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Evaluating the mobility and safety benefits of adaptive signal control technology (ASCT)

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EVALUATING THE MOBILITY AND SAFETY BENEFITS OF ADAPTIVE SIGNAL CONTROL TECHNOLOGY (ASCT)

By

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The thesis “Evaluating the Mobility and Safety Benefits of Adaptive Signal Control Technology (ASCT)” submitted by John Herman Kodi in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering has been

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DEDICATION

I would like to dedicate this thesis to my lovely mother, JANE KIMEY

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LIST ACRONYMS

AADT	Annual Average Daily Traffic
AIC	Akaike Information Criterion
ASCT	Adaptive Signal Control Technology
BCI	Bayesian Credible Interval
BCR	Benefit-to-Cost Ratio
BHT	Bayesian Hypothesis Test
BNB	Bayesian Negative Binomial
BSR	Bayesian Switch-point Regression
CFP	Cyclic Flow Profile
CI	Confidence Interval
CMF	Crash Modification Factor
DCI	Deviance Information Criterion
EB	Empirical Bayes
FDOT	Florida Department of Transportation
FGDL	Florida Geographical Data Library
FHWA	Federal Highway Administration
FI	Fatalities plus Injuries

GIS	Geographical Information System
GOF	Goodness-of-fit
HDI	Highest Density Interval
HSM	Highway Safety Manual
ITS	Intelligent Transportation Systems
MAC	Media Access Control
MCMC	Markov Chain Monte Carlo
MEF	Mobility Enhancement Factor
MOE	Measure of effectiveness
NB	Negative Binomial
NUTS	No-U-Turn Sampler
PDO	Property Damage Only
RCI	Roadway Characteristics Inventory
RHODES	Real Time Hierarchical Optimized Distributed Effective System
SCATS	Sydney Coordinated Adaptive Traffic System
SCOOT	Split Cycle Offset Optimization Technique
SSAM	Surrogate Safety Assessment Model
SPF	Safety Performance Function

TMC	Transportation Management Center
TOD	Time-of-a-Day
WAIC	Widely Applicable Information Criterion

ABSTACT

The Adaptive Signal Control Technology (ASCT) is a traffic management strategy that optimizes signal timing based on real-time traffic demand. This thesis proposes a comprehensive methodology of quantifying the mobility and safety benefits of the ASCT deployed in the state of Florida. A Bayesian switch-point regression model was proposed to evaluate the mobility benefits of ASCT. The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida. The proposed analysis was used to estimate the possible dates that separate the two operating characteristics, i.e., with and without ASCT. Also, the posterior estimated distributions were used for the Bayesian hypothesis test to investigate if there is a significant difference in the operating characteristics for two scenarios - with and without ASCT. The results revealed that ASCT increases travel speeds by 4% in typical days of the week (Tuesday, Wednesday and Thursday) in the northbound direction. However, the implementation of ASCT did not yield a significant increase in travel speed in the southbound direction. In addition, ASCT exhibited more benefits in AM peak in the northbound direction indicating a 7% increase in travel speeds. A Bayesian hypothesis test revealed that there is a significant difference in the operating characteristics between scenarios with and without ASCT.

Moreover, an observational before-after Empirical Bayes (EB) with a comparison-group approach was adopted to develop the Crash Modification Factors (CMFs) for certain crash types (total and rear-end crashes) and crash severity levels (fatalities and injury crashes). The CMFs developed were used to quantify the safety benefits of the ASCT. The analysis was based on 42 treatment intersections with ASCT and their corresponding 47 comparison intersections without ASCT. Florida-specific Safety Performance Functions (SPFs) for total and rear-end crashes and for fatal plus injury crashes were also developed. The deployment of ASCT was found to reduce total crashes and rear-end crashes by 5.2% (CMF = 0.948) and 10.6% (CMF = 0.894), respectively. On the other hand, fatal plus injury crashes and PDO crashes were reduced by 6.1% (CMF = 0.939) and 5.4% (CMF = 0.946), respectively, after the ASCT deployment. The CMFs for total crashes and rear-end crashes, and for fatal plus injury crashes and PDO crashes were found to be statistically significant at 95% confidence level. These findings provide researchers and practitioners with an effective means for quantifying the mobility and safety benefits of ASCT, economic appraisal of the ASCT as well as a key consideration to transportation agencies for future ASCT deployment in the state.

Keywords: Bayesian Switch-point Regression, Adaptive Signal Control Technology, Bayesian hypothesis test, Crash Modification Factors, Safety Performance Functions, Empirical Bayes

CHAPTER 1

INTRODUCTION

Background

Increasing traffic congestion is one of the sources of frustration, time loss, and expense to road users. Transportation agencies are persistently searching for ways to alleviate urban traffic congestion while minimizing cost and maintenance requirements. Half of the congestion experienced by motorists in the United States (U.S.) is caused by temporary disruptions, i.e., non-recurring congestions which are associated with bad weather (15%), work zones (10%), and incidents (25%) and the other half fall under recurring category which happens due to lack of enough capacity to accommodate high traffic demand (FHWA, 2019). In urban areas, poor traffic signals control at intersections contribute to traffic congestion and delays. Therefore, controlling traffic congestion relies on having an efficient and well-managed traffic signal control system at the intersections.

Most agencies use conventional signal timing plans that are programmed based on historical travel turning movement counts (Sari et al., 2018). These systems do not adjust to accommodate variability in demand and remain fixed until they are manually adjusted. However, the frequency of traffic signal retiming is constrained by state and local transportation agencies' capabilities and resources limitations. Some more progressive systems use actuated-coordinated signals, which allow unused side-street green time to be utilized by the major street traffic. This provides more capacity to the main street, but results in less efficient coordination, as the offsets do not adjust in real-time to the early platoon arrival at downstream intersections (Sari et al., 2018). Even these progressive actuated systems do not adjust the cycle and therefore a single peak period is controlled by a constant cycle length. Incidents on arterials raise another concern for congestion since conventional signal systems control does not respond to real-time traffic demand changes.

The Adaptive Signal Control Technology (ASCT) belongs to the latest generation of urban signalized intersections control systems after pre-timed and actuated-coordinated signal systems (Martin, 2003). In contrast to fixed time signal plans, ASCT uses real-time traffic data to optimize signal timing parameters such as cycle length, splits, and offsets to minimize traffic delays and stops (FHWA, 2017a). ASCT systems are expected to be more efficiency for signal system operations since it can detect vehicular traffic volume instantaneously and can proactively respond to real-time traffic flow changes, traffic incidents, special events, road constructions and other occurrences (FHWA, 2017a, 2017b; Zhao et al., 2012).

The concept of ASCT was first conceived by Miller in 1963 when he proposed a traffic signal control strategy that was based on an online traffic model. This model can compute time wins and losses and combined these criteria for different stages in a performance index to be optimized (Zhao et al., 2012). However, the first real-world application occurred in the early 1970s when Sydney Coordinated Adaptive Traffic System (SCATS) was first implemented in Australia. A few years later the Split Cycle Offset Optimization Technique (SCOOT) was developed and implemented by the United Kingdom (U.K) Transport Research Laboratory. After many applications of SCOOT and SCATS in different countries, the Federal Highway Administration (FHWA) sponsored several ASCT developments, including OPAC, RHODES and ACS Lite.

Adaptive Signal Control Technology (ASCT)

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, 2017b). 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, 2017a, 2017b).

Many studies have shown that ASCT can reduce traffic delays, increase average speeds, improve travel times and travel time reliability (DKS Associates, 2010; Dutta, et al., 2010; Fontaine et al., 2015; Zheng et al., 2017). It can also decrease emissions and fuel consumption hence environmental conservation (FHWA, 2017a). In contrast to fixed time signal plans, ASCT can react to traffic incidents, special events, road constructions and other occurrences (FHWA, 2017b, 2017a).

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 (Sari 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 (Sari et al., 2018). SCATS adjusts 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 has 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 (Sari 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 (Sari 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 (Sari 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 (Trafficware, 2012). 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).

Benefits of the ASCT

ASCT can improve a traffic signal system in the form of improved measures of effectiveness (MOEs) and cost savings. Numerous studies on ASCT have quantified MOEs of the ASCT deployment in before and after studies. While results vary greatly, in general, the greatest observed improvements following ASCT deployment are shown when ASCT is compared to; (i) previously uncoordinated systems; (ii) coordinated system with outdated signal timings and (iii) system with variable non-recurring congestion.

Successful ASCT can provide quantitative benefits in the form of improved MOEs which include; improvement of travel time and travel time reliability, travel speed, fewer stops, reduced fuel consumption, and emissions and improved safety. The benefits achieved with ASCT depend on the existing condition, level of existing timing optimization and traffic and geometric characteristics of the given roadway. Moreover, ASCT can have cost savings to the operating agencies by reducing the frequency of regularly updating signal timing plans although most ASCT will need back-up TOD plans when ASCT failed. Additionally, reduced fuel consumption, travel time and accidents can provide a cost saving to the community as well.

Limitations of the ASCT

ASCT is a tool to manage traffic, it does not add capacity to the roadway nor eliminate oversaturated conditions. Most agencies report that ASCT performs the same or worse than actuated-coordinated signal timing when operated in oversaturated conditions. Despite that ASCT minimize the need to develop and updated timing plans all systems require oversight to verify efficient operation. Agency operators need to monitor the ASCT to verify that algorithms are working to meet the system goals (e.g. serving protected turns and side streets). All ASCT give the operator some ability to configure the system to meet their goals, with some systems having a greater ability to customize.

Moreover, ASCT has more components than other traffic signal systems with each component playing a critical role in the operation of the system. The ASCT processor requires significant up-front configuration, periodic tuning, and regular maintenance in order to maximize the benefits of the system.

Study objectives

Although ASCT is widely used in the U.S., comprehensive studies that have evaluated the operational and safety benefits of ASCT are sparse. This thesis proposes the comprehensive methodology of quantifying the mobility and safety benefits of the ASCT. Specifically, the objectives are;

1. Quantifying mobility benefits of ASCT using Bayesian switch-point regression to account for uncertainty.
2. Safety performance evaluation of ASCT using an observational before-after Empirical Bayes (EB) approach with comparison-group.

Thesis Organization

This thesis is a combination of two potential journal papers which are under review. Chapter 1 presents the study background, an overview of the ASCT, various ASCT deployments and the study objectives. Chapter 2 presents the first paper that quantifies the mobility benefits of the ASCT. Chapter 3 entails the second journal paper that evaluates the safety benefits of the ASCT. Finally, the thesis discusses the conclusive summary of the findings from the two papers.

CHAPTER 2

PAPER 1

Quantifying Mobility Benefit of Adaptive Signal Control Technology (ASCT) Using a Bayesian Switch-point Regression to Account for Uncertainty

INTRODUCTION

Motorists in the United States (U.S) waste more than $87 billion per year on gas and lost productivity due to congestion (Schrank., 2015). This cost is more than $700 per driver. These costs are estimated to increase by 50% over the next 15 years (Cebr, 2014). Traffic congestion not only increases delay and traffic crashes, but also increases emissions and fuel consumption. Given these issues, agencies are constantly seeking new approaches to manage the perplexities associated with traffic congestion and delays, especially on urban arterials. Transportation agencies have been considering the Adaptive Signal Control Technology System (ASCT), an advanced and major technological component of the intelligent transportation system (ITS), to improve the operational performance of signalized intersections in particular and the arterial network in general (Shafik, 2017).

The ASCT is a traffic management strategy that optimizes signal timing in real-time to improve traffic flow. This system continuously monitors traffic conditions and queues at intersections using detectors to improve different operational objectives by dynamically adjusting the signal timing parameters (e.g., phase length, offset, cycle length) (FHWA, 2017a). ASCT has become more widespread in the U.S. and several studies have been conducted to evaluate its operational performance. However, most of these studies compared the performance measures of the time-of-the-day (TOD) signal plans versus ASCT through field measurement and simple statistical analysis (Martin, 2008; DKS Associates, 2010; Dutta et al., 2010; Hutton et al., 2010; Tian et al., 2011; Fontaine et al., 2015). A robust statistical approach that quantifies the benefit of ASCT accounting for data variation as well as incorporating uncertainty in the estimates is therefore needed.

This study proposes a new statistical approach that quantifies the mobility benefits of the ASCT. Unlike previous studies, the proposed approach has the ability to; (a) evaluate the hypothesis if there is a significant difference in the operating characteristics with and without ASCT, and (b) identify the possible dates that ASCT started to have an impact on the operating characteristics of the corridor. The possible dates as well as the other parameters' posterior distribution, were estimated using a probabilistic approach, the Markov Chain Monte Carlo (MCMC) simulations. In this aspect, uncertainty is incorporated in the model estimates. The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida. To the best of the authors' knowledge, none of the existing studies on ASTCS have used the approach proposed in this paper.

LITERATURE REVIEW

Although ASCT is widely used in the U.S., comprehensive studies that have evaluated the operational benefits of ASCT are sparse. Several previous studies focused on evaluating the operational performance of the ASCT using simple descriptive statistics. 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.

A study by Dutta et al. (Dutta et al., 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 intervals (CI) 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, 2008). 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.

Moreover, Fontaine et al. (Fontaine et al., 2015) focused on the impact of ASCT on travel time, travel time reliability, side-street delays and the number of stops. Analyses were based on the field data collected by probe vehicles. Descriptive statistics revealed an improvement in travel times along the major roads. More specifically, the number of stops was reduced by 20-40% while traffic speeds increased by 3-5 mph (Fontaine et al., 2015). Another study was conducted along Route 291 in Lee's Summit, Missouri, to evaluate the performance of ASCT based on travel time, delay, vehicle emissions, fuel consumption, and the number of stops (Hutton et al., 2010). Simple descriptive statistics with two sample t-test were used to determine if there is a significant change in the performance measure before and after ASCT deployment. Results revealed that travel times, delay, vehicle emission, fuel consumption, and the number of stops were reduced.

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). 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%.

The study further concluded that 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).

While a majority of the studies evaluated the operational performance of ASCT using simple statistical approaches (Martin, 2008; DKS Associates, 2010; Dutta et al., 2010; Hutton et al., 2010; Tian et al., 2011; Fontaine et al., 2015), only a few studies used robust statistical approaches (Khattak et al., 2019; Zheng et al., 2017). Zheng et al. (Zheng et al., 2017) developed a linear regression model to examine the impact of different site characteristics on the ASCT effectiveness. The results revealed an average reduction in travel time of 0.59 minutes and 0.08 minutes for InSync ASCT and SychroGreen ASCT, respectively. In addition, the free-flow speed ratio, the number of access points per mile, annual average daily traffic (AADT) and the average distance between intersections were found to significantly influence the performance of the ASCT. Khattak et al. (Khattak et al., 2019) evaluated the operational performance of SUTRAC ASCT deployed at 23 intersections in Pittsburg, Pennsylvania. The results exhibited significant improvement in the travel times, and travel speed along the corridors. A Bayesian model performed to account for the volatility in driving behavior revealed that driving was less volatile along the corridors with ASCT, pointing towards improvement in uniformity of flow.

In summary, most of the previous studies have evaluated the mobility benefits of the ASCT using descriptive statistics, while a few studies have used linear regression and Bayesian approaches. This study proposes a Bayesian switch-point regression model (BSR) to evaluate the mobility benefits of ASCT deployed in Florida.

METHODOLOGY

Data

The Mayport Road (Hwy A1A) corridor in Jacksonville, Florida, was selected to analyze the mobility benefits of ASCT. As shown in Figure 2.1, the study segment spans from the Atlantic Boulevard (SR-10) to Wonderwood Drive (SR-116), for a total of 3.3 miles. This corridor has 10 adaptive (SynchroGreen) signalized intersections and a posted speed of 45 mph. The ASCT was activated at all 10 intersections on June 25th, 2018. 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.

BlueToad® devices are Bluetooth signal receivers, which read the Media Access Control (MAC) addresses of active Bluetooth devices of vehicles passing through their area of influence. These devices record the time when a vehicle passes nearby. To deduce the travel time of a vehicle, a pair of devices is used to estimate the difference of times. Speed is calculated from travel time and a known path distance (not Euclidean distance) between the devices.

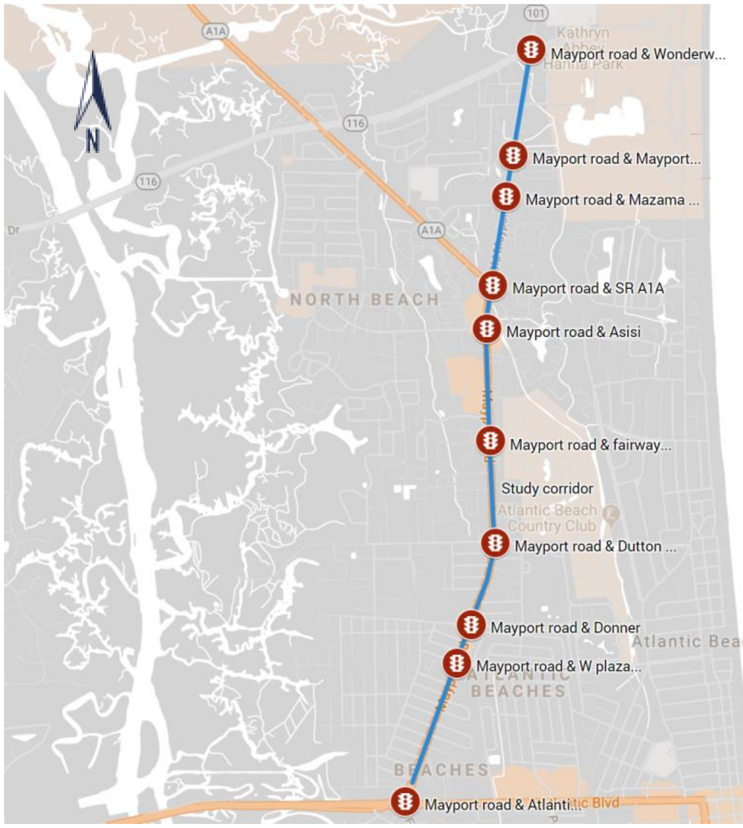


Figure 2.1: Study corridor

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 2.1 presents travel speed descriptive statistics for the typical days of the week. As indicated in Table 2.1, 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.

Table 2.1: Descriptive statistics of speed data

Day of the week	Northbound		Southbound	
	Mean (mph)	**Standard deviation (mph)**	**Mean (mph)**	**Standard deviation (mph)**
Tuesday	36.54	3.41	32.22	3.48
Wednesday	36.53	3.25	32.45	2.93
Thursday	36.41	3.69	32.34	3.46

Theoretical Concept of a Bayesian Switch-point Regression (BSR)

The BSR is a common model in calibrating time series data (Kidando et al., 2019), particularly when identifying the unknown location in which patterns change is one of the primary goals (Lin et al., 2012). The pattern change in data characteristics could be due to change in sequence, data variations or shift in mean between before and after the threshold (Ankoor Bhagat et al., 2017; Kidando et al., 2017; Kruschke et al., 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., 2019).

As it was expected, the general trend of the speed time series reveals that there are fluctuations in daily data as shown in Figure 2.2. 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 as presented in Equation 2.1.

Suppose that the average speed with ASCT $\mu_1$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.

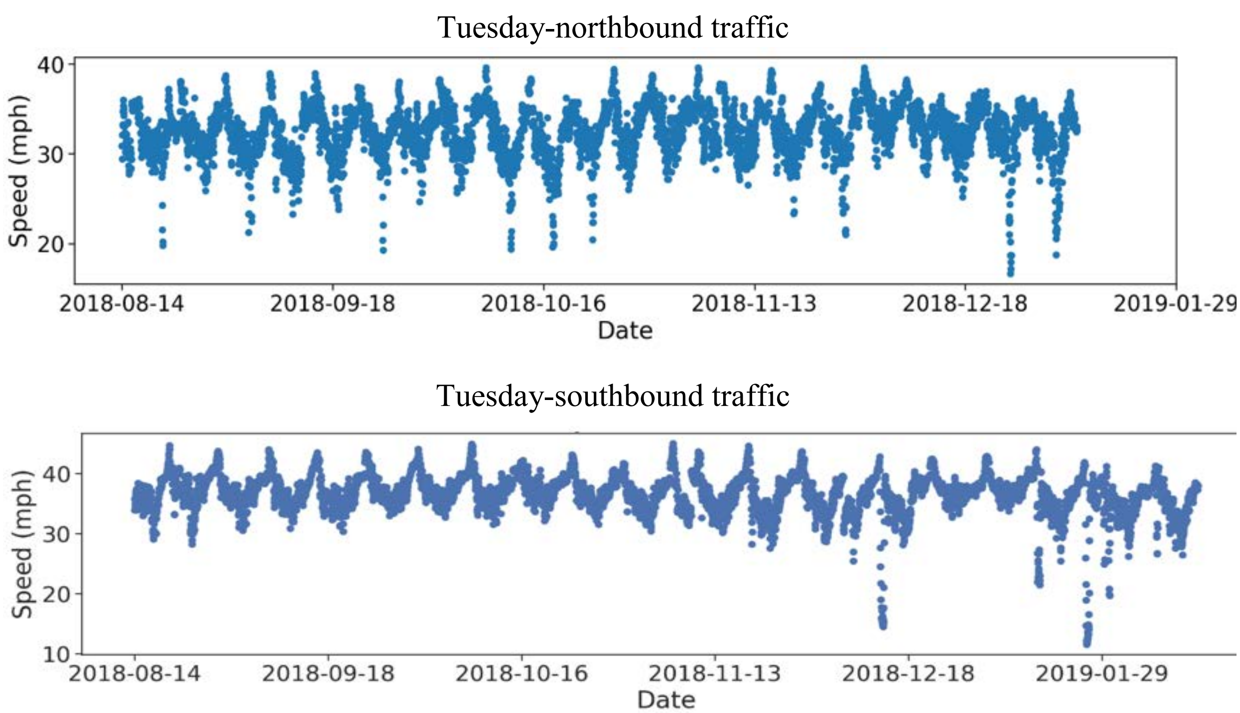


Figure 2.2: Time series of travel speed collected at 5-min interval

$$Y_i \sim \begin{cases} N(\alpha_{1i}, \sigma_1), & if \;\; x_i \;\leq\; \tau \\ N(\alpha_{2i}, \sigma_2), & otherwise \end{cases} \tag{2.1}$$

where,

$$\alpha_{1i} = \mu_1 + \beta_{11} sin(2\pi \emptyset x_i) + \beta_{12} cos(2\pi \emptyset x_i) + \varepsilon_{i1}$$
$$\alpha_{2i} = \mu_2 + \beta_{21} sin(2\pi \theta x_i) + \beta_{22} cos(2\pi \theta x_i) + \varepsilon_{i2}$$
$$\varepsilon_{i1} \sim N(0, \sigma_1)$$
$$\varepsilon_{i2} \sim N(0, \sigma_2)$$

μ_1 *and* μ_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,

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 distributions for the switch-point τ were 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 were used to estimate the posterior distributions (Salvatier et al., 2015).

Model evaluation

The proposed model was evaluated its goodness of fit by comparing it 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 information criterion (AIC) and Bayesian Information criterion (BIC), 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 2.2.

$$WAIC = -2 * lppd + 2 * p\_wic \tag{2.2}$$

where,

p_waic is the effective number of parameters,

$lppd$ is the log point-wise posterior predictive density

Bayesian hypothesis test (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 accept or 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 (Kidando et al., 2019; Kruschke, 2010, 2013). The null hypothesis (H_0) was formulated that there is no difference between the two patterns (i.e., the two patterns with and without ASCT 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:

$$\begin{aligned} &\text{Null hypothesis } (H_0)\text{: } \mu_1 - \mu_2 = 0 \\ &\text{Alternative hypothesis } (H_1)\text{: } \mu_1 - \mu_2 \neq 0 \end{aligned} \tag{2.3}$$

For the standard deviation of speeds:

$$\begin{aligned} &\text{Null hypothesis } (H_0)\text{: } \sigma_1 - \sigma_2 = 0 \\ &\text{Alternative hypothesis } (H_1)\text{: } \sigma_1 - \sigma_2 \neq 0 \end{aligned} \tag{2.4}$$

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 includes zero as one of the credible values in the 95% HDI, the null hypothesis is not rejected (Kruschke, 2010) as illustrated in Figure 2.3. 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 ($\sigma_1 - \sigma_2$).

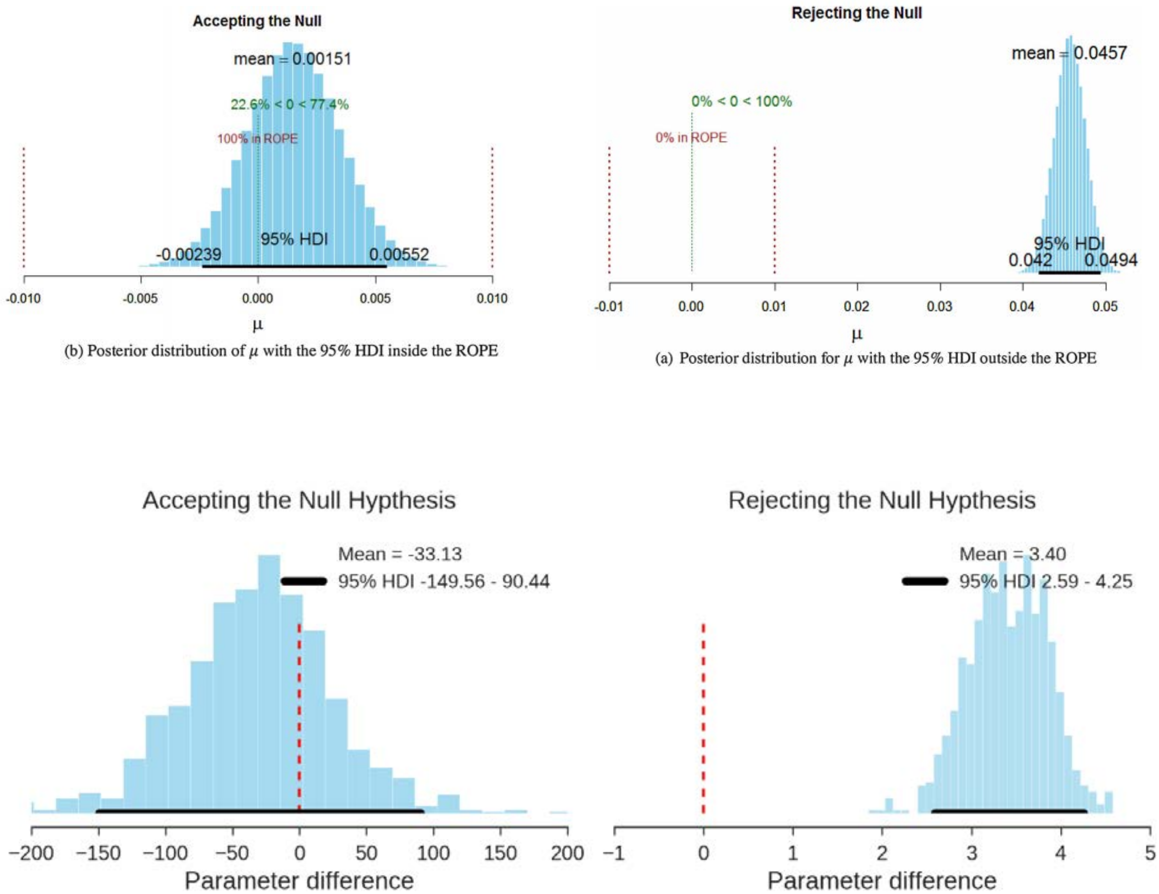


Figure 2.3: Rejecting or accepting the null hypothesis (Kidando et al., 2019)

Mobility enhancement factors (MEFs)

A 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. The MEF was calculated as the ratio of the posterior distributions of the average speed without ASCT and with ASCT as presented in Equation 2.5.

$$\mathrm{MEF} = \frac{\mu_2}{\mu_1} \tag{2.5}$$

The overall MEF for the ASCT was calculated using Equation 2.6.

$$MEF_{overall} = \frac{\sum_{i=1}^{n} MEF}{n} \tag{2.6}$$

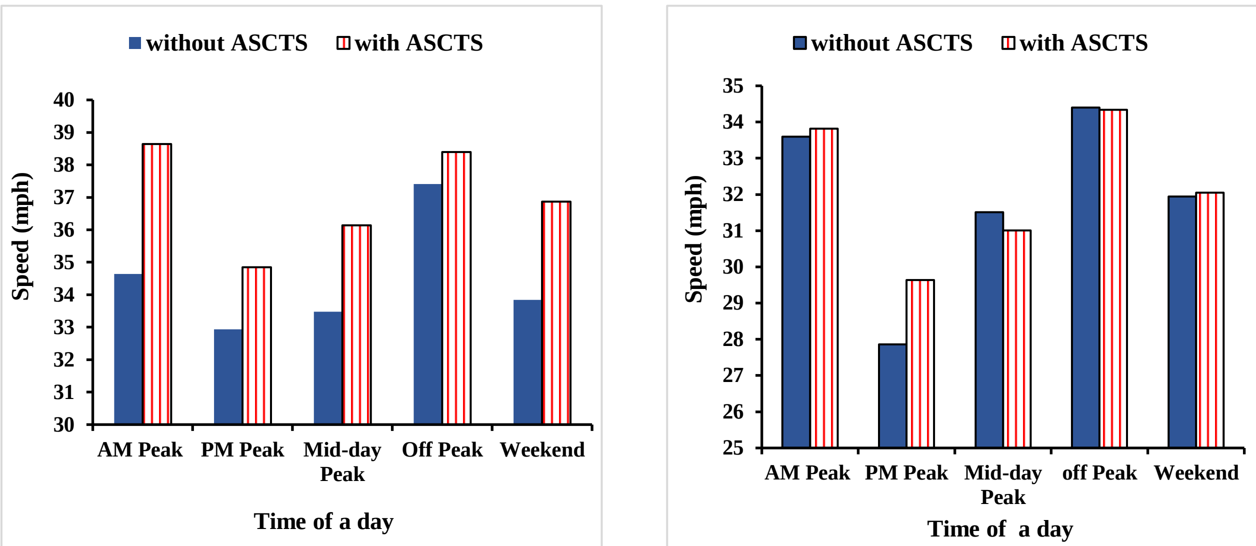
where *n* represents the number of days analyzed in the study.

RESULTS AND DISCUSSION

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. Descriptive statistics of the travel speed data, Model comparison, BSR, BHT and MEFs results are presented in this section.

Descriptive Statistics

Descriptive statistics of travel speed as the performance measure is presented in Figure 2.4. As shown in 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 without ASCT 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 deployment during mid-day hours (-1.6% decrease) and off-peak hours (-0.2% decrease).

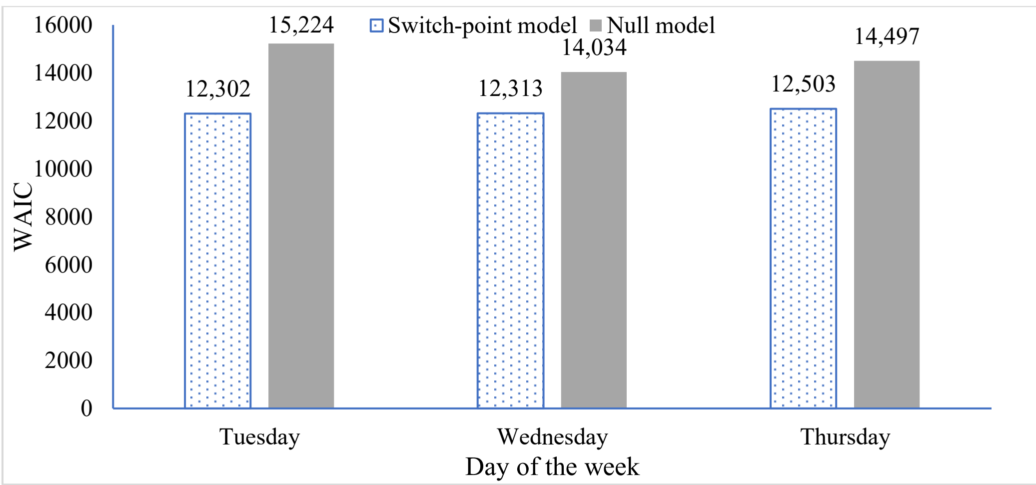


(a) Travel speed northbound (b) Travel speed southbound

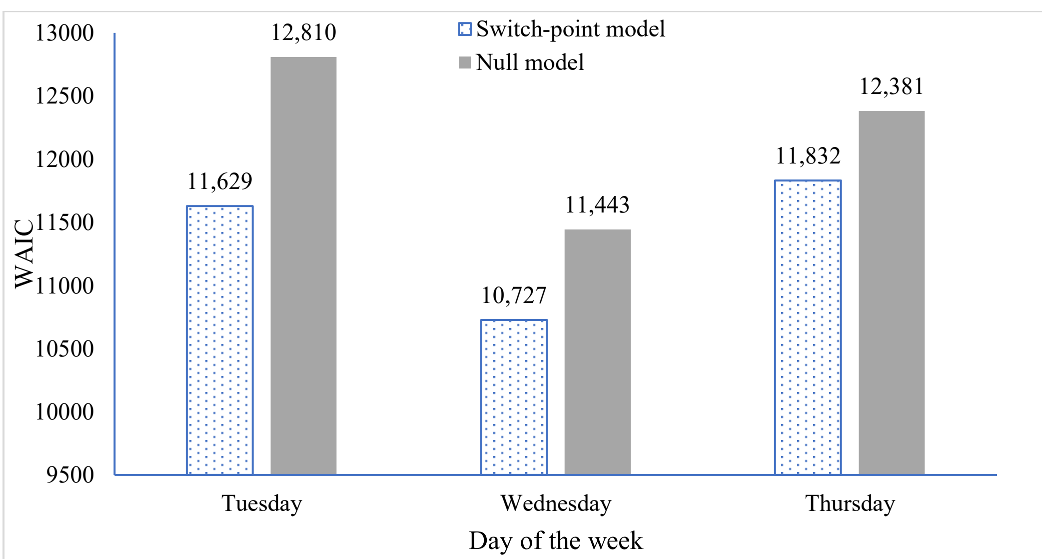
Figure 2.4: Travel speed

Model goodness-of-fit evaluation

Fitting the BSR can be viewed as a hypothesis test (Liu et al., 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 (Richard Mcelreath, 2016). Figure 2.5 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 2.5 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 northbond and southbound directions, respectively.



(a) Northbound traffic



(b) Southbound traffic

Figure 2.5: Model goodness-of-fit statistic

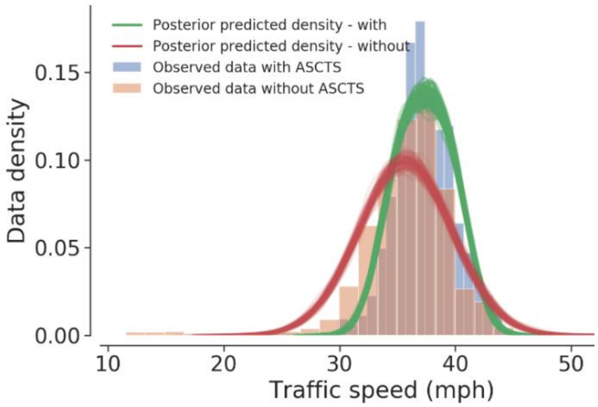
The estimated switch-points, τ, were compared to the date that the ASCT was turned-off to check the accuracy of the model in calibrating this parameter. As presented in Table 2.2, the average estimated switch-point date for southbound and northbound traffic on Tuesday by the BSR is November 06, 2018. 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 traffic, 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.

Table 2.2: Posterior summary of the BSR

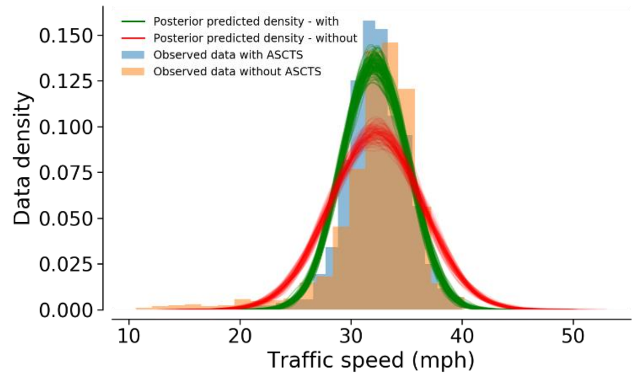
Tuesday northbound					Tuesday southbound			
Parameter	**Mean**	**Sd**	**95% BCI**		**Mean**	**Sd**	**95% BCI**	
β_{11}	-0.54	0.02	-0.58	-0.50	-0.65	0.02	-0.69	-0.61
β_{12}	-0.56	0.02	-0.61	-0.52	0.02	0.05	-0.08	0.10
β_{21}	-0.25	0.12	-0.47	-0.02	0.63	0.04	0.55	0.71
β_{22}	-0.42	0.08	-0.54	-0.25	-0.06	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

Figure 2.6 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

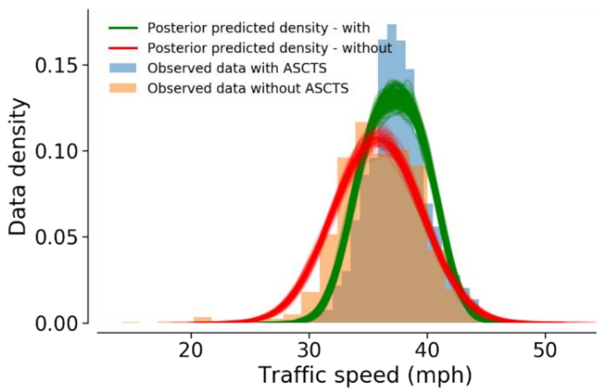
predicted data densities are too close and superimpose the histograms for the observed data densities indicating that the BSR can be used to fit the data. This suggests that the BSR model can calibrate the data trend with a reasonable accuracy including the switch-point dates. Note that the field observed 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.



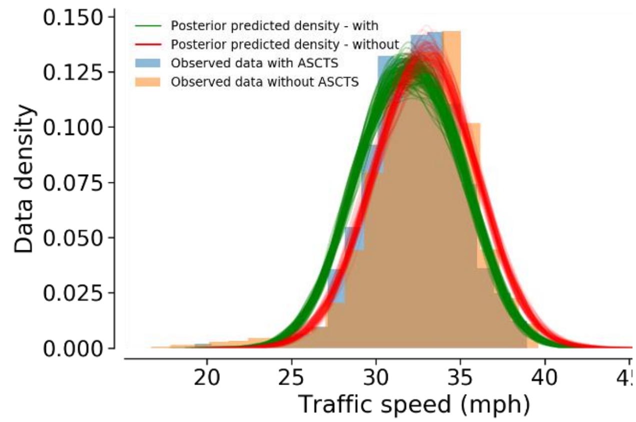
(a) Tuesday northbound



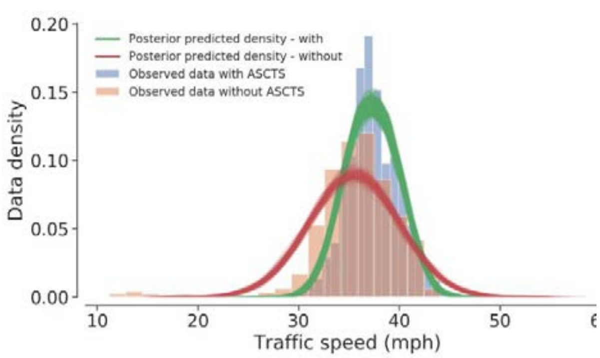
(b) Tuesday southbound



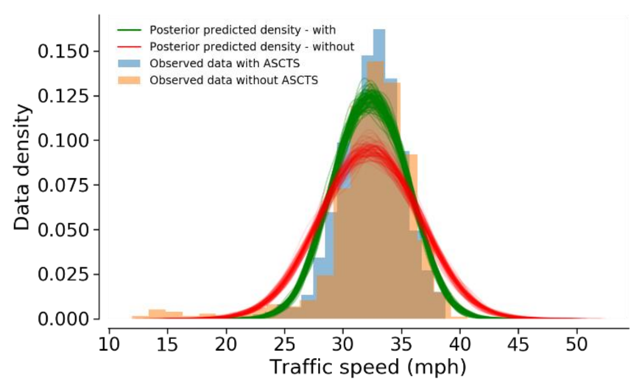
(c) Wednesday northbound



(d) Wednesday southbound



(e) Thursday northbound

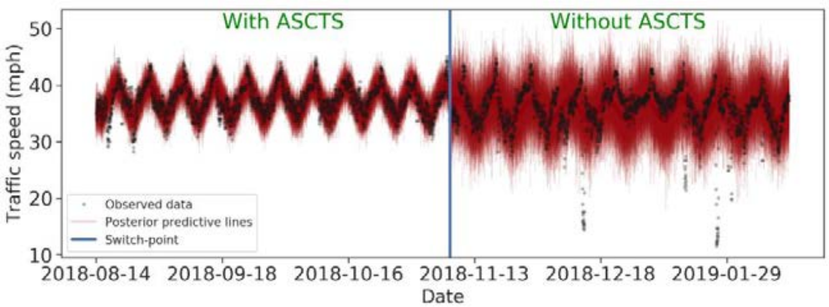


(f) Thursday southbound

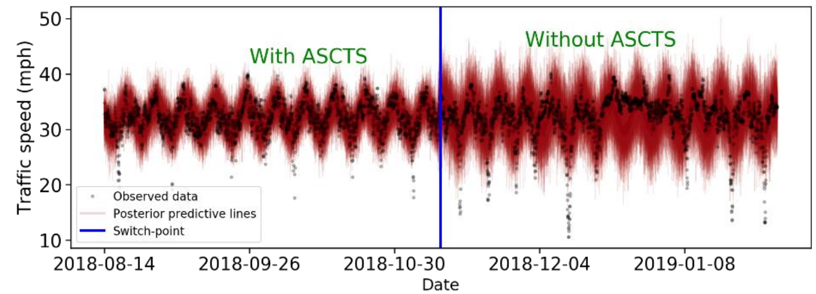
Figure 2.6: Posterior predicted and observed data densities

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.

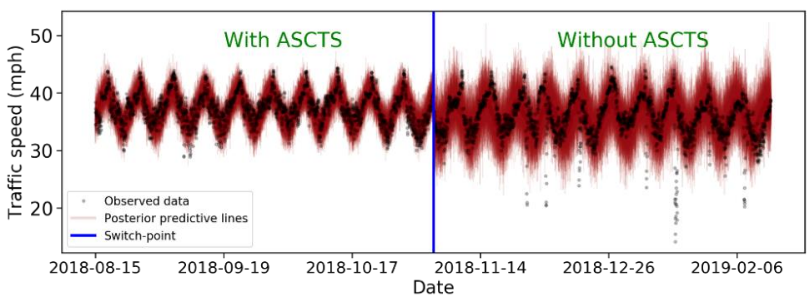
Figure 2.7 shows how the model performed in predicting the time series data. As seen in this figure, the proposed model estimates and the actual data trend are close. More specifically, the predicted posterior lines follow daily data fluctuations. Moreover, Figure 2.7 clearly portrays that there is a 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 is not visible.



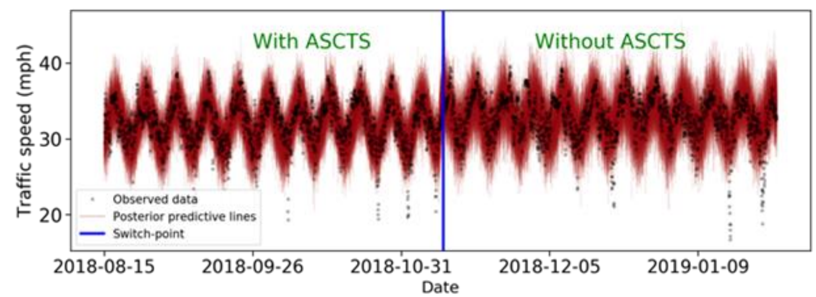
(a) Tuesday northbound



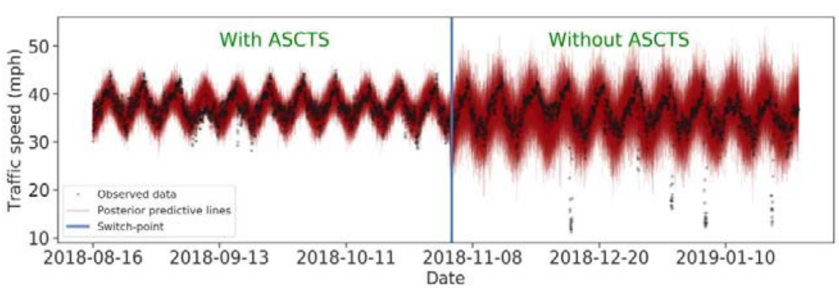
(b)Tuesday southbound



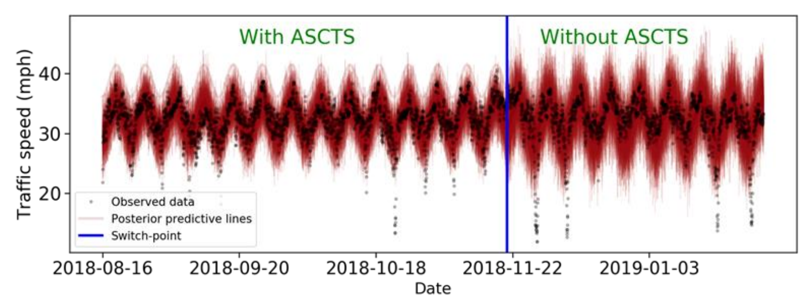
(c) Wednesday northbound



(d) Wednesday southbound



(e) Thursday northbound



(f) Thursday southbound

Figure 2.7: Time series plot of actual traffic speed data and the posterior predictive estimates

BSR Model Results

Results from the BSR are presented in Table 2.2. Note that in estimating the parameters' posterior distributions of the model, the travel speeds data were standardized following a z-score approach for the model to easily convergence in the analysis. Transforming the estimated coefficients to speed posterior distributions Equation 2.7 was used. For instance, Tuesday northbound traffic, the estimated average speed with ASTCS, $speed_{with} = 0.23 \times 3.41 + 36.54 = 37.32$ mph (95% BCI = [37.26, 37.39]) and 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. For clarification, the average speed and standard deviation of speed for this calculation are presented in Table 2.1.

For the southbound traffic, speeds of 32.21 mph (95% BCI = [32.08, 32.36]) and 32.18 mph (95% BCI = [32.12, 32.29]) with and without ASCT were the estimates, respectively. However, for southbound travel speeds with and without ASCT are approximately equal indicating that there is no change following ASCT deployment.

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. The values of the estimated average speeds are higher with ASCT in the northbound direction, indicating a significant improvement in travel speed following ASCT deployment. However, in the southbound direction, the 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 deployment. However, the southbound estimated average speeds with and without ASCT are approximately equal, indicating that there is no significant change following ASCT deployment. Parameters β_{11}, β_{12}, β_{21}, β_{22}, $\emptyset$, and θ listed in Table 2.2, are sinusoidal parameters for the sine and cosine function, which in this study were considered to calibrate daily speed due to demand variations.

$$speed_{with} = \mu_1 \times s + \bar{x} \tag{2.7}$$
$$speed_{without} = \mu_2 \times s + \bar{x}$$

where,

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

s is the standard deviation of the observed speed data,

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

BHT Results

Table 2.3 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 the decision to accept or reject the null hypothesis at 95% HDI. As stated earlier, the null hypothesis (H_0) was formulated that there is no difference between the two patterns (i.e., the two patterns with and without ASCT are the same) while the alternative hypothesis (H_1) was expressed that the patterns with and without ASCT are credibly different.

Table 2.3: Bayesian hypothesis testing

Day of the week	Parameter	Northbound Mean (mph)	Northbound 95% HDI Upper limit (mph)	Northbound 95% HDI Lower limit (mph)	Northbound Decision	Southbound Mean (mph)	Southbound 95% HDI Upper limit (mph)	Southbound 95% HDI Lower limit (mph)	Southbound Decision
Tuesday	Av. 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	Av. 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	Av. speed	1.80	1.60	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: Av. speed represents an estimated average speed difference between with and without ASCT and Speed std. is the difference in the estimated standard deviation of speed between with and without ASCT.

As shown in Table 2.3, 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 speed and standard deviation of speed 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 a 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.

Mobility benefits of ASCT

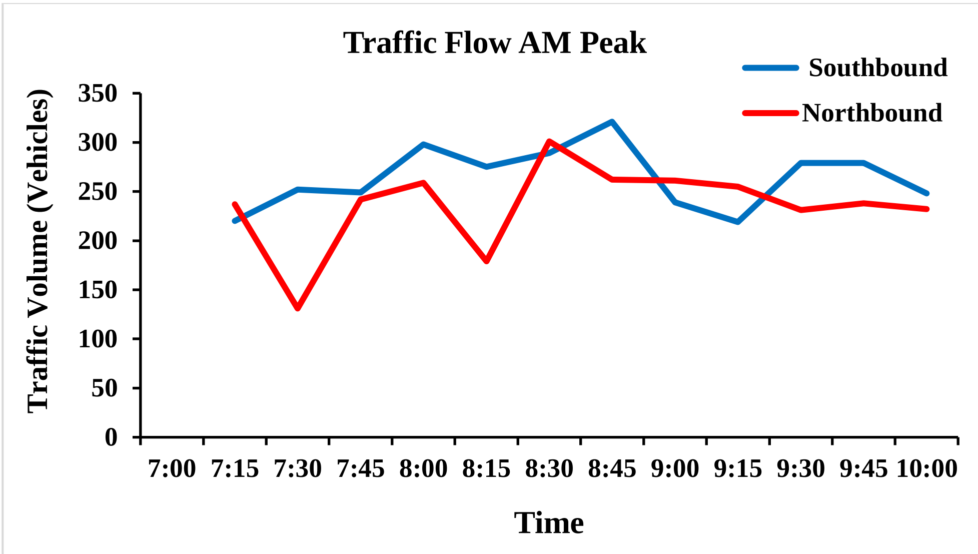
From the BSR model's posterior distributions, the MEFs were computed to quantify the operational benefits of the ASCT. Table 2.4 presents the estimated MEFs for the typical days, PM peak, AM peak, and off-peak hours for both directions of travel.

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) who suggested that ASCT improves speed by 11%. Moreover, during the PM peak hour, ASCT shows less improvement in travel speed, this may be attributed to congestion due to the increase in the traffic demand at this specific period. It has been observed that ASCT cannot perform well in congested or oversaturated conditions since 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 following ASCT deployment. This observation is supported by other studies (Hutton et al., 2010) in which ASCT shows 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). In addition, the driveway density for each direction of travel was determined and the results show that northbound direction has lower driveway density with 8.5 driveways/mile compared to southbound with 11.5 driveways/mile.

Furthermore, the traffic volume collected on one of the intersections along the Mayport corridor indicates that there are more traffic volume in the southbound direction compared to the northbound direction. On average the traffic volume on the southbound direction was 1056 veh/h and 1334 veh/h for AM and PM Peak respectively. On the other hand, the traffic volumes on the northbound direction are 942 veh/h and 1248 veh/h for AM and PM Peak respectively. The large traffic volumes on the southbound direction could be one of the reasons for the lower performance of the ASCT in the southbound direction. Moreover, the traffic flow in the northbound is more variable and unpredictable compared to the traffic flow in the southbound direction as shown in

Figure 2.8. This also could be one of the reasons for the higher performance of the ASCT in the northbound direction as ASCT performs well when the traffic flow varies.



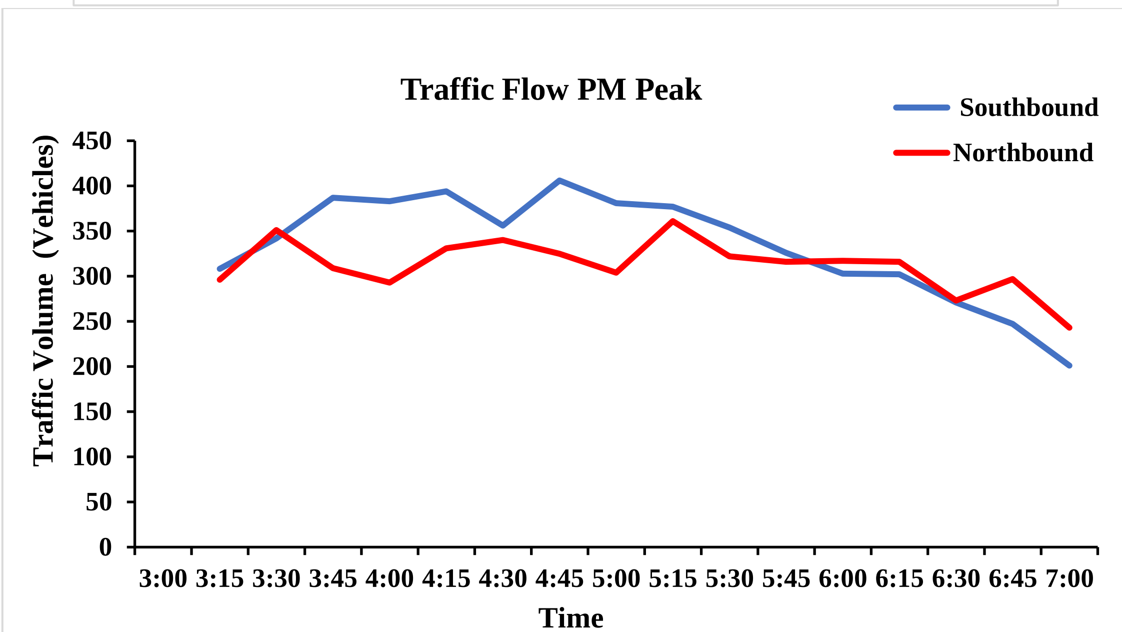


Figure 2.8: Traffic flow during peak hours

Table 2.4: Mobility enhancement factors (MEFs)

	Northbound				Southbound			
		95% HDI				95% HDI		
Day of the week	**Avg. MEF**	**Lower Limit**	**Upper Limit**	**% Speed increase**	**Avg. MEF**	**Lower Limit**	**Upper Limit**	**% Speed increase**
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 of a day								
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%
Overall MEF	**0.96**	**0.95**	**0.96**	**4%**	**1.0**	**1.01**	**1.0**	**0%**

Note: Avg. represents estimated average.

CONCLUSIONS AND RECOMMENDATIONS

To the best of author's knowledge, this study introduced a new approach to evaluate the operational benefits of ASCT. The proposed BSR model was used to; (i) estimate the possible dates that define the boundary between two different operating conditions (ii) conduct the Bayesian hypothesis test (BHT) and (iii) estimate the mobility enhancement factors (MEFs). The analysis was based on a 3.3-mile corridor along Mayport Road from Atlantic Boulevard to Wonderwood Drive in Jacksonville, Florida for the periods July 08, 2018 through February 10, 2019.

The findings indicate that the BSR can estimate the dates at which the ASCT was switched-off in the study corridor. This is important in the analysis especially when the possible switch-off dates of the systems 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 ASCT deployment 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 points.

The current study could be extended in the future by incorporating other variables in the model. Examples of variable that are thought to influences the operating characteristics of ASCT include weather conditions, incidents, traffic volume, site characteristics such as access point, intersection spacing and unsignalized intersections present in the study corridor. These variables could be integrated as explanatory variables or formulated in the hierarchical structure to improve the model GOF.

Moreover, a study of pedestrian volumes and frequency of push button use may help assess how the presence of pedestrians can affect system performance, and how the system affects pedestrian delay and crossing behavior. These findings may provide researchers and practitioners with an effective means for conducting the economic appraisal of the ASCT as well as a key consideration to transportation agencies for future ASCT deployment.

CHAPTER 3

PAPER 2

Safety Performance Evaluation of Adaptive Signal Control Technology (ASCT)

INTRODUCTION

The Adaptive Signal Control Technology (ASCT) is a traffic management strategy that optimizes signal timings in real-time to improve traffic flow. This strategy continuously monitors arterial traffic conditions and the queuing at intersections and dynamically adjusts the signal timing to optimize operational objectives (FHWA, 2017a). Since ASCT optimize signal timing plans in real-time, it is expected to reduce traffic congestion and improve traffic safety, especially when the traffic conditions are highly variable and unpredictable (FHWA, 2017a). 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 substatntial safety improvements on the other hand. For example, reduced vehicle stops frequency reduces the chance of rear-end crashes (NCHRP, 2010). Similarly, previous studies have shown that operational improvement as a result of ASCT installations can also create secondary safety benefits (Khattak et al., 2018; Wilsone et al., 2003).

Even though the primary focus on evaluating ASCT has been on quantifying its mobility benefits, a few studies have analyzed the safety benefits of ASCT in terms of crash reduction (Ma et al., 2016; Khattak et al., 2018). These studies relied on calibrated Safety Performance Functions (SPFs) from Highway Safety Manual (HSM) (AASHTO, 2010) and a simple observational before-after Empirical Bayes (EB) approach to estimate the CMFs for ASCT (Dutta et al., 2010; Fontaine et al., 2015). The utilization of calibrated SPFs did not account for the effect of other variables that influence changes in crash frequency and crash severity patterns at the treatment sites independent of the ASCT. Furthermore, a simple observational before-after EB approach used in the previous studies did not account for the confounding factors. A robust statistical approach for the estimation of ASCT CMFs that accounts for confounding factors as well as incorporating the effect of other variables in SPFs is therefore needed.

The objective of this study was to estimate the safety benefits of ASCT. An observational before-after EB approach with comparison-group was used to estimate Crash Modification Factors (CMFs) for ASCT. This study incorporates more variables in addition to annual average daily traffic (AADT) for the major and minor approaches in the development of SPFs to account for the influence of these variables in crash frequency and crash severity. The SPFs were developed separately for total crashes, rear-end crashes, and fatal plus injury (FI) crashes.

LITERATURE REVIEW

Although ASCT is widespread in the U.S., comprehensive studies that evaluate the safety effectiveness of ASCT are sparse. Several previous studies focused on evaluating the safety effectiveness of ASCT based on simple observational before-after EB approach with calibrated SPFs. Dutta et al., (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 interval (CI). 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 (Fink et al., 2016). A recent survey

(Lodes et al., 2013) evaluated the safety effectiveness of the ASCT using crash data for three sites for only one year of before and after ASCT deployment and concluded that all three sites experienced a reduction in crashes, although the sample size was too small to yield statistically reliable results.

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 (Clements et al., 2016)Khattak et al., (2018) evaluated the safety improvements of two ASCT (SURTRAC and InSync) deployed at 41 intersections in Pennsylvania. The study was based on multivehicle crashes, calibrated SPFs, and the CMFs were estimated based on an observational before-after EB approach. The analysis revealed an average value of CMFs of 0.87 and 0.64 for total crashes and FI crashes, respectively, at a 95% CI. Furthermore, a reduction in the proportional of rear-end crashes was also observed although the change was not statistically significant.

Several studies have also used microscopic simulation approaches to appraise the safety benefits of ASCT, typically using surrogate safety measures. Stevanovic et al., (2011) used a microscopic simulation model connected to SCATS to generate vehicular trajectories, which were fed into the Surrogate Safety Assessment Model (SSAM) (Gettman et al., 2003, 2008) to assess the safety benefits of SCATS. The results revealed that SCATS simulations generated fewer rear-end and total conflicts but more crossing and lane changing conflicts than traditional control. Similarly, Shahdah et al., (2015) used a VISSIM microscopic simulation to develop a statistical relationship between traffic conflicts estimated from simulation and observed crashes at signalized intersections to evaluate the safety performance of ASCT. The study concluded that countermeasure effects can be estimated reliably from conflicts derived from microscopic simulation when a suitable number of simulations runs, and conflict tolerance thresholds are used to create the crash-conflict relationship. However, the study was only able to prove the validity of using the relationship to evaluate safety performance and did not estimate the accuracy of crash estimates.

Most of the previous studies focused on the evaluation of the safety effectiveness of the ASCT using simple observational before-after EB approach and calibrated SPFs to develop the CMFs for ASCT. The method that has been used did not account for the confounding factors and the use of calibrated SPFs did not consider the effect of other variables since calibrated SPFs use only two variables i.e., AADT for major and minor approaches. This paper fills the existing gap in the literature through using rigorous EB before-after evaluation with comparison-group to examine the safety effectiveness of the ASCT. The use of the comparison group accounts for the confounding factors (Elvik, 2002). Moreover, SPFs for total crash,rear-end crashes, and FI crashes were developed separately to incorporate the influence of other variables in addition to AADT for major and minor approaches that have been used by previous studies. SPFs were then used in the estimation of the CMFs for ASCT.

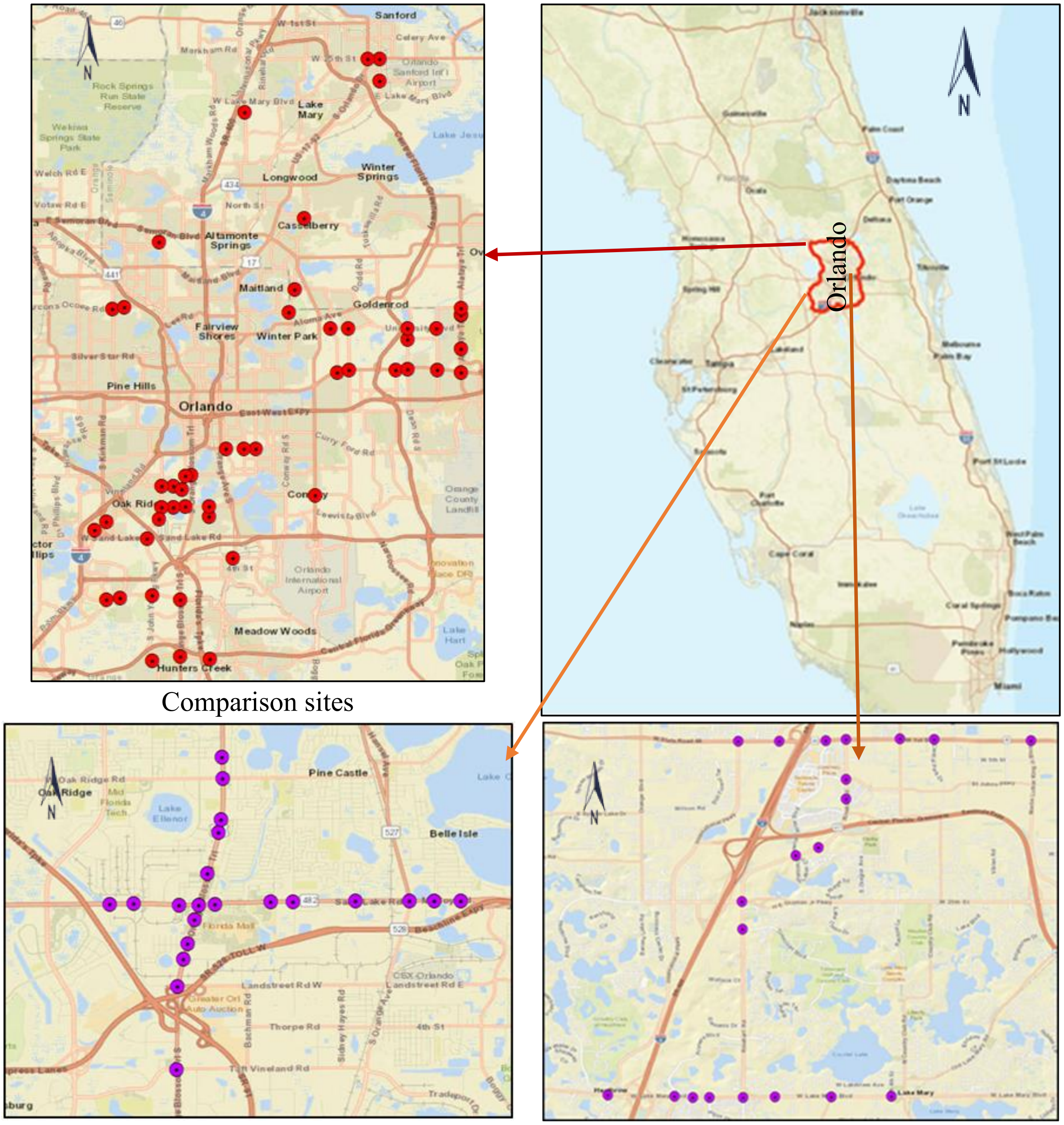
METHODOLOGY

Site Description

An observational before-after EB approach with comparison-groups recommended by the HSM (AASHTO, 2010) was used to evaluate the safety effectiveness of the ASCT deployed in Florida. The sites selected for safety effectiveness evaluation of the ASCT have to be homogenous as recommended in the HSM (AASHTO, 2010). The potential characteristics that have been considered in identifying the treatment sites for ASCT intersections are intersection geometry four-legged or three-legged intersections with the same characteristics 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 3.1 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 the existing ASCT system. 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 SPFs development. These sites were located within the same jurisdiction as the treatment sites and had similar geometric characteristics and traffic volumes as the treatment sites. Similar criteria have been used in previous studies (Fink et al., 2016; Kitali et al., 2018). Figure 3.1 shows the locations of the selected comparison sites used in this study.



Comparison sites

Orange County treatment sites

Seminole County treatment sites

Figure 3.1: Treatments and comparison intersections

Data Collection

The following data were needed to evaluate the safety performance of ASCT using the EB approach: crash, 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 the Florida Department of Transportation (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 et al., 2009; 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 the 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 software 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 Signal Four 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 3.1 provides the descriptive statistics of annual crash data both before and after ASCT deployment at the selected treatment sites.

Table 3.1: 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	5.70	0	27
PDO crashes	25.29	0	70	17.02	0	84

Note: Units reflect crashes/year/intersection

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 et al., 2009). 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 are 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 EB analysis to estimate CMFs for the ASCT strategy. As such, SPFs were developed from the reference sites that are similar to the treated sites (Srinivasan et al., 2009). A total of 47 comparison sites were selected for SPFs development. These sites were located within the same jurisdiction as the treatment sites and had similar geometric characteristics and traffic volumes as the treatment sites.

A Negative Binomial (NB) model is better suited for modeling crash data, rather than a Poisson regression model since a NB model accounts for the over-dispersion of crash data (Srinivasan et al., 2009). The degree of over-dispersion in the NB model is represented by the overdispersion parameter which is then used to determine the value of a weight factor to be used in the EB 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 posteriori 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 et al., 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 NB distribution with a mean and variance equal to λ_i, as presented in Equation 3.1.

$$Y_i \sim NegBinomial(\lambda_i, \alpha) \tag{3.1}$$

Where;

$$ln(\lambda_i) = \beta_0 + \beta_1 X_i \tag{3.2}$$

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.

The model parameters of the NB model presented in Equation 3.2 are estimated using a full Bayes approach through the Markov Chain Monte Carlo (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 has 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.

Empirical Bayes (EB) Method

The empirical Bayes (EB) method with comparison-groups prescribed in the HSM (AASHTO, 2010) was used to estimate the CMFs for the ASCT strategy. The EB 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 EB before-after approach for developing CMFs for ASCT systems (Khattak et al., 2018, 2019) for developing the CMFs for ASCT.

An observational before-after EB with 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 3.2 shows the process of the EB approach used to estimate CMFs in this study.

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 at 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 (Daniel Carter, 2017). A CMF of 1.0 serves as a reference below or above which an expected decrease or increase in crash frequencies is indicated after implementing a specific countermeasure.

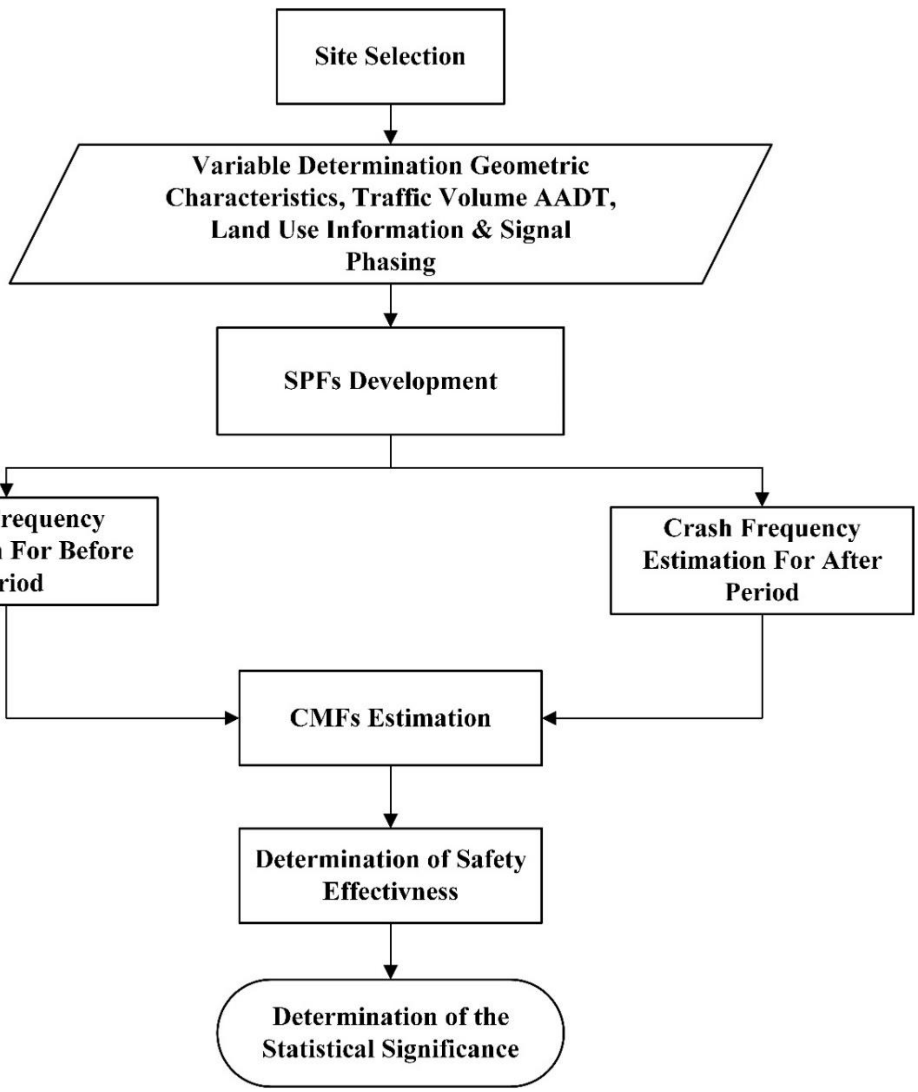


Figure 3.2: Flow chart for the Empirical Bayes method.

RESULTS AND DISCUSSION

Safety Performance Function Results

SPFs for the four-legged ASCT intersections for total and rear-end crashes and for FI crashes were developed using the BNB model. SPFs were used in the EB before-after approach with comparison-group for CMFs estimations. Significant variables at 95% Bayesian Credible Interval (BCI) were used as SPFs model variables. The computed SPFs for total and rear-end crashes are presented in Tables 3.2, and for FI crashes are shown in Table 3.3.

Table 3.2: SPF results for crash types

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 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.
NA – Not Applicable.

Table 3.3: SPF 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.

Crash Modification Factors Results

Table 3.4 shows the results of the estimated CMFs for intersection with ASCT. As indicated in Table 3.4, all the estimated CMFs are statistically significant at 95% CI. 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 0.894, indicating a 10.6% 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, 2017b). 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 are expected. Khattak et al. (2018) also observed a similar reduction in rear-end crashes although the reduction was not statistically significant at 95% CI.

The CMF for FI crashes is 0.939, indicating a 6.1% reduction in FI crashes following ASCT deployment. This result is consistent with several previous studies (Khattak et al., 2018, 2019). The CMF for PDO crashes is 0.946, indicating a 5.4% reduction in PDO crashes following ASCT deployment. This finding is also consistent with previous studies (Khattak et al., 2019).

Table 3.4: Crash Modification Factors

Crash Category	Mean	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	0.894	0.902	0.885	0.004	10.6%
FI crashes	0.939	0.952	0.926	0.007	6.1%
PDO crashes	0.946	0.953	0.938	0.004	5.4%

ASCT Deployment Cost

Deployment of the ASCT considers both the initial installation cost of the system as well as the ongoing system maintenance and operation cost. The deployment costs of the ASCT can vary widely and are dependent on several factors including the type of ASCT used, existing infrastructure in place (i.e., detection, communications, compatible controllers, etc.). The installation cost of the ASCT ranges between $10,000 to $120,000 per intersection with an average of $65,000 per intersection (NCHRP, 2010). The wide range of cost per intersection can be attributed to the different needs of each unique ASCT installation. Differences between systems that can affect the cost of the ASCT include the ASCT software selected, the amount of compatible infrastructure that can be reused, management of traffic for construction of new infrastructure, decision to use in-house staff or outside consultant to implement the system, and economics of scale when implementing large systems compared to small systems (FDOT, 2016).

The operation and maintenance costs of ASCT can also vary between different systems and from the previous non-adaptive system. Unlike non-adaptive systems, signals in the ASCT network do not need any resources to continuously updating and optimizing signal timing plans. As in a non-adaptive signal system, the installed infrastructure also requires continual maintenance. The estimated costs associated with ASCT per intersection are listed in Table 3.5.

Table 3.5: Cost associated with ASCT deployment per intersection

Item		Costs
Initial installation cost	$	30,000
Swap out an old controller to ASTCS	$	5,000
CCTV camera	$	5,000
Network equipment to existing fiber (cost per mile)	$	100,000
Stop bar and advanced detector	$	7,000
Software and configuration	$	3,000
Communication links	$	15,000
Maintenance cost (Annually)	$	2,000
Operation cost (Annually)	$	500
Staffing cost (Annually)	$	2,000

Source: TSM&O District 2

Economic Cost Saving Analysis

Economic cost saving following the ASCT deployment can be accounted for by monetizing the crash reductions at the treatment intersections. The comprehensive crash cost associated with each crash severity were listed in Table 3.6. Since the analysis combines the crash severity in two categories i.e., FI (KABC) and PDO, the original values for KABC were combined to obtain the weighted crash cost for KABC. Equation 3.3 was used in the determination of the severity-weighted cost for KABC (Harmon et al., 2018). Based on the crash data collected from 42 treatment sites the weighted-severity cost for KABC was $305,516.

$$SWC_{KABC} = C_K \frac{N_K}{N_{KABC}} + C_A \frac{N_A}{N_{KABC}} + C_B \frac{N_B}{N_{KABC}} + C_C \frac{N_C}{N_{KABC}} \quad (3.3)$$

Where;

SWC represent the severity-weighted cost

C represents the crash unit cost for a given severity

N represents the number of crashes of a given severity or group of severity

Table 3.6: FDOT comprehensive crash cost by severity

Crash Severity	Comprehensive Crash Cost
Fatal (K)	$ 10,120,000
Severe injury (A)	$ 574,080
Moderate injury (B)	$ 155,480
Minor injury (C)	$ 96,600
PDO (O)	$ 7,600

Source: highway safety improvement program (HSIP) manual (FDOT, 2019)

Benefits-Cost Ratio (BCR)

The BCR establishes the relationship between the cost and benefits of the proposed project. It is an essential parameter to evaluate the value of money that would be expended on the project. The BCR is given as the ratio of the net present benefits to the net present cost (Equation 3.4). BCR of greater than 1 implies ASCT has more benefits than costs related to installation, operation and maintenance thus having more net benefits than costs. On the other hand, if a BCR is less than 1.0, the project's costs outweigh the benefits, and it should not be considered. The discount rate of 4% was adopted in this study to determine the present cost and benefits associated with the ASCT. Note that a similar discount rate has been used by other studies (Dutta et al., 2010).

$$BCR = \frac{Net\ Present\ Benefits}{Net\ Present\ Cost} \tag{3.4}$$

Economic Cost Saving Analysis Results

Economic cost saving following the ASCT deployment was accounted for by monetizing the crash reductions at the treatment intersections. The upper limit values of CMF at 95% CI were used to determine the reduction in the number of crashes following ASCT deployment. There was an average of 8.08 FI crashes per intersection per year before the deployment of ASCT. If the CMF of 0.952 is applied, it can be broadly estimated that there would be a reduction of 0.39 crashes per intersection per year following ASCT deployment. Converting this to monetary value using the severity-weighted cost of $305,516 for FI, ASCT results in the economic cost saving of $119,151 per intersection per year. Alternatively, CMF of 0.946 for PDO results in the reduction of 1.37 crash per intersection per year which is equivalent to an economic saving of $10,412 per year per intersection following ASCT deployment. On average the deployment of ASCT results to the economic cost saving of $129,563 per year per intersection as stipulated in Table 3.6. Furthermore, analysis shows that ASCT deployment results in the BCR of approximately 3.9. These results are based only on the cost savings due to the reduction in the number of crashes following ASCT deployment.

Table 3.7: Cost Saving following ASCT deployment

	Before ASCT	CMF	Crash reduction	Crash cost	Cost Saving
FI crashes	8.08	0.952	0.39	$305,516	$119,151
PDO crashes	25.29	0.946	1.37	$7,600	$10,412
Total saving per year per intersection					**$129,563**

Note: Units reflect crashes/year/intersection

CONCLUSIONS AND RECOMMENDATIONS

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 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 certain crash types (i.e., total and rear-end crashes) 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 frequency 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), posted speed, number of bus stops within 1,000 ft of the intersection, signal phasing, and land use information.

CMFs for total crashes, rear-end crashes, FI and PDO crashes were developed using EB 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 10.6% (CMF=0.894), FI crashes by 6.1% (CMF=0.939), and PDO crashes by 5.4% (CMF=0.946). Note that these results are statistically significant at 95% confidence level.

The findings in the current study, may provide researchers and practitioners with means to quantify the safety benefits of ASCT. Also, the findings of this study provides transportation agencies with an economic appraisal that can be used to inform future decisions to deploy the ASCT systems.

It is worth mentioning that on evaluating the safety benefits of ASCT, the evaluation focused only on the intersection related crashes. Since ASCT improves the traffic flow along the segment, future studies may seek to expand this study to determine the safety benefits of the ASCT along segment as well. Moreover, the study did not account for the operational differences between InSync and SynchroGreen ASCT due to the limited number of intersections deployed with InSync and SynchroGreen ASCT. Since the two systems optimize signal timing differently, future studies may seek to expand this study to determine the safety benefits of each system separately.

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