combines it with long term expected crash frequencies estimated using statistical models (i.e., SPFs) (Gross et al., 2010). Previous studies have used a similar empirical Bayes before-after approach for developing CMFs for ASCT systems (Khattak et al., 2018; Khattak et al., 2019).

An observational before-after empirical Bayes with a comparison group accounts for confounding factors. A confounding factor is a variable that completely or partially accounts for the apparent association between an outcome and a treatment (Elvik, 2002; Gross et al., 2010). The use of the comparison-group method has been proven to control the confounding factors whose effect cannot be estimated statistically (Elvik, 2002). Figure 5-14 shows the process of the empirical Bayes approach used to estimate CMFs in this study.

5.5.3.3 Crash Modification Factors (CMFs)

A CMF is a measure of the estimated effectiveness of a safety countermeasure. Specifically, it is a multiplicative factor used to compute the expected number of crashes on a specific roadway facility after implementing a specific countermeasure. It can be presented in terms of a single value (point estimate) or a function that considers relevant site characteristics (Carter, 2017). A CMF of 1.0 serves as a reference, below or above which a decrease or increase in crash frequency, respectively, is expected after implementing a specific countermeasure. CMFs were developed for the ASCT strategy to determine the expected safety benefits of ASCT in terms of crash reduction.

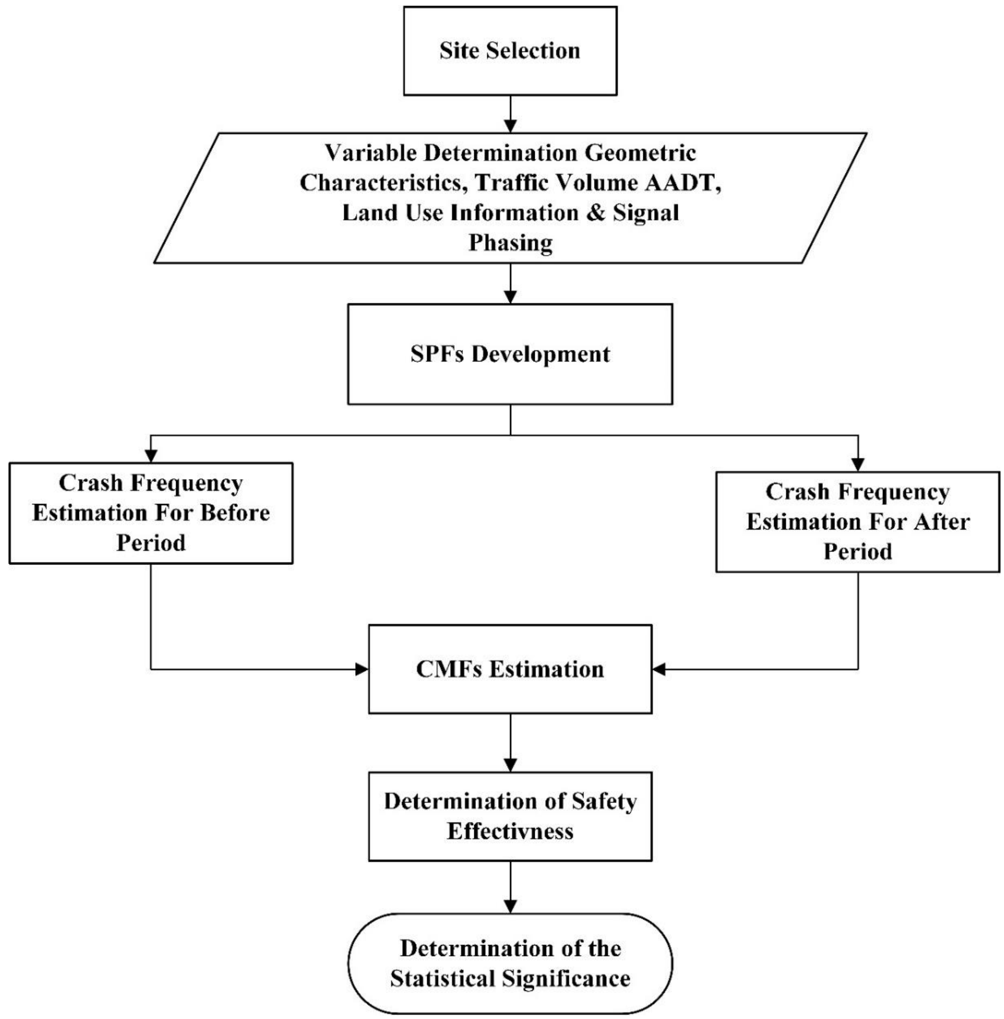


Figure 5-14: Flow Chart for the Empirical Bayes Method

5.5.4 Results

5.5.4.1 Safety Performance Function Results

SPFs for total crashes, rear-end crashes and FI crashes at four-legged ASCT enabled intersections were developed using the BNB model. SPFs were developed to be used in the empirical Bayes before-after approach with comparison groups to estimate CMFs for the ASCT strategy. Significant variables at 95% BCI were used as SPF model variables. Table 5-15 shows the computed SPFs for total and rear-end crashes, and Table 5-16 shows the computed SPFs for FI crashes.

5.5.4.2 Crash Modification Factors Results

Table 5-17 shows the results of the estimated CMFs for intersections with ASCT. As indicated in the table, all the estimated CMFs are statistically significant at a 95% confidence level. The CMF for total crashes is 0.948, indicating a 5.2% reduction in total crashes following ASCT deployment. This finding is consistent with several previous studies (Ma et al., 2016; Khattak et al., 2018).

The CMF for rear-end crashes is 0.878, indicating a 12.2% reduction in rear-end crashes following ASCT deployment. Rear-end crashes are associated with unsafe stopping or a reduction in speed of the leading vehicle due to wait, go, and stop movements caused by poor signal timing (FHWA, 2017). Since ASCT systems improve traffic flow, reduce the number of stops, and control delay at an intersection, a reduction in rear-end crashes with ASCT enabled were expected. Khattak et al. (2018) also observed a similar reduction in rear-end crashes although the reduction was not statistically significant at a 95% confidence level.

The CMF for FI crashes is 0.958, indicating a 4.2% reduction in FI crashes following ASCT deployment. This result is consistent with several previous studies (Khattak et al., 2018; Khattak et al., 2019). The CMF for PDO crashes is 0.943, indicating a 5.7% reduction in PDO crashes following ASCT deployment. This finding is also consistent with previous studies (Khattak et al., 2019).

Table 5-15: SPF Model Results for Total and Rear-end Crashes

Variables	Total Crashes				Rear-end Crashes			
	Estimates	Standard Error	95% BCI		Estimates	Standard Error	95% BCI	
			2.5	97.5			2.5	97.5
Intercept	-6.164	0.587	-7.298	-4.989	-8.061	0.745	-9.683	-6.898
Ln Avg. AADT (major)	0.612	0.065	0.496	0.734	0.817	0.084	0.675	0.971
Ln Avg. AADT (minor)	0.264	0.026	0.21	0.313	0.131	0.029	0.078	0.185
Excl. right lane (major)	-0.226	0.030	-0.284	-0.168	-0.279	0.038	-0.358	-0.205
Excl. right (minor)	0.113	0.042	0.028	0.194	0.164	0.055	0.073	0.279
Median width (major)	-0.006	0.003	-0.011	-0.001	-0.018	0.004	-0.026	-0.011
Median width (minor)	0.021	0.003	0.015	0.027	0.026	0.004	0.019	0.033
Speed limit (major)	-0.093	0.046	-0.180	-0.010	0.193	0.062	0.073	0.303
Speed limit (minor)	0.205	0.026	0.156	0.256	0.151	0.043	0.051	0.233
Number of lanes (major)	0.183	0.03	0.126	0.236	0.115	0.041	0.032	0.187
Number of lanes (minor)	-0.068	0.023	-0.115	-0.027	NA	NA	NA	NA
Median presence (major)	-0.382	0.107	-0.573	-0.158	-0.430	0.155	-0.687	-0.120
Median presence (minor)	-0.247	0.047	-0.336	-0.146	-0.351	0.069	-0.471	-0.230
Land use (commercial)	0.103	0.055	-0.005	0.204	0.187	0.079	0.01	0.331
Land use (public)	0.229	0.059	0.112	0.333	0.254	0.091	0.064	0.424
Left turn phase (major) PO	0.417	0.068	0.289	0.540	0.636	0.097	0.477	0.828
Left turn phase (major) PS	-0.926	0.53	-2.009	-0.010	-1.563	0.739	-3.138	-0.248
Left turn phase (minor) PO	-0.130	0.035	-0.199	-0.060	-0.191	0.064	-0.296	-0.058
Left turn phase (minor) PS	-0.373	0.070	-0.525	-0.243	-0.376	0.086	-0.585	-0.229
Bus stop (minor)	0.109	0.009	0.089	0.126	0.067	0.013	0.043	0.092
Intersection geometry	NA	NA	NA	NA	0.184	0.087	0.039	0.346
Excl. left (major)	NA	NA	NA	NA	0.222	0.075	0.078	0.356
Family specific parameter	282.471	105.869	137.26	547.383	309.775	129.886	138.266	621.131

Note: PO - Protected Only for the left-turn phase at major and minor approaches; PS - Permissive Only for left turns at major and minor approaches; Excl. - Exclusive lane in major and minor approaches; Ln Avg. AADT - Natural logarithm of average AADT for major and minor approaches.
NA – Not Applicable

Table 5-16: SPF Model Results for FI Crashes

Variables	Estimates	Standard Error	95% BCI	
			2.5	97.5
Intercept	-6.975	0.954	-8.751	-4.835
Ln Avg. AADT (major)	0.598	0.117	0.333	0.832
Ln Avg. AADT (minor)	0.249	0.043	0.174	0.331
Excl. right lane (major)	-0.282	0.052	-0.379	-0.167
Excl. right (minor)	0.273	0.072	0.140	0.402
Median width (major)	0.013	0.005	0.002	0.024
Speed limit (minor)	0.233	0.047	0.148	0.319
Number of lanes (major)	0.176	0.058	0.064	0.298
Median presence (major)	-0.682	0.146	-0.977	-0.382
Median presence (minor)	-0.459	0.077	-0.618	-0.322
Land use (commercial)	-0.021	0.089	-0.195	0.149
Land use (public)	0.268	0.101	0.068	0.455
Left turn phase (major) PO	0.322	0.109	0.120	0.545
Left turn phase (major) PS	-1.297	0.835	-3.244	0.040
Left turn phase (minor) PO	-0.139	0.066	-0.276	-0.018
Left turn phase (minor) PS	-0.401	0.107	-0.587	-0.197
Bus stop (minor)	0.134	0.018	0.096	0.166
Family specific parameter	389.737	138.609	165.38	688.99

Note: PO - Protected only for the left-turn phase at the major and minor approaches; PS - Permissive only for a left turn at the major and minor approaches; Excl. - Exclusive lane in major and minor approaches;
Ln Avg. AADT - Natural logarithm of average AADT for major and minor approaches.

Table 5-17: CMFs for ASCT

Crash Type	Mean (i.e., CMF)	95% CI		Standard Error	% Reduction in Crashes
		Upper Limit	Lower Limit		
Total crashes	0.948	0.955	0.942	0.003	5.2%
Rear-end crashes	0.878	0.886	0.870	0.004	12.2%
FI crashes	0.958	0.971	0.945	0.007	4.2%
PDO crashes	0.943	0.951	0.936	0.004	5.7%

5.5.5 Conclusions

This study evaluated the safety effectiveness of ASCT, a traffic management strategy that optimizes signal timing based on real-time traffic demand. The evaluation examined the safety benefits of ASCT using field crash data collected for the years 2011 – 2018 from signalized intersections in Orange and Seminole Counties, Florida. The analysis was based on 42 treatment sites (with ASCT deployed) and 47 corresponding comparison sites (without ASCT).

The BNB model was used to develop SPFs for total, rear-end, and FI crashes. The SPFs were developed from comparison intersections based on heterogeneous characteristics with ASCT treatment sites. These characteristics include additional factors that influence changes in crash frequencies and crash severity patterns at the treatment sites independent of the deployed ASCT. The heterogeneous factors incorporated in this study include traffic volume (AADT) on major and minor streets, geometric characteristics (number of lanes, intersection geometry, and median characteristics), and posted speed, number of bus stops within 1,000 ft of the intersection, signal phasing, and land use information.

CMFs were developed using an empirical Bayes before-after approach with comparison-group. The analysis revealed that ASCT installations reduce total crashes by 5.2% (CMF = 0.948), rear-end crashes by 12.2% (CMF = 0.878), FI crashes by 4.2% (CMF = 0.958), and PDO crashes by 5.7% (CMF = 0.943). Note that these results are statistically significant at a 95% confidence level.

These findings provide researchers and practitioners with an effective means for quantifying the safety benefits of ASCT, an economic appraisal of the ASCT strategy, as well as a key consideration to transportation agencies for future ASCT deployments.

5.6 Summary

This chapter discussed in detail the adopted study locations, research methodology, data, and the analysis results to quantify the safety benefits of the TSM&O strategies that have been deployed in Florida, with a specific focus on the following strategies:

Freeways

- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers

Arterials

- Transit Signal Priority (TSP)
- Adaptive Signal Control Technology (ASCT)

5.6.1 Safety Benefits of Ramp Metering

The study analyzed the benefits of ramp metering by analyzing the crash risk on the freeway mainline. Results indicate safety improvements on freeways resulting from ramp metering operations. Study results reveal a 41% decrease in the risk of crashes when RMSs are operational compared to the time periods when RMSs are not operational. However, the improvements evaluated in this study are applicable to the mainline traffic when ramp metering is operational during peak hours.

5.6.2 Safety Benefits of Dynamic Message Signs

The safety analysis of DMSs was conducted using the coefficient of variation (CV) of vehicle speeds as a surrogate safety measure. The variations were determined when the displayed messages on DMSs did not require drivers to take action (i.e., when the DMSs display advisory messages) versus when the DMSs displayed messages about downstream crashes.

The number of crashes downstream during crash messages was relatively small. Out of 21,016 crashes that occurred on I-75 during the 3-year study period, 18 crashes occurred 10 miles downstream of the DMSs 30 minutes after the *crash* message started displaying, and 23 crashes occurred 30 minutes prior to the *crash* message (i.e., during the *clear* message displays). Overall, displaying crash messages on DMSs was found to result in fewer crashes despite the increase in speed variances.

5.6.3 Safety Benefits of Road Rangers

This study evaluated the safety performance of the Road Ranger freeway service patrol, a mobile-based program administered by FDOT to assist motorists and minimize the impacts of freeway incidents on non-recurring traffic congestion. Specifically, this study examined the benefits of the Road Ranger program in reducing the risk of secondary crash occurrence.

Overall, statistics showed that Road Rangers responded to over three-quarters (76.94%) of the 6,865 incidents analyzed and were associated with shorter average incident durations compared to other responding agencies. Since there exists a relationship between incident duration and secondary crashes (Khattak et al., 2009), these reductions in incident impact duration can translate into substantial travel time and fuel consumption savings for motorists, as well as a potential reduction in secondary crash occurrence.

Based on average incident duration reduction, the results suggest that the Road Ranger program may reduce the likelihood of secondary crashes by 20.9%. By controlling the traffic at an incident scene, Road Rangers reduce the probability of secondary crashes by 17.9%.

5.6.4 Safety Benefits of Transit Signal Priority

A full Bayesian before-after approach was used for the analysis of TSP enabled corridors (treatment corridors) with comparison groups (non-treatment corridors). CMFs were developed to quantify the safety effectiveness of the TSP strategy. The study results indicated that the implementation of TSP resulted in a 12% reduction in total corridor-level crashes, 15% reduction in FI crashes, and 8% reduction in PDO crashes.

5.6.5 Safety Benefits of Adaptive Signal Control Technology

This study evaluated the safety effectiveness of ASCT, a traffic management strategy that optimizes signal timing based on real-time traffic demand. The analysis was based on 42 treatment sites (with ASCT deployed) and 47 corresponding comparison sites (without ASCT). CMFs were developed using an empirical Bayes before-after approach with comparison-group. The analysis revealed that ASCT installations reduce total crashes by 5.2% (CMF = 0.948), rear-end crashes by 12.2% (CMF = 0.878), FI crashes by 4.2% (CMF = 0.958), and PDO crashes by 5.7% (CMF = 0.943), and these results are statistically significant at a 95% confidence level.

CHAPTER 6
USER MANUAL FOR TSM&O STRATEGIES ASSESSMENT TOOL

This chapter presents the user manual for the TSM&O Strategies Assessment Tool. The Tool is intended to provide support and guidance to transportation practitioners to quantify the safety and mobility benefits of the following TSM&O strategies:

Freeways

- Ramp Metering System
- Dynamic Message Signs (DMSs)
- Road Rangers
- Express Lanes (ELs)

Arterials

- Adaptive Signal Control Technology (ASCT)
- Transit Signal Priority (TSP)

6.1 Getting Started

This section describes the basic interactions needed to complete an evaluation using the Tool. It consists of the following subsections.

- Enabling Macros: guidance for setting worksheet security to enable macros.
- Navigation: guidance for selecting and using the worksheets.
- Info Worksheet: a brief overview of TSM&O strategies.
- Entering Data and Reviewing Results: guidance for entering data in a worksheet, reviewing, saving, and printing results.

6.1.1 Enabling Macros

The Tool contains computer code written in the Visual Basic for Applications (VBA) programming language and is referred to as a "macro" code in Excel®. If prompted, the macro code must be enabled when first loading the Tool. To enable macros, click on the "Enable Content", as shown in Figure 6-1.

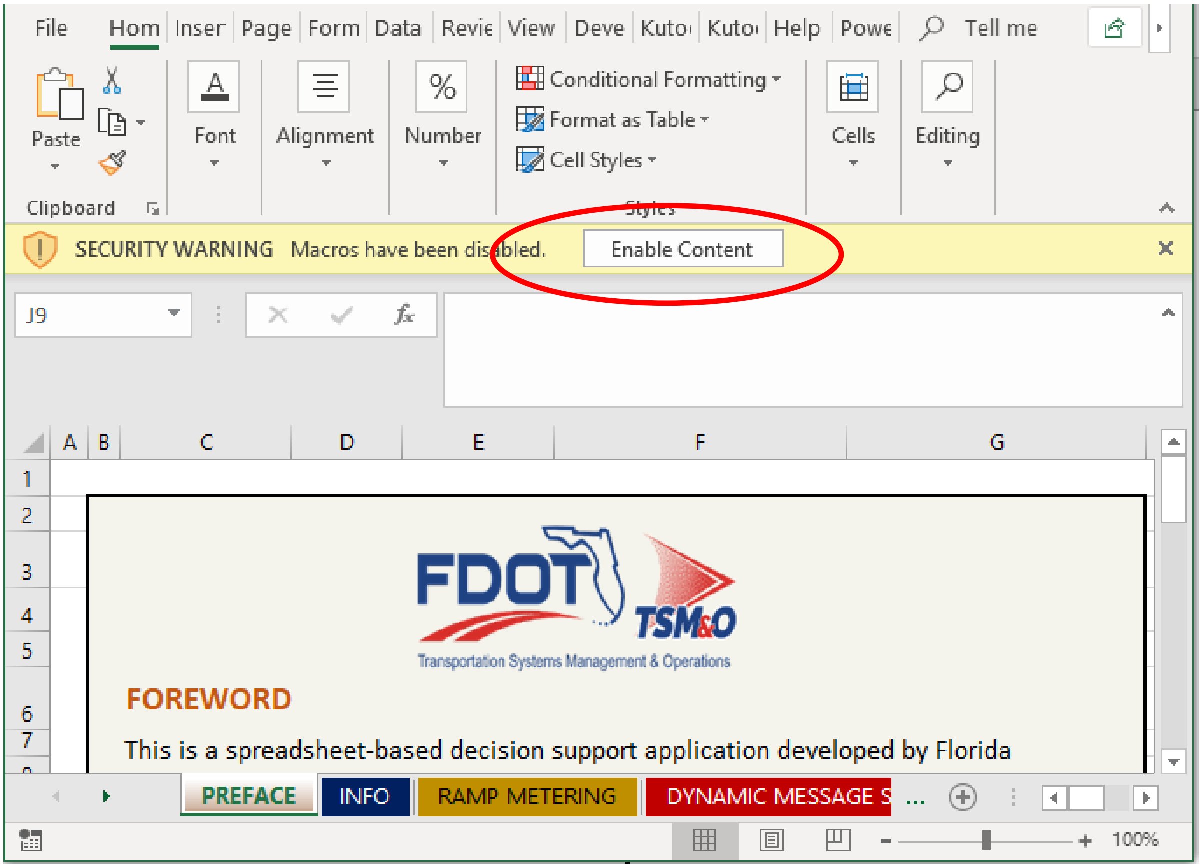


Figure 6-1: Enabling Macros in MS Excel

6.1.2 Navigation

The Tool contains a total of nine (9) worksheets. To navigate among worksheets, click on the worksheet tabs at the bottom of the workbook window. Worksheets have the following contents:

- Preface – includes a foreword, acknowledgments, and a disclaimer.
- Info – provides a brief overview of TSM&O strategies.
- Worksheets for each TSM&O strategy – includes a separate worksheet for each TSM&O strategy (ramp metering, dynamic message signs, Road Rangers, express lanes, adaptive signal control technology, and transit signal priority).
- Input Data Description – includes step-by-step procedures to calculate the input values for the Tool.

6.1.3 Info Sheet

The "INFO" sheet provides useful information about each strategy. This information should be read prior to first use of the worksheet application. The worksheet consists of a short description of the strategy, performance measures used to quantify the benefits, and definitions of the input variables. This information is given in the following subsections.

6.1.3.1 Ramp Metering Systems

Definition

A ramp metering system (RMS) is a strategy that uses signals installed at freeway on-ramps to control and regulate the frequency at which vehicles join the flow of traffic on the freeway mainline.

Performance Measures

Mobility Performance Measure: *Travel Time Reliability - Buffer Index (unitless)*
Safety Performance Measure: *Crash Occurrence Risk - Percentage (unitless)*

Table 6-1: RMS – Input Data Needed for Mobility Performance Measure

Variable	Description	Thresholds
Average Mainline Traffic Speed (mph)	Average traveling speed on the segment mainline	15 - 50 mph
Ramp Volume (vph/lane)	Average volume of vehicles entering the mainline	216 - 660 vph/lane
Off-ramp Density (ramp/mile)	Number of exit-ramps per mile	0.5 - 1.4 ramp/mile
On-ramp Density (ramp/mile)	Number of entry-ramps per mile	1.2- 1.6 ramp/mile
Level of Service (LOS)	Level of service on the mainline	C - F

Table 6-2: RMS – Input Data Needed for Safety Performance Measure

Variable		Description	Thresholds
Mainline Standard Deviation (S.D.) of Speed		S.D. of Speed 5 minutes prior to RMS activation	0.05 - 16 mph
Mainline Standard Deviation (S.D.) of Occupancy		S.D. of Occupancy 30 minutes prior to RMS activation	0.15 - 15%
RMS Operations	ON	Ramp metering signal on the nearest upstream ramp is operational	Not Applicable
	OFF	Ramp metering signal on the nearest upstream ramp is not operational	Not Applicable

Note:

- The analysis involved RMS operations for recurrent congestion only.
- Step-by-step procedures to calculate the input values are provided in the INPUT DATA DESCRIPTION tab.

6.1.3.2 Dynamic Message Signs

Definition

Dynamic message signs (DMSs) are programmable electronic signs used for disseminating real-time information to road users.

Performance Measures

Mobility Performance Measure*: Average Speed Adjustment (mph)*
Safety Performance Measure: *Crash Frequency (number of crashes per year)*
Coefficient of Variation of Speed (unitless)

Table 6-3: DMS – Input Data Needed for Mobility Performance Measure

Attribute		Description	Thresholds
Traffic volume (vph/lane)		Average traffic volume when crash message is displayed	1 - 1,500 vph/lane
Occupancy (%)		Percentage of time the detector is occupied by vehicles	0 - 12 %
Time of Day	AM Peak	6:00 am - 10:00 am	Not Applicable
	PM Peak	4:00 pm - 6:30 pm	Not Applicable
	Off Peak	10:00 am - 4:00 pm & 6:30 pm - 6:00 am	Not Applicable
Lane Blocked	Use Caution	Drivers advised to proceed cautiously	Not Applicable
	All Lanes Closed	All travel lanes are closed	Not Applicable
	Left Lane(s) Closed	Left lane(s) closed	Not Applicable
	Right Lane(s) Closed	Right lane(s) closed	Not Applicable
	Other	Shoulder, ramp ahead or any other closure	Not Applicable

Note:

- The analysis was conducted for only messages displaying crash information and those displaying advisory information.
- The speed reduction and higher variations when the DMSs displayed crash-related messages may be attributed to other sources of information, such as navigation maps and Highway Advisory Radio.
- The analysis did not consider other potential factors, such as incidents downstream which may result in reduction in speeds and increased speed variations.

6.1.3.3 Road Rangers

Definition

Road Rangers are freeway service patrollers on major roadways in Florida. The Road Rangers, by virtue of their roving presence, arrive at an incident scene quickly to assist with incident clearance, improve traffic conditions, and improve safety.

Performance Measures

Mobility Performance Measure: *Incident Clearance Duration (minutes)*

Safety Performance Measure: *Secondary Crash Occurrence Risk - Percentage (unitless)*

Table 6-4: Road Rangers – Input Data Needed for Mobility and Safety Performance Measures

Incident Attribute	Categories	Element Components
Incident Type	Crash	All crash types
	Vehicle Problems	Mechanical breakdown, out of gas, etc.
	Traffic Hazards	Debris, spillage, flooding
Incident Severity	Minor	No lane closure
	Moderate	One lane closure
	Severe	Multiple to full lane closure
Time of Day	Peak	6:00 am - 10:00 am & 3:30 pm - 6:30 pm
	Off peak	10:00 am - 3:30 pm & 6:30 pm - 6:00 am
Day of the Week	Weekday	Monday 6:00 am through Friday 6:00 pm
	Weekend	Friday 6:00 pm through Monday 6:00 am
Lighting Condition	Daylight	Daytime hours (depending on sunrise and sunset)
	Night	Nighttime
Towing Involved	Yes	An incident involves towing
	No	An incident does not involve towing

Note:

- The evaluation did not account for disaggregate-level operational details of the program (e.g., day-to-day or seasonal variations in Road Ranger activities, fleet sizes, beat lengths, probe vehicle types, and pickup versus tow trucks).

6.1.3.4 Express Lanes

Definition

Express lanes (ELs) are managed toll lanes, separated from general-purpose lanes or general toll lanes within a freeway facility. They provide a high degree of operational flexibility, which enables the express lanes to be actively managed to respond to changing traffic demands.

Performance Measures

Mobility Performance Measure: *Travel Time Reliability using the Buffer Index (unitless)*

$$Buffer\ index = \frac{(95^{th}\ Percentile\ travel\ time - Average\ travel\ time)}{Average\ travel\ time} \qquad (6\text{-}1)$$

Performance was compared for two scenarios:

1. The performance of express lanes with that of their adjacent general-purpose lanes, and
2. Operational performance of the general-purpose lanes when the express lanes were operational versus when they were closed.

For each scenario, the average and the 95th percentile travel times were calculated.

Table 6-5: ELs – Input Data Needed for Mobility Performance Measure

Attribute	Description
Average Travel Time (min)	Average travel time along the corridor on typical weekdays
95th Percentile Travel Time (min)	95th percentile of the travel times along the corridor on typical weekdays

Note:

- The analysis was conducted for typical weekdays.
- Weekends, federal holidays, and the time periods affected by hurricanes were not included in the analysis.

6.1.3.4 Adaptive Signal Control Technology

Definition
Adaptive signal control technology (ASCT) is a traffic management strategy that optimizes signal timings based on real-time traffic demand. It continuously monitors the arterial traffic conditions and queues at intersections and dynamically adjusts the signal timings.

Performance Measures
Mobility Performance Measure: *Average Travel Speed (mph)*
Safety Performance Measure: *Crash Frequency (number of crashes per year)*

Table 6-6: ASCT – Input Data Needed for Mobility and Safety Performance Measures

Attribute	Categories	Description	Thresholds
Time of Day	AM peak	6:00 am - 10:00 am	Not Applicable
	PM Peak	3:00 pm - 7:00 pm	Not Applicable
	Off Peak	10:00 am - 3:00 pm & 7:00 pm - 6:00 am	Not Applicable
Crash Type	Total Crashes	All crashes along the study corridor within the analysis period	Not Applicable
	Rear-end Crashes	Rear-end crashes along the study corridor within the analysis period	Not Applicable
	Fatal and Injury (FI) Crashes	Crashes resulting in fatalities or injuries	Not Applicable
	Property Damage Only (PDO) Crashes	Crashes resulting in no injuries	Not Applicable
Land Use	Commercial	Intersection is close to financial institutions, malls, restaurants, markets, etc.	Not Applicable
	Institutional	Intersection is close to churches, schools, hospitals, etc.	Not Applicable
	Residential	Intersection is close to residential buildings/apartments	Not Applicable
AADT (vpd)	Major Street	Average AADT for the major approach to an intersection	< 20,000
			20,000 - 40,000
			> 40,000
	Minor Street	Average AADT for the minor approach to an intersection	< 4,000
			4,000 - 8,000
			> 8,000

Note:

- The analysis was conducted for only intersection-related crashes.
- The analysis did not separately analyze the safety performance of InSync and SynchroGreen technologies.
- The analysis did not consider the effect of pedestrians on the performance of ASCT.
- The analysis did not consider other potential factors, such as incidents and adverse weather.

6.1.3.5 Transit Signal Priority

Definition
Transit signal priority (TSP) is an operational strategy that facilitates the movement of transit vehicles (e.g., buses) through signalized intersections.

Performance Measures
Mobility Performance Measure: *Average Travel Time (minutes) & Average Delay Time (minutes)*
Safety Performance Measure: *Crash Frequency (number of crashes per year)*

Table 6-7: TSP – Input Data Needed for Mobility and Safety Performance Measures

Attribute	Categories	Description
Time of Day	AM peak	6:00 am - 10:00 am
	PM Peak	4:00 pm - 6:00 pm
	Off Peak	10:00 am - 4:00 pm & 6:00 pm - 6:00 am
Crash Type	Total Crashes	All crashes along the study corridor within the analysis period
	Fatal and Injury (FI) Crashes	Crashes resulting in fatalities or injuries
	Property Damage Only (PDO) Crashes	Crashes resulting in no injuries
Target Vehicles	Buses	Buses only
	All Vehicles	All vehicle types
Travel Time	Continuous	Average travel time along the corridor

Note:
- The mobility study on TSP considered only PM peak periods in the analysis.
- Average stopped delay for buses and all vehicles were not considered in the analysis.

6.2 Entering Data

The cells with a white or off-white background are for user input. Other cells are locked to prevent inadvertent changes to cell content. Left click the mouse over the input cells to see the input message box, which gives thresholds relevant to the respective input variables, as shown in Figure 6-2. These threshold values are also provided in the INFO worksheet.

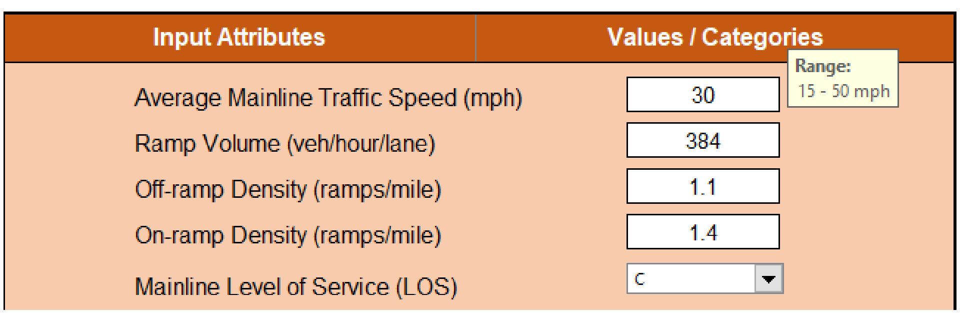


Figure 6-2: Sample Interactive Input Message Box for Continuous Variables

A drop-down list is provided for some cells with a drop-down combo box, as shown in Figure 6-3. Left click on the drop-down arrow to see the list of input choices. Use the mouse pointer to select the desired choice.

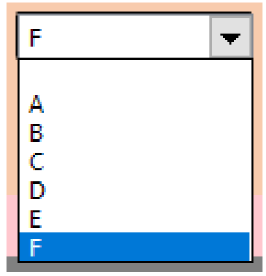


Figure 6-3: Sample Drop-down List for Categorical Variables

The data entered into the worksheets can be saved by saving the entire workbook as a separate file. On the main menu, select *File > Save As* and enter a new file name when prompted (i.e., avoid overwriting the original Tool workbook). Select *File > Print* on the main menu. Click on *Print Preview* to see and print the one-page printout of the results. If the information shown is acceptable, press the *Print* button at the top of the window to print the results page. Ensure that the printer is turned on prior to clicking the *Print* button. The following sections explain data input and the interpretation of the results for each strategy in the Tool.

6.2.1 Ramp Metering Systems

To quantify the mobility benefits of a ramp metering system, the user is required to collect data on the mainline and the ramp. Collected data includes mainline traffic speed, ramp volume, mainline occupancy, off-ramp density, on-ramp density, and level of service (LOS). Mainline traffic speed, volume, and occupancy is required to quantify the safety benefits of the ramp metering system.

Input Variables: All input variables are added by filling in the Tool cells with a white or off-white background, except the mainline LOS, which is selected from the drop-down options. Some input values need to be computed before they are keyed. The following sections provide step-by-step examples on how to quantify these input values for mobility and safety performance measures.

Input Values for Mobility Performance Measure - Buffer Index

Figure 6-4 shows a typical freeway segment with ramp metering systems on both on-ramps (i.e., Ramp 1 and Ramp 2). The study segment is defined by the detector locations. Other features, such as on-ramps or off-ramps, can also be used to define the study segment. The zones (i.e., Zone 1, Zone 2, Zone 3, and Zone 4) represent locations with detectors for collecting data from each lane. The ramp detectors are passage detectors, which measure the number of vehicles joining the freeway mainline. Sample traffic data collected from the detectors, corresponding with Figure 6-4, are presented in Table 6-8. The data are used to demonstrate the calculation of input values for evaluating the mobility benefits of ramp metering in the *TSM&O Strategies Assessment Tool*.

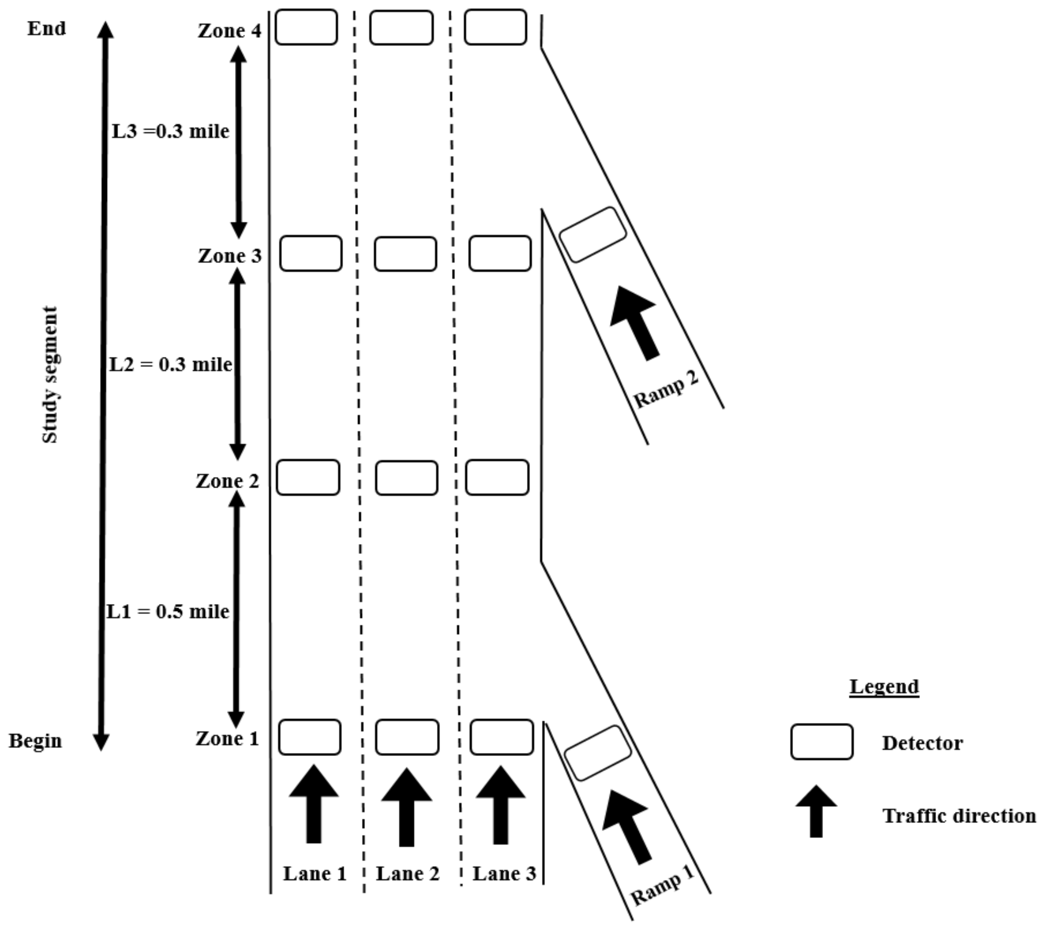


Figure 6-4: Typical Segment for Analyzing the Mobility Benefits of Ramp Metering

Table 6-8: Sample Data Collected from Freeway Segment Detectors

Detectors	Time	Lane 1			Lane 2			Lane 3		
		Sp. 1 (mph)	Vol. 1	Occ. 1 (%)	Sp. 2 (mph)	Vol. 2	Occ. 2 (%)	Sp. 3 (mph)	Vol. 3	Occ. 3 (%)
Zone 1	8:00 am	33	580	12	58	485	18	33	432	29
	7:55 am	37	613	11	54	502	19	23	431	25
Zone 2	8:00 am	28	605	12	56	548	24	32	441	30
	7:55 am	31	633	12	54	550	22	26	410	27
Zone 3	8:00 am	37	637	14	54	552	25	30	417	11
	7:55 am	35	657	13	54	487	21	31	456	14
Zone 4	8:00 am	35	654	12	56	494	15	58	457	24
	7:55 am	41	578	25	24	512	23	31	454	30
Ramp 1	8:00 am	38	18	21	---	---	---	---	---	---
Ramp 2	8:00 am	40	20	15	---	---	---	---	---	---

Note: Sp. = Speed; Vol. = Volume (veh per 5 min); Occ. = Occupancy, "---" indicates Not applicable

Using the collected data shown in Table 6-8, input variables for the mainline traffic speed, ramp volume, off-ramp density, on-ramp density, and mainline LOS are calculated as follows:

Average mainline traffic speed (mph), a 5-minute intervals illustration:

$$\boldsymbol{a})\ Speed\ at\ Zone_n\ = \frac{\sum_1^n Speed\ at\ Lane_n}{n}$$

$$Speed\ at\ Zone_1 at\ 8{:}00\ am\ = \frac{Sp.1 + Sp.2 + Sp.3}{3} = \frac{33 + 58 + 33}{3} = 41.3\ mph$$

$$Speed\ at\ Zone_2\ at\ 8{:}00\ am\ = \frac{Sp.1 + Sp.2 + Sp.3}{3} = \frac{28 + 56 + 32}{3} = 38.7\ mph$$

$$Speed\ at\ Zone_3 at\ 8{:}00\ am\ = \frac{Sp.1 + Sp.2 + Sp.3}{3} = \frac{37 + 54 + 30}{3} = 40.3\ mph$$

$$Speed\ at\ Zone_4\ at\ 8{:}00\ am\ = \frac{Sp.1 + Sp.2 + Sp.3}{3} = \frac{35 + 56 + 58}{3} = 49.7\ mph$$

$$\boldsymbol{b})\ Speed\ of\ segment\ L_n\ (SPL_n) = \frac{Speed\ at\ Zone_n +\ Speed\ at\ Zone_{n+1}}{2}$$

$$Speed\ of\ segment\ L_1\ \ (SPL_1)\ at\ 8{:}00\ am = \frac{Speed\ at\ Zone_1 +\ Speed\ at\ Zone_2}{2}$$
$$= \frac{41.3 + 38.7}{2} = 40\ mph$$

$$Speed\ of\ segment\ L_2\ \ (SPL_2)\ at\ 8{:}00\ am = \frac{Speed\ at\ Zone_2 +\ Speed\ at\ Zone_3}{2}$$
$$= \frac{38.7 + 40.3}{2} = 40\ mph$$

$$Speed\ of\ segment\ L_3\ \ (SPL_3)\ at\ 8{:}00\ am = \frac{Speed\ at\ Zone_3 +\ Speed\ at\ Zone_4}{2}$$
$$= \frac{40.3 + 49.7}{2} = 45\ mph$$

$$\boldsymbol{c})\ Mainline\ speed\ at\ 8{:}00\ am = \frac{\sum_1^n SPL_n * L_n}{\sum_1^n L_n}$$

$$Mainline\ speed\ at\ 8{:}00\ am = \frac{(SPL_1 * L_1) + (SPL_2 * L_2) + (SPL_3 * L_3)}{L_1 + L_2 + L_3}$$

$$Mainline\ speed\ at\ 8{:}00\ am = \frac{(40*0.5)+(40*0.3)+(45*0.3)}{0.5+0.3+0.3} = \frac{45.5}{1.1} = 41\ \text{mph}$$

Ramp volume (vph/lane):

$$\boldsymbol{a})\ Ramp\ volume\ \ = \frac{\sum_1^n Volume\ ramp_n}{n}$$

$$Ramp\ volume\ at\ 8{:}00\ am\ = \frac{Volume\ ramp_{\ 1} + \ Volume\ ramp_{\ 2}}{2}$$

$$Ramp\ volume\ at\ 8{:}00\ am\ = \frac{18 + \ 20}{2} = \frac{38}{2} = 19\ veh/5min/lane$$

b) *Ramp volume to an hourly volume becomes;*

$$19\ veh/5min/lane \equiv 228\ veh/hr/lane$$

Off-ramp density (ramp/mile):

$$Off - ramp\ density\ = \frac{Number\ of\ off - ramps}{Length\ of\ the\ segment}$$

$$Off - ramp\ density\ = \frac{Number\ of\ off - ramps}{\sum_1^n L_n}$$

$$Off - ramp\ density\ = \frac{Number\ of\ off - ramps}{L_1 + L_2 + L_3} = \frac{0}{0.5+0.3+0.3} = 0\ ramp/mile$$

On-ramp density (ramp/mile):

$$On - ramp\ density\ = \frac{Number\ of\ on - ramps}{Length\ of\ the\ segment}$$

$$On - ramp\ density\ = \frac{Number\ of\ on - ramps}{\sum_1^n L_n}$$

$$On - ramp\ density\ = \frac{Number\ of\ on - ramps}{L_1 + L_2 + L_3} = \frac{2}{0.5+0.3+0.3} = 1.82\ ramp/mile$$

Level of Service (LOS):

$$\boldsymbol{a})\ Occupancy\ at\ Zone_n\ = \frac{\sum_1^n Occupancy\ at\ Lane_n}{n}$$

$$Occupancy\ at\ Zone_1 at\ 8{:}00\ am\ = \frac{Occ.1 + Occ.2 + Occ.3}{3} = \frac{12 + 18 + 29}{3} = 19.7\%$$

$$Occupancy\ at\ Zone_2\ at\ 8{:}00\ am\ = \frac{Occ.1 + Occ.2 + Occ.3}{3} = \frac{12 + 24 + 30}{3} = 22.0\%$$

$$Occupancy\ at\ Zone_3 at\ 8{:}00\ am\ = \frac{Occ.1 + Occ.2 + Occ.3}{3} = \frac{14 + 25 + 11}{3} = 16.7\%$$

$$Occupancy\ at\ Zone_4\ at\ 8{:}00\ am\ = \frac{Occ.1 + Occ.2 + Occ.3}{3} = \frac{25 + 23 + 30}{3} = 26.0\%$$

$$\boldsymbol{b})\ Occupancy\ of\ segment\ L_n\ (OCL_n) = \frac{Occupancy\ at\ Zone_n + \ Occupancy\ at\ Zone_{n+1}}{2}$$

$$Occupancy\ of\ segment\ L_1\ \ (OCL_1)\ at\ 8{:}00\ am = \frac{Occupancy\ at\ Zone_1 +\ Occupancy\ at\ Zone_2}{2}$$

$$= \frac{19.7 + 22.0}{2} = 20.8\%$$

$$Occupancy\ of\ segment\ L_2\ \ (OCL_2)\ at\ 8{:}00\ am = \frac{Occupancy\ at\ Zone_2 +\ Occupancy\ at\ Zone_3}{2}$$

$$= \frac{22.0 + 16.7}{2} = 19.3\%$$

$$Occupancy\ of\ segment\ L_3\ \ (OCL_3)\ at\ 8{:}00\ am = \frac{Occupancy\ at\ Zone_3 +\ Occupancy\ at\ Zone_4}{2}$$

$$= \frac{16.7 + 26.0}{2} = 21.3\%$$

$$\boldsymbol{c})\ Mainline\ occupancy\ at\ 8{:}00\ am = \frac{\sum_1^n OCL_n * L_n}{\sum_1^n L_n}$$

$$Mainline\ occupancy\ at\ 8{:}00\ am = \frac{(OCL_1 * L_1) + (OCL_2 * L_2) + (OCL_3 * L_3)}{L_1 + L_2 + L_3}$$

$$Mainline\ occupancy\ at\ 8{:}00\ am = \frac{(20.8*0.5)+(19.3*0.3)+(21.3*0.3)}{0.5+0.3+0.3} = \frac{22.6}{1.1} = 20.5\%$$

d) *The mainline LOS is determined using the calculated mainline occupancy criteria listed in Table 6-9. For example, a calculated mainline occupancy of 20.5% implies the freeway mainline is operating at a LOS E.*

Table 6-9: LOS Criteria

LOS	**Occupancy (%)**
A	0 ≤ Occupancy < 5
B	5 ≤ Occupancy < 8
C	8 ≤ Occupancy < 12
D	12 ≤ Occupancy < 17
E	17 ≤ Occupancy < 28
F	Occupancy ≥ 28

Source: (Bertini et al., 2004)

Input Values for Safety Performance Measure (Crash Occurrence Risk)

Figure 6-5 shows a typical freeway segment downstream of an on-ramp with a ramp metering system. The study segment boundaries are defined by detector locations. Tables 6-10 and 6-11 contain sample traffic data collected from the detectors on each lane downstream and upstream of the on-ramp, respectively, corresponding with the Figure 6-5 freeway segment. The data are used to demonstrate the procedures for calculating the input values for the safety performance measure of ramp metering in the *TSM&O Strategies Assessment Tool.*

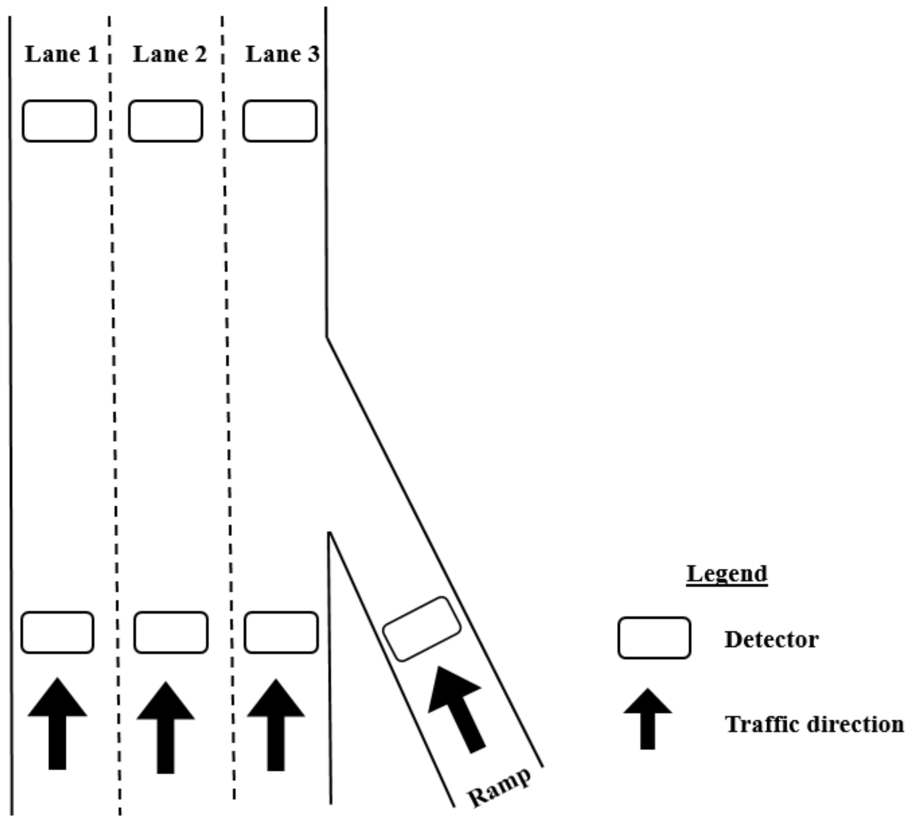


Figure 6-5: Typical Segment Downstream of an On-Ramp with Ramp Metering

Table 6-10: Sample Data from Downstream Detectors

	Downstream Detectors								
Time	**Lane 1**			**Lane 2**			**Lane 3**		
	Sp. 1 (mph)	**Vol. 1**	**Occ. 1 (%)**	**Sp. 2 (mph)**	**Vol. 2**	**Occ. 2 (%)**	**Sp. 3 (mph)**	**Vol. 3**	**Occ. 3 (%)**
8:00 am	33	580	12	58	485	18	33	432	29
7:55 am	37	613	11	54	502	19	23	431	25
7:50 am	28	605	12	56	548	24	32	441	30
7:45 am	31	633	12	54	550	22	26	410	27
7:40 am	37	637	14	54	552	25	30	417	11
7:35 am	35	657	13	54	487	21	31	456	14
7:30 am	35	585	12	56	580	15	58	579	24

Note: Sp. = Speed; Vol. = Volume; Occ. = Occupancy

Table 6-11: Sample Data from Upstream Detectors

Upstream Detectors									
Time	Lane 1			Lane 2			Lane 3		
	Sp. 1 (mph)	Vol.1	Occ. 1 (%)	Sp. 2 (mph)	Vol. 2	Occ. 2 (%)	Sp. 3 (mph)	Vol. 3	Occ. 3 (%)
8:00 am	36	540	24	32	440	15	34	474	23
7:55 am	39	593	22	30	519	27	39	478	30
7:50 am	41	578	25	24	512	23	31	454	30
7:45 am	38	572	21	56	498	30	32	439	12
7:40 am	40	588	15	50	402	29	34	565	12
7:35 am	32	551	13	38	474	28	23	520	21
7:30 am	40	589	14	39	591	29	26	587	26

Notes: Sp. = Speed; Vol. = Volume; Occ. = Occupancy

In this example, it is assumed that the activation time of the ramp metering system is 8:00 am. Using the collected data shown in Tables 6-10 and 6-11, input variables for the standard deviation of speed, and occupancy are calculated as follows:

Mainline standard deviation (S.D.) of speed, 5 minutes prior to activation time:

$$Standard\ deviation\ at\ 7{:}55\ a.m. = S.D(speed\ in\ lane\ 1, speed\ in\ lane\ 2, speed\ in\ lane\ 3)$$

The calculations of the speed in lane 1, speed in lane 2, and speed in lane 3 are as shown in CVS calculation

$$Standard\ deviation\ at\ 7{:}55\ a.m. = S.D\ (38, 42{,}31) = 5.57\ mph$$

Mainline standard deviation (S.D.) of occupancy, 30 minutes prior to activation time:

a) $Occupancy\ in\ lane\ 1\ at\ 7{:}30\ a.m. = \frac{Downstream\ Occ.1\ + Upstream\ Occ.1}{2} = \frac{12+14}{2} = 13\%$

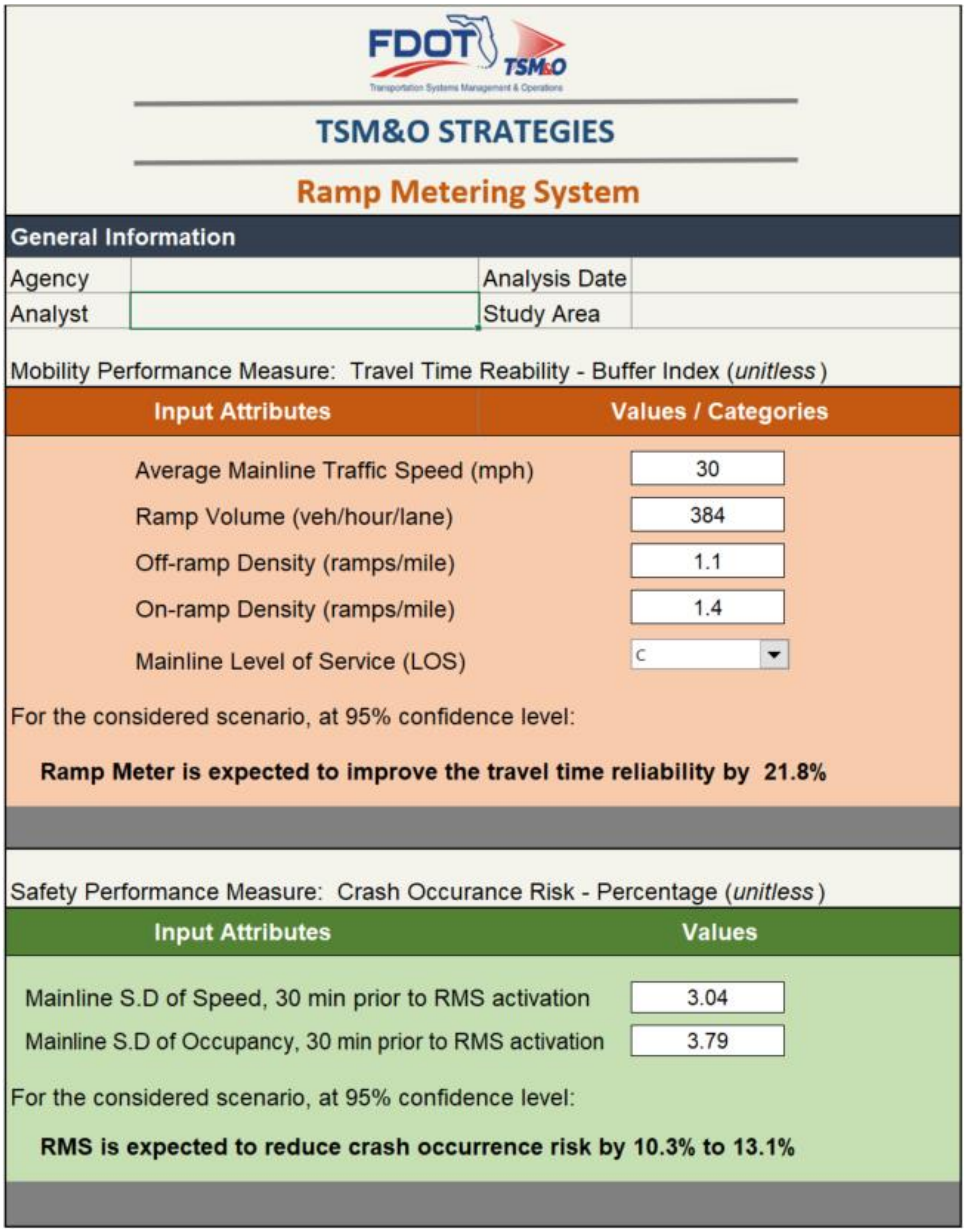
b) $Occupancy\ in\ lane\ 2\ at\ 7{:}30\ a.m. = \frac{Downstream\ Occ.2\ + Upstream\ Occ.2}{2} = \frac{15+29}{2} = 22\%$

c) $Occupancy\ in\ lane\ 3\ at\ 7{:}30\ a.m. = \frac{Downstream\ Occ.3\ + Upstream\ Occ.3}{2} = \frac{24+26}{2} = 25\%$

d) $S.D\ at\ 7{:}30\ a.m. = S.D(occ.in\ lane\ 1, occ.in\ lane\ 2, occ.in\ lane\ 3)$

$$Standard\ deviation\ at\ 7{:}30\ a.m. = S.D\ (13, 22{,}25) = 6.24\%$$

Ramp metering systems are usually turned on when the freeway mainline LOS drops below LOS B (i.e., LOS C through F). Figure 6-6 provides an example of the input-output scenario for LOS C.



TSM&O STRATEGIES

Ramp Metering System

General Information

Agency		Analysis Date	
Analyst		Study Area	

Mobility Performance Measure: Travel Time Reability - Buffer Index (*unitless*)

Input Attributes	Values / Categories
Average Mainline Traffic Speed (mph)	30
Ramp Volume (veh/hour/lane)	384
Off-ramp Density (ramps/mile)	1.1
On-ramp Density (ramps/mile)	1.4
Mainline Level of Service (LOS)	C

For the considered scenario, at 95% confidence level:

Ramp Meter is expected to improve the travel time reliability by 21.8%

Safety Performance Measure: Crash Occurance Risk - Percentage (*unitless*)

Input Attributes	Values
Mainline S.D of Speed, 30 min prior to RMS activation	3.04
Mainline S.D of Occupancy, 30 min prior to RMS activation	3.79

For the considered scenario, at 95% confidence level:

RMS is expected to reduce crash occurrence risk by 10.3% to 13.1%

Figure 6-6: Ramp Metering Strategy Sample Input-Output

Error Checks

All input values must be entered to obtain the results. When LOS A and B are selected, ramp meters are not turned on, and the worksheet will return an error message, as shown in Figure 6-7.

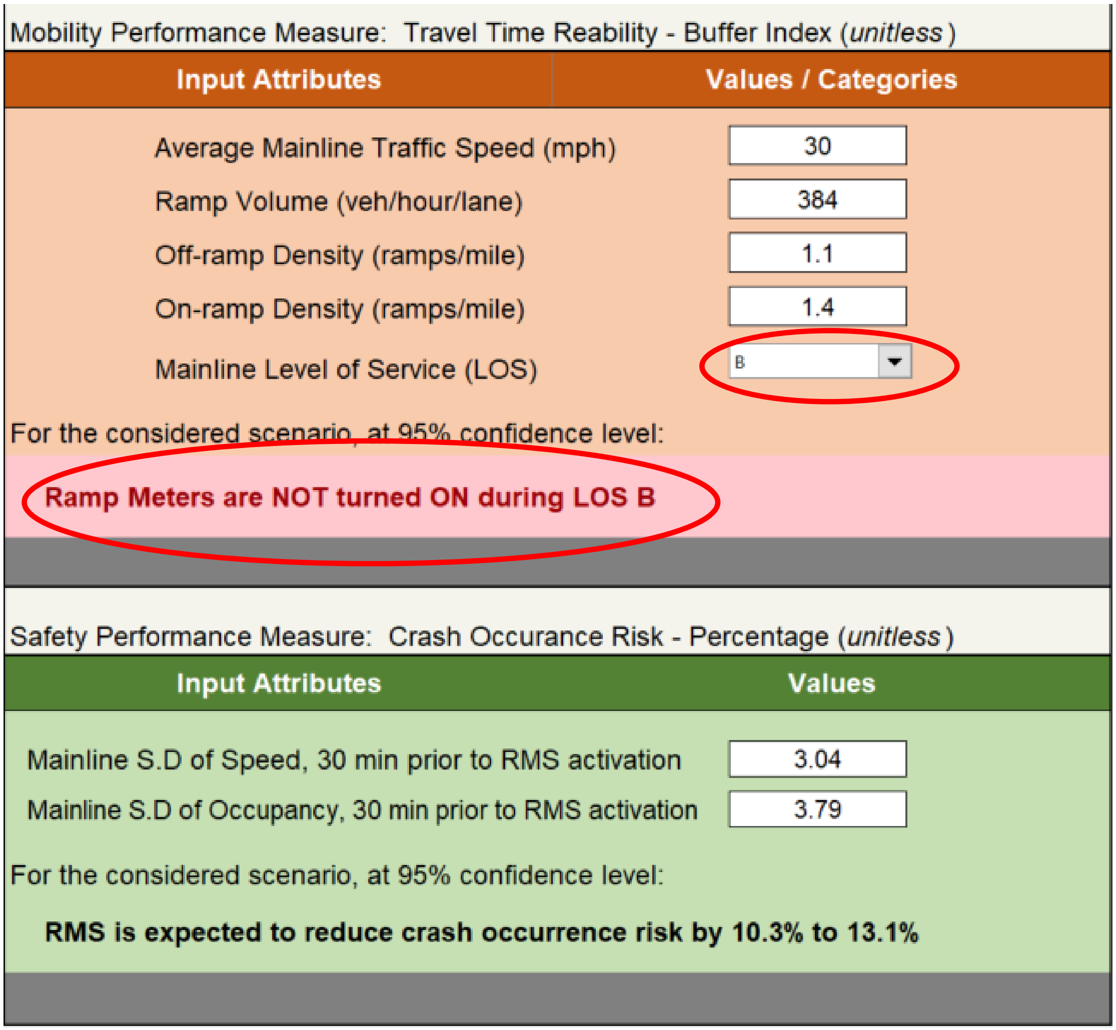


Figure 6-7: Ramp Metering Strategy Sample Input Error Check

6.2.2 Dynamic Message Signs

To quantify the mobility and safety benefits of DMSs, the user is required to collect the following data: traffic volume, occupancy, time of day, day of the week, and lane blockage information. Lane blockage information is gathered from the DMS displayed messages. Examples of such messages include "CRASH 1 MI AHEAD **USE CAUTION**", "CRASH I-75 AT SR-222/NW 39TH AVE **RT LANE BLOCKED**", CRASH I-75 BEYOND CR-234 **ALL LANES BLOCKED",** etc.

Input Variables: All continuous input variables are added by keying-in a value in the cells with a white background. Categorical input variables are added by selecting categories from the respective drop-down lists that represent the best possible condition or situation.

Input Values for Mobility Performance Measure

Traffic Volume and Occupancy:

For a location with a DMS, traffic data (traffic volume in veh/hr/lane and occupancy in percent) are collected from the immediate downstream detectors. The analysis is performed for a specific DMS displaying crash information for at least 30 minutes. The goal is to look at the changes in average traffic speed 30 minutes before displaying the crash information and 30 minutes during the display of crash information. The time (Peak/Off-peak) and day of the week (weekday/weekend) are recorded. Table 6-12 contains a sample of collected traffic data from the detectors. The data are used to demonstrate the calculation of the input values for evaluating the mobility benefits of DMSs in the *TSM&O Strategies Assessment Tool*. This example assumes a crash-related message was displayed during AM peak hours on a weekday, and displays a "CRASH AHEAD **ALL LANES BLOCKED**" message.

Table 6-12: Sample Data from the Immediate Downstream Detectors

Time	Lane 1		Lane 2		Lane 3		Averages	
	Vol. 1 (veh/hr)	Occ. 1 (%)	Vol. 2 (veh/hr)	Occ. 2 (%)	Vol. 3 (veh/hr)	Occ. 3 (%)	Avg. Vol. (veh/hr/ln)	Avg. Occ. (%)
8:00 AM - 8:30 AM	630	8.2	608	7.8	598	7.9	612	8.0

Note: Vol. = Volume; Occ. = Occupancy; Avg. = Average.

For this example, the average traffic volume and occupancy is used as the input values. From the data listed in Table 6-12, the average traffic volume is 612 veh/hr/lane, and the average occupancy rate is 8.0%, assuming an AM Peak hour, on a weekday, and all lanes closed.

Categorical variables as defined in Table 6-3 (in this chapter) and INFO tab in the Tool.

- Time of Day: Please select from the respective drop-down list.
- Day of the Week: Please select from the respective drop-down list.
- DMS Lane Blockage Message: Please select from the respective drop-down list.

Figure 6-8 shows the worksheet interface of the sample scenario for a traffic volume of 612 veh/hr/lane and an occupancy rate of 8.0% during AM Peak, on a weekday, and a DMS message display of “All Lanes Closed”.

TSM&O

Transportation Systems Management & Operations

TSM&O STRATEGIES

Dynamic Message Signs (DMSs)

General Information

Agency		Analysis Date	
Analyst		Study Area	

Data Input

Input Attributes	Values / Categories
Traffic Volume (veh/hour/lane)	612
Occupancy (%)	8
Time of Day	AM Peak
Day of the Week	Weekday
DMS Lane Blockage Message	All Lanes Closed

Mobility Performance Measure: Average Speed Adjustment (*mph*)

For the considered scenario, at 95% confidence level:

DMS is expected to reduce travel speed by 6.6%

For example,

If the average speed of vehicles when there is no crash message displayed on the DMS is 60 mph, the average speed during crash message is expected to be 56.0 mph

Safety Performance Measure: Crash Frequency (*number of crashes per year*)

Coefficient of Variation of Speed (unitless)

For the considered scenario, at 95% confidence level:

When the DMS displayed messages related to crashes downstream, the coefficient of variaton of speeds were significantly higher than during advisory messages.

Displaying messages related to crashes on DMSs was found to result in fewer crashes despite the increase in speed variations.

Figure 6-8: DMS Strategy Sample Input-Output

Error Checks

All inputs must be entered to obtain the results. The worksheet will return an error message if one or more input attribute(s) is not selected or keyed-in, as shown in Figure 6-9.

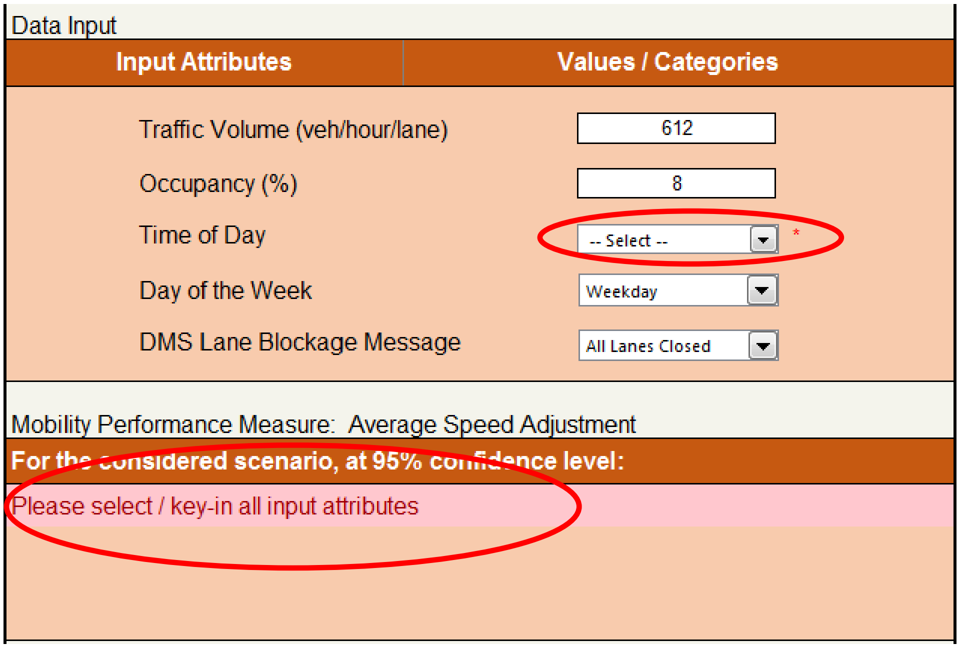


Figure 6-9: DMS Strategy Sample Input Error Check

6.2.3 Road Rangers

To quantify the mobility and safety benefits of Road Rangers, required collected data by the user includes the following incident attributes: incident type, incident severity, time of day, day of the week, lighting condition, and if towing was involved. These attributes are also described in the INFO sheet in the Tool.

Input Variables: All variables are categorical. Categorical input variables are added by selecting categories that represent the best possible condition (or, situation) from their respective drop-down lists. No calculations are needed.

Categorical variables as defined in Table 6-4 (in this chapter) and INFO tab in the Tool.

- Incident Type: Please select from the respective drop-down list.
- Incident Severity: Please select from the respective drop-down list.
- Time of Day: Please select from the respective drop-down list.
- Day of the Week: Please select from the respective drop-down list.
- Lighting Condition: Please select from the respective drop-down list.
- Towing Involved: Please select from the respective drop-down list.

Figure 6-10 shows the worksheet interface of the sample output scenario for the Road Rangers strategy. This example considered a severe crash on a weekday, during a daylight peak period, and involved towing.

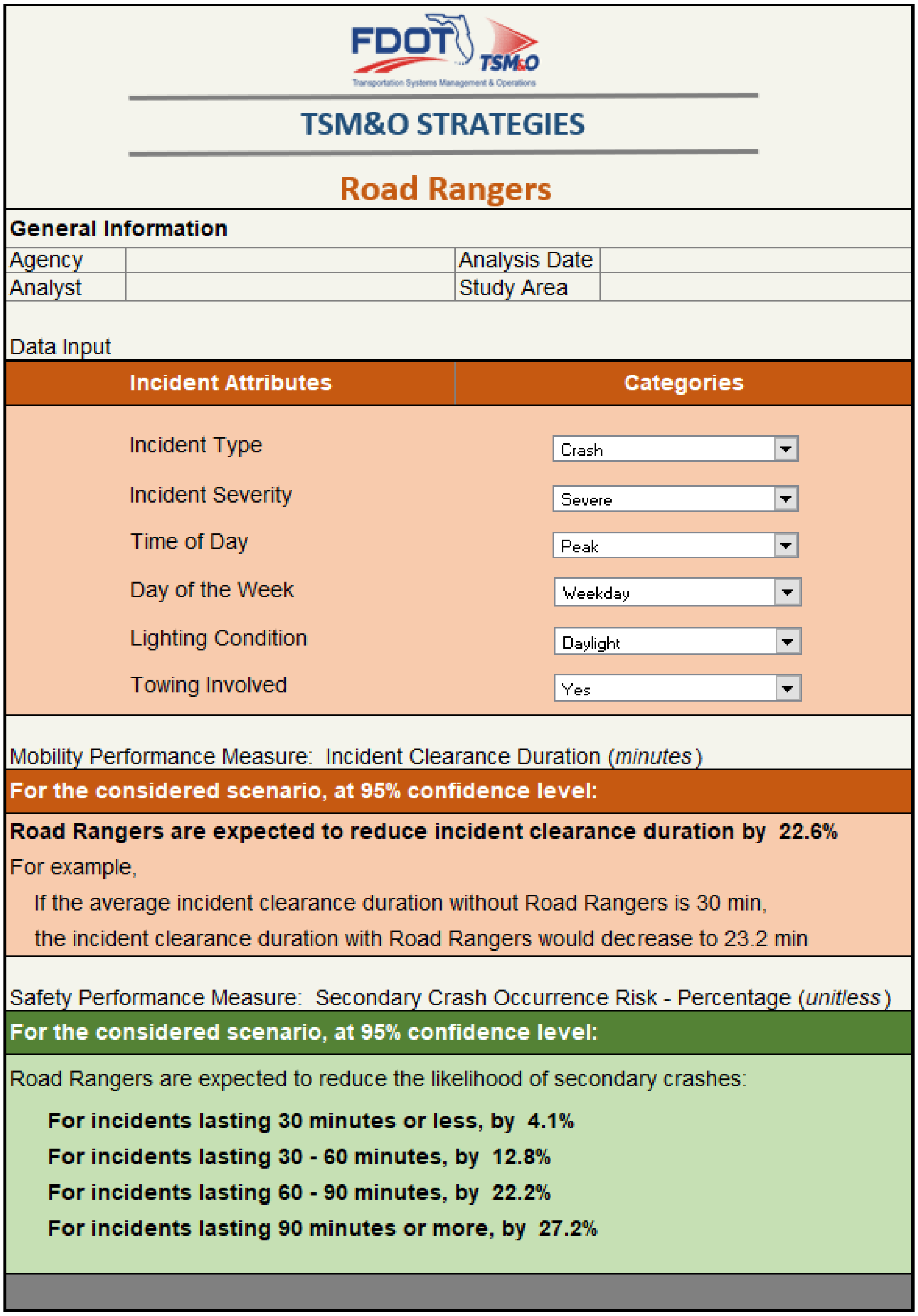


Figure 6-10: Road Rangers Strategy Sample Input-Output

Error Checks

All input variables are categorical and can be added by clicking the drop-down arrow and selecting a category that best represents an "incident". At least one category must be selected for the Tool to calculate and display the results. Otherwise, the worksheet will give error messages, as shown in Figure 6-11.

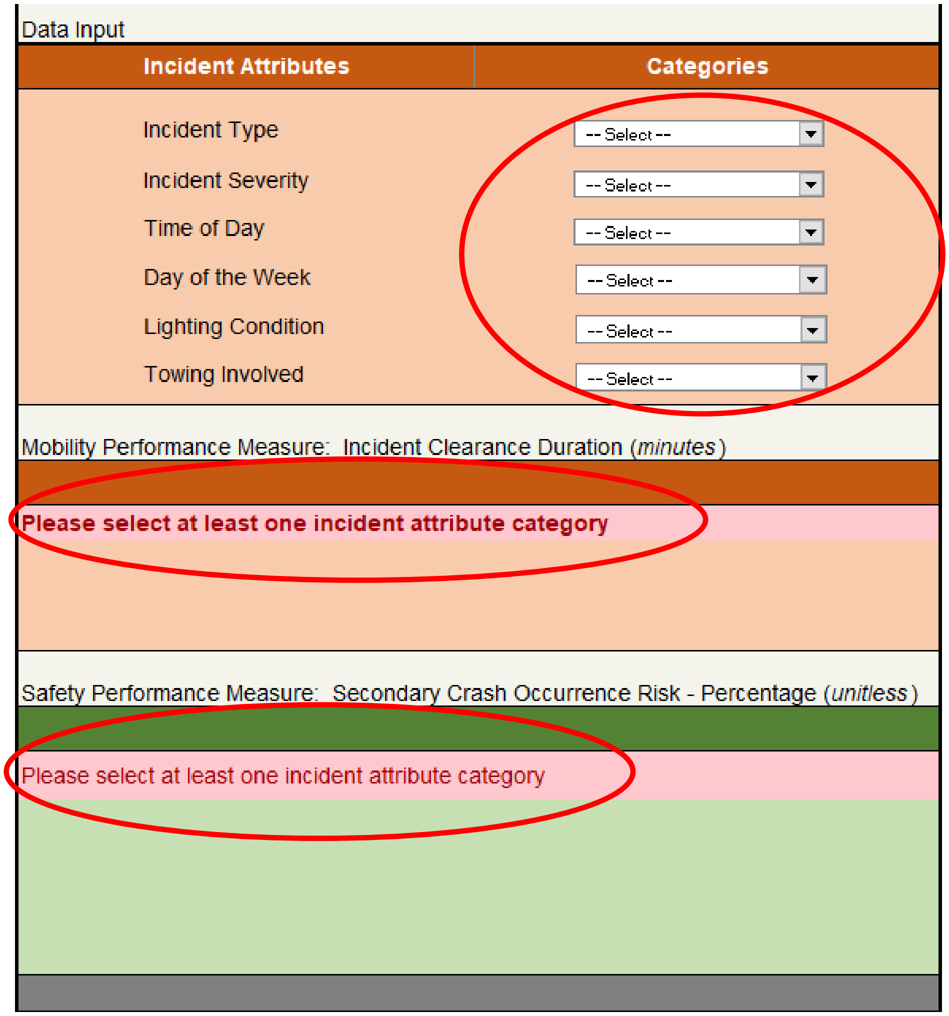


Figure 6-11: Road Rangers Strategy Sample Input Error Check

6.2.4 Express Lanes

To quantify the mobility benefits of express lanes (ELs), the user is required to collect data on the travel time to determine the average and the 95th percentile travel times. The worksheet considers two scenarios to calculate the mobility benefits of the ELs: (a) when both ELs and general-purpose lanes (GPLs) were open, and (b) when ELs were closed and only GPLs were operating. A sample input-output scenario is given in Figure 6-13.

Input Values for Mobility Performance Measure

Consider segment A-B, with four GPLs and two ELs, as shown in Figure 6-12. Travel time data are collected from all the detectors within the segment for each lane, and for every interval (e.g., 5-minute) for typical weekdays (288 observations per day) over a certain period for the two scenarios. The travel time between point A and B is the summation of travel times between individual detectors.

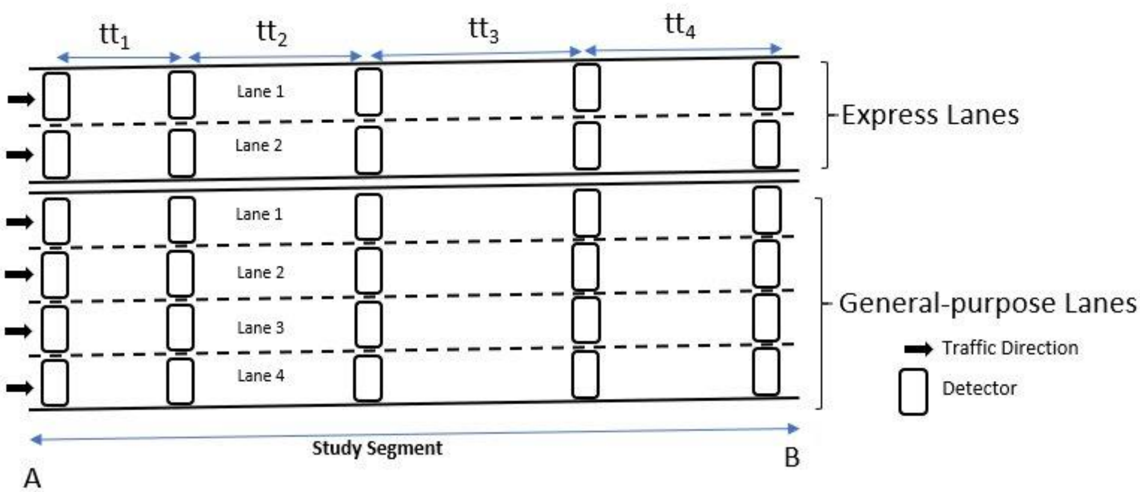


Figure 6-12: Typical Segment with Express Lanes

The average travel time and corresponding 95th percentile travel time are calculated as follows:

$$Average\ travel\ time\ on\ ELs = \frac{(tt_1 + tt_2 + tt_3 + tt_4)\ for\ EL_1 + (tt_1 + tt_2 + tt_3 + tt_4)\ for\ EL_2}{2}$$

$$Average\ travel\ time\ on\ GPLs = \frac{(tt_1 + tt_2 + tt_3 + tt_4)\ for\ GPL_1 + (tt_1 + tt_2 + tt_3 + tt_4)\ for\ GPL_n}{n}$$

The 5-minute travel times are collected for typical week days (288 observations per day) over a certain period for two scenarios: (a) on ELs and GPLs when both are operational; and (b) on GPLs when ELs are closed. The average travel time and corresponding 95th percentile travel time are then calculated.

TSM&O STRATEGIES

Express Lanes (ELs)

General Information			
Agency		Analysis Date	
Analyst		Study Area	

Data Input

Input Attributes	Values
Express Lanes (ELs)	
Average Travel Time (min)	10
95th Percentile Travel Time (min)	12
Express Lanes Buffer Index	0.20
General-purpose Lanes (GPLs) when ELs are open	
Average Travel Time (min)	12
95th Percentile Travel Time (min)	15
General Purpose Lanes Buffer Index	0.25
General Purpose Lanes (GPLs) when ELs are closed	
Average Travel Time (min)	15
95th Percentile Travel Time (min)	20
General Purpose Lanes Buffer Index	0.33

Mobility Performance Measure: Travel Time Reliability - Buffer Index (*unitless*)

Performance of ELs vs GPLs

Express Lanes are expected to be 20.0% more reliable compared to GPL when both the Els and GPLs are operational.

Performance of GPLs When ELs are open vs when ELs are closed

When ELs are open, GPLs are expected to be 25.0% more reliable compared to when ELs are closed.

Figure 6-13: Express Lanes Strategy Sample Input-Output

Error Checks

All input variables are added by keying-in the collected travel times. No output is calculated when input cells are empty. A “Please key-in all input values” error message will appear if input cells are incomplete. A buffer index value will also show the error “#DIV/0!”, as shown in Figure 6-14.

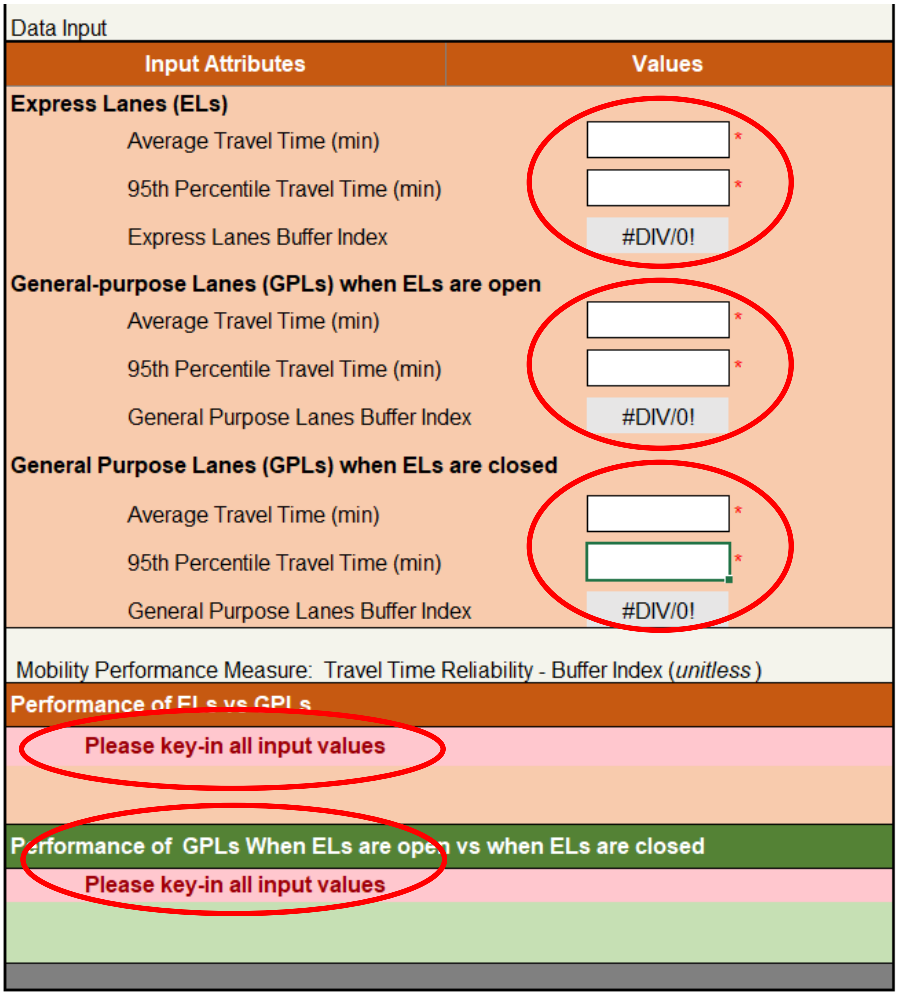


Figure 6-14: Express Lane Strategy Sample Input Error Check

6.2.5 Adaptive Signal Control Technology

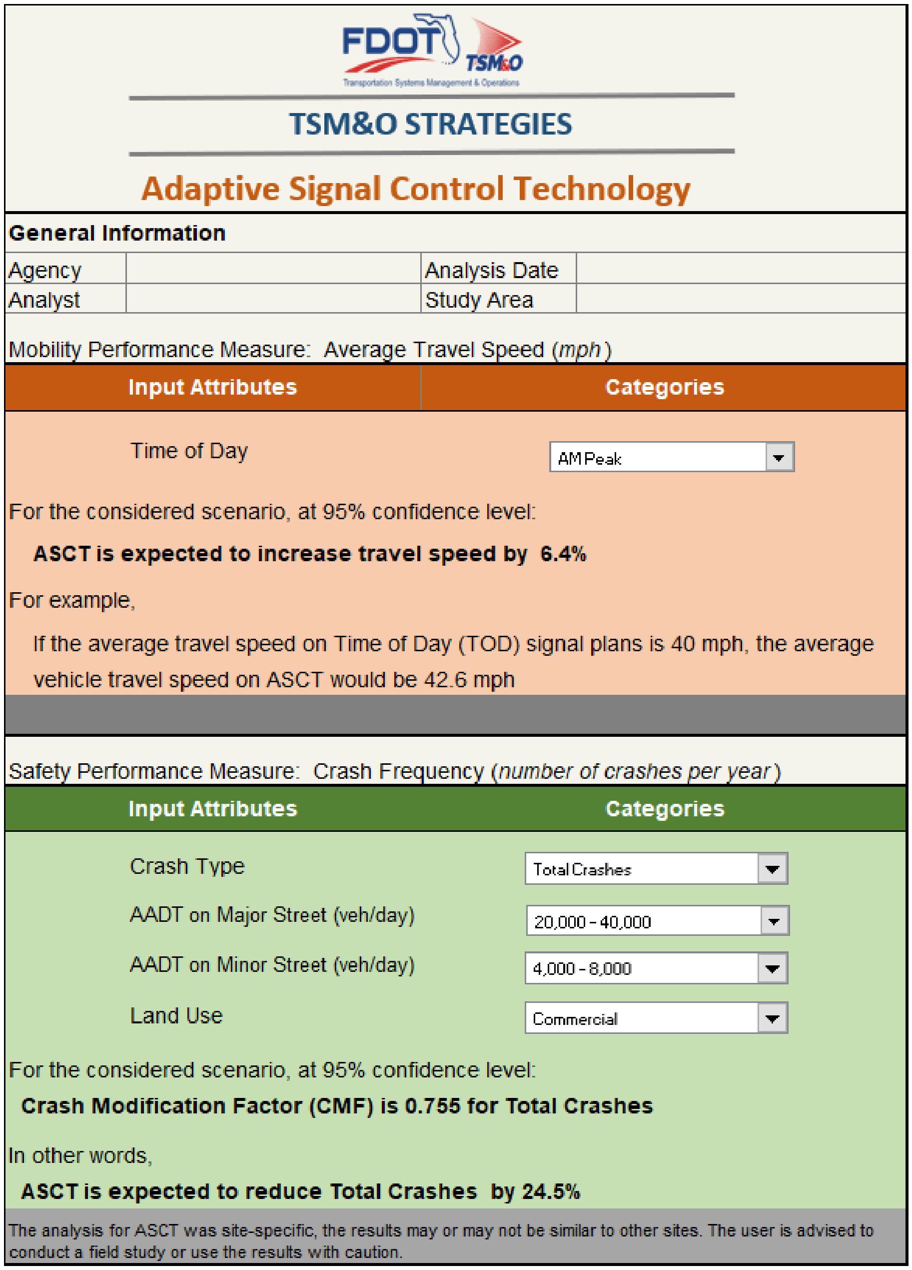
To quantify the mobility and safety benefits of adaptive signal control technology (ASCT), the user is required to collect the following data: crash attributes, land use information, roadway geometric characteristics (median width, median, left and right turn lane), and historical AADT. A sample input-output scenario is shown in Figure 6-15.

Input Variables: All variables are categorical in this strategy. Categorical input variables are added by selecting categories that represent the best possible condition / situation from their respective drop-down lists. No calculations are needed.

Categorical variables as defined in Table 6-6 (in this chapter) and INFO tab in the Tool.

- Time of Day: Please select from the respective drop-down list.
- Crash Type: Please select from the respective drop-down list.
- AADT on Major Street (veh/day): Please select from the respective drop-down list.
- AADT on Minor Street (veh/day): Please select from the respective drop-down list.

- Land Use: Please select from the respective drop-down list.


FDOT TSM&O
Transportation Systems Management & Operations
TSM&O STRATEGIES
Adaptive Signal Control Technology

General Information			
Agency		Analysis Date	
Analyst		Study Area	

Mobility Performance Measure: Average Travel Speed (*mph*)

Input Attributes	Categories
Time of Day	AM Peak

For the considered scenario, at 95% confidence level:

ASCT is expected to increase travel speed by 6.4%

For example,

If the average travel speed on Time of Day (TOD) signal plans is 40 mph, the average vehicle travel speed on ASCT would be 42.6 mph

Safety Performance Measure: Crash Frequency (*number of crashes per year*)

Input Attributes	Categories
Crash Type	Total Crashes
AADT on Major Street (veh/day)	20,000 - 40,000
AADT on Minor Street (veh/day)	4,000 - 8,000
Land Use	Commercial

For the considered scenario, at 95% confidence level:

Crash Modification Factor (CMF) is 0.755 for Total Crashes

In other words,

ASCT is expected to reduce Total Crashes by 24.5%

The analysis for ASCT was site-specific, the results may or may not be similar to other sites. The user is advised to conduct a field study or use the results with caution.

Figure 6-15: ASCT Strategy Sample Input-Output

Error Checks

All the input variables are added by clicking the drop-down arrow and selecting a category that represents the site conditions. Time-of-day must be selected for the Tool to calculate and display the mobility results. At least one category must be selected for each input attribute for the Tool to calculate and display the safety results. The errors shown in Figure 6-13 will appear when an input is not selected.

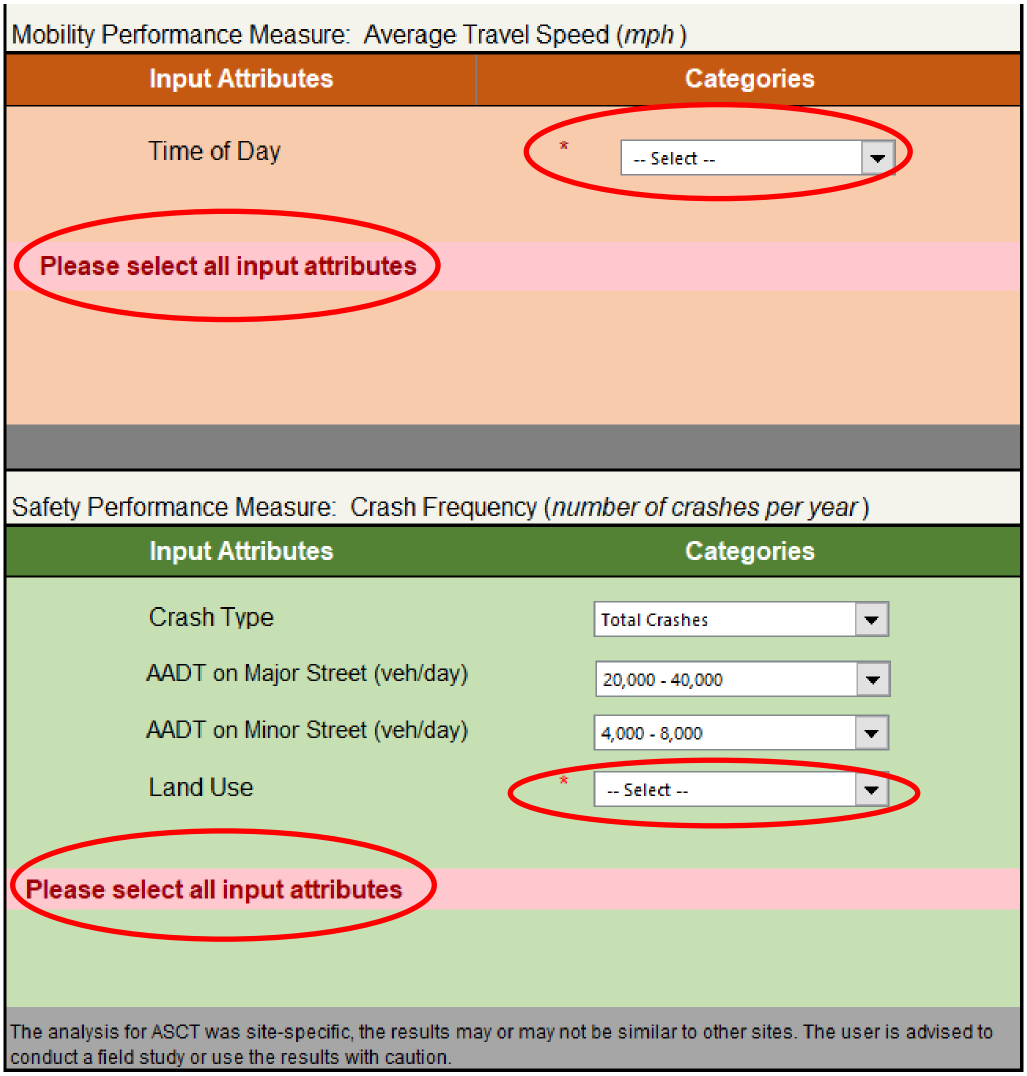


Figure 6-16: ASCT Strategy Sample Input Error Check

6.2.6 Transit Signal Priority

To quantify the mobility benefits of transit signal priority (TSP), the user is required to collect data on the average travel time along the corridor. For the safety benefits of TSP, the user is required to collect crash type data. A sample input-output scenario is shown in Figure 6-17.

Input Values for Mobility Performance Measure

Input values for the average travel time

Field Measurements: Total travel time is measured by driving a vehicle along a preselected corridor from the beginning to the ending point of that corridor. This process uses a stopwatch to record the time and a global positioning system (GPS) to record the distance. While driving, it is suggested to drive at the median speed of traffic. The average travel time is calculated by averaging the total travel time of all the runs along the corridor.

Simulation Measurements: Average travel time is calculated by averaging the travel time collected from each data collection point in the VISSIM model. The data collection points are located at the beginning, the center of each signalized intersection, and the ending point of the corridor.

Other input variables are categorical and are added by selecting categories that represent the best possible condition / situation from their respective drop-down lists as shown below. No calculations are needed.

Categorical variables as defined in Table 6-7 (in this chapter) and INFO tab in the Tool.

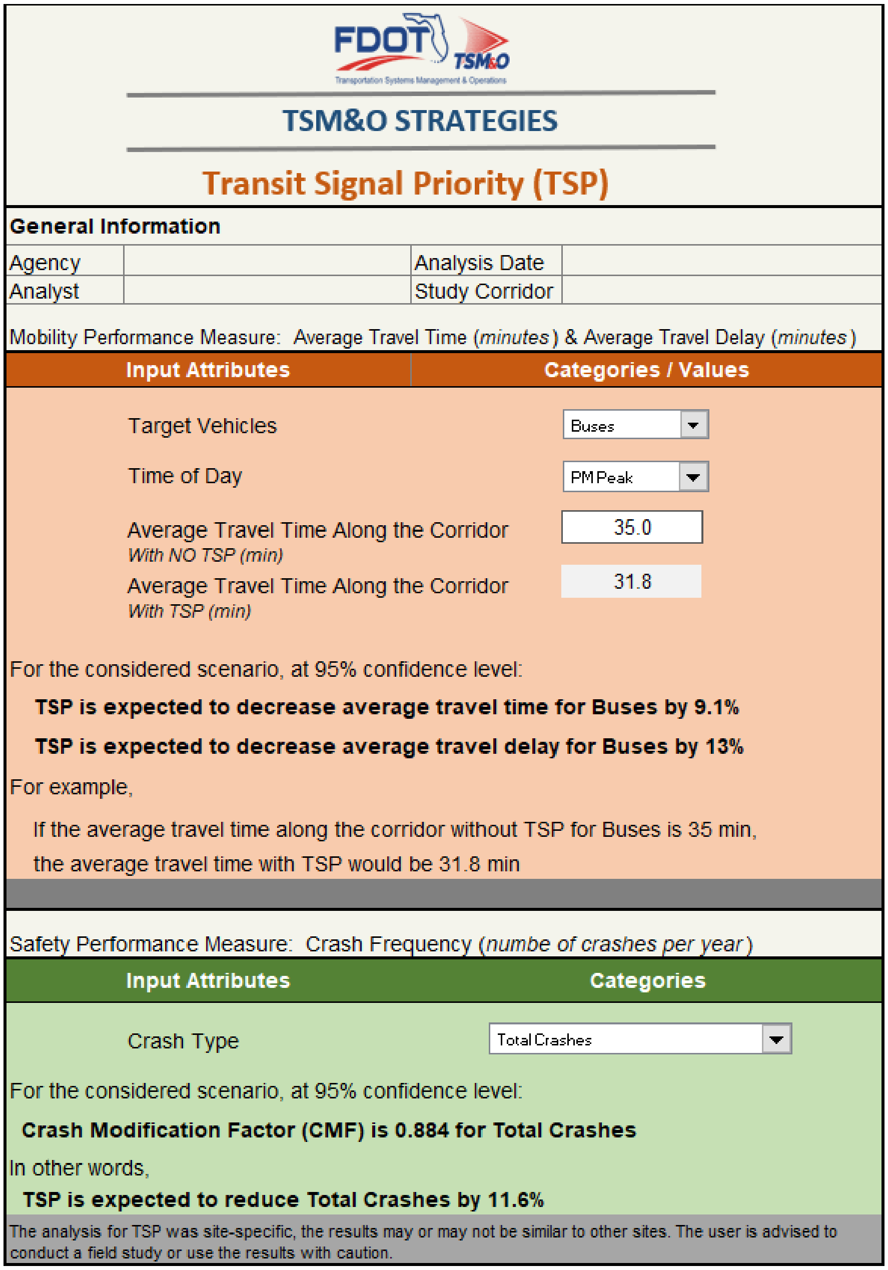
- Target Vehicles: Please select from the respective drop-down list.
- Time of Day: Please select from the respective drop-down list.

Input Values for Safety Performance Measure

Input variable for safety performance measure is categorical and is added by selecting categories that represent the best possible condition / situation from their respective drop-down lists.

Categorical variable as defined in Table 6-7 (in this chapter) and INFO tab in the Tool.

- Crash Type: Please select from the respective drop-down list.


TSM&O STRATEGIES

Transit Signal Priority (TSP)

General Information

Agency		Analysis Date	
Analyst		Study Corridor	

Mobility Performance Measure: Average Travel Time (*minutes*) & Average Travel Delay (*minutes*)

Input Attributes	Categories / Values
Target Vehicles	Buses
Time of Day	PM Peak
Average Travel Time Along the Corridor *With NO TSP (min)*	35.0
Average Travel Time Along the Corridor *With TSP (min)*	31.8

For the considered scenario, at 95% confidence level:

TSP is expected to decrease average travel time for Buses by 9.1%

TSP is expected to decrease average travel delay for Buses by 13%

For example,

If the average travel time along the corridor without TSP for Buses is 35 min, the average travel time with TSP would be 31.8 min

Safety Performance Measure: Crash Frequency (*numbe of crashes per year*)

Input Attributes	Categories
Crash Type	Total Crashes

For the considered scenario, at 95% confidence level:

Crash Modification Factor (CMF) is 0.884 for Total Crashes

In other words,

TSP is expected to reduce Total Crashes by 11.6%

The analysis for TSP was site-specific, the results may or may not be similar to other sites. The user is advised to conduct a field study or use the results with caution.

Figure 6-17: TSP Strategy Sample Input-Output

Error Checks

The input variables are added by clicking the drop-down arrow and selecting a category that represents the site conditions. At least one category must be selected for each variable for the Tool to calculate and display the results. An error message will appear if input fields are not populated, as shown in Figure 6-18.

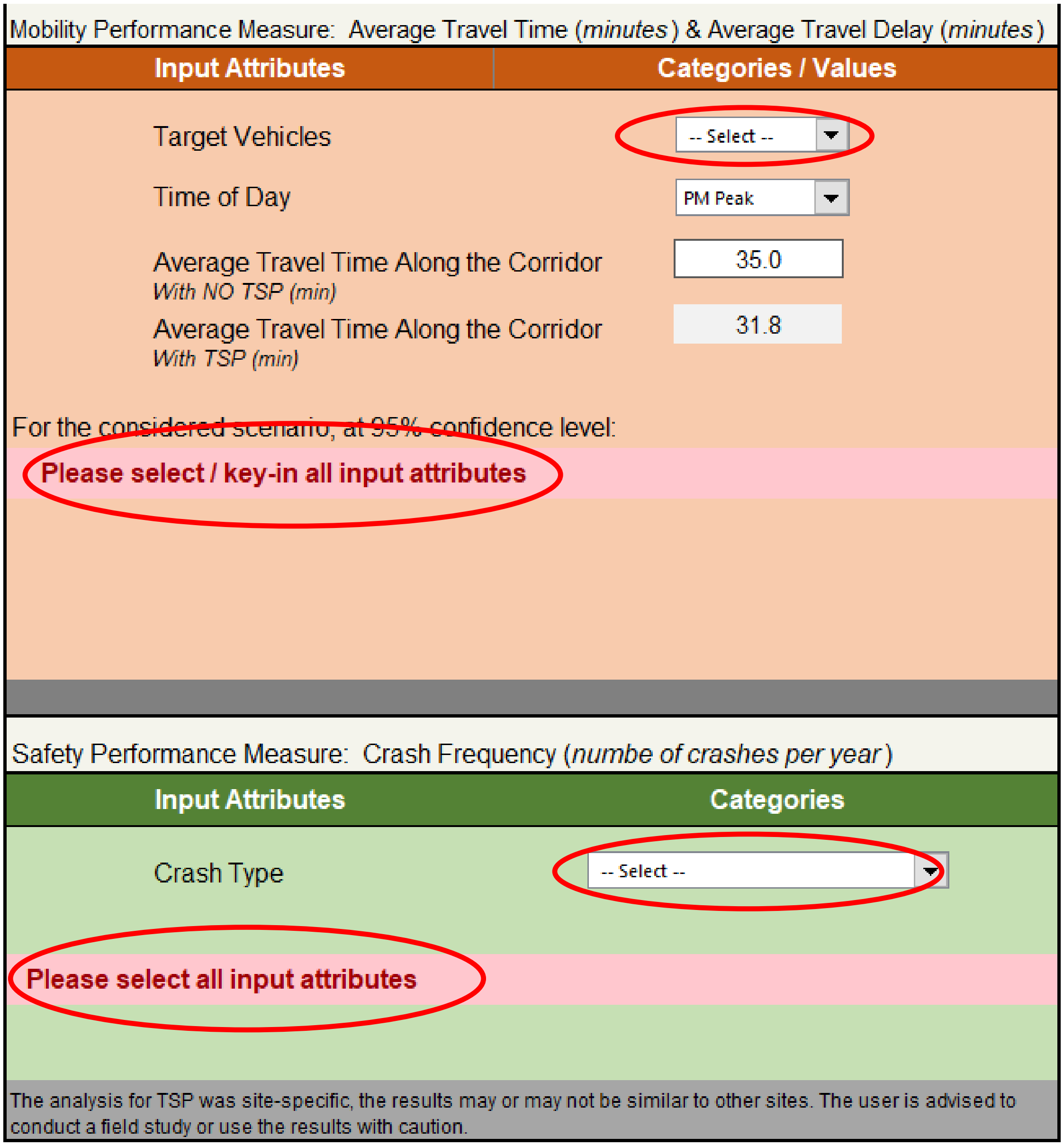


Figure 6-18: TSP Strategy Sample Input Error Check

6.3 Summary

This chapter provides the user manual for the TSM&O Strategies Assessment Tool. The Tool assesses the safety and mobility benefits of the following TSM&O strategies:

Freeways

- Ramp Metering Systems
- Dynamic Message Signs (DMSs)
- Road Rangers
- Express Lanes (ELs)

Arterials

- Adaptive Signal Control Technology (ASCT)
- Transit Signal Priority (TSP)

CHAPTER 7
SUMMARY AND CONCLUSIONS

Transportation Systems Management and Operations (TSM&O) is a program based on actively managing the multimodal transportation network, measuring performance, and streamlining and improving the existing system to deliver positive safety and mobility outcomes to the traveling public. TSM&O comprises a set of strategies that focus on operational improvements that can maintain or restore the performance of the existing transportation system before extra capacity is needed. The Florida Department of Transportation (FDOT) has been a pioneer in adopting TSM&O strategies to improve safety and mobility along Florida's highways. Several TSM&O strategies such as ramp metering, Dynamic Message Signs, Road Rangers, TSP, ASCT, etc., have currently been deployed in Florida. Since each project is unique, the selection of the most suitable TSM&O strategy and its deployment depends on the region's needs and requirements.

The primary goal of this research was to develop resources to assist FDOT and other agencies in evaluating the effectiveness of the strategies identified in the 2017 Florida's TSM&O Strategic Plan (FDOT, 2017a). The developed resources will enable FDOT and local agencies to prioritize TSM&O strategies using quantifiable safety and mobility metrics.

The study goals were achieved through the following objectives:

- Identify and discuss existing TSM&O strategies that have been deployed in Florida.
- Develop research approaches to quantify the safety and mobility benefits of the identified TSM&O strategies.
- Quantify the mobility benefits of the identified TSM&O strategies.
- Quantify the safety benefits of the identified TSM&O strategies.

The following six TSM&O strategies were evaluated in this research project:

1. Ramp Metering System
2. Dynamic Message Signs
3. Road Rangers
4. Express lanes
5. Transit Signal Priority
6. Adaptive Signal Control Technology

The following sections discuss the conclusions for each of the above-listed TSM&O strategies. A quick one-page summary of the description, methodology, and results of each strategy is provided in Appendix A.

7.1 Ramp Metering System

Ramp metering or signaling is a traffic management strategy that installs traffic signals along freeway on-ramps to control and regulate the frequency at which vehicles enter the flow of traffic on the freeway mainline (Gan et al., 2011; Mizuta et al., 2014). The primary operational objectives of ramp metering system include: controlling the frequency of vehicles entering the freeway, reducing freeway demands, and breaking up platoons of vehicles released from the upstream traffic signals (Balke et al., 2009).

Travel time reliability was selected as the mobility performance measure for estimating the Mobility Enhancement Factors (MEFs) of the ramp metering system. The MEFs were developed based on the analysis of a corridor with system-wide ramp metering in Miami-Dade County, Florida. Buffer index (BI), estimated using the 95th percentile travel time and average travel time, was adopted as the travel time reliability measure for the analysis. The MEF for ramp metering at LOS C&D was 0.784, equivalent to a 22% reduction in the BI values. The MEF for ramp metering operations during LOS E&F was 0.701, indicating a 30% reduction in the BI values. These results indicate that ramp metering operations improve mobility on freeway, regardless of the LOS on the freeway mainline.

The study analyzed the safety benefits of the ramp metering system using the crash occurrence risk on the freeway mainline. The risk of traffic crashes was estimated using a *case-control* study design of crash and non-crash cases. The crash cases were identified using the crash data, while the non-crash cases were identified using the spatial and temporal criteria of each crash case. Results showed that the crash occurrence risk at a particular time was significantly affected by the standard deviation of speed 30 minutes before the time, standard deviation of occupancy 30 minutes before the time, and the ramp metering operations during that time. Moreover, results revealed a 41% decrease in the risk of crashes when RMSs were operational compared to when they were not operational. Based on the study results, it can be concluded that ramp metering operations improve safety on the freeway mainline.

7.2 Dynamic Message Signs

Dynamic message signs, or DMSs, also referred to as changeable message signs (CMSs) or variable message signs (VMSs), are programmable electronic signs that appear along highways and typically display information about real-time alerts related to unusual traffic conditions, such as adverse weather conditions, construction activities, travel times, road closures or detours, advisory phone numbers, roadway incidents, etc. These messages are intended to affect the behavior of drivers by providing real-time traffic-related information to warn drivers, regulate traffic flow, and manage congestion on the roadways (Edara et al., 2011; Wang et al., 2017). DMSs are usually permanently mounted, while VMSs are commonly used in work zones, or where temporary messaging is needed.

The methodology for quantifying the mobility benefits of DMSs involved assessing the reaction of drivers to *crash* messages by observing their speed adjustments between the *clear* and *crash* message display durations. For every *crash* message that had been displayed for at least 30 minutes, the message that was displayed 30 minutes prior was checked. The average speed ratio (calculated as the ratio of the average speed during *crash* messages to the average speed during *clear* messages) was then used as a performance measure to estimate the MEFs for DMSs. The overall MEF was found to be 0.94, implying that there was a 6% reduction in average speeds when the DMSs displayed *crash* information. Results also revealed that among messages displaying *crash* information, if secondary information required drivers to "use caution", there were less speed reductions compared to lane blockage information (i.e., DMSs displaying lane blockage information such as all lanes blocked, left lane blocked, right lane blocked, etc.). This implies that drivers were more willing to reduce speeds if lanes were blocked downstream as a result of a crash.

The safety benefits of DMSs were quantified using the coefficient of variation of speeds (CVS) as a surrogate safety measure. The coefficient of variation of speeds when the displayed messages on DMSs did not require drivers to take action (clear condition/information messages) were compared to the coefficient of variation of speeds when the DMSs displayed messages about downstream crashes. Out of 21,016 crashes that occurred on I-75 during the three-year analysis period, 18 crashes occurred 10 miles downstream of the DMSs and 30 minutes after the *crash* message was displayed, and 23 crashes occurred 30 minutes prior to the *crash* message (i.e., during the *clear* message displays). Within two miles downstream, five crashes occurred during the time when *crash* messages were displayed on the DMS and eight crashes occurred during the time when the DMSs displayed *clear* messages. Overall, displaying crash messages on DMSs was found to result in fewer crashes despite the increase in speed variations. It is worth noting that higher variations in vehicle speeds observed when the DMSs display *crash messages* may be attributed to other sources of information such as navigation maps, Highway Advisory Radio, etc.

7.3 Road Rangers

Road Rangers are a crucial component of incident management systems that facilitate a quick clearance of incidents through faster response and reduced clearance time. Florida's Road Rangers provide free highway assistance services during incidents on Florida's roadways to reduce delays and improve safety for the motorists and incident responders. Road Rangers in Florida assist the Florida Highway Patrol (FHP) to reduce incident duration, provide assistance to disabled or stranded vehicles, remove road debris, and increase safety at incident sites.

Incident clearance duration was selected as the performance measure to quantify the mobility benefits of Road Rangers. Quantile regression was applied to predict incident clearance duration and identify factors that may affect the clearance duration. The following variables were included in the analysis: incident attributes (event type, detection method, incident severity, shoulder blockage, and percentage of lane closure), temporal attributes (time of day, day of the week, and lighting condition), and operational attributes (number and type of responding agencies, and towing). The following seven factors were found to be significantly associated with longer incident clearance durations: crashes, severe incidents, shoulder blockage, peak hours, weekends, nighttime, number of responding agencies, and towing involvement. Analysis results revealed that crashes generally have longer clearance durations than the incidents involving vehicle problems and traffic hazards. Incidents first detected by responding agencies other than Road Rangers were associated with longer incident clearance durations.

The likelihood of secondary crash (SC) occurrence was used as a surrogate safety measure to evaluate the safety benefits of Road Rangers. A complimentary log-log regression model was developed to associate the probability of SC occurrence with potential contributing factors. Of the factors analyzed, traffic volume, incident impact duration, moderate/severe crashes, weekdays, peak periods, percentage of lane closure, shoulder blockage, and towing involving incidents were found to significantly increase the likelihood of SCs. Road Ranger involvement, weekend days, off-peak periods, minor incidents, vehicle problems, and traffic hazard related incidents were associated with relatively lower probabilities of SC occurrence. Based on average incident duration reduction, the results suggest that the Road Ranger program may reduce SC likelihood by 20.9%.

7.4 Express Lanes

Express lanes are a type of managed travel lanes physically separated from general-purpose or general toll lanes within a roadway corridor. They use dynamic pricing through electronic tolling in which toll amounts are set based on traffic conditions (Neudorff, 2011). Express lanes provide a high degree of operational flexibility, which enable them to be actively managed to respond to changing traffic demands. Aspects of express lanes include congestion pricing, vehicle restrictions, and may be operated as reversible flow or bi-directional facilities to best meet peak demands.

Buffer index (BI) was selected as the performance measure to quantify the mobility benefits of express lanes. The MEFs were estimated by considering the BI as a performance measure. Overall, on 95Express northbound lanes, the express lanes resulted in a 50% reduction in BI (MEF = 0.5) compared to their adjacent general-purpose lanes, while the reduction was 60% (MEF = 0.4) for southbound lanes. When the express lanes were operational, the performance of the adjacent general-purpose lanes improved. The BIs for the general-purpose lanes improved by 20% (MEF = 0.8) and 60% (MEF = 0.4), respectively, for the northbound and the southbound directions, when the express lanes were operational compared to when they were closed. Overall, both the express lanes and the general-purpose lanes were found to perform better when the express lanes were operational. The study results showed mobility improvements on both the express lanes and the general-purpose lanes, although the extent of the improvement varied by direction and the time-of-day (i.e., AM peak, PM peak, off-peak).

7.5 Transit Signal Priority

Transit Signal Priority (TSP) modifies the signal timing at intersections to better accommodate transit vehicles. Typically, a bus approaching a traffic signal will request priority. This request for transit priority is often transmitted directly from an approaching bus to a traffic signal or originated by a centralized transit priority management system (FHWA, 2018). When a request is received, the traffic signal controller applies logical rules to decide whether or not to allow priority to the bus (FHWA, 2018). These rules typically include consideration of whether the bus is behind schedule; the length of time since the last priority was awarded to a bus; the state of the traffic signals along the route; and the time of day (FHWA, 2018).

The analysis was based on a 10-mile corridor along US-441 between SW 8th Street and the Golden Glades Interchange in Miami, Florida. Two microsimulation VISSIM models, the Base model with no TSP integration and the TSP-integrated model, were developed and used to estimate MEFs for TSP considering transit buses and all vehicles. The MEFs based on travel time were 0.96 for all vehicles and 0.91 for buses, and the MEF based on average vehicle delay time was 0.87 for all vehicles and buses. Based on the analysis results, TSP was found to improve the operational performance of the corridor.

A full Bayesian (FB) before-after approach was used to quantify the safety benefits of TSP. The safety performance of TSP-enabled corridors (i.e., treatment corridors) was compared to the safety performance of non-TSP corridors (i.e., non-treatment corridors). The FB before-after study was performed using data on 12 transit corridors in Orange and Seminole Counties in Florida, which had TSP activated in the years of 2016 and 2017. A total of 29 street sections without the TSP treatment were selected as a reference group to compare with the treatment sites. The study results indicated that the implementation of TSP resulted in a 12% reduction in total corridor-level crashes, 8% reduction in PDO crashes, and 15% reduction in FI crashes.

7.6 Adaptive Signal Control Technology

Adaptive Signal Control Technology (ASCT) is an Intelligent Transportation Systems (ITS) strategy that optimizes signal timings in real-time to improve traffic flow along the corridor. This strategy continuously monitors arterial traffic conditions and the queuing at intersections and dynamically adjusts the signal timing to optimize and improve operational performance. ASCT has historically been deployed to reduce traffic congestion, particularly during highly volatile traffic conditions. Signal timing and phasing scenarios are adjusted in real-time with ASCT, which allows the signal to better adjust the changes in demand created by incidents, special events, seasonal variation, or traffic growth over time (United States Department of Transportation [USDOT], 2017).

Average speed was selected as the performance measure to quantify the mobility benefits of ASCT. The Bayesian Switch-point Regression (BSR) model was used to evaluate the operational benefits of the ASCT. The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida. The ASCT was found to improve the average travel speeds by 4% during a typical weekday, 7% during AM peak hours, 5% during off-peak hours, and 2% during PM peak hours, in the northbound direction.

Mixed results were observed in the southbound direction. The overall MEFs show no improvement with ASCT on Tuesdays and Thursdays and 2% decrease in average travel speed on Wednesdays. Moreover, the analysis based on peak and off-peak hours revealed that ASCT increased the average travel speed by 3% and 2% during AM peak and off-peak hours, respectively. In contrast, during PM peak hours, ASCT showed a 5% reduction in average travel speeds in the southbound direction. The inconsistent results in the southbound direction may be attributed to traffic congestion and the relatively higher driveway density (11.5 driveways per mile in the southbound direction versus 8.5 driveways per mile in the northbound direction).

The Bayesian Negative Binomial (BNB) model was used to develop SPFs for total crashes, rear-end crashes, and FI crashes. The CMFs were developed using an empirical Bayes before-after approach with the comparison-group. The following factors were considered in the analysis: traffic volume (AADT) on major and minor streets, geometric characteristics (number of lanes, intersection geometry, and median characteristics), posted speed limit, number of bus stops within 1,000 ft of the intersection, signal phasing, and land use information. The analysis revealed that ASCT installations reduce total crashes by 5.2% (CMF = 0.948), rear-end crashes by 12.2% (CMF = 0.878), FI crashes by 4.2% (CMF = 0.958), and PDO crashes by 5.7% (CMF = 0.943).

7.7 TSM&O Strategies Assessment Tool

The TSM&O Strategies Assessment Tool is a spreadsheet application that was developed to automatically estimate the safety and mobility benefits of deploying the TSM&O strategies. The Tool contains a total of nine worksheets:

- Preface - includes a foreword, acknowledgments, and a disclaimer
- Info - a brief overview of TSM&O strategies
- Worksheets for each TSM&O strategy - includes a separate worksheet for each TSM&O strategy (Ramp Metering, Dynamic Message Signs, Road Rangers, Express Lanes, Adaptive Signal Control Technology, and Transit Signal Priority)
- Input Data Description – includes step-by-step procedures to calculate the input values for the Tool.

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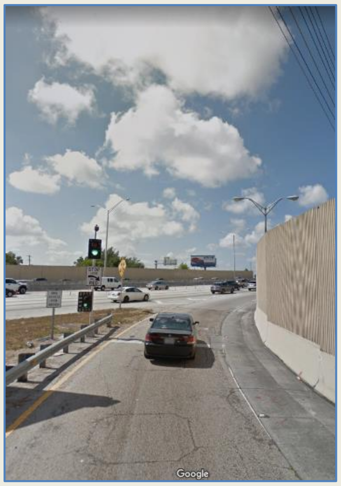
APPENDIX A: ONE-PAGE SUMMARIES

FDOT TSM&O
Transportation Systems Management & Operations

TSM&O STRATEGIES



Ramp Metering Signal (RMS)

Ramp Meters

Ramp Metering Signals (RMSs) are installed at freeway on-ramps to control and regulate the frequency at which vehicles join the flow of traffic on the freeway mainline.

About 22 Ramp Metering Signals (RMSs) are on a 10-mile section of I-95 in FDOT District 6 between Ives Diary Road and NW 62nd Street.

Ramp Metering Deployment along I-95

Mobility Benefits

- Performance Measure: Buffer Index
- When the freeway mainline Level of Service (LOS) was D or better, activating RMSs resulted in a 22% reduction in Buffer Index.
- When freeway mainline LOS was E or worse, activating RMSs resulted in a 30% reduction in Buffer Index.
- The reduction in Buffer Indices indicates that ramp metering signals improve travel time reliability.

Safety Benefits

- Performance Measure: Crash Risk
- The crash risk on segments downstream of an on-ramp decreased by 41% when RMSs were operational compared to when not operational

Study Constraints

- The mobility impacts of ramp meters on the adjacent arterials were not evaluated
- The safety impacts of ramp meters on the adjacent arterials and the ramps were not evaluated

For more information, please refer to the report BDV29 977-46

Transportation Systems Management & Operations

TSM&O STRATEGIES

Dynamic Message Signs (DMS)

Dynamic Message Sign (DMS)

Dynamic Message Signs (DMSs) are programmable electronic signs used for disseminating real-time information to road users.

~869 DMSs display real-time messages on major roadways in Florida. Operational 24/7.

DMS Deployed on Florida Freeways

Mobility Benefits

- Performance Measure: Average Speed
- A 6% reduction in average speeds was observed when the DMS messages displayed crash-related information, compared to when they displayed advisory information.
- Among messages displaying crash information, if secondary information required drivers to “use caution”, fewer drivers seemed to reduce speed compared to lane blockage information (e.g. all lanes blocked, left lane, blocked, etc.).

Safety Benefits

- Performance Measures:
  - Number of Crashes
  - Coefficient of Variation of Speed (CVS)
- When the DMS displayed messages related to crashes downstream, the CVS of speeds were significantly higher than during advisory messages, at a 95% confidence level.
- Displaying messages related to crashes on DMSs was found to result in fewer crashes despite the increase in speed variations.

Study Constraints

- The analysis was conducted for only messages displaying crash information and those displaying advisory information.
- The speed reduction and higher variations when the DMSs displayed crash-related messages may be attributed to other sources of information such as navigation maps, Highway Advisory Radio, etc.
- The analysis did not consider other potential factors, such as incidents downstream which may result in a reduction in speeds and speed variations.

For more information, please refer to the report BDV29 977-46

Transportation Systems Management & Operations

TSM&O STRATEGIES

Road Rangers

FDOT Road Rangers

Freeway Service Patrol on major roadways in Florida.

Road Rangers are often able to arrive at an incident scene quickly to enable advance safety protection, traffic control, and incident clearance.

Road Rangers Coverage Areas

Mobility Benefits

- Performance Measure: Incident Clearance Duration
- The Road Rangers program, by virtue of its roving presence on the freeways, can substantially reduce the time it takes to detect and respond to an incident.
- On average, the Road Rangers program offers a 25.3% reduction in incident clearance duration at a 95% confidence level.

Safety Benefits

- Performance Measure: Secondary Crashes (SCs)
- For each additional minute associated with a freeway incident, there is a 1.2% chance of a SC occurrence.
- The reduction in SCs because of Road Rangers (or any FSP) is a result of the reduced incident duration realized from the program. Thus, through reduced incident duration, Road Rangers lower the risk of SCs by 20.9% at a 95% confidence level.

Study Constraints

- The evaluation did not account for disaggregate-level operational details of the program (e.g., day-to-day or seasonal variations in Road Rangers activities, fleet sizes, beat lengths, and probe vehicle types (pickup versus tow trucks, etc.).

For more information, please refer to the report BDV29 977-46

Transportation Systems Management & Operations

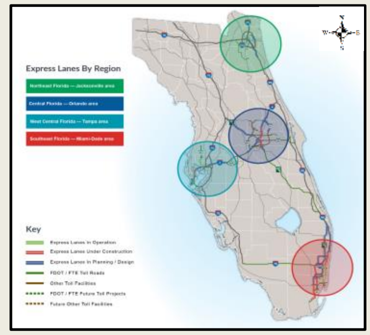
TSM&O STRATEGIES

Express Lanes (ELs)

Express Lanes (ELs)

Express lanes (ELs) are managed toll lanes, separated from general-purpose lanes (GPLs) or general toll lanes within a freeway facility

~62 miles in operation, 100 miles under construction, and 298 miles in planning/design stage.



Express Lanes Deployed on Florida

Mobility Benefits of Express Lanes (ELs)

- Performance Measure: Travel time reliability (Buffer Index)
- Performance of the ELs was compared to that of GPLs when both were operational.
- When the ELs were operational, the performance of the adjacent GPLs improved.
- For example, on the 95Express northbound direction, the ELs resulted in a 50% reduction in buffer index compared to their adjacent GPLs. The reduction was 60% for the 95Express southbound direction.

Mobility Benefits of General-purpose Lanes (GPLs)

- Performance Measure: Travel time reliability (Buffer Index)
- Performance of GPLs when the ELs were operational was compared to that of the GPLs when ELs were closed.
- GPLs were more reliable when the ELs were operational compared to when they were closed.
- For example, the buffer indices for the GPLs improved by 20% and 60% for the 95Express northbound and the southbound directions, respectively.

Study Constraints

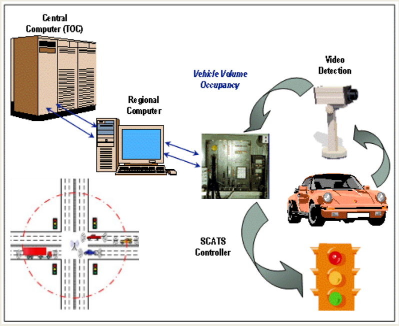
- The mobility benefits for both ELs and GPLs are specific to 95Express, but the methodology adopted in this study is transferable.
- The analysis did not consider the influence of other factors such as peak hour vs off-peak hour, etc.

For more information, please refer to the report BDV29 977-46

Transportation Systems Management & Operations

TSM&O STRATEGIES

Adaptive Signal Control Technology (ASCT)



ASCT System

Traffic management strategy that optimizes signal timing based on real-time traffic demand.

ASCT deployed in Florida

Mobility Benefits

- Performance Measure: Average Speed
- A 4% increase in average speeds was observed after ASCT deployment in the northbound direction of Mayport Road in Jacksonville.
- Mixed results were observed in the southbound direction of Mayport Road after ASCT deployment.

Safety Benefits

- Performance Measure: Crash Frequency
- ASCT resulted to the decrease in:
  - Total crashes by 5.2%
  - Fatal and Injury crashes by 4.2%
  - Rear-end crashes by 12.2%
  - PDO crashes by 5.7%

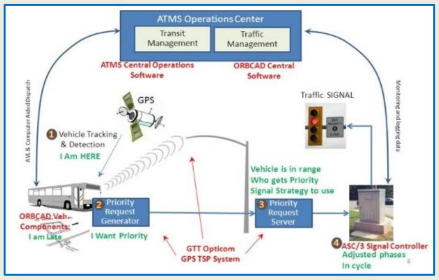
Study Constraints

- The analysis was conducted for only intersection-related crashes.
- The analysis did not account for safety benefits of InSync and SynchroGreen separately.
- The analysis did not consider the effect of pedestrians on the performance of ASCT.
- The analysis did not consider other potential factors such as incidents and weather effects which may result in speed reduction and variations.

For more information, please refer to the report BDV29 977-46

TSM&O STRATEGIES

Transit Signal Priority (TSP)



A Transit Signal Priority (TSP) System

Operational strategy that facilitates the movement of transit vehicles through signalized intersections.

Mobility analysis was based on a 10-mile arterial corridor, and the safety analysis was based on 12 corridors.

Transit Bus of Miami

Mobility Benefits

- Performance Measure:
  - Travel Time
  - Average Vehicle Delay Time
- TSP deployment resulted in a 9% reduction in travel time for the buses. For all other vehicles, a 4% reduction in travel time was observed after TSP was deployed.
- TSP deployment resulted in a 13% reduction in average vehicle delay for buses and all other vehicles.
- On side streets with traffic volumes greater than capacity, a 5.8% increase was observed in average delay after TSP was deployed.

Safety Benefits

- Performance Measures: Crash Frequency
- TSP deployment resulted in:
  - 12% reduction in total crashes at the corridor-level.
  - 15% reduction in FI crashes at the corridor-level.
  - 8% reduction in PDO crashes at the corridor-level.

Study Constraints

- The mobility benefits of TSP were quantified only for the evening peak hour.
- The average stopped delay for buses and all vehicles was not considered in the analysis.
- The safety analysis of TSP did not consider specific crash types.

For more information, please refer to the report BDV29 977-46