Final Report

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Evaluation of Incident Response Improvements for Statewide Application: Learning from the New Regional Traffic Management Center in Jacksonville, Florida

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DISCLAIMER

METRIC CONVERSION TABLE

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

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

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

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

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

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16. Abstract

Regional transportation management centers (RTMCs) are multimillion-dollar projects that serve as the hub of most freeway systems. A new RTMC in Jacksonville, FL, became operational in November 2015. This new facility replaces the old RTMC that was housed in the Florida Department of Transportation (FDOT) District 2 Urban Office building. The new facility co-locates multiple stakeholders under one roof. Although this strategy is expected to improve traffic incident management, its impact has not yet been quantified. As such, this research has two main goals: (a) evaluate the performance of the new RTMC in Jacksonville; and (b) quantify the impact of incidents on the operational and safety performance of the freeway network. The specific objectives were to (a) compare the performance of the new RTMC where multiple response agencies are physically co-located in the RTMC building with the performance of the old RTMC where most of the incident response agencies were housed at their respective agency locations; (b) estimate the delays caused by incidents on freeways and determine the factors affecting these delays; and (c) develop a reliable approach to identify secondary crashes (SCs) and determine the risk factors associated with SCs.

The first goal was achieved by comparing the incident verification and response durations before and after the opening of the new RTMC where multiple response agencies are housed under one roof. In general, the new RTMC was found to improve the incident verification and incident response durations. The factors affecting the incident verification and response durations before and after co-location were also investigated using hazard-based models. The second goal of quantifying the impact of incidents on the performance of the freeway network was achieved by estimating incident impact durations and incident-related delays and identifying and analyzing SCs. Data-driven methodologies using real-time traffic data were developed to estimate the incident impact duration and the incident-related delays. Hazard-based models were developed to investigate factors affecting these performance measures. SCs were identified using a dynamic method which considers flexible spatiotemporal impact ranges of primary incidents (PIs). The results from this approach were compared with the traditional static method which identifies SCs based on fixed spatiotemporal thresholds of PIs. The risk factors associated with SCs were also investigated using the Bayesian random effect complementary log-log model.

This research provides an in-depth understanding of the impact of incidents on traffic flow characteristics such as speed, density, and volume. The study results help develop incident management procedures for specific incidents that have a higher likelihood of adversely impacting traffic operations and safety along the freeways. Enhancements to traffic incident management (TIM) strategies and timely dissemination of incident information to the traffic upstream of the incident have the potential to reduce incident-related delays and the likelihood of SCs.

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EXECUTIVE SUMMARY

Transportation management centers (TMCs) serve as the hub of most freeway systems. A total of eleven regional TMCs (RTMCs) and two satellite TMCs are currently operational in the state of Florida. In November 2015, a new RTMC became operational in Jacksonville, Florida. This new facility replaced the old RTMC that was housed in the Florida Department of Transportation (FDOT) District 2 Urban Office building. The new facility has FDOT staff, TMC operators, local agency traffic signal operators, traffic monitoring consultants, Florida Fish and Wildlife Conservation (FWC), and the Florida Highway Patrol (FHP) personnel under one roof. The presence of these incident management stakeholders under one roof is expected to improve traffic incident management (TIM) on the interstate system. As such, this research had two main goals:

1. evaluate the performance of the new RTMC in Jacksonville, FL; and
2. quantify the impact of incidents on the operational and safety performance of the freeway network.

The project had three specific objectives:

- compare the performance of the new RTMC in Jacksonville where multiple response agencies are physically co-located in the RTMC building with the performance of the old RTMC where most of the incident response agencies were housed at their respective agency locations;
- estimate the delays caused by incidents on freeways and determine the factors affecting these delays; and
- develop a reliable approach to identify secondary crashes (SCs) and determine the risk factors associated with SCs.

To achieve the study goals and objectives, the following five performance measures of the RTMC were investigated: incident verification duration, incident response duration, incident impact duration, incident-related delays, and SCs.

Incident Verification Duration

Incident verification duration is the time between an incident being reported and the incident being confirmed by the TMC. In this study, the performance of the new RTMC where multiple response agencies are physically co-located in the RTMC building was evaluated by analyzing incident verification durations before and after co-location of response agencies. In general, descriptive statistics indicated shorter average incident verification durations after co-location than before. Crashes were verified more quickly after co-location than before. Incidents that occurred during peak hours after co-location showed shorter verification durations than incidents before co-location. The factors affecting the incident verification duration both before and after co-location of response agencies were identified using hazard-based models. The model results suggested that the following eight variables significantly affect incident verification duration both before and after co-location of response agencies: incident type, percent of lane closure, incident severity, roadway, traffic volume, time of the day, day of week, and detection method.

Incident Response Duration

Incident response duration is measured from the time incident response team is notified of an incident to when they arrive at the incident scene. Response time includes dispatch duration and travel time to the incident scene. In general, crashes had longer average response duration than other types of incidents. The factors affecting the incident response duration were identified using hazard-based models. The model results suggested that the following six variables significantly affect incident response duration both before and after co-location: incident type, percent of lane closure, roadway, day of week, detection method, and traffic volume. In addition to these variables, ramp involvement was significant in the before-period, while incident severity was significant in the after-period.

Incident Impact Duration

Incident impact duration includes the total time the traffic is impacted by an incident. In other words, it includes the time taken since the incident occurred to when the affected operational characteristics (i.e., speed and travel time) of a roadway segment return to normal. The study proposed a technique that uses historical traffic speed data to estimate the incident impact duration. The method uses the speed data reported by the BlueToad® devices to create a bandwidth of mean speed profiles, within one standard deviation, for the times when there were no incidents. In the event of an incident, the algorithm checks if the speeds drop below the lower bound (i.e., one standard deviation below the historical mean) and tracks the traffic flow speed until it returns to within the one standard deviation bandwidth. The incident impact duration is computed as the time elapsed from the speed dropping below the bandwidth to the time it returns to normal. The factors affecting the incident impact duration were identified using hazard-based models. The model results suggested that the following five variables significantly affect incident impact duration: incident type, incident severity, percent of lane closure, time of the day, and co-location of response agencies.

Incident-related Delays

This study estimated incident-related delays on freeways using real-time traffic flow data and also evaluated the impact of incident characteristics, traffic conditions, and roadway geometric conditions on the extent of the incident-related delays. Incident-related delays were estimated from the incident impact duration and the prevailing traffic volumes at the time of the incident. Next, the factors affecting these delays were investigated using hazard-based models. The results indicated that the following eight variables had significant influence on the incident-related delays at the 95% confidence interval: incident type, incident severity, time of the day, day of week, median width, vertical curvature, Emergency Medical Services (EMS) involvement, and detection method.

Secondary Crashes

SCs were identified using both the static and the dynamic methods. SCs were identified using a 2-mile-2-hour spatiotemporal threshold. Dynamic approach based on speed profile data was also used to identify SCs. Descriptive statistics of the SCs identified using the dynamic method indicated that 87% of the SCs occurred within two hours after the occurrence of primary incidents (PIs). Spatially, 73% of the SCs occurred within two miles from the PI. Overall, 66% of SCs occurred within two hours of the onset of a PI and within two miles upstream of the PI. About 34% of SCs occurred beyond the most commonly used 2-mile-2-hour spatiotemporal threshold. These statistics confirm that the proposed dynamic approach identified more SCs than the traditional static method.

A Bayesian random effect complementary log-log model was used to link the probability of SC occurrence with the real-time traffic flow variables, PI characteristics, environmental, and geometric characteristics. The results indicated that several PI characteristics and real-time traffic variables influence the occurrence of SCs. The following seven variables were found to be significant at the 95% Bayesian credible interval (BCI): average detector occupancy, primary incident severity, percent of lane closure, primary incident type, primary incident clearance duration, primary incident impact duration, and primary incident occurrence time.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS/ABBREVIATIONS

AADT	Annual Average Daily Traffic
AFT	Accelerated Failure Time
ATMS	Advanced Traffic Management System
BCI	Bayesian Credible Interval
CCTV	Closed Circuit Television
D2	District 2
DMS	Dynamic Message Signs
EMS	Emergency Medical Service
FDOT	Florida Department of Transportation
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
FWC	Fish and Wildlife Conservation
GIS	Geographic Information System
HELP	Highway Emergency Local Patrol
HSM	Highway Safety Manual
ITS	Intelligent Transportation System
JSO	Jacksonville Sheriff's Office
MAC	Media Access Control
PI	Primary Incident
RCI	Roadway Characteristics Inventory
RF	Random Forests
RITIS	Regional Integrated Transportation Information System
RTMC	Regional Transportation Management Center
SC	Secondary Crash
SR	State Road
TIM	Traffic Incident Management
TMC	Transportation Management Center
USDOT	United States Department of Transportation
VBA	Visual Basic for Application

CHAPTER 1
INTRODUCTION

1.1 Background

A transportation management center (TMC) is the hub of most freeway management systems. TMC staff collect and process the data about the freeway system, combine with other operational and control data, synthesize the information, and distribute to stakeholders such as the media, other agencies, and the traveling public. This information is used to monitor the freeway operations, and to coordinate agencies' responses to traffic situations and incidents (FHWA, 2017).

With the ever-increasing deployment of Intelligent Transportation System (ITS) infrastructures across the road network, TMCs have begun to play an increasingly critical role in ensuring that these deployments are well managed and are successful in achieving their intended goals and objectives. As can be observed from Figure 1-1, a total of eleven regional TMCs (RTMCs) and two satellite TMCs are currently operational in the state of Florida.

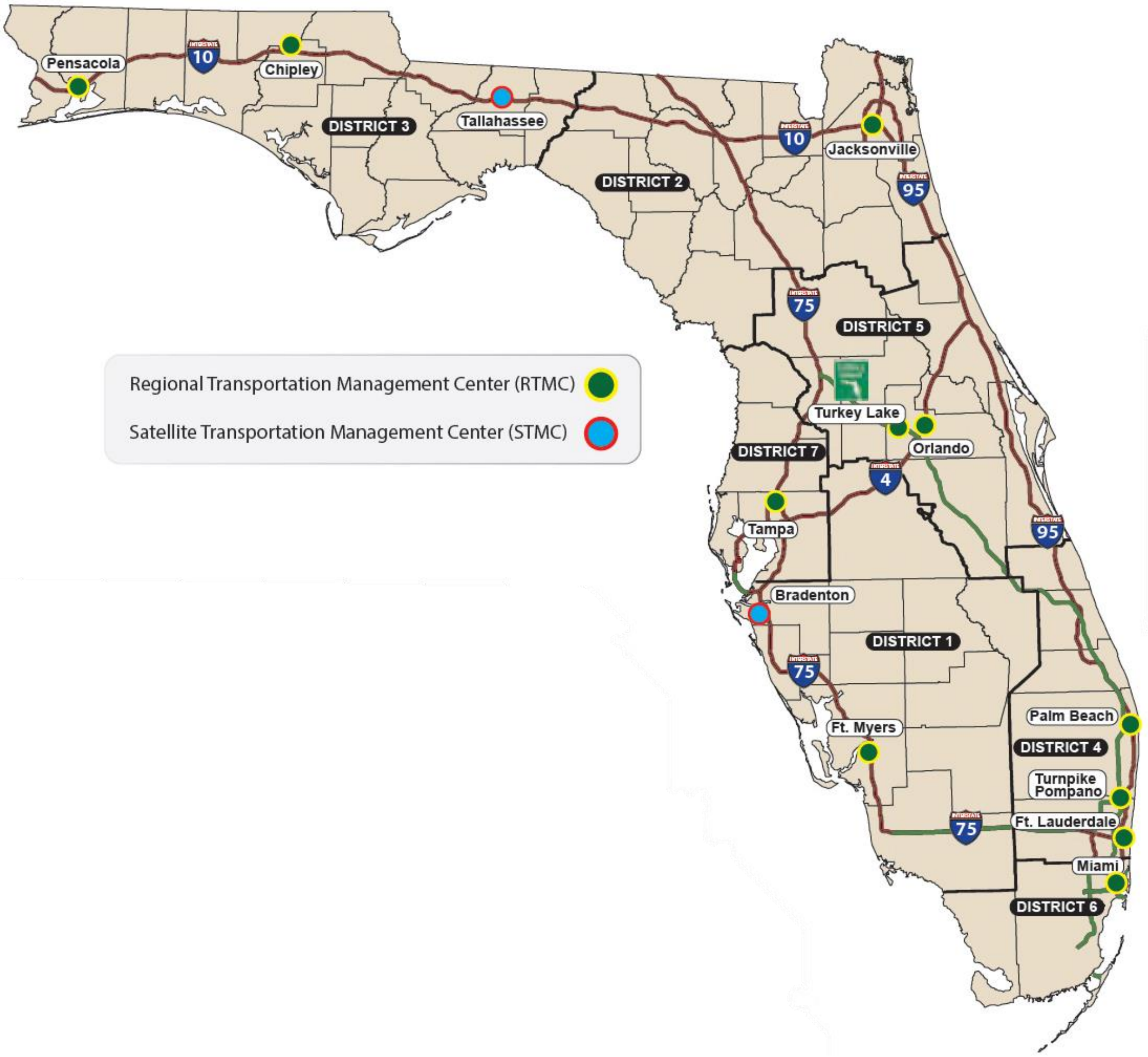


Figure 1-1: Map of Regional and Satellite TMCs in Florida (FDOT, 2017)

One of the key functions of TMCs in general, and RTMCs in particular, is traffic incident management (TIM) on the interstate system. By definition, TIM is a planned and coordinated program to detect and remove incidents and restore traffic capacity as safely and as quickly as possible (Amer et al., 2015; Carson, 2010). Table 1-1 lists the TIM program objectives and the related performance measures.

Table 1-1: TIM Program-level Performance Measures (Owens et al., 2010)

TIM Program Objective		Related Performance Measure
Traffic Incident Timeline	Reduce roadway clearance time	Time between first recordable awareness of incident by a responsible agency and first confirmation that all lanes are available for traffic flow.
	Reduce incident clearance time	Time between first recordable awareness of incident by a responsible agency and time at which the last responder has left the scene.
Reduce the number of secondary crashes		Number of unplanned incidents beginning with the time of detection of the primary incident where a collision occurs either a) within the incident scene or b) within the queue, including the opposite direction, resulting from the original incident.

A typical incident timeline, as shown in Figure 1-2, has the detection, verification, response, clearance, and recovery durations (Amer et al., 2015). In general, the timeline starts when an incident occurs, identifies key interim activities, and ends with traffic returning to normal. The specific traffic incident elements include:

- Incident detection time: the time it takes for the RTMC staff to detect an incident (i.e., $T_0 – T_1$ in Figure 1-2).
- Incident verification time: the time it takes for the RTMC staff to verify an incident (i.e., $T_1 – T_2$ in Figure 1-2).
- Incident response time: the time it takes for the agencies to respond to an incident (i.e., $T_2 – T_4$ in Figure 1-2).
- Roadway clearance time: the time between first recordable awareness of incident by a responsible agency and first confirmation that all lanes are available for traffic flow (i.e., $T_1 – T_5$ in Figure 1-2).
- Incident clearance time: the time between first recordable awareness of incident by a responsible agency and the time at which the last responder has left the scene (i.e., $T_1 – T_6$ in Figure 1-2).
- Incident impact duration: the total time the traffic is impacted by an incident (i.e., $T_0 – T_7$ in Figure 1-2).

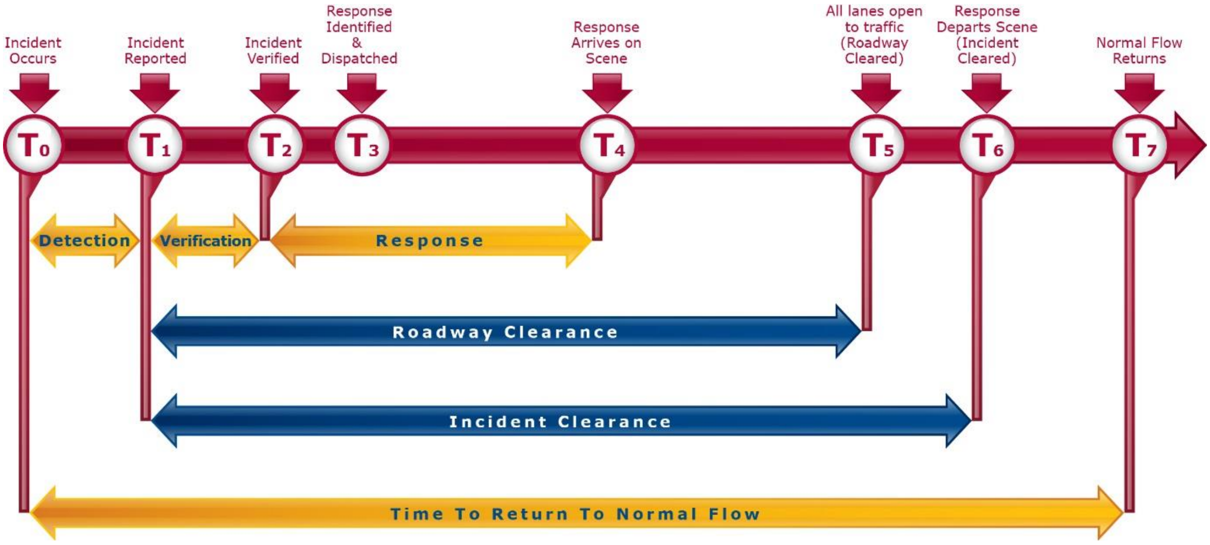


Figure 1-2: Timeline of Traffic Incident Elements (Amer et al., 2015)

Of the aforementioned incident duration elements, some elements (e.g., verification and response durations) are critical to the entire incident management process even though they are not long. Verification duration is important in determining accurate and detailed information which enables the dispatch of the most appropriate personnel and resources to the scene (USDOT-ITS, 2000). Response duration is also important since it helps save lives by ensuring rapid deployment of appropriate personnel and resources to the incident scene before the traffic backup becomes lengthy (Carson, 2010).

In addition to the verification and response durations, the incident impact duration, defined as the time taken for the traffic to return back to normal after the occurrence of the primary incident, is also critical since it affects the overall operational and safety performance of the freeway. For example, the total delay as a result of incidents is affected by the total incident impact duration (Hojati et al., 2014).

One of the strategies to reduce incident impact duration is to have better interagency coordination, which has the potential to improve incident detection and response times (USDOT-ITS, 2000). In fact, one of the Transportation Management Systems (TMS) strategies in Florida is to encourage co-location of Florida Department of Transportation (FDOT) TMC and law enforcement dispatch centers (PB Farradyne, 2006). As such, a new RTMC facility recently became operational in Jacksonville, FL, replacing the old RTMC that was housed in the FDOT District 2 Urban Office building. The old facility housed only FDOT and traffic monitoring consultant staff while other incident response agencies were located at their respective agency locations. The new facility that became operational in November 2015 has FDOT staff, TMC operators, local agency traffic signal operators, traffic monitoring consultants, and the Florida Highway Patrol (FHP) personnel under one roof. This strategy relies primarily on improving communication between agencies by providing the necessary details for optimum response which depends on accurate and rapid verification (USDOT-ITS, 2000).

Considering that incident response can be controlled by incident management teams (Lee and Fazio, 2005), co-location of incident response agencies is expected to improve incident management procedures, and hence, the overall performance of freeways. However, the actual impact of this strategy has not yet been quantified. As such, this research focuses on evaluating the performance of the new RTMC using the following five performance measures: incident verification duration, incident response duration, incident impact duration, incident-related delays, and secondary crashes.

1.2 Research Goals and Objectives

This research has two main goals:

1. evaluate the performance of the new RTMC in Jacksonville, FL; and
2. quantify the impact of incidents on the operational and safety performance of the freeway network.

The specific objectives include:

- compare the performance of the new RTMC in Jacksonville where multiple response agencies are physically co-located in the RTMC building with the performance of the old RTMC where most of the incident response agencies were housed at their respective agency locations;
- estimate the delays caused by incidents on freeways, and determine the factors affecting these delays; and
- develop a reliable approach to identify secondary crashes, and determine the factors that could potentially lead to secondary crashes.

1.3 Report Organization

The rest of this report is organized as follows:

- Chapter 2 discusses the incident verification and response durations. It discusses the incident verification and response durations before and after co-location of response agencies. It also presents the factors that influence the verification and response durations before and after co-location of response agencies.
- Chapter 3 focuses on incident impact duration. It presents a data-driven methodology to estimate the incident impact duration. It also discusses the factors that affect the incident impact durations.
- Chapter 4 discusses the delays caused by incidents on freeways. A data-driven methodology for estimating the incident-related delays is provided in this chapter. It further includes a discussion on the factors that affect these delays.
- Chapter 5 presents the analysis of secondary crashes. It discusses the static and the dynamic approaches used to identify SCs. It also presents the factors contributing to SCs.
- Chapter 6 provides a summary of this research effort and the relevant findings, conclusions, and recommendations.

CHAPTER 2
INCIDENT VERIFICATION AND RESPONSE DURATION

This chapter focuses on evaluating the impact of co-locating response agencies under one roof, i.e., RTMC facility, on the operational performance of the RTMC. Since co-location effectiveness relies on improving communication between agencies by providing the necessary details for optimum response which depends on accurate and rapid verification (USDOT-ITS, 2000), the effectiveness of co-location of response agencies was quantified using incident response and verification durations. This chapter also discusses the factors that influence the verification and response durations of incidents.

2.1 Existing Studies

2.1.1 Incident Verification and Response Duration Definitions

Incident verification is the process of determining the precise location and nature of the incident (USDOT-ITS, 2000). Incident verification duration is the time between an incident being reported and the incident being verified (Amer et al., 2015). During verification, response agencies confirm the occurrence of an incident, determine its exact location, and obtain all relevant details about the incident (Amer et al., 2015).

On the other hand, incident response duration is measured from the time an incident response team was notified of an incident to when they arrived at the incident scene (Nam and Mannering, 2000). Response time includes dispatch duration and travel time to the incident scene (Nam and Mannering, 2000). The optimum response is sending the right equipment to the incident scene quickly to avoid deploying either too few or too many resources which could potentially increase the cost and adversely impact the effectiveness of the response (USDOT-ITS, 2000).

2.1.2 Factors Affecting Incident Duration

Incident duration is a function of various factors. For example, a Michigan study (Ghosh et al., 2014) that analyzed factors that affect clearance time suggested that the following factors affect the incident clearance time: time of the day, season, location of incident (i.e., at ramp, or on freeway mainline), and number of vehicles involved in the incident. It was observed that clearance times were 12% shorter at night than during daytime, and 21% quicker during weekends compared to weekdays. Winter and absence of exit ramps were associated with longer incident clearance duration. In addition, single vehicle incidents were cleared 37% sooner than multi-vehicle incidents, incidents on the right shoulder were cleared 31% quicker while incidents on a single lane were cleared 28% faster than incidents on multiple lanes.

Another study that evaluated incidents caused by disabled and abandoned vehicles (Chimba et al., 2014) identified number of lanes, the percentage of lanes closed, presence of work zone, and truck involvement as significant factors that affect incident duration. In addition, the authors suggested that incident duration can be influenced by the incident notification agency; incidents that were assisted by Highway Emergency Local Patrol (HELP), synonymous to the Florida Road Ranger Service Patrol, had shorter durations compared to the incidents that were assisted by law enforcement agencies and the general public.

Furthermore, a study by Zhang et al. (2012) analyzed large-scale incidents which were characterized by having an incident duration of more than 2 hours. Results of the study indicated that crashes, vehicle fire, number of vehicles involved in an incident, rain, and peak hours were associated with longer incident durations for non-large-scale incidents. However, large-scale incidents had longer durations when an incident occurred within a work zone, on a curved roadway segment, and during morning peak hours. On the other hand, incidents occurring in the afternoon peak hours tend to have shorter durations. The large-scale incident duration was found to be 15% longer on curved roadway segments than on straight segments and 13% longer when the incident resulted in a secondary crash compared to when it did not result in a secondary crash.

In summary, the existing studies have shown that incident duration is affected by several factors including spatial factors such as presence of a work zone, involvement of a ramp; roadway characteristics such as shoulder type, lane width, number of lanes; temporal factors such as time of the day, weather conditions; and incident related attributes such as incident notification agency and number of involved vehicles. In addition to these factors, the analysis in this study considered other attributes such as the detection method, incident severity, and number of response agencies.

2.2 Data

Traffic incident data were required to evaluate the incident verification and response durations. These data were retrieved from the District 2 SunGuide® database. SunGuide® is an Advanced Traffic Management System (ATMS) software used for incident management to process and archive incident data on freeways. For this study, the following information was retrieved from the SunGuide® database for the years 2015-2017.

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

All the aforementioned variables are easy to understand except event type and detection method, and these are discussed below.

The SunGuide® database has numerous categories describing the type of an incident that occurred on a freeway. The categories include: crash, disabled vehicles, debris on roadway, emergency vehicles, police activity, vehicle fire, flooding, pedestrian, abandoned vehicles, construction, and other. For this study, traffic incidents were categorized into three groups: crashes, vehicle problems, and hazards. Crashes are self-explanatory. Vehicle problems included all events that are not crashes but are vehicle-related, e.g., disabled vehicles, abandoned vehicles, etc. Hazards included all objects on the roadway with the potential of causing crashes, e.g., debris on roadway, flooding, wildlife, etc.

The database has various detection methods that are used in identifying incidents. Some of the detection methods in the database are Road Rangers, Florida Highway Patrol (FHP), 511 Probe, closed circuit televisions (CCTVs), County Police, Jacksonville Sheriff's Office (JSO), WAZE, and motorists. In this study, the incident detection methods were grouped into two categories: off-site detection methods and on-site detection methods. Off-site detection methods included methods that detect incidents remotely, i.e., from the TMCs through CCTVs, motorists' phone calls, or WAZE (a mobile-based software application which utilizes information provided by road users). The on-site detection methods involved detecting incidents by highway patrol services such as District 2 Road Rangers, FHP, and JSO, who are at the incident scene.

2.3 Methodology

Hazard-based models are suitable for analyzing time-dependent variables and facilitating the interpretation of data using a sequence of probabilities (Li, 2017). This study intended to analyze the incident verification and response durations. Hazard-based models are suitable for analyzing incident verification and response durations since these are time-dependent variables. Hazard-based models provide the probabilities that change over time (Washington et al., 2003) and allow the explicit study of the relationship between incident durations and the explanatory variables (Chung, 2010). These models enable the determination of the likelihood of duration to end in the next short time period given it has lasted for as long as it has (Nam and Mannering, 2000).

Hazard-based models were developed to describe the conditional likelihood of an incident ending at some time $t+\delta t$ given that the duration has continued until time t. These models consider T as a random variable time and t as a specific time. The cumulative density function and the density function are represented in Equations 2-1 and 2-2, respectively. In Equation 2-1, P represents the probability of the incident duration to end before time t. The hazard function is described by Equation 2-3 that shows the conditional probability for an event to occur at time $t+\delta t$ given that it has not occurred until time t. The denominator in Equation 2-3 represents the survivor function which shows the probability of a duration being equal to or greater than some specified time t (Washington et al., 2003).

$$F(t) = P(T < t) \tag{2-1}$$

$$f(t) = \frac{dF(t)}{dt} \tag{2-2}$$

$$h(t) = \frac{f(t)}{[1 - F(t)]} \tag{2-3}$$

The first derivative of the hazard function with respect to time shows the probability of the duration ending soon after it has lasted for as long as it has. If $(dh(t))/dt > 0$ for all values of t, then the hazard is monotonically increasing, which means the probability that the incident will end soon increases as the incident duration increases. If $(dh(t))/dt < 0$ for all values of t, then the hazard is monotonically decreasing, which means the probability that the incident will end soon decreases as the incident duration increases. If $(dh(t))/dt < 0$ for some values of t and

$(dh(t))/dt > 0$ for other values of t, then hazard is non-monotonically decreasing, which means the probability that the incident will end soon decreases or increases depending on how long the incident has lasted. Finally, if $(dh(t))/dt = 0$ for all values of t, then the probability that the incident will end soon does not depend on how long it has lasted (Nam and Mannering, 2000; Washington et al., 2003).

For the hazard-based models to take account of the covariates, the accelerated failure time model, shown in Equation 2-4, is used. This model type assumes that covariates rescale time directly in the survivor function. The $h_o(t)$ denotes the baseline hazard function, X is a covariate vector, and β is a vector of estimable parameters (Washington et al., 2003). For the applied accelerated failure time model, there is a need to assume a particular shape for the hazard rate. In this study, three shapes, Weibull, log-logistic, and lognormal distributions, were examined.

$$h(t|X) = h_o[tEXP(\beta X)]EXP(\beta X) \tag{2-4}$$

The Weibull distribution allows for monotonically increasing, monotonically decreasing, and independent hazard. The hazard is monotonically increasing in duration if the Weibull distribution parameter $p > 1$; if $p < 1$, the hazard is monotonically decreasing in duration; finally, if $p = 1$, the hazard is constant in duration. The log-logistic distribution allows for non-monotonic hazard functions such that the hazard is monotonically decreasing in duration for a log-logistic distribution with $p < 1$. If $p > 1$ then the hazard increases in duration from zero to an inflection point and decreases towards zero after that but if $p = 1$ then the hazard is monotonically decreasing in duration from parameter λ of the log-logistic distribution (Washington et al., 2003).

The AFT model is a fully parametric model that has various distribution alternatives, e.g., Weibull and lognormal distributions. Selection of the best fit parametric distribution is achieved through comparison of the likelihood ratio statistics of the candidate distributions. The likelihood ratio statistic is chi-squared distributed with degrees of freedom equal to the number of parameters analyzed in the model. Equation 2-5 shows the formula of likelihood ratio statistics where LL (0) is the initial log likelihood when all parameters are equal to zero and LL (β) is log likelihood at convergence.

$$X^2 = -2(\mathrm{LL}(0) - \mathrm{LL}(\beta_C)) \tag{2-5}$$

Determination of changes in incident response and verification durations after incident response agencies were co-located under the same roof was achieved by comparing the 95% confidence interval of the model coefficients in the respective study periods (i.e., before and after co-location). This comparison was performed for coefficients that were observed to be significant in the before- and after-periods. The coefficients whose 95% confidence interval did not overlap showed a significant change in the variable.

2.4 Results

2.4.1 Incident Verification Duration

The new RTMC in Jacksonville was opened in November 2015 with the intention of improving incident management procedures by co-locating multiple incident response agencies. A before-and-after analysis was conducted to gain insights on the impact of co-location of incident management agencies (i.e., FDOT, FHP, etc.) on incident verification duration. At the time of this research, incident data were available till June 2017. Hence, the after-period included 18 months of data from January 2016 to June 2017. To be consistent, the before-period also included 18 months of data from January 2014 to June 2015.

The incident data for the before-period (January 2014 – June 2015) and the after-period (January 2016 – June 2017) for freeways in Duval County comprised 41,378 and 43,086 incidents, respectively. About 36,594 incidents in the before-period and 36,654 incidents in the after-period contained verification duration information. Some incidents were not analyzed because the verification duration was negative, which could be attributed to data input errors.

Table 2-1 provides the summary statistics of incident verification durations in the before- and after-periods. For some of the incident categories, shorter average incident verification durations were observed after co-location than before. For example, the average verification duration for hazards was 8 minutes before co-location and 7 minutes after co-location. The average verification duration for incidents on weekends was 18 minutes before co-location compared to 17 minutes after co-location. Also, the average verification duration for incidents detected by FHP was 17 minutes before co-location and 15 minutes after co-location.

As expected, crashes were found to take longer to be verified compared to vehicle problems, Table 2-1 shows that the average verification duration for vehicle problems both before and after co-location was 3 minutes while the average verification duration for crashes was 15 minutes. Incidents that resulted in less than 25% of lane closure had the average verification duration of 7 and 8 minutes before and after co-location, respectively. In this study, the percentage of lane closure is computed by comparing the number of lanes closed against the total number of travel lanes, e.g., for a four-lane freeway, closing one lane is considered as 25% lane closure. The average verification duration for incidents that occurred in off-peak hours (8 and 9 minutes before and after co-location, respectively) were found to be longer than the average verification duration during peak hours (6 and 7 minutes before and after co-location, respectively). Moreover, the average verification duration for incidents that were verified by the on-site detection methods (i.e., District 2 Road Rangers, JSO, FHP, etc.) was 7 and 8 minutes before and after co-location, respectively. Off-site detection methods led to relatively shorter average verification duration (3 and 4 minutes before and after co-location, respectively) compared to the average verification duration for incidents detected using on-site detection methods. It is worth noting that the partnership with WAZE has sometimes led to slightly longer verification times due to location mapping issues and has potentially impacted incident verification durations. The incident verification durations with respect to incident, spatiotemporal, and agency operations attributes before and after the opening of the new RTMC are discussed below.

- *Incident Type:* Crashes had the highest percentage of incidents that were verified during both the before-period (Jan 2014 - June 2015) and the after-period (Jan 2016 - June 2017). Figure 2-1(a) shows that the proportion of crashes in the after-period (74%) was greater than the proportion of crashes in the before-period (67%). This increase in crashes could be attributed to the increasing crash rate being observed nationwide in recent years (NHTSA, 2017). Conversely, the proportion of hazards (9%) and vehicle problems (61%) in the before-period were found to be higher than the proportion of hazards (7%) and vehicle problems (54%) in the after-period. This observed decrease in the frequency of verified hazards and vehicle problems could be attributed to the improved on-road help services which have ensured that most of the hazards and vehicle problems were dealt with as soon as detected.

According to Figure 2-1(b), verification of crashes was slightly quicker after co-location than before. For example, 81% of crashes were verified within 30 minutes in the after-period, while 78% of crashes were verified within 30 minutes in the before-period. Figures 2-1(c) and 2-1(d) show a similar trend in the verification duration of vehicle problems and hazards. For instance, approximately 88% of vehicle problems were verified within 30 minutes in the before-period, while about 89% of vehicle problems were verified within 30 minutes in the after-period. Similarly, 85% of hazards were verified within 30 minutes before co-location while 89% were verified within 30 minutes after co-location.

- *Time of the Day:* Incidents were verified quicker after co-location than before during both peak and off-peak hours. For example, Figure 2-2(a) shows that 40%, 65%, and 81% of the incidents in the after-period during off-peak hours were verified within 10, 20, and 30 minutes, respectively. On the other hand, 31%, 59%, and 78% of the incidents in the before-period were verified within 10, 20, and 30 minutes, respectively. Figure 2-2(b) shows that during peak hours, 43%, 69%, and 85% of the incidents in the after-period were verified within 10, 20, and 30 minutes, respectively. Conversely, 37%, 67%, and 84% of the incidents were verified within similar durations in the before-period.

- *Day of Week:* As can be observed from Figures 2-2(c) and 2-2(d), the incident verification durations were found to be longer in the before-period compared to the after-period for incidents that occurred on both weekdays and weekends. For example, on weekdays, 35% of the incidents were observed to be verified within 10 minutes before co-location, while 43% of the incidents were verified within 10 minutes after co-location. Conversely, 29% of the incidents were verified within 10 minutes on weekends before co-location, while 34% of the incidents were verified within 10 minutes on weekends after co-location.

- *Detection Method:* District 2 (D2) Road Rangers and FHP detected most of the incidents. These methods account for the detection of approximately 89% and 90% of the incidents that were detected before and after co-location of response agencies, respectively. Figure 2-3 shows that D2 Road Rangers detected most of the incidents that were verified before co-location while FHP detected most of the incidents that were verified after co-location.

Table 2-1: Summary of Incident Verification Duration with Respect to Various Attributes

Variable	Categories	Before Period Jan 2014 - June 2015					After Period Jan 2016 - June 2017				
		Frequency	Average (min.)	Standard Deviation (min.)	Minimum (min.)	Maximum (min.)	Frequency	Average (min.)	Standard Deviation (min.)	Minimum (min.)	Maximum (min.)
Incident attributes											
Incident type	Hazards	5,182	8	13.2	1	189	5,064	7	11.7	1	130
	Crashes	13,720	15	20.6	1	279	18,034	15	19.6	1	286
	Vehicle problems	22,476	3	7.2	1	156	19,988	3	7.4	1	118
Lane closure	≤ 25%	35,899	7	14.9	1	279	37,904	8	15.5	1	286
	> 25%	3,431	6	10.6	1	186	4,003	6	10.7	1	268
Ramp involvement	No	40,217	7	14.5	1	279	42,010	8	15.0	1	286
	Yes	1,161	5	9.8	1	131	1,076	6	8.1	1	61
Severity	Minor	39,166	7	14.5	1	279	40,136	8	15.2	1	286
	Moderate	1,608	7	12.2	1	97	1,940	6	11.2	1	268
	Severe	509	6	12.0	1	186	1,010	6	10.5	1	130
Spatiotemporal attributes											
Time of the day	Peak hour	22,242	6	12.7	1	178	22,063	7	14.1	1	268
	Off-peak	19,136	8	16.2	1	279	21,023	9	15.7	1	286
Roadway	I-10	5,113	10	16.8	1	279	5,601	10	16.8	1	238
	I-95	12,112	7	13.9	1	214	14,121	7	14.2	1	258
	I-295	17,955	5	13.0	1	226	16,873	6	13.6	1	286
	SR 202	3,402	7	15.0	1	189	3,091	6	13.4	1	177
	I-75	2,796	17	16.9	1	148	3,404	17	19.5	1	221
Day of week	Weekends	3,816	18	22.2	1	214	4,510	17	21.3	1	286
	Weekdays	37,562	6	13.1	1	279	38,577	7	13.7	1	263
Agency operations attributes											
Detection method	Off-site	3,460	3	6.9	1	156	3,639	4	8.9	1	150
	On-site	37,821	7	14.8	1	279	39,359	8	15.3	1	286

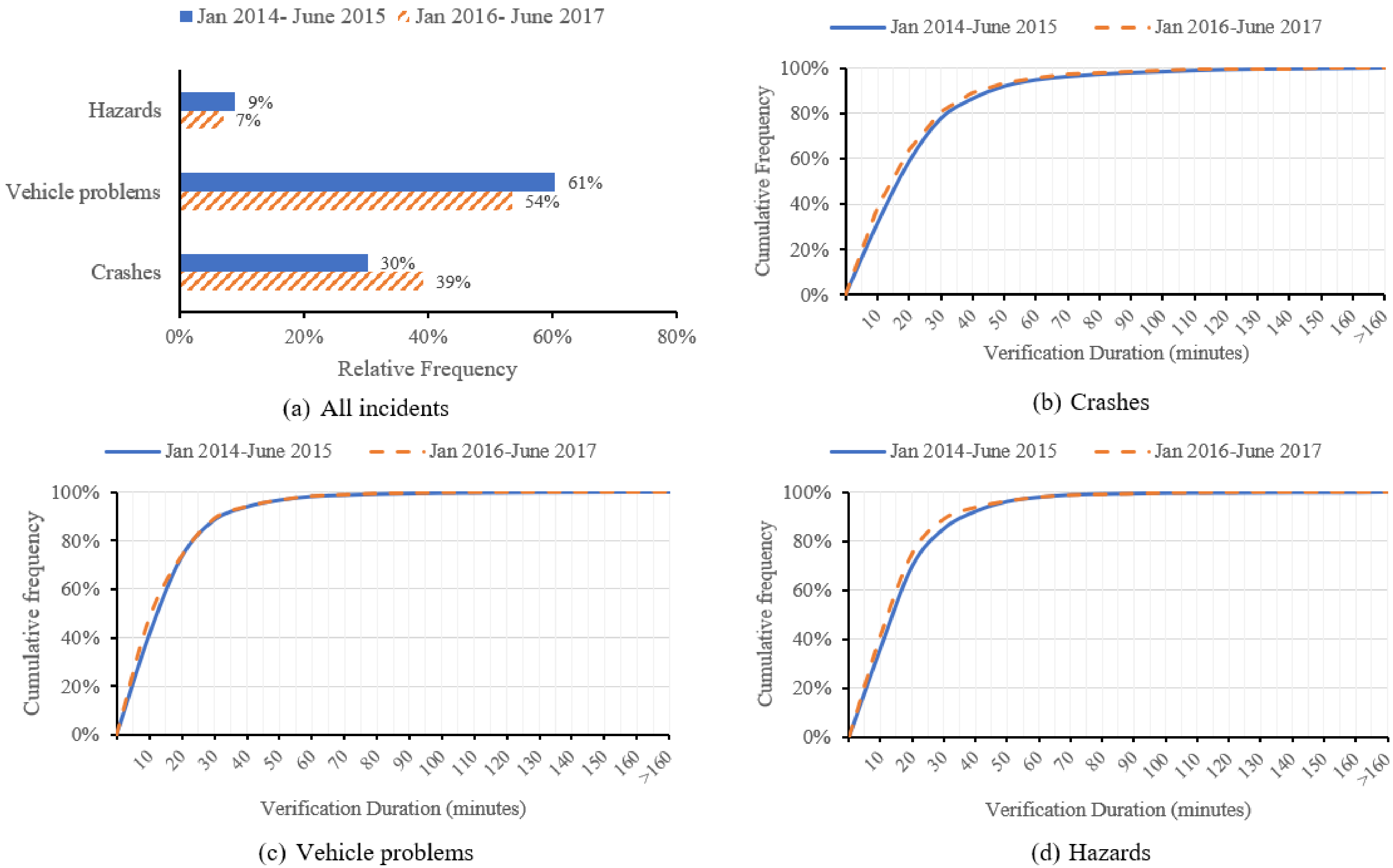
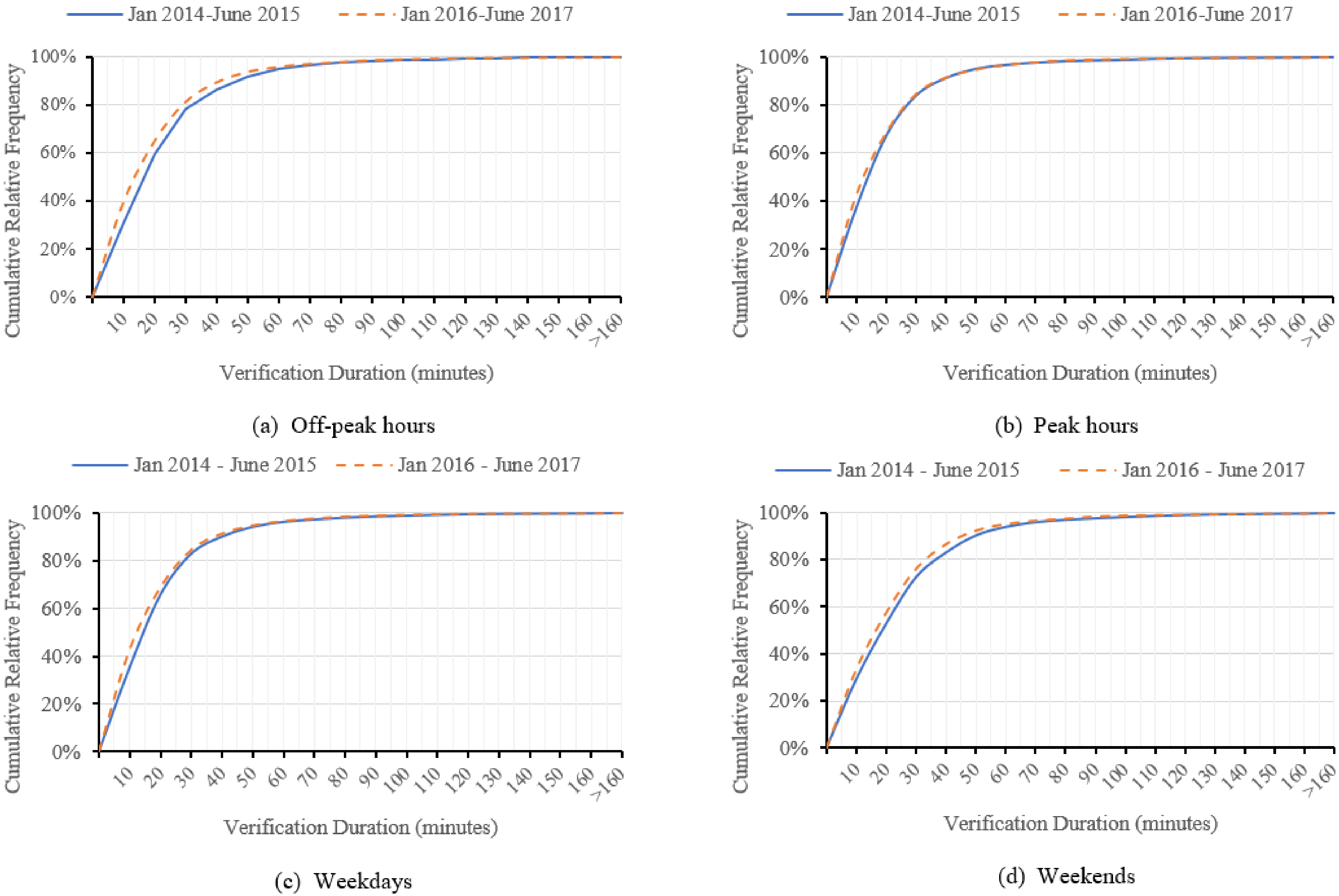


Figure 2-1: Distribution of Incident Verification Duration with Respect to Incident Type



(a) Off-peak hours

(b) Peak hours

(c) Weekdays

(d) Weekends

Figure 2-2: Distribution of Incident Verification Duration with Respect to Various Temporal Attributes

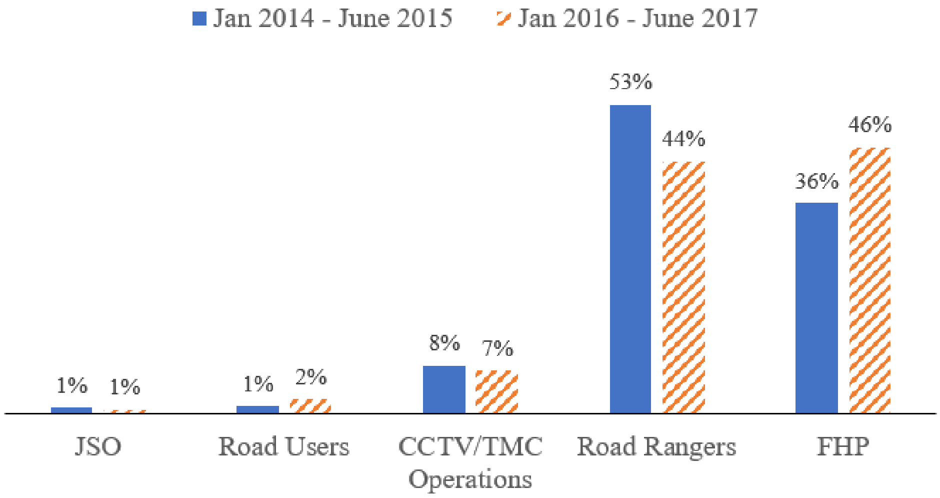


Figure 2-3: Distribution of Incident Verification Duration with Respect to Detection Method

2.4.2 Factors Affecting Incident Verification Duration

Table 2-2 presents the model results. It can be inferred from that table that incident type, percent of lane closure, incident severity, roadway, detection method, time of the day, day of week, and traffic volume were significant factors during both before- and after-periods. These factors are discussed below. Only the incident verification duration of incidents on I-95 showed a significant difference before and after co-location at the 95% level of confidence.

- *Incident Type:* Crashes had verification durations that are longer than hazards both before and after co-location. The verification durations for vehicle problems were shorter than the verification durations for hazards. Verification of crashes is expected to take longer because of the need for accurate information in selection and dispatch of appropriate response personnel.

  Table 2-2 shows that the verification duration of crashes was 188% and 220% longer than the verification of hazards before and after co-location, respectively. However, the difference between the verification duration of crashes before and after co-location of response agencies was not significant. Verification duration of vehicle problems was 39% and 37% quicker than verification of hazards both before and after co-location, respectively. This could be attributed to the effectiveness of on-road help services (i.e., Road Rangers) in detecting and verifying vehicle problems. The differences between the average verification durations for vehicle problems before and after co-location was not significant at 95% confidence interval.

- *Lane Closure:* Higher percentage of lane closure led to a decrease in the verification duration both before and after co-location. The verification duration of incidents associated with lane closure of more than 25% was 29% and 28% quicker than the verification duration of incidents that caused lane closure of less than 25% during before- and after-periods, respectively. A higher percentage of lane closure can cause unexpected traffic congestion, potentially leading to quicker detection by the TMC personnel through CCTV cameras. RTMC staff detect severe incidents using the roadway congestion maps. The effectiveness of CCTV cameras and roadway congestion maps was improved by having response agencies under one roof, sharing similar video feed of incidents and communicating directly while making decisions.

- *Incident Severity:* Severe and moderate incidents had quicker verification durations than minor incidents both before and after co-location. The verification duration of severe incidents was 21% and 26% quicker than the verification duration of minor incidents for before- and after-periods, respectively. The verification duration of moderate incidents was 26% and 19% quicker than the verification duration of minor incidents for before- and after-periods, respectively. However, the average verification durations for both severe and moderate incidents that occurred in before- and after-periods were not statistically different at 95% confidence interval.

- *Roadway:* Incidents that occurred on both I-95 and I-295 had shorter verification durations compared to incidents that occurred on I-10 both before and after co-location. Moreover, the average verification durations of incidents that occurred before and after co-location on I-295 were significantly different at 95% confidence interval. The relatively longer incident verification durations on I-10 could at least in part be due to limited ITS coverage along the I-10 corridor.

- *Time of the Day:* Incidents that occurred during peak hours had shorter verification durations than incidents during the off-peak hours in the period before co-location of response agencies. It is assumed that due to the expectation of incidents during the peak hours, RTMC operators handle incidents that occur during peak hours quicker compared to incidents that occur during off-peak hours. Also, off-peak hours include nighttime when the response agencies are short staffed. However, the average verification durations of incidents during peak hours was not significantly quicker than during off-peak hours after co-location of response agencies.

- *Day of Week:* Incidents that occurred on weekends had longer verification durations compared to incidents that occurred on weekdays both before and after co-location. Incidents that occurred on weekends had 88% longer verification durations than incidents that occurred during weekdays in the before-period. Incidents that occurred on weekends had 73% longer verification durations than incidents that occurred during weekdays in the after-period. Incidents were verified quicker during the weekdays because of the availability of response personnel. For example, within the study area, Road Rangers do not work during weekends.

- *Traffic Volume (AADT):* Incidents that occurred on corridors with higher AADT were associated with quicker verification durations. Increase in the AADT led to 8% shorter verification durations in the period before co-location of response agencies. Similarly, increase in the AADT was associated with 9% quicker verification durations in the period after co-location of response agencies.

- *Detection Method:* Incidents that were detected by off-site detection methods had shorter verification durations than incidents detected by on-site detection methods both before and after co-location. The verification duration of incidents by off-site detection methods was 32% quicker than on-site detection methods both before and after co-location. However, the difference between the average verification durations before and after co-location of response agencies was not significant at 95% confidence interval.

Table 2-2: Factors Affecting Incident Verification Duration before and after Co-location of Response Agencies

		Before Period Jan 2014 – June 2015				After Period Jan 2016 – June 2017			
Variable	**Categories**	**Estimates**	***p*-value**	**% Change**	**CI of the Coefficient**	**Estimates**	***p*-value**	**% Change**	**CI of the Coefficient**
Incident attributes									
Incident type	Hazards								
	Crashes	**1.058**	**0.000**	**188**	0.987 - 1.129	**1.163**	**0.000**	**220**	1.089 - 1.237
	Vehicle problems	**-0.495**	**0.000**	**-39**	(-0.556) - (-0.434)	**-0.464**	**0.000**	**-37**	(-0.532) - (-0.395)
Lane closure	≤ 25%								
	> 25%	**-0.349**	**0.000**	**-29**	(-0.421) - (-0.277)	**-0.331**	**0.000**	**-28**	(-0.400) - (-0.262)
Ramp involvement	Absent								
	Present	-0.110	0.130	-10	--	-0.200	0.071	-18	--
Severity	Minor								
	Moderate	**-0.303**	**0.000**	**-26**	(-0.415) - (-0.191)	**-0.213**	**0.000**	**-19**	(-0.313) - (-0.113)
	Severe	**-0.234**	**0.001**	**-21**	(-0.433) - (-0.035)	**-0.302**	**0.000**	**-26**	(-0.457) - (-0.148)
Spatiotemporal attributes									
Roadway	I-10								
	I-95	**-0.201**	**0.000**	**-18**	**(-0.258) - (-0.145)**	**-0.107**	**0.000**	**-10**	**(-0.163) - (-0.051)**
	I-295	**-0.238**	**0.000**	**-21**	(-0.291) - (-0.184)	**-0.130**	**0.000**	**-12**	(-0.184) - (-0.075)
	SR 202	**-0.212**	**0.000**	**-19**	(-0.281) - (-0.142)	**-0.152**	**0.000**	**-14**	(-0.225) - (-0.078)
	I-75	**0.399**	**0.000**	**49**	0.303 - 0.495	**0.347**	**0.000**	**41**	0.254 - 0.440
Time of the day	Off-peak								
	Peak hour	**-0.043**	**0.000**	**-4**	(-0.073) - (-0.012)	**-0.022**	**0.044**	**-2**	(-0.055) – (0.010)
Day of week	Weekday								
	Weekend	**0.631**	**0.000**	**88**	0.557 - 0.705	**0.551**	**0.000**	**73**	0.483 - 0.618
AADT		**-0.081**	**0.000**	**-8**	(-0.116) - (-0.046)	**-0.099**	**0.000**	**-9**	(-0.135) - (-0.064)
Agency operations attributes									
Detection method	On-site								
	Off-site	**-0.385**	**0.000**	**-32**	(-0.439) - (-0.330)	**-0.427**	**0.000**	**-35**	(-0.484) - (-0.371)

Note: Bold values represent significant estimates at 95% confidence interval; "CI" means confidence interval.

2.4.3 Incident Response Duration

Incident response duration is the time from the verification of an incident by the RTMC operator to the time the first responder arrives at the incident location (Amer et al., 2015). It includes the time required to determine appropriate equipment and response personnel, the time to communicate between related agencies, and the travel time to the incident site (Nam and Mannering, 2000). In this study, the incident response duration is defined, as described by FHWA and SunGuide®, as the time between incident verification and the arrival of the first responder at the incident scene. It includes the dispatch duration and responders' travel time to the incident scene. The responders include but are not limited to FHP, Fire Department, D2 Road Rangers, JSO, Florida Fish and Wildlife Conservation (FWC), and Emergency Medical Services (EMS).

A before-and-after analysis was conducted to gain insights on the impact of co-location of incident management agencies (i.e., FDOT, FHP, etc.) on incident response duration. As discussed earlier, January 2014 to June 2015 was considered as the before-period, while January 2016 to June 2017 was considered as the after-period. The analysis was based on approximately 36,594 incidents that occurred in the before-period and 36,654 incidents that occurred in the after-period. Some incidents were not analyzed because the response duration was negative, which could be attributed to data input errors.

Table 2-3 provides the summary statistics of incident response durations in before- and after-periods. For some variables, shorter average response durations were observed in the after-period compared to the before-period. For example, the average response duration for severe incidents was 6 minutes in the before-period and 5 minutes in the after-period.

Crashes had longer average response durations compared to vehicle problems. Table 2-3 shows that in the before-period, the average response duration for vehicle problems was 2 minutes while the average response duration for crashes was 6 minutes. In the after-period, the average response duration of vehicle problems and crashes was 3 minutes and 7 minutes, respectively. The incident response durations with respect to incident, spatiotemporal, and agency operations attributes before and after the opening of the new RTMC are discussed below.

- *Incident Type:* Figure 2-4(a) shows the distribution of incidents analyzed in the study with respect to the incident type. An 8% increase in crashes was observed in the after-period compared to the before-period. This increase could be attributed to the increasing crash rate being observed nationwide in recent years (NHTSA, 2017). On the contrary, the proportion of hazards and vehicle problems in the before-period were found to be higher than the proportion of hazards and vehicle problems in the after-period. This observed decrease could be attributed to the improved on-road help services which have ensured that most of the hazards and vehicle problems were dealt with as soon as detected.

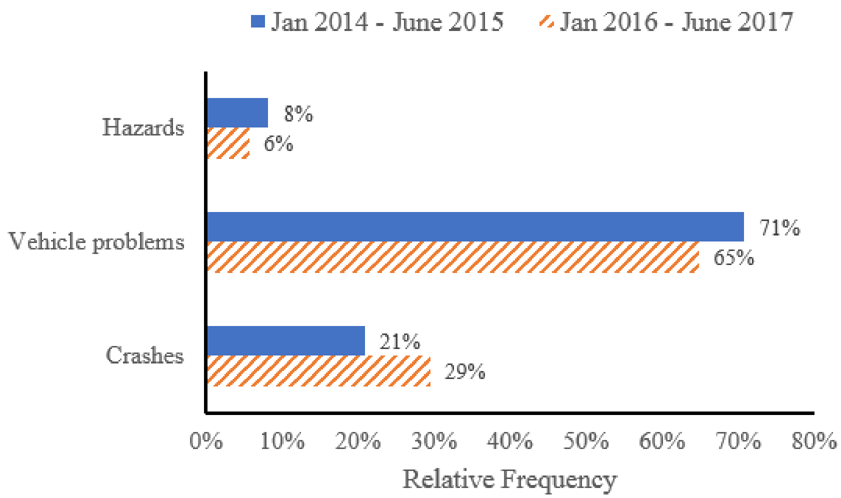
  Figures 2-4(b), 2-4(c), and 2-4(d) show the distributions of the incident response durations before and after co-location for crashes, vehicle problems, and hazards, respectively. These figures show similar distributions between before- and after-periods. However, all these figures show that the highest percentage of incidents (approximately 90%) are responded within 30 minutes.

Table 2-3: Summary of Incident Response Duration with Respect to Various Attributes

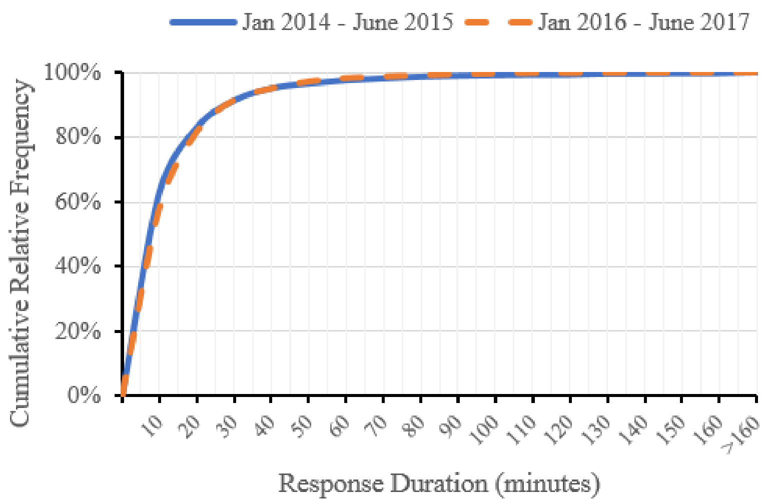
Variable	Categories	Before Period January 2014 – June 2015					After Period January 2016 – June 2017				
		Frequency	Average (min.)	Standard Deviation (min.)	Minimum (min.)	Maximum (min.)	Frequency	Average (min.)	Standard Deviation (min.)	Minimum (min.)	Maximum (min.)
Incident attributes											
Incident type	Hazards	5,182	3	7.2	1	148	5,064	3	8.5	1	152
	Crashes	13,720	6	12.8	1	206	18,034	7	12.0	1	187
	Vehicle problems	22,476	2	6.3	1	162	19,988	3	6.7	1	172
Lane closure	≤ 25%	35,899	3	7.8	1	206	37,904	4	8.6	1	187
	> 25%	3,431	5	9.6	1	162	4,003	6	10.4	1	175
Ramp involvement	No	40,217	3	8.1	1	206	42,010	4	8.9	1	187
	Yes	1,161	5	11.2	1	188	1,076	5	7.3	1	55
Severity	Minor	39,166	3	7.9	1	206	26,909	4	8.6	1	187
	Moderate	1,608	6	11.9	1	188	1,524	7	10.4	1	130
	Severe	509	6	14.1	1	148	633	5	10.5	1	131
Spatiotemporal attributes											
Time of the day	Peak hour	22,242	3	8.5	1	206	22,063	4	8.6	1	175
	Off-peak	19,136	3	7.7	1	188	21,023	4	9.1	1	187
Roadway	I-10	5,113	4	9.6	1	179	5,601	4	7.9	1	152
	I-95	12,112	4	9.2	1	178	14,121	4	9.3	1	150
	I-295	17,955	3	7.4	1	206	16,873	4	8.9	1	187
	SR 202	3,402	2	6.3	1	206	3,091	2	5.7	1	107
	I-75	2,796	6	13.1	1	108	3,404	5	13.2	1	172
Day of week	Weekend	3,816	9	17.3	1	162	4,510	9	15.2	1	187
	Weekday	37,562	3	7.7	1	206	38,577	4	8.3	1	175
Agency operations attributes											
Detection method	On-site	37,828	2	6.7	1	188	39,359	3	7.9	1	187
	Off-site	3,460	10	14.7	1	206	3,639	10	13	1	172

- *Day of Week:* Figure 2-5(a) shows the distribution of response duration for the incidents that occurred on weekdays. Almost 80% of the incidents were responded to within 20 minutes before and after co-location. Figure 2-5(b) shows the distribution of the response duration of incidents that occurred on weekends. Approximately 80% of the incidents were responded to within 20 minutes. The distributions of incidents before and after co-location showed only a slight difference. For example, 54%, 72%, and 84% of the incidents in the before-period were responded to within 10, 20, and 30 minutes, respectively. Approximately 51%, 74%, and 88% of the incidents in the after-period were responded to within 10, 20, and 30 minutes, respectively.

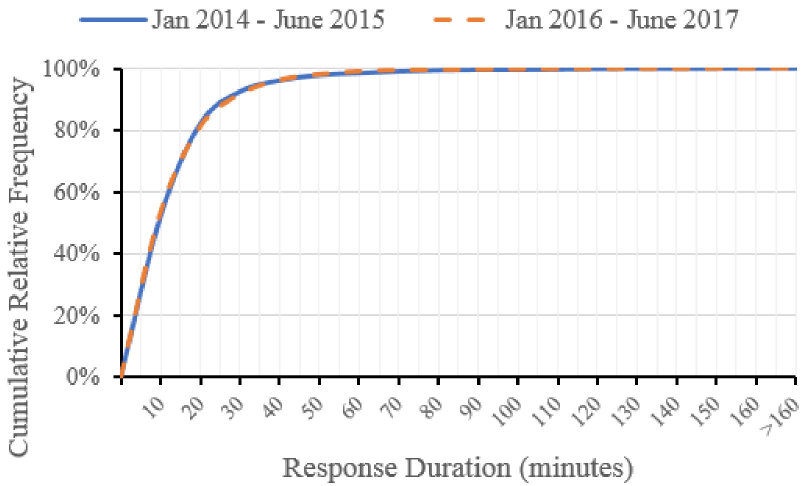
- *Time of the Day:* Figure 2-5(c) shows the distribution of the response duration for incidents that occurred during off-peak hours. Approximately, 80% of the incidents that occurred during off-peak hours were responded to within 20 minutes. Similarly, Figure 2-5 (d) shows that almost 80% of the incidents that occurred during peak hours were responded to within 20 minutes. The response duration for incidents that occurred during off-peak hours and peak hours exhibited similar distributions before and after co-location, respectively. For example, for both before- and after-periods, approximately 55%, 80%, and 90% of the incidents were responded to within 10, 20, and 30 minutes, respectively. For both before- and after-periods, almost 60%, 80%, and 90% of the incidents were responded to within 10, 20, and 30 minutes, respectively.



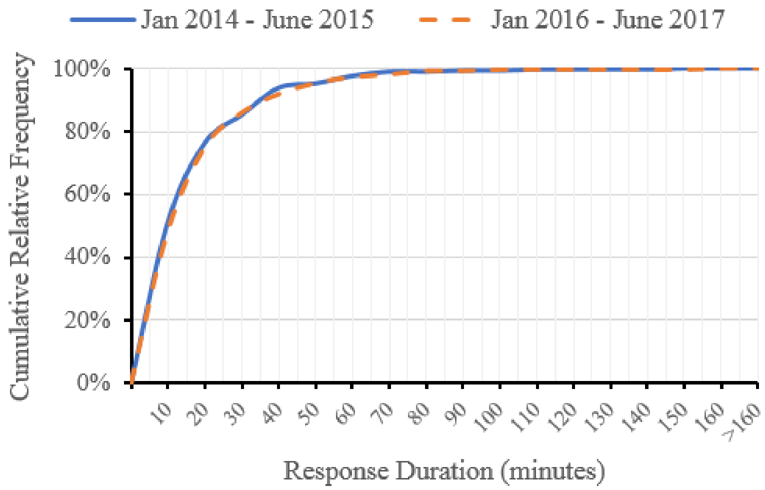
(a) All Incidents



(b) Crashes

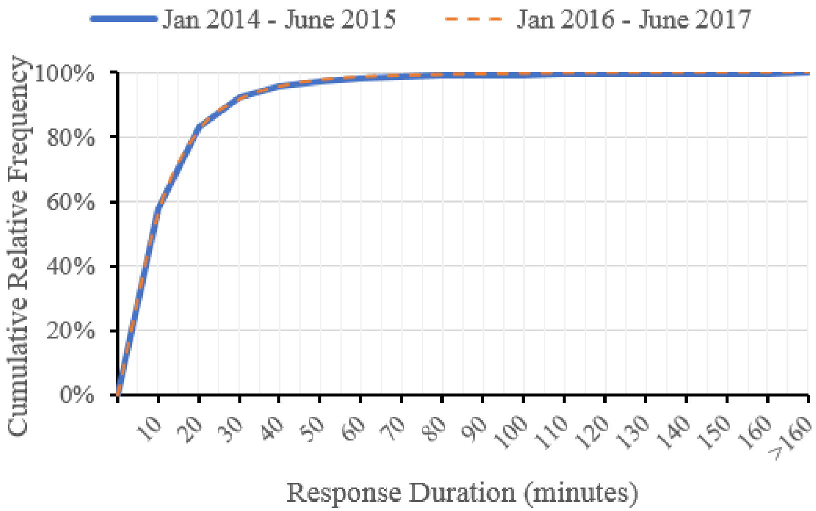


(c)Vehicle Problems

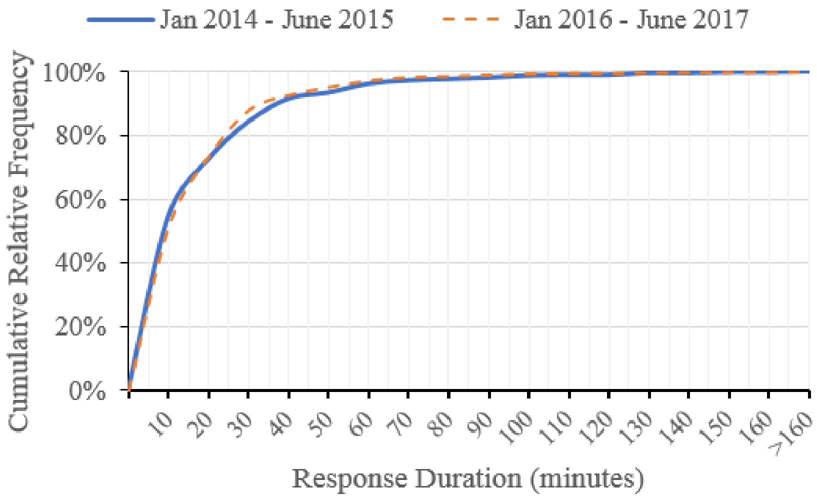


(d) Hazards

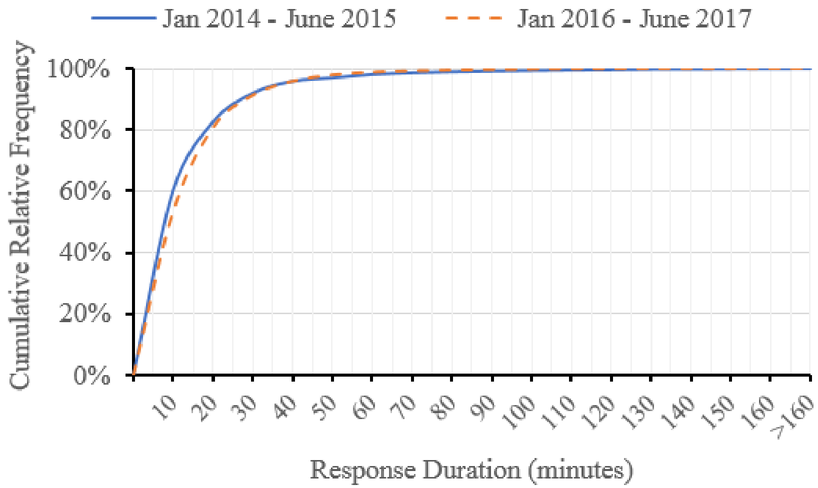
Figure 2-4: Distribution of Incident Response Duration with Respect to Incident Type



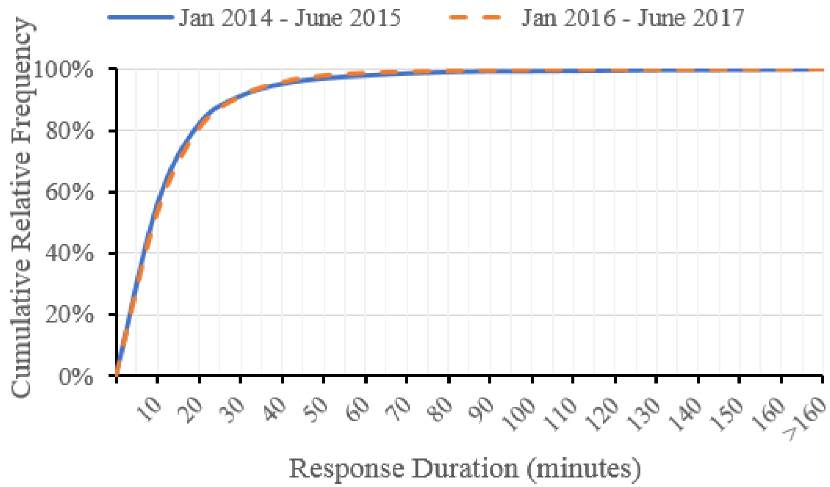
(a) Weekdays



(b) Weekends



(c) Off-peak hours



(d) Peak hours

Figure 2-5: Distribution of Incident Response Duration with Respect to Various Temporal Attributes

2.4.4 Factors Affecting Response Duration

Table 2-4 presents the model results. Incident type, percent of lane closure, roadway, day of week, traffic volume, and detection method were found to be significant during both before- and after-periods, and are discussed below.

- *Incident Type:* Crashes had 111% and 126% longer response durations than hazards before and after co-location, respectively. Vehicle problems had 4% and 8% shorter response durations than hazards before and after co-location, respectively. The response for hazards was quicker compared to crashes because most of the hazards were detected by on-road help services. Note that on-road help services verify and respond to hazards at the same time. Moreover, the difference between the average response durations for vehicle problems before and after co-location of response agencies was not significant at 95% confidence level.

- *Lane Closure:* Over 25% of lane closure was associated with 21% and 16% increase in the response duration before and after co-location, respectively. Longer response durations for incidents with a high percentage of lane closure were observed because most of these incidents were crashes. The difference between the average response durations for incidents that caused a lane closure >25% before and after co-location was not significant at 95% confidence interval.

- *Roadway:* Incidents that occurred on I-95 had significantly longer response durations than incidents on I-10 in the after-period. The difference in the average response duration on I-295 before and after co-location was significant at 95% confidence interval. The response durations before co-location for incidents on I-295 and SR-202 were shorter than on I-10 both before and after co-location.

- *Day of Week:* The average response duration of incidents on weekends was significantly longer than on weekdays. Fewer operating personnel are usually available on weekends in most of the response agencies. The difference between the average response duration for incidents that occurred on weekends before and after co-location was significant at 95% confidence level.

- *Traffic Volume (AADT):* An increase in the AADT led to incidents with 4% and 7% increase in incident response durations both before and after co-location. The difference in response durations before and after co-location was not significant at 95% confidence interval.

- *Detection Method:* Incidents that were detected by off-site detection methods had longer response durations than incidents that were detected by on-site detection methods. Detection of incidents using off-site methods can take longer depending on the incident location and traffic condition at the time of the incident. The difference between the average response duration for the incidents detected by off-site detection methods and on-site detection methods before and after co-location of response agencies was significant at 95% confidence interval.

Table 2-4: Factors Affecting Incident Response Duration before and after Co-location of Response Agencies

		Before Period January 2014 – June 2015				After Period January 2016 – June 2017			
Variable	**Categories**	**Estimates**	***p*-value**	**% Change**	**CI of the Coefficient**	**Estimates**	***p*-value**	**% Change**	**CI of the Coefficient**
Incident attributes									
Incident type	Hazards								
	Crashes	**0.745**	**0.000**	**111**	0.663 - 0.827	**0.813**	**0.000**	**126**	0.716 - 0.911
	Vehicle problems	-0.036	0.146	-4	--	**-0.079**	**0.013**	**-8**	--
Lane closure	≤ 25%								
	> 25%	**0.191**	**0.000**	**21**	0.104 - 0.277	**0.149**	**0.000**	**16**	0.065 - 0.234
Ramp involvement	No								
	Yes	**-0.162**	**0.047**	-15	--	-0.271	0.051	-24	--
Severity	Minor								
	Moderate	0.002	0.959	0	--	**0.146**	**0.000**	**16**	--
	Severe	0.011	0.915	1	--	0.101	0.189	11	--
Spatiotemporal attributes									
Roadway	I-10								
	I-95	-0.002	0.942	0	--	**0.098**	**0.000**	**10**	--
	I-295	**-0.154**	**0.000**	**-14**	**(-0.222) - (-0.086)**	**0.167**	**0.000**	**18**	**0.094 - 0.239**
	SR 202	**-0.377**	**0.000**	**-31**	(-0.465) - (-0.289)	**-0.309**	**0.000**	**-27**	(-0.405) - (-0.212)
	I-75	**0.196**	**0.004**	**22**	(-0.008) - (0.400)	-0.087	0.157	-8	--
Time of the day	Off-peak								
	Peak hour	0.025	0.061	3	--	0.018	0.218	2	--
Day of week	Weekday								
	Weekend	**0.938**	**0.000**	**156**	**0.814 - 1.062**	**0.704**	**0.000**	**102**	**0.597 - 0.811**
AADT		**0.037**	**0.012**	**4**	0.007 – 0.067	**0.065**	**0.000**	**7**	0.020 - 0.109
Agency operations attributes									
Detection method	On-site				--				--
	Off-site	**1.671**	**0.000**	**432**	**1.604 - 1.738**	**1.364**	**0.000**	**291**	**1.291 - 1.496**

Note: Bold values represent significant estimates at 95% confidence interval; "CI" means confidence interval.

In addition to the above-discussed variables, ramp involvement was also found to be significant in the before-period. Incidents that occurred in close proximity to the ramps had 15% quicker response duration compared to those that occurred outside the vicinity of the ramps. Similarly, incident severity was also found to be significant in the after-period. Moderate incidents had longer incident response durations than minor incidents after co-location of response agencies.

2.5 Summary

This chapter compared the performance of the new RTMC in Jacksonville where multiple response agencies are physically co-located in the RTMC building with the performance of the old RTMC where most of the incident response agencies were housed at their respective agency locations. The comparison was based on the incident verification and response durations before and after the new RTMC became operational. The new RTMC became operational in November 2015. The before-period included 36,594 incidents that occurred from January 2014 to June 2015. The after-period included 36,654 incidents that occurred between January 2016 and June 2017.

2.5.1 Incident Verification Duration

Incident verification duration is the time between an incident being reported and the incident being confirmed by the TMC. In general, shorter average incident verification durations were observed in the after-period than in the before-period. The proportion of crashes in the incidents was 39% in the after-period and 30% in the before-period. Vehicle problems constituted 61% and 54% of the incidents that were verified before and after co-location, respectively. Crashes were found to be verified quicker in the after-period than in the before-period. Incidents that occurred during peak hours in the after-period were found to have shorter verification durations than incidents in the before-period.

Results suggested that incident type, percent of lane closure, incident severity, roadway, traffic volume, time of the day, day of week, and detection method significantly affect incident verification durations both before and after co-location. Incident verification duration was longer for crashes compared to hazards both before and after co-location. Verification of incidents both before and after co-location was quicker when the lane closure was more than 25%. Incidents that occurred on I-95 were found to have shorter verification durations compared to incidents that occurred on I-10 both before and after co-location. Incidents that occurred during peak hours were found to have shorter verification durations compared to incidents during the off-peak hours in the before-period. Moreover, incidents that occurred on weekends were found to have longer verification durations compared to incidents that occurred on weekdays. Incidents that were detected by on-site detection methods were found to have longer verification durations than incidents detected by off-site detection methods both before and after co-location.

2.5.2 Incident Response Duration

Incident response duration is measured from the time incident response team was notified of an incident to when they arrived at the incident scene. Response time includes dispatch duration and travel time to the incident scene. Crashes had longer average response duration than vehicle problems. In the after-period, the average response duration of vehicle problems and crashes was 3 minutes and 7 minutes, respectively.

Results showed that incident type, percent of lane closure, roadway, day of week, traffic volume, and detection methods significantly affect incident response durations both before and after co-location. Crashes had longer response durations than hazards both before and after co-location. A high percentage of lane closure (> 25%) was associated with longer response durations before and after co-location. Incidents that occurred on I-95 were found to have longer response durations compared to incidents on I-10 in the after-period. Incidents that were detected by off-site detection methods were found to have longer response durations than incidents that were detected by off-site methods. The average response duration of incidents during weekends was significantly longer than during weekdays. In addition to the afore-mentioned variables, ramp involvement was found to be significant in the before-period, while incident severity was found to be significant in the after-period.

The comparison of 95% confidence interval of the model estimates showed the differences between the verification and response durations before and after co-location of response agencies. Results indicated slight improvements in the verification of incidents with respect to various incident attributes such as incident type, incident severity, and lane closure. Similar results were observed for the comparison of incidents response durations before and after co-location of response agencies. For example, the response durations for incidents that occurred on weekends were 156% and 102% longer than incidents that occurred on weekdays before and after co-location, respectively. These improvements could be attributed to co-location of response agencies within the new RTMC facility.

CHAPTER 3
INCIDENT IMPACT DURATION

This chapter focuses on establishing a framework for estimating the incident impact duration and identifying factors affecting the impact duration on freeways. A brief background on incident impact duration is first provided. The next section discusses the data and methodology used to estimate and quantify factors affecting incident impact duration. The analysis results and discussion are then presented.

3.1 Background

Precise and accurate estimation of incident duration assists incident management agencies in: (1) providing accurate information to road users, (2) applying the most suitable incident management measures, and (3) assessing the effectiveness of incident management strategies (Margiotta et al., 2012). Consequently, it is important for incident management agencies to have reliable information on the incident timeline. While most agencies use incident clearance duration, as a performance measure, it does not incorporate the duration after which traffic returns to normal. Understandably, as much as it is important to clear the incident scene, it is equally important to return the traffic condition back to normal after the incident occurs. For instance, road users will be more interested on when the congestion will end and not only when the incident will be cleared to be able to better plan their trip, e.g., use alternate routes, shift the time for starting a trip, etc. In this study, the time taken since the incident occurred to when the affected operational characteristics (i.e., speed and travel time) of a roadway segment return to normal is referred to as the incident impact duration. Figure 3-1 illustrates this concept.

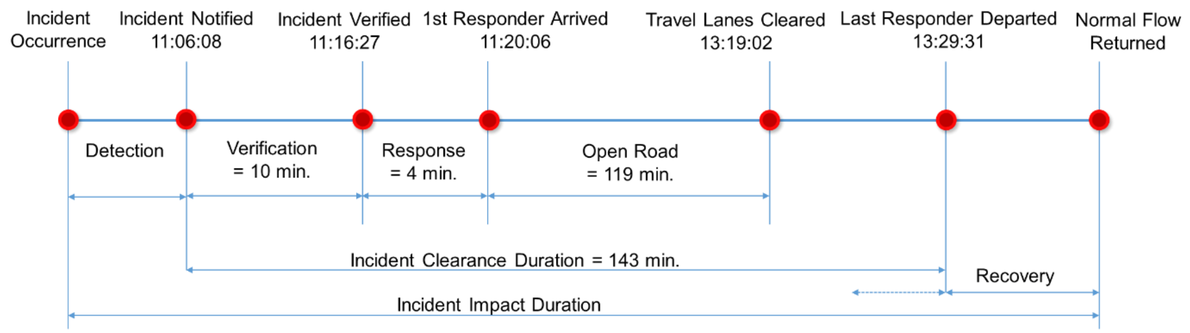


Figure 3-1: Simplified Incident Timeline

As indicated in Figure 3-1, incident impact duration includes incident clearance duration and incident recovery duration. The incident clearance duration can be easily derived from incident reports because they usually record the time that the incident occurs – as recorded by the incident management agencies – until the time the responders depart the incident scene. On the other hand, the time taken from incident clearance until traffic return to normal, conventionally referred to as the recovery time (Ghosh et al., 2014; Hojati et al., 2014; Garib et al., 1997), is not included in the incident reports.

Incident recovery time and incident detection time are incident timeline elements that are difficult to measure. Although some studies have reported analyzing incident detection time (Kaabi, 2013; Nam and Mannering, 2000), there are limitations in deducing the exact time when an incident occurred (Nam and Mannering, 2000). For example, it is not feasible for incident management agencies to record the exact time when the incident occurred. On the other hand, estimation of recovery time is unpredictable due to its dependency on traffic conditions, i.e., speed and travel time. Therefore, estimating the recovery time requires cumbersome and unconventional methodologies that utilizes the traffic parameters on the roadway when an incident has occurred and when there is no incident.

One of the objectives of this research was to estimate and analyze incident-related delays. In this case, incident impact duration is required to quantify delays caused by incidents. Since the recovery time is not recorded in the SunGuide® system, this study first developed an approach to estimate the incident impact duration for each incident, and then evaluated factors affecting the incident impact duration. Previous studies (Hojati et al., 2014; Chung 2010; Smith and Smith 2001) described recovery time as the period after the recorded clearance duration. However, as shown in Figure 3-1, there are instances where traffic operations return to normal before the incident is cleared such as incidents involving abandoned vehicles. As such, incident impact duration can be either longer or shorter than the incident clearance duration depending on the incident characteristics.

3.2 Data

Traffic incident and real-time traffic data were required to estimate the incident impact durations. Incident data were retrieved from the SunGuide® database, which is discussed in Section 2.2. Real-time traffic speed data were retrieved from the BlueToad® database.

BlueToad® devices are Bluetooth signal receivers which read the media access control (MAC) addresses of active Bluetooth devices in vehicles passing through their area of influence. These devices act in pairs or network (i.e., BlueToad® pairs) by recording the time when a vehicle passes both devices. This information is used to deduce the travel time of the vehicle between a pair of devices. The speed is calculated from the obtained travel time and a known path distance (not Euclidean distance) between the devices. Figure 3-2 shows the network of BlueToad® devices in Jacksonville, Florida. For this research, the following information was retrieved from the BlueToad® database for the years 2015-2017.

- Traffic speed
- Date and time
- BlueToad® device location (i.e., latitude and longitude)
- Distance between devices

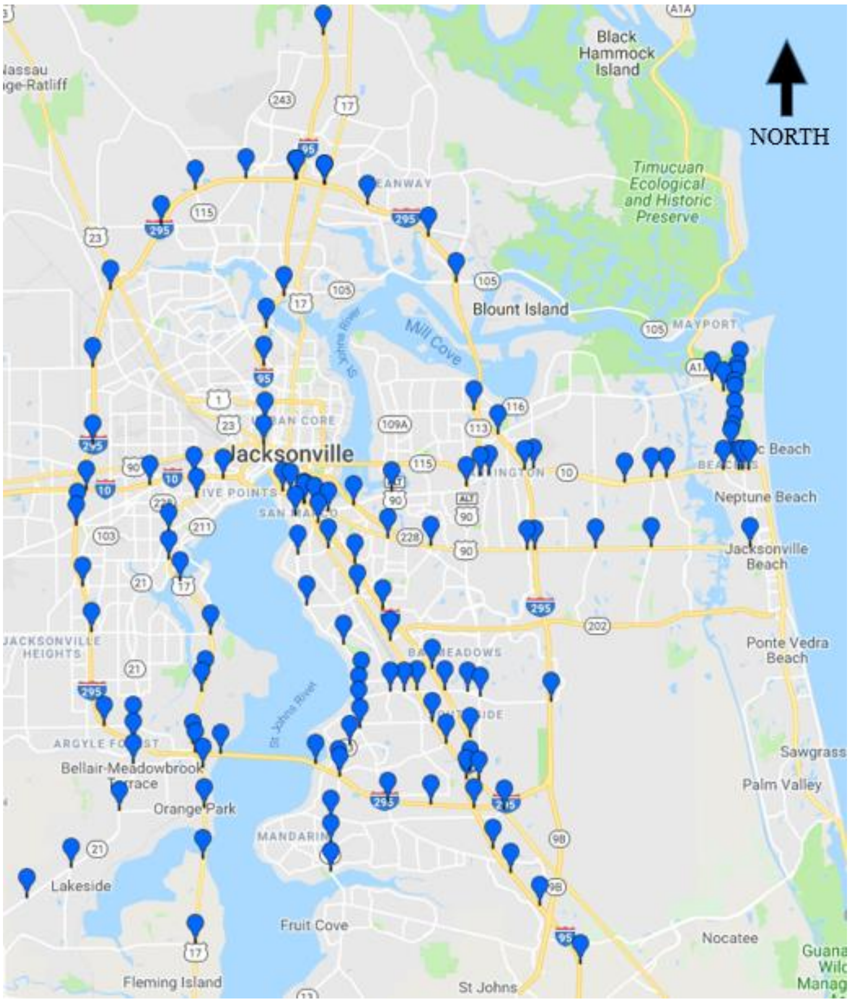


Figure 3-2: Network of BlueToad® Devices in Jacksonville, Florida

3.3 Methodology

3.3.1 Estimation of Incident Impact Duration

A major step would be to compute the time it takes for traffic to return to normal after the incident occurs. With the availability of traffic flow data from BlueToad® devices, data-driven techniques were used to estimate the time at which the traffic flow of the roadway affected by incident returns to normal. Figure 3-3 shows the flowchart for estimation of incident impact duration. The following are the specific steps used to estimate the incident impact duration.

- *Extract Speed Data:* Speed data aggregated in 15-min intervals were collected from all the BlueToad® pairs in the study network for the years 2015-2017. The data were aggregated in 15-min intervals following the works of Guo et al., (2018) which observed lack of stability in traffic flow data for short time intervals, and Smith and Ulmer (2003) which suggested 15 minutes as a measurement interval to obtain stable traffic flow rates.

- *Establish the Normal Speed Profile:* The speed data aggregated at 15-min intervals were used to establish the recurrent speed profile of each BlueToad® pair for each day of week. The 95% confidence interval of the average speed was calculated to define the upper and lower bounds of the recurrent speed profile. This 95% confidence interval accounted for the variation in speeds on a roadway segment. For each BlueToad® pair, a total of seven traffic speed profiles were generated, one for each day of week. Figure 3-4 shows a typical speed profile and the speeds on the roadway segment during an incident.

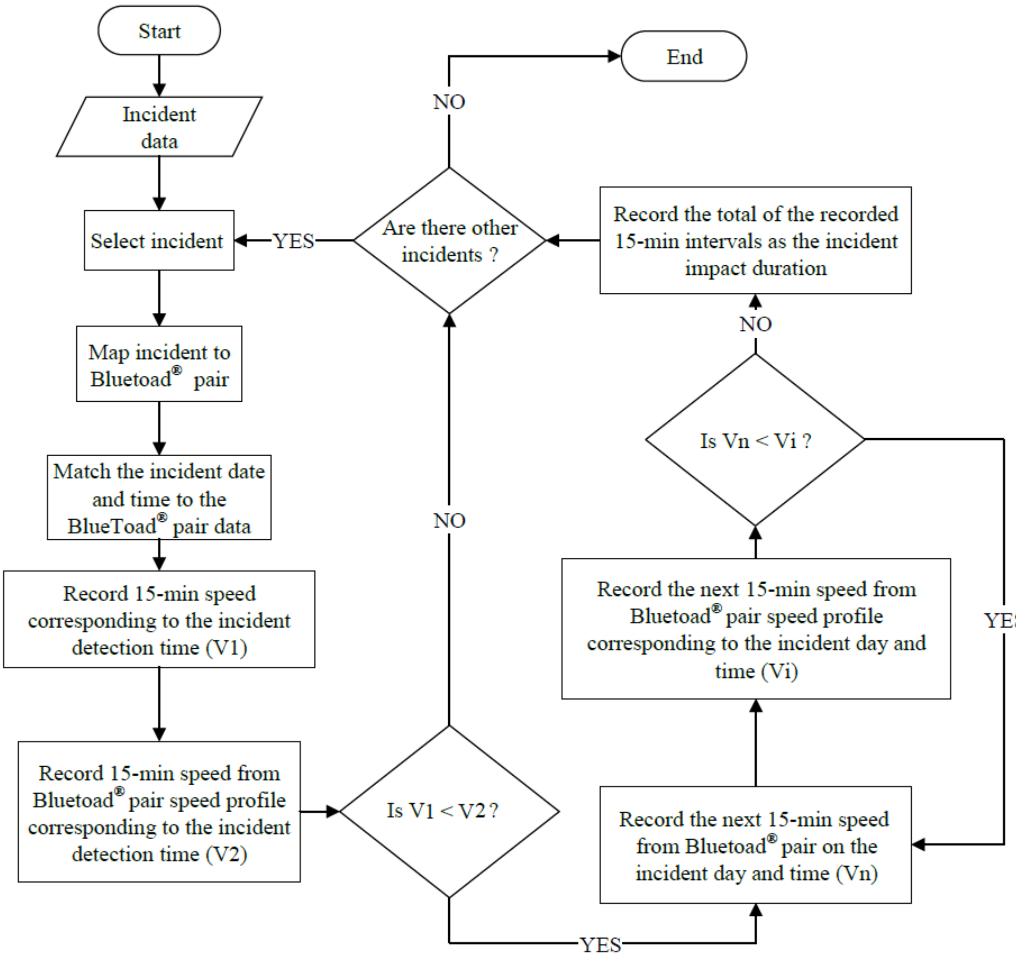


Figure 3-3: Process to Estimate Incident Impact Duration

- *Prepare the Incident Data:* Each incident was matched to a BlueToad® pair at the incident location based on geographical coordinates (i.e., latitude and longitude). The date, day, and reported time of the incident were extracted and used for extraction of speed data from the BlueToad® pair.

- *Extract Traffic Speeds During an Incident:* The traffic speed data of the BlueToad® pair affected by the incident were extracted. The traffic speed was compared to the normal traffic speed profile. An incident is considered to affect the traffic characteristics of the segment when the average speed along the segment was found to be less than the lower speed profile boundary. The same procedure was repeated for all the upstream BlueToad® devices affected by the incident.

- *Establish the Incident Impact Duration:* The time from when the incident occurred to the time when the speed during an incident returned to normal traffic speed was recorded. The longest duration from the affected BlueToad® pairs was recorded as the incident impact duration.

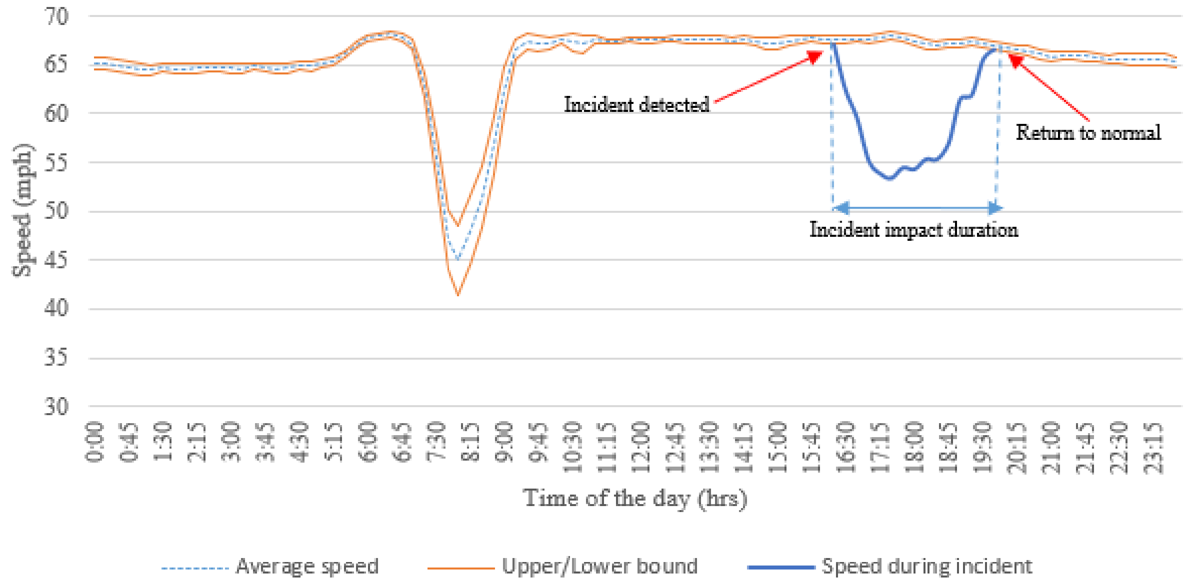


Figure 3-4: Estimation of the Incident Impact Duration from Speed Profile

3.3.2 Factors Affecting Incident Impact Duration

Similar methodology that was used to analyze the incident verification and response durations, which is discussed in Section 2.3, was used to identify the factors affecting incident impact duration. The methodology involved developing hazard-based models using the elements of incident timeline as the dependent variable, and all the investigated factors as the independent variables. The independent variables included incident type, incident severity, detection method, shoulder blockage, lane closure, time of the day, lighting condition, day of week, detection method, co-location of agencies, number of response agencies, EMS and involvement of towing services. The variable *co-location of agencies* was categorized into *with* and *without* co-location. The new RTMC where the FDOT, FHP, and Road Rangers began to manage incidents from the same TMC building became operational in November 2015. January 2014 to June 2015 was considered as the period *without* co-location, and January 2016 to June 2017 was considered as the period *with* co-location. Finally, the EMS and towing involvement variables were categorized into two groups each, i.e., when the EMS or towing services were or were not one of the response agencies.

3.4 Results and Discussion

3.4.1 Estimation of the Incident Impact Duration

The algorithm provided in Figure 3-3 was used to estimate the incident impact duration (including recovery time) for a total of 8,248 incidents that occurred from 2015-2017. Note that some BlueToad® devices were inactive along the study corridors and within the analysis period, and all the incidents along these corridors were excluded from the analysis. Furthermore, incidents with missing geographical coordinates in the incidents database were also not included in the analysis. Some of the incidents had no speed data from the BlueToad® database during the time of the incident, and were excluded. Also, incidents with incomplete incident duration data were excluded from the analysis.

Finally, the estimation of the incident impact duration was successful for only 1,793 incidents, and this subset of data was used for statistical modeling. The incident impact duration extraction process was observed to produce a small sample of incidents, a challenge that was also observed in the study by Hojati et al. (2014). Table 3-1 shows the summary of the incident impact duration estimated using the methodology described in Section 3.3.1.

Table 3-1: Summary of the Estimated Incident Impact Duration and Clearance Duration

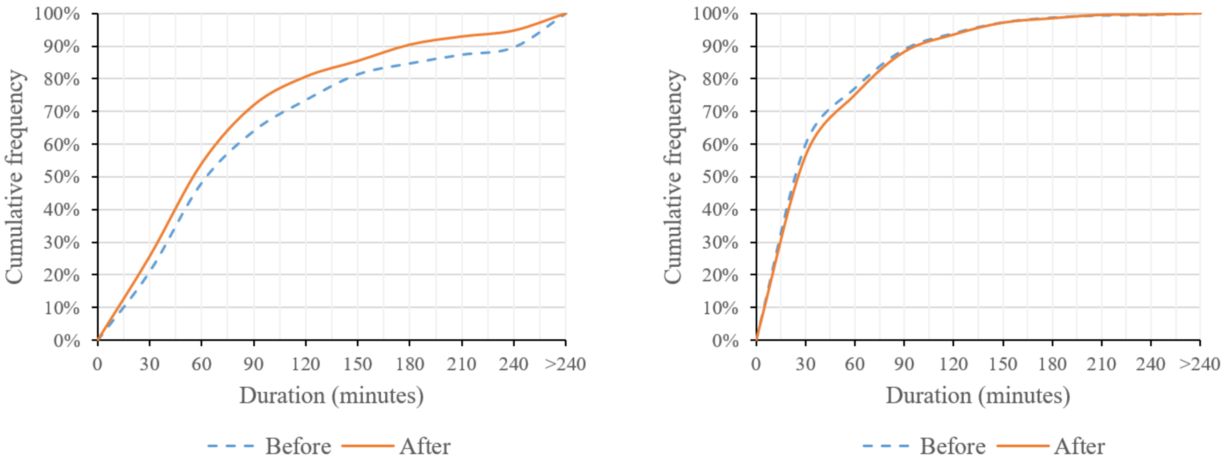
Variables	Categories	Frequency	Percentage (%)	Average impact duration (mins)	Average clearance duration (mins)
Incidents attributes					
Incident type	Crash	664	37%	115	72
	Vehicle problems	1,047	58%	90	21
	Hazards	82	5%	109	20
Shoulder blocked	No	841	47%	100	35
	Yes	952	53%	99	44
Lane closure	≤ 25%	1,562	56%	95	35
	> 25%	231	12%	136	71
Incident severity	Minor	1,663	93%	96	36
	Moderate	101	6%	140	77
	Severe	23	1%	182	158
Temporal attributes					
Time of the day	Peak hour	1,520	85%	95	39
	Off-peak	273	15%	129	41
Lighting condition	Day	1,716	96%	99	38
	Night	77	4%	122	86
Day of week	Weekday	1,441	80%	99	38
	Weekend	352	20%	106	46
Agency operations attributes					
Detection method	On-site	1,595	89%	99	38
	Off-site	198	11%	111	51
Co-location of agencies	Without co-location	750	42%	116	39
	With co-location	1,043	58%	89	40
Number of response agencies*	---	---	---	---	---
EMS	Present	111	6%	141	82
	Absent	1,682	94%	97	37
Towing involved	No	1,553	87%	98	35
	Yes	240	13%	114	73

Note: * Continuous variable; "---" is Not Applicable.

The table also provides a summary of the recorded incident clearance duration; this provides a comparison between the incident clearance duration and the incident impact duration, and can be used to analyze the performance of incident management strategies.

Crashes constituted 37% of all incidents, and had the mean impact and clearance duration of 115 and 72 minutes, respectively. As shown in Table 3-1, disabled and abandoned vehicles constituted a majority of incidents (58%) while hazards constituted only 5% of total incidents. The mean incident impact duration of crashes (115 minutes) was longer than the mean clearance duration (72 minutes). Also, Table 3-1 shows that the mean incident impact duration of hazards was 109 minutes while the mean incident clearance duration was 20 minutes. The mean incident impact duration for incidents that were detected by the on-road help services (99 minutes) was shorter that the incident impact duration of incidents detected by off-site detection approach. Table 3-1 shows that the average incident impact duration of incidents detected after and before co-location of response agencies in the RTMC was 89 minutes and 116 minutes, respectively. The difference between average incident clearance duration before and after co-location of response agencies was not significant.

It is evident from Figure 3-5(a) that incidents had longer impact durations (including recovery time) before co-location of response agencies. Also, Figure 3-5(b) suggests that the incident clearance durations before co-location of response agencies was not significantly different from the clearance durations after co-location of response agencies.



(a) Incident Impact Duration (b) Incident Clearance Duration

Figure 3-5: Distribution of the Incident Impact and Clearance Durations before and after Co-location of Response Agencies

3.4.2 Factors Affecting Incident Impact and Clearance Duration

The analysis was based on 2015 and 2016 incident data for I-95 section in Duval County in Jacksonville, Florida. The dataset included 8,248 incidents with critical incident information such as detection duration, response duration, and spatiotemporal attributes of the incident. All types of incidents were included in the dataset: crashes, vehicle problems (e.g., disabled or abandoned vehicles, etc.), and hazards (e.g., flooding, debris is on roadway, etc.). All variables were categorical except the variable for number of response agencies. The variable *co-location of agencies* was categorized into *with* and *without* co-location. The new RTMC where the FDOT, FHP, and Road Rangers began to manage incidents from the same TMC building became operational in November 2015. January 2014 to June 2015 was considered as the period *without* co-location, and January 2016 to June 2017 was considered as the period *with* co-location.

The methodology described in Section 2.3 involves selection of the model with the best parametric fit to the applied distribution. The log-logistic distribution was observed to provide the best fit compared to Weibull and log-normal distributions for both the response variables (i.e., incident impact and clearance duration). Table 3-2 provides a summary of the log-logistic distribution models for the two response variables, incident impact duration and incident clearance duration.

For each model, the first column of the results shows the fitted model coefficients based on Equation 2-4. This study adopted a 95% confidence level to test the significance of the effects of model variables on incident duration. Therefore, a *p*-value of 0.05 is a threshold for the significance level. The column that depicts the percentage (%) change shows the difference in the percentage of the incident duration of a corresponding factor-level compared to the base factor-level. For example, for incident type factor, hazards is the base level. A -18% change shown in Table 3-2 for vehicle problems factor is the difference in incident impact duration between vehicle problems and hazards. A more detailed discussion of the significant results presented in Table 3-2 is provided below.

- *Incident Type:* Compared to hazards, the model results presented in Table 3-2 show an increase of 21% and 303% in incident impact duration and incident clearance duration for crashes, respectively. Incident management procedures for crashes require a longer time for the police investigation and for emergency treatment to the injured parties in case of severe crashes. Additionally, crashes lead to longer recovery time due to their type of management strategies, which sometimes involve lane closures and route diversion.

- *Incident Severity:* Severe incidents had 69% longer incident impact duration and 130% longer incident clearance duration than minor incidents. Moderate incidents had 42% longer incident impact duration than minor incidents. Moderate and severe incidents can lead to longer recovery duration because of longer clearance procedures, which greatly affect the traffic conditions upstream of the incident.

- *Shoulder Blockage:* Shoulder blockage led to longer incident duration (4% and 33% for impact and clearance duration, respectively) than when there is no blockage. However, shoulder blockage was not a significant factor affecting incident impact duration. The analysis did not include shoulder offset (i.e., inside or outside shoulder) because of the high correlation between shoulder offset and shoulder blockage. It would be interesting to use this distinction in the analysis to determine whether the inside shoulder blockage leads to significantly longer durations than the outside shoulder blockage. Anecdotal observations suggest that greater impact is expected for the left shoulder blockage compared to the right shoulder blockage.

- *Lane Closure:* The percentage of lane closure greater than 25% led to longer incident impact durations. To illustrate the definition of percentage of lane closure, for a four-lane freeway, closing one lane is considered as 25% lane closure. As expected, the incident impact duration increases with the increase in the percentage of the lane closure because the effect of closed lanes extends much further upstream of the incident scene, thus increasing the incident recovery time. Contrary to expectations, the results suggest a decrease in incident clearance duration with an increase in the percentage of lane closure. However, the results on the incident clearance duration were not significant at 95% confidence interval. It is possible that incidents that result in more lane closures are given preference in dispatching first responders. This observation deserves further investigation to decipher if there are any confounding factors that were not considered in the model.

- *Time of the Day:* Incidents that occurred during peak hours had 26% shorter impact duration than incidents during off-peak hours. Previous studies by Li et al. (2017) and Zhou and Tian (2012) observed shorter incident durations during peak hours, and attributed the finding to the conscious efforts of management agencies in dealing with incidents that occur during peak hours. For example, because of the known threat of incidents during peak hours, extra attention is usually given to the incidents and response agencies are located closer to crash hotspots. Moreover, during peak hours, it does not take long for vehicle speeds to return to normal. This is because normal speeds during this period are usually low as a result of recurrent traffic congestion.

- *Lighting Condition*: Incidents had longer impact and clearance durations at night. However, lighting condition had a significant impact on only incident clearance duration (and not on incident impact duration). This finding is consistent with the results from Nam and Mannering (2000). A possible explanation can be, at night, drivers are able to spot responders on the scene from a distance and thus reduce speeds to those below one standard deviation of the normal traffic condition. Also, nighttime crashes tend to be more severe, hence involving more responders and become complex to execute. It is also possible that fewer responders are on duty at night, resulting in dispatch delays.

- *Detection Method:* Incidents detected using off-site detection methods had longer incident impact duration (4%) and clearance duration (42%) than incidents that were detected by on-site detection methods. Note that off-site detection method had a significant impact on incident clearance duration (and not on incident impact duration). It is possible that because the on-site detection methods include on-road help services who are already on the scene, their response to incidents is quicker. The longer durations for incidents detected off-site might be attributed to the delay in information dissemination, response dispatch delays, and difficulty in getting to the incident scene due to deteriorated traffic conditions caused by the incident.

- *Co-location of Agencies:* The results indicate that incident impact duration and incident clearance duration decreased because of co-location of response agencies. Incidents with co-location of response agencies were associated with a significant 14% and 13% decrease in incident impact and clearance durations, respectively. Co-location involved having FDOT staff, TMC operators, local agency traffic signal operators, traffic monitoring consultants, and the FHP personnel under one roof. The shorter incident impact durations with co-location of response agencies may be attributed to quicker detection, verification, and dispatch due to seamless information dissemination amongst personnel of all incident management stakeholders.

- *Number of Response Agencies:* An increase in the number of response agencies at the incident scene was associated with an insignificant 2% decrease (at 95% confidence interval) in the impact duration. However, more response agencies on the scene were associated with a significant 50% longer incident clearance duration. Clearance procedures become complex when many response agencies are at the scene, and as a result, could result in longer incident clearance durations. It is somewhat surprising that the impact duration did not significantly increase with the number of response agencies. Further research is needed to evaluate the influence of the number of response agencies on the incident impact duration.

- *EMS Involvement:* Contrary to the expectations, the presence of EMS resulted in a significant 57% decrease in the incident clearance duration. EMS are usually deployed when the incidents result in injuries. It is possible that responders are dispatched quicker when injuries are involved than for non-critical incidents. For example, it is common for an abandoned vehicle to stay longer on a blocked shoulder than for a severe crash on a blocked lane.

- *Towing Involvement:* Incidents that required towing had longer clearance durations than incidents that did not involve towing. Incidents that required towing led to a significant 34% longer incident clearance duration compared to the incidents that were cleared without involving towing services. These results are comparable to Chimba et al. (2014) and Khattak et al. (1995).

Table 3-2: Factors Influencing the Incident Impact and Clearance Duration

	Categories	Incident Impact Duration			Incident Clearance Duration		
		Estimates	*p*-value	% Change	Estimates	*p*-value	% Change
Incidents attributes							
Incident type	Hazards						
	Crashes	**0.195**	**0.024**	**21**	**1.393**	**0.000**	**303**
	Vehicle problems	-0.062	0.467	-18	0.194	0.101	21
Incident severity	Minor						
	Moderate	**0.353**	**0.000**	**42**	0.156	0.198	17
	Severe	**0.522**	**0.001**	**69**	**0.831**	**0.000**	**130**
Shoulder blockage	No						
	Yes	0.037	0.315	4	**0.288**	**0.000**	**33**
Lane closure	≤ 25%						
	> 25%	**0.208**	**0.003**	**23**	-0.166	0.074	-15
Temporal attributes							
Time of the day	Off-peak						
	Peak hour	**-0.296**	**0.000**	**-26**	0.110	0.083	12
Lighting condition	Day						
	Night	0.122	0.166	13	**0.668**	**0.000**	**95**
Day of week	Weekday						
	Weekend	-0.063	0.143	-6	-0.113	0.051	-11
Agency operations attributes							
Detection method	On-site						
	Off-site	0.042	0.435	4	**0.349**	**0.000**	**42**
Co-location of agencies	Without co-location						
	With co-location	**-0.148**	**0.000**	**-14**	**-0.143**	**0.004**	**-13**
Number of response agencies*	---	-0.017	0.549	-2	**0.404**	**0.000**	**50**
EMS involved	Absent						
	Present	-0.021	0.867	-2	**-0.849**	**0.000**	**-57**
Towing involved	No						
	Yes	0.025	0.703	3	**0.293**	**0.001**	**34**

Note: * Continuous variable; "---" is Not Applicable; Bold values represent significant estimates at 95% confidence interval.

3.5 Summary

Most agencies use incident clearance duration to measure how well incident management strategies work. At the same time, incident management agencies focus on restoring normal traffic conditions as quickly as possible after an incident occurs. While most previous studies have focused on analyzing the incident clearance duration, little has been done to examine the incident recovery duration. This study introduced a measure that was referred to as the incident impact duration, which stands for the duration from the reporting of the incident to the time when traffic condition returns to normal. Depending on the type of incident and the prevailing traffic conditions, the incident impact duration could be shorter or longer than the incident clearance duration.

This chapter demonstrated a method to estimate the incident impact duration, and investigate the effects of various factors on the incident impact and clearance durations. A new algorithm using historical traffic speed data was developed to estimate the incident impact duration. The method uses the speed data reported by the BlueToad® devices to create a bandwidth of mean speed profiles within one standard deviation for the times when there were no incidents (i.e., during recurring congestion). In the event of an incident, the algorithm checks if the speeds drop below the lower bound (one standard deviation below the historical mean) and tracks the traffic flow speed until it returns to within the one standard deviation bandwidth. The incident impact duration is computed as the time elapsed from the speed dropping below the bandwidth to the time it returns within one standard deviation of the historical mean.

The factors affecting incident impact and clearance duration were identified using two hazard-based models. Results from the statistical models underline a range of factors that influence the impact and clearance durations. Significant variables affecting the incident impact and clearance durations include: incident type, incident severity, shoulder blockage, lane closure, time of the day, lighting condition, co-location of response agencies, number of response agencies, EMS involvement, and towing involvement. These results provided an insight on how these variables affect the incident impact and clearance duration.

Crashes had 21% longer incident impact durations than hazards while severe incidents caused longer incident impact and clearance durations than minor incidents. Incidents involving over 25% of lane closure resulted in longer incident impact durations. The incident impact duration was observed to increase when there is a high percentage of lane closure because the closed lanes can affect traffic that is further upstream of the incident scene. Incidents that occurred during peak hours had shorter impact durations than incidents during off-peak hours. Moreover, incidents had longer clearance durations at night. Incidents that were detected using off-site detection methods had longer clearance durations than incidents detected by on-site detection methods. Co-location of response agencies was observed to decrease the incident impact and clearance durations. Contrary to towing services, involvement of EMS services was associated with shorter incident impact durations.

CHAPTER 4
INCIDENT-RELATED DELAYS

This chapter focuses on establishing a framework for estimating the delays caused by incidents and identifying factors affecting these delays. A brief background on incident-related delays is first provided. The data used to estimate delays caused by incidents on freeways were then discussed. The next section presents the approaches used to estimate incident-related delays and to investigate the factors that influence incident-related delays. Finally, the study results are discussed.

4.1 Background

Delay is one of the metrics used to measure the highway system performance. Delays have a direct association with economic consequences, quality of life, and perceived level of service (Weisbrod et al., 2002). It is important to note that incident-induced delays can result from either recurrent or non-recurrent incidents. Recurrent incidents include special events such as game days for roadways near stadiums. Non-recurrent events include all unplanned roadway events, e.g., crashes, vehicle breakdowns, etc. Figure 4-1 shows a crash that led to traffic congestion (and, as a result, increased delay) on I-95 northbound.

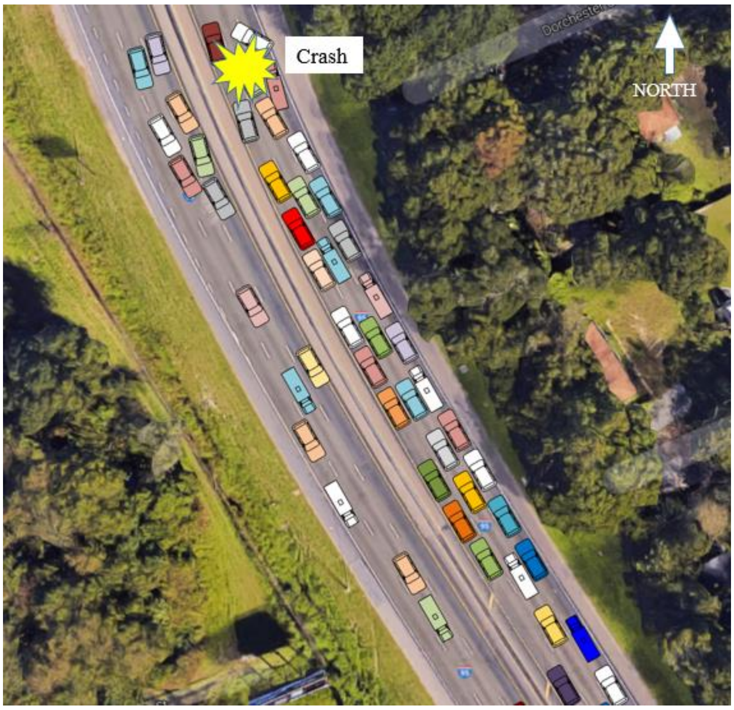


Figure 4-1: Non-recurrent Congestion Due to a Traffic Crash

Understanding the delays caused by incidents and the factors affecting the extent of these delays is critical for transportation agencies. This information enables agencies to device effective strategies to reduce the impacts of incidents and assess the performance of their incident management strategies. Despite its significance, estimation of incident-related delays remains a challenge. This is because of the stochastic and dynamic nature of incidents and traffic conditions. For example, the traffic demand on a roadway segment during the first few minutes after the occurrence of an incident may vary from the demand after an incident remains uncleared for a while. Therefore, many studies have focused on different methods to accurately estimate incident-induced delays.

Dynamic queuing and shockwave analysis are the most common methods to estimate incident-related delays. Some studies (e.g., Khattak et al., 2012; and Morales, 1987) have used a simple deterministic queuing model to estimate delays. Other studies including Sullivan (1997) have used a conventional cumulative arrival-departure curve method, which assumes that all delays from incidents are an outcome of demand flow exceeding capacity due to temporary capacity reduction. This approach has limitations since it assumes known arrival and departure rates after the incidents and do not reflect the dynamic conditions on the transportation network (Zeng and Songchitruksa, 2010).

More recently, microscopic simulation models have been used to estimate incident-related delays based on incident durations. The simulation-based methods include a wide range of scenarios. For instance, Zhang et al. (2012) developed a simulation model to assess the influence of traffic composition (i.e., truck ratio) on delays resulting from traffic incidents. Rompis et al. (2014) developed a methodology for modeling incidents in microscopic simulation environment and analyzed queue length due to an incident blocking one or both lanes on the two-lane freeway. The main drawback of simulation-based method is the calibration and validation of numerous incident scenarios (Habtemichael et al., 2015). Simulation-based estimation of the incident delays requires a well-calibrated and validated model for both incident and incident-free scenarios. Furthermore, calibration and validation of a simulation model for incident scenarios is cumbersome and time consuming (Hadi and Zhan, 2006).

In order to overcome the limitations of the aforementioned methods, some studies have estimated delays by applying data-driven techniques which use ground-truth data and do not require many assumptions or rigorous model calibrations (Snelder et al., 2013; Zeng and Songchitruksa, 2010). For example, Habtemichael et al. (2015) proposed a method for establishing reference profile of traffic characteristics (e.g., travel time, traffic volume, etc.) on a freeway from which incident-induced delays can be deduced. The method estimated the incident-induced delay as the excess duration between incident-influenced travel-time profile and the reference (i.e., non-incident) travel-time profile. Likewise, other studies have estimated delays by comparing the existing traffic condition during an incident (i.e., incident-influenced profile) to the historical normal traffic condition (i.e., reference profile). The main difference between these studies is the metric used in the analysis (i.e., speed, traffic volume, etc.) and the extent of the analysis (i.e., freeway segment or network). Wang et al. (2008) used profile based on traffic volume while Hallenbeck et al. (2003) used lane occupancy profile both downstream and upstream of the incident location. Both Zeng and Songchitruksa (2010) and Snelder et al. (2013) used extra travel time as a parameter in estimating incident-induced delays, but Snelder et al. (2013) extended the analysis to the opposite approach to estimate the delay caused as a result of rubbernecking.

One of the objectives of this research was to estimate and evaluate incident-related delays on freeways. This objective was achieved by: (1) developing an enhanced algorithm to estimate incident-related delays using real-time BlueToad® travel speed data and Regional Integrated Transportation Information System (RITIS) traffic volume data; and (2) examining the relationship between the numerous factors associated with incidents and the incident-related delays. The incident-related delays were estimated using the extra travel time and the traffic volume during incidents. Hazard-based models were applied to evaluate the factors that influence these delays.

4.2 Data

Traffic incident and real-time traffic data were required to estimate the incident-related delays. Incident data were retrieved from the SunGuide® database; real-time traffic speed data were retrieved from the BlueToad® database; and real-time traffic volume data were obtained from the RITIS database. In addition to the aforementioned data, roadway characteristics data were used to evaluate factors affecting incident-related delays. Detailed roadway characteristics information was extracted from the 2016 FDOT's Roadway Characteristics Inventory (RCI) database. Since the SunGuide® database and the BlueToad® database are already discussed in Section 2.2 and Section 3.2, respectively, only RITIS and RCI databases are discussed in the following sections.

4.2.1 RITIS Database

RITIS is an automated data sharing, dissemination, and archiving system that includes real-time data feeds and archive data analysis tools such as probe, detector, and transit data analytics. These tools assist agencies to gain situational awareness, measure performance, and communicate information between agencies and to the public. The following information was retrieved from the RITIS database. Figure 4-2 shows the network of RITIS devices in Jacksonville, Florida.

- Traffic volume data at 15-min intervals
- Date and time
- Detector location (i.e., latitude and longitude)

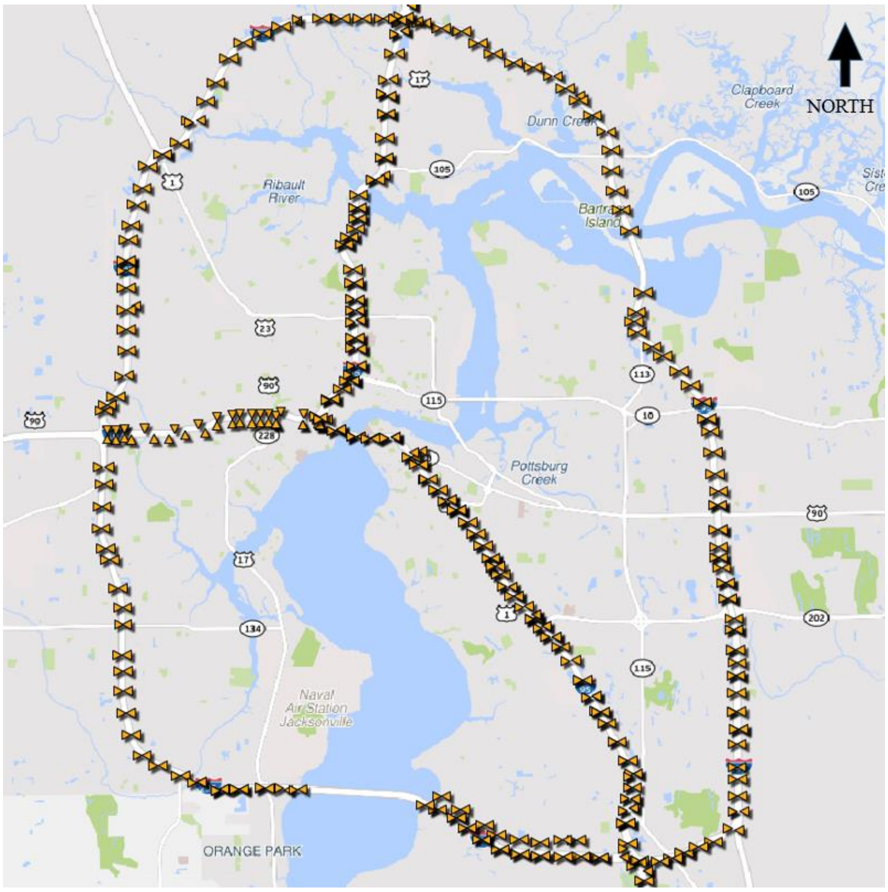


Figure 4-2: Network of RITIS Devices in Jacksonville, Florida

4.2.2 RCI Database

Detailed roadway characteristics information was extracted from the 2016 FDOT-RCI database. Of over 200 variables that are available in the RCI database, only the following variables that could potentially affect delays when an incident occurs were extracted:

- AADT,
- number of lanes,
- median type,
- median width,
- shoulder type,
- speed limit,
- presence of horizontal curvature,
- presence of vertical curvature, and
- surface width.

Lane width was derived from surface width and total number of lanes information. Lane width, median width, and shoulder width were rounded per the Highway Safety Manual (HSM) guidelines (AASHTO, 2010). Segmentation was performed per the guidelines provided in the HSM, i.e., a new segment starts whenever there is a slight change in any of the aforementioned variables (AASHTO, 2010).

4.3 Methodology

The incident-related delays were calculated from the increase in travel time for traffic upstream of the incident location and the number of vehicles affected by the incident. The process involved estimating the extra travel time due to incidents and the real-time traffic volume upstream of the incident location. Once the incident-related delays were estimated, duration-based models were used to identify the factors affecting these delays. The following sections provide more details on the methodology adopted to estimate the incident-related delays on freeways, and to investigate the factors influencing these delays.

4.3.1 Establish the Normal Travel Time Profile

Freeway traffic congestion is classified into recurrent and non-recurrent congestion (Chung, 2011). Recurrent congestion is the predictable traffic delay caused by regularly occurring events such as the daily variation in highway traffic demand (Chung, 2011; Hallenbeck et al., 2003). Non-recurrent congestion is the un-predictable traffic delay resulting from incidents, e.g., crashes, disabled vehicles, etc. (Hallenbeck et al., 2003).

Incident-related delays constitute the extra delay caused to the travelers in addition to the regular recurrent delays. As such, the first step in estimating the incident-related delays focuses on determining the recurrent delays along the study corridor. Recurrent delays are estimated by establishing the normal travel time profile of a roadway segment, and deducing the delays from the normal travel time profiles. The normal travel time profile represents the typical traffic conditions at 15-min intervals and shows the recurrent delays along a roadway segment. Figure 4-3 outlines the procedure adopted to establish the normal travel time profiles for roadway segments. The following are the specific steps used to establish the normal travel time profiles.

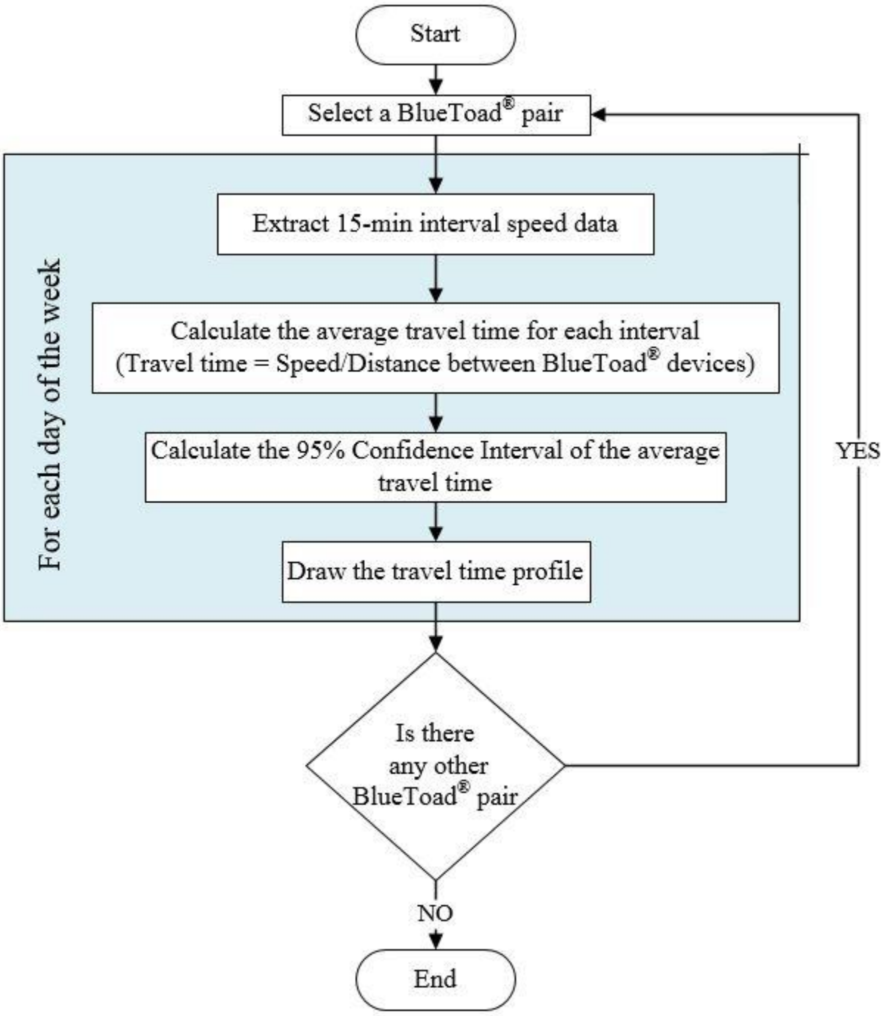


Figure 4-3: Algorithm to Establish the Normal Travel Time Profile

- *Extract Speed Data:* Speed data aggregated in 15-min intervals were collected from all the BlueToad® pairs in the study network for the years 2015-2017. The data were aggregated in 15-min intervals following the works of Guo et al., (2018) which observed lack of stability in traffic flow data for short time intervals, and Smith and Ulmer (2003) which suggested 15 minutes as a measurement interval to obtain stable traffic flow rates.

- *Prepare Speed Data:* The speed data aggregated at 15-min intervals were used to establish the recurrent speed profile of each BlueToad® pair for each day of week. The 95% confidence interval of the average speed was calculated to define the upper and lower bounds of the recurrent speed profile. This 95% confidence interval accounted for the variation in speeds on a roadway segment. For each BlueToad® pair, a total of seven traffic speed profiles were generated, one for each day of week.

- *Calculate the Normal Travel Time:* The distance between each BlueToad® pair devices were extracted from the BlueToad® database. The travel time, at 15-min interval, between each BlueToad® pair device was estimated using the corresponding average speed. The 95% confidence interval was calculated to account for the variations in travel time. Seven travel-time traffic profiles, one for each day of week, were generated for each BlueToad® pair.

Example of the Estimated Travel Time Profile

Figure 4-4 shows the estimated travel time profile on a Wednesday for a location on I-95 SB between two BlueToad® devices which are 1.49 miles apart. Longer travel times were observed between 4 PM and 7 PM. It can be inferred from the figure that the average travel time at 6 PM was approximately 140 seconds while the average travel time during most hours of the day was within 80 seconds.

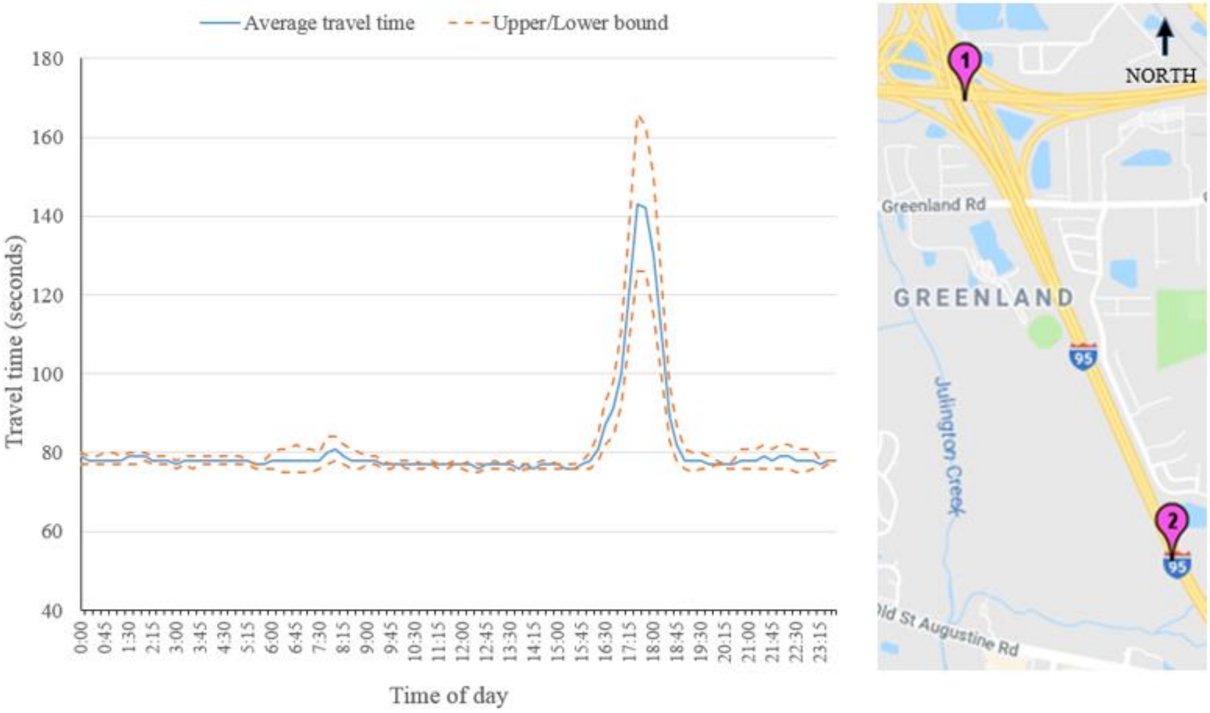


Figure 4-4: Travel Time Profile and its Corresponding Location of BlueToad® Pair

4.3.2 Estimate the Extra Travel Time Due to Incident

Estimation of the incident-related delays requires two inputs: extra travel time because of an incident, and the traffic volume affected by the incident. The extra travel time is the increase in duration for traveling from one point to another because of the congestion as a result of an incident. The increase in duration (i.e., the extra travel time) is calculated by comparing the normal travel time and the travel time during an incident. Figure 4-5 outlines the procedure adopted to estimate the extra travel time. The following are the specific steps used to estimate the extra travel time profiles.

- *Prepare the Incident Data:* Each incident was matched to a BlueToad® pair at the incident location based on geographical coordinates (i.e., latitude and longitude). The date, day, and reported time of the incident were extracted and used for extraction of speed data from the BlueToad® pair.

- *Estimate Travel Time During an Incident:* The traffic speed data of the BlueToad® pair where an incident occurred and the distance between BlueToad® pair devices were used to estimate the travel time during an incident.

- *Calculate the Extra Travel Time:* The estimated travel time was compared to the corresponding normal travel time. Travel time longer than the upper boundary of the travel time profile suggested that the BlueToad® pair was affected by the incident. The extra travel time for each 15-min interval was recorded and the procedure was repeated for every BlueToad® pair upstream of the incident location that was affected by the incident. Figure 4-6 shows an example of the travel time profile and the estimated extra travel time at a BlueToad® pair.

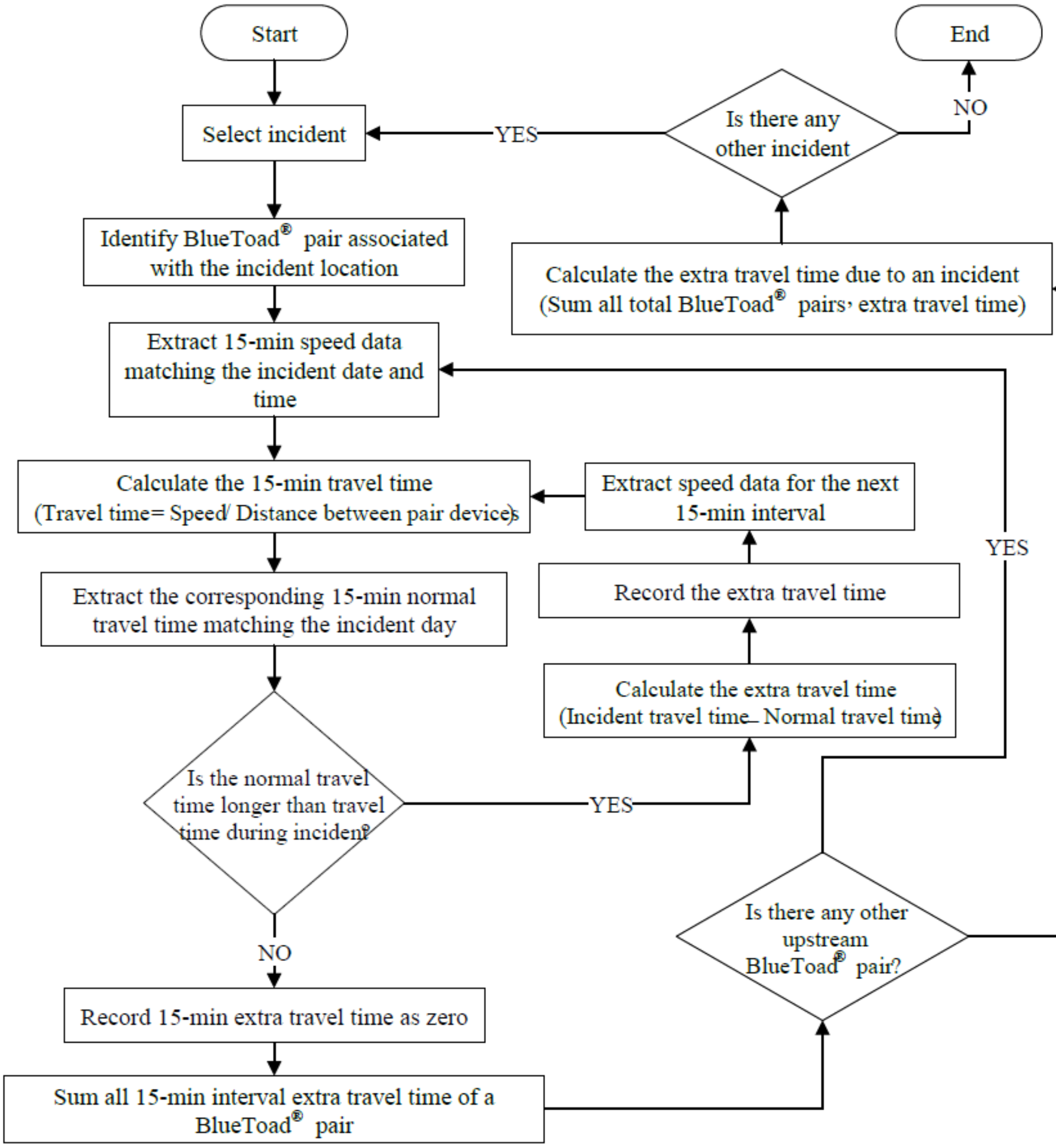


Figure 4-5: Algorithm to Estimate Extra Travel Time Due to an Incident

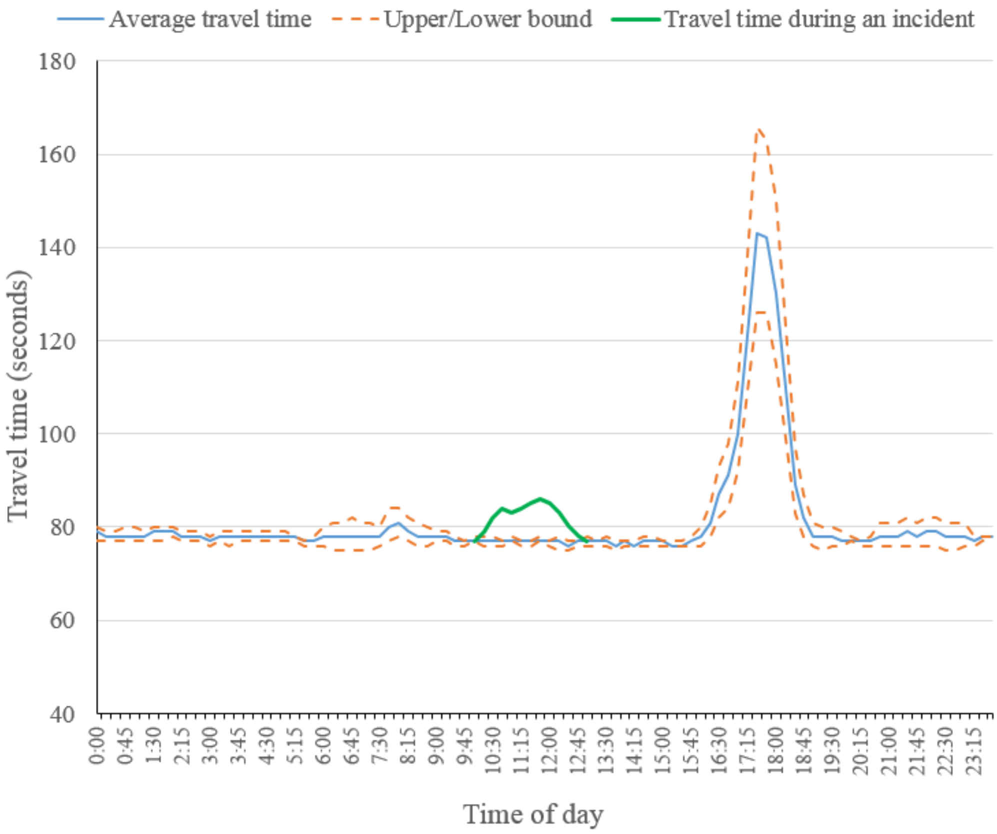


Figure 4-6: Travel Time during an Incident as Compared to Normal Travel Time

4.3.3 Calculate the Incident-related Delays

Incident-related delays were calculated based on the extra travel time due to an incident and the traffic volume extracted from RITIS devices. RITIS devices associated with the affected BlueToad® pairs were first identified, and the corresponding traffic volume data affected by the incidents were extracted. The traffic volume data were aggregated in 15-min intervals to be consistent with the travel time and speed data from BlueToad® pairs. Figure 4-7 describes the process of estimating the traffic volume affected by an incident and calculating the incident-related delays. The following are specific steps for calculating the incident-related delays.

- *Identify RITIS Devices Corresponding to BlueToad® Pairs:* For each BlueToad® pair segment, only the RITIS devices on the mainline were used. Note that the RITIS devices that collect traffic volume data on exit and entry ramps were not used. Figure 4-8 shows a typical example of the location of RITIS devices and BlueToad® pairs along a roadway section on I-95.

- *Extract Real-time Traffic Volume Data:* Traffic volume data for the entire duration of the incident were extracted from the RITIS devices. For each BlueToad® pair, the retrieved traffic volume data were recorded at 15-min intervals. The process was repeated for all the BlueToad® pairs affected by the incident.

- *Calculate the Incident-related Delays:* The recorded traffic volume was multiplied by the extra travel time to obtain the incident-related delay for each BlueToad® pair for each 15-min interval of the incident duration. This delay was calculated and summed for all the affected BlueToad® pairs and recorded as the total incident-related delay.

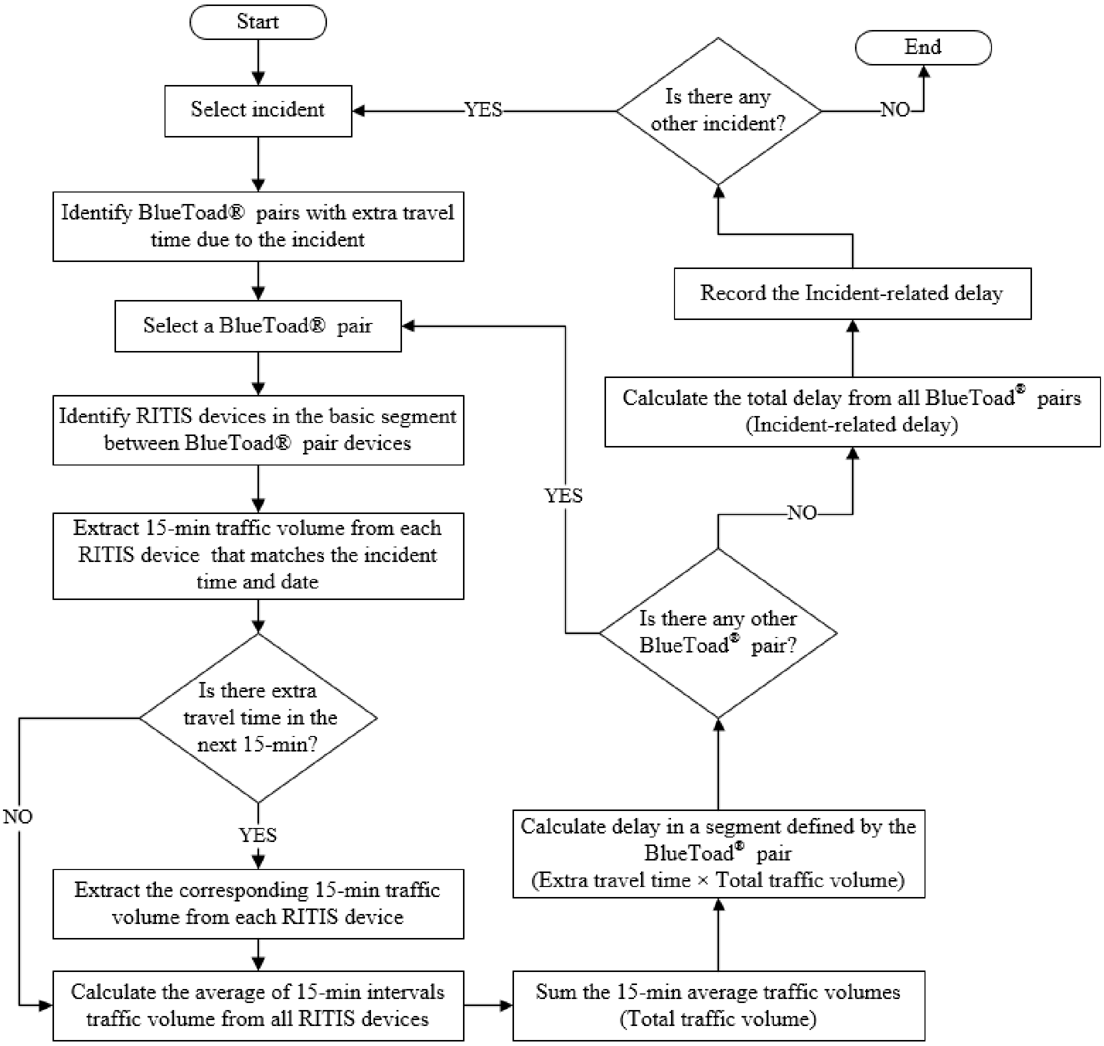
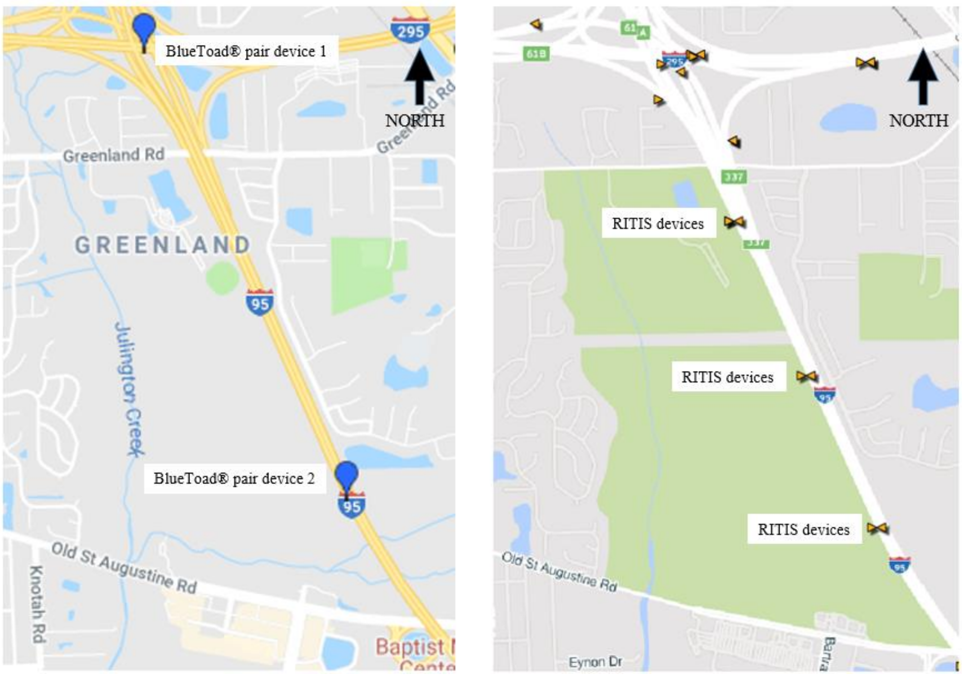


Figure 4-7: Algorithm to Estimate Delays Caused by Incidents



(a) BlueToad® Pair (b) RITIS Devices

Figure 4-8: Location of BlueToad® Pair and RITIS Devices along a Section on I-95

4.3.4 Evaluate Factors Affecting Incident-related Delays

Hazard-based models are suitable for time-dependent variables. Moreover, these models facilitate the interpretation of data using a sequence of probabilities (Li, 2017). Since incidents are cleared with time (Chung, 2011), hazard-based models are suitable for the analysis of incident-related delays and causative factors. The hazard-based model formulation is similar to the one described in the Section 2.3.

4.4 Results and Discussion

The analysis was based on three years of traffic incident data (2015-2017) retrieved from SunGuide® database. Incident-related delays were estimated using the methodology discussed in Sections 4.3.1 through 4.3.3. The methodology utilized data retrieved from three sources, SunGuide®, BlueToad®, and RITIS. The speed data were obtained from the BlueToad® devices while the traffic volume data were retrieved from the RITIS database. The duration-based models were developed to investigate the influence of various incident attributes on the estimated incident-related delays. Attributes related to the incident location, e.g., median type and median width at the incident location, were obtained from the RCI database. The following sections discuss the study location, the estimated incident-related delays, and the factors affecting incident-related delays.

4.4.1 Study Location

The study area includes a 35-mile section on I-95, a 21-mile section on I-10, a 61-mile section on I-295, and a 13-mile section on SR-202 located in Jacksonville, Florida. In summary, the total study area covers 130 miles. Figure 4-9 shows the study corridors.

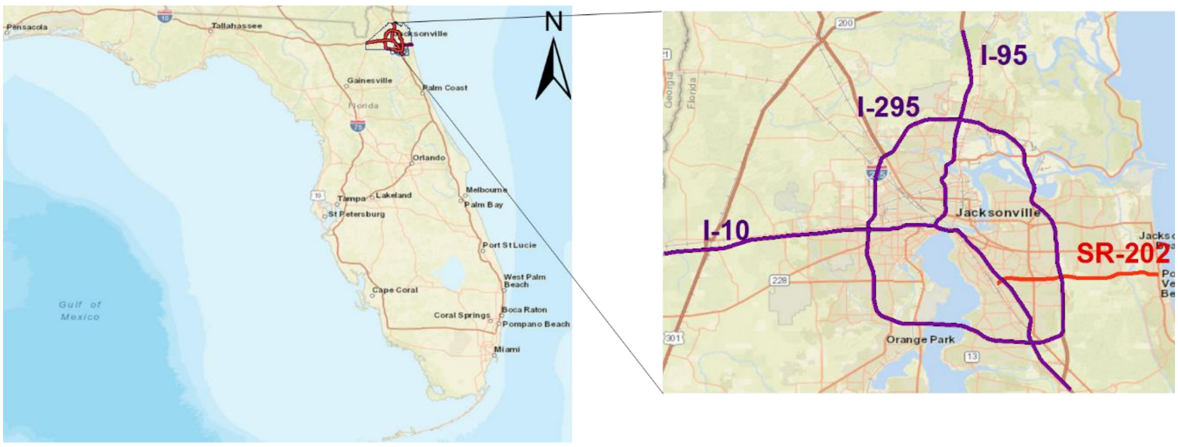


Figure 4-9: Study Area

4.4.2 Data Description

A total of 73,430 incidents that occurred from 2015-2017 along the study corridors (I-95, I-295, I-10, and SR-202) were extracted from the SunGuide® database. However, due to the absence of BlueToad® devices, 6,675 incidents that occurred on SR-202 were excluded from further analysis. A total of 15,730 incidents that occurred on ramps were also excluded. Furthermore, 47,642 incidents were excluded for several other reasons such as at locations with inactive BlueToad® devices, at work zones, etc. Finally, a total of 3,383 incidents (i.e., 5.1%) were included in this analysis.

Table 4-1 shows the summary of the estimated incident-related delays, along with the summary description of the various attributes used in the analysis. Table 4-1 shows that the frequency of hazards, vehicle problems, and crashes in the analyzed data was 313 (9%), 1,323 (39%), and 1,747 (52%), respectively. Minor incidents (96%) were more frequent than moderate (3%) and severe (1%) incidents. Other incident attributes included time of the day, day of week (weekend or weekday), median type, median width, speed limit, and presence of horizontal or vertical curve. The time of the day variable was divided into morning peak hours (6:30 AM – 10:00 AM), evening peak hours (3:30 PM – 7:00 PM), and off-peak hours (all other hours not in peak hours). Almost 31% (1,054) of the incidents occurred during morning peak hours, 22% (761) during evening peak hours, and 46% (1,568) during off-peak hours.

Table 4-1: Estimated Incident-related Delays

Variables	Categories	Frequency	Average (veh-hrs)	S.D. (veh-hrs)	Minimum (veh-hrs)	Maximum (veh-hrs)
Incident attributes						
Incident type	Hazards	313	4	5	0.010	21
	Crashes	1,323	62	81	0.005	343
	Vehicle problems	1,747	11	17	0.007	83
Incident severity	Minor	3,242	28	56	0.005	343
	Moderate	119	77	86	0.067	340
	Severe	22	65	69	0.120	268
Temporal and roadway geometric attributes						
Time of the day	Off-peak hours	1,568	17	41	0.005	337
	Morning peak hours	1,054	40	67	0.013	343
	Evening peak hours	761	42	68	0.023	342
Day of week	Weekday	3,138	30	58	0.005	343
	Weekend	245	29	58	0.011	337
Median type	Paved	492	41	71	0.011	332
	Vegetation	2,891	28	55	0.005	343
Median width*	---	---	---	---	---	---
Speed limit	40-60 mph	572	41	70	0.011	343
	65-70 mph	2,811	28	55	0.005	342
Horizontal curve	No	2,328	31	59	0.008	342
	Yes	1,055	28	55	0.005	343
Vertical curve	No	3,040	30	59	0.005	343
	Yes	343	28	54	0.013	319
Agency operations attributes						
Towing involved	No	3,024	27	55	0.005	343
	Yes	359	58	76	0.052	342
EMS involved	No	3,216	27	55	0.005	343
	Yes	167	85	89	0.067	340
Fire Department involved	No	3,207	27	55	0.005	343
	Yes	176	83	85	0.067	340
Detection method	Off-site	327	62	78	0.030	342
	On-site	3,056	27	55	0.005	343

Note: * Continuous variable; "---" is Not Applicable.

The median at the incident location was categorized into two groups: paved medians (15%, 492) and medians with vegetation (85%, 2,891). Median width was the only continuous variable in the study. Speed limit was categorized into two groups, 40-60 mph (17%), and 65-70 mph (83%). Horizontal and vertical curve variables had two groups each, representing presence (Yes) or absence of horizontal (or vertical) curves (No). The attributes for towing services, the EMS and the Fire Department had two categories each, identifying the involvement of the service during the incident clearance time. It can be inferred from Table 4-1 that 3,024 (89%) incidents did not require towing services; 3,216 (95%) incidents did not involve the EMS; and 3,207 (95%) incidents did not involve the Fire Department. A total of 3,056 (90%) incidents were detected using on-site detection methods while the remaining 327 (10%) were detected through off-site detection techniques.

4.4.3 Estimation of Incident-related Delays

Table 4-1 shows the incident-related delays estimated using the methodology discussed in Sections 4.3.1 through 4.3.3. The average delay due to hazards, crashes, and vehicle problems was 4 vehicle-hours, 62 vehicle-hours, and 11 vehicle-hours, respectively. The average delay for incidents that occurred during morning peak hours (40 vehicle-hours) and evening peak hours (42 vehicle-hours) was higher compared to the average delay during off-peak hours (17 vehicle-hours). Severe incidents resulted in an average delay of 65 vehicle-hours, while moderate and minor incidents resulted in an average delay of 77 vehicle-hours and 28 vehicle-hours, respectively. A more detailed discussion of the results presented in Table 4-1 is provided below:

- *Incident Type:* Figure 4-10(a) shows the distribution of incident-related delays with respect to incident type. Almost 100% of the hazards caused delays shorter than 20 vehicle-hours. Vehicle problems caused 82% of the incident-related delays shorter than 20 vehicle-hours, 10% of the incident-related delays were between 20 and 40 vehicle-hours, and 5% of the incident-related delays were between 40 and 60 vehicle-hours. Crashes led to more varying delays than other incident types, with only 48% causing delays shorter than 20 vehicle-hours, and 20% resulting in incident-related delays longer than 120 vehicle-hours.

- *Incident Severity:* Figure 4-10(b) shows that 72% of minor incidents caused incident-related delays shorter than 20 vehicle-hours; while 7% of minor incidents led to incident-related delays longer than 120 vehicle-hours. It was surprising to observe that a greater proportion of severe incidents than moderate incidents resulted in delays shorter than 20 vehicle-hours. Similarly, 24% of moderate incidents resulted in incident-related delays longer than 120 vehicle-delays, while only 14% of severe incidents resulted in incident-related delays longer than 120 vehicle-hours.

- *Time of the Day:* Figure 4-10(c) shows that 80% of the incidents during off-peak hours led to delays shorter than 20 vehicle-hours. Only 3% of the incidents during off-peak hours had incident-related delays longer than 120 vehicle-hours. The morning peak hours had 62% of incident-related delays shorter than 20 vehicle-hours and 11% of incident-related delays longer than 120 vehicle-hours. The evening peak hours had 60% of incident-related delays shorter than 20 vehicle-hours and 12% of incident-related delays longer than 120 vehicle-hours. As expected, the distributions of incident-related delays during the morning peak hours and the evening peak hours were found to be similar.

- *Day of week:* Figure 4-10(d) shows that 70% of the incidents that occurred on weekdays had incident-related delays shorter than 20 vehicle-hours. About 9% of the incidents that occurred on weekdays had incident-related delays between 20 and 40 vehicle-hours, and 8% had incident-related delays longer than 120 vehicle-hours. About 75% of the incidents that occurred on weekends had incident-related delays shorter than 20 vehicle-hours, while 9% of the incidents on weekends caused incident-related delays longer than 120 vehicle-hours.

- *Agency Involvement:* Figure 4-11(a) shows that 73% of the incidents where towing services were not involved had incident-related delays shorter than 20 vehicle-hours. Only 7% of the incidents that did not involve towing service had incident-related delays longer than 120 vehicle-hours. However, 48% of the incidents that required towing services led to incident-related delays shorter than 20 vehicle-hours. About 17% of the incidents that involved towing operations resulted in incident-related delays longer than 120 vehicle-hours.

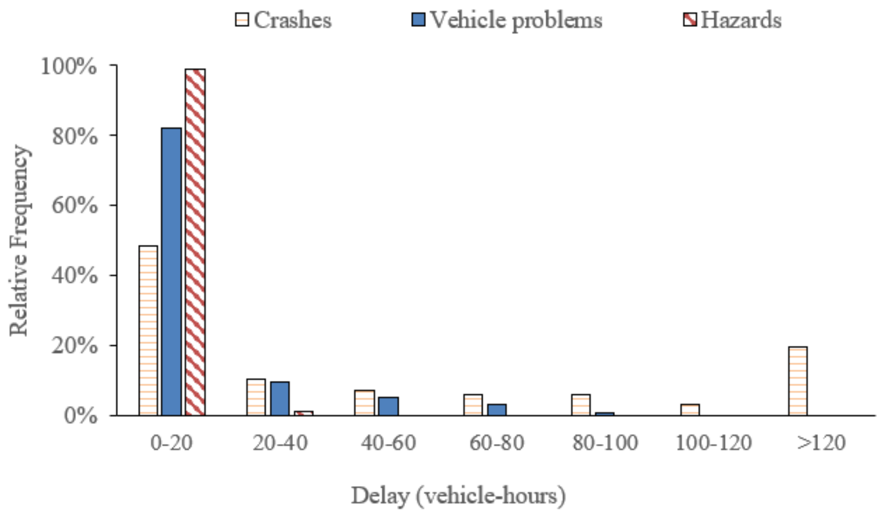
  Figure 4-11(b) shows that 72% of the incidents that did not involve EMS led to incident-related delays shorter than 20 vehicle-hours. About 7% of the incidents that involved EMS led to incident-related delays longer than 120 vehicle-hours. Only 31% of the incidents that required the EMS had incident-related delays shorter than 20 vehicle hours. As expected, 25% of the incidents that involved EMS led to incident-related delays longer than 120 vehicle-hours.

- *Detection Method:* Figure 4-11(c) shows that almost 75% of the incidents that were detected on-site led to delays shorter than 20 vehicle-hours. Only 6% of the incidents that were detected on-site caused incident-related delays longer than 120 vehicle-hours. About 45% of the incidents that were detected off-site led to incident-related delays shorter than 20 vehicle-hours. About 18% of the incidents that were detected off-site resulted in incident-related delays longer than 120 vehicle-hours.

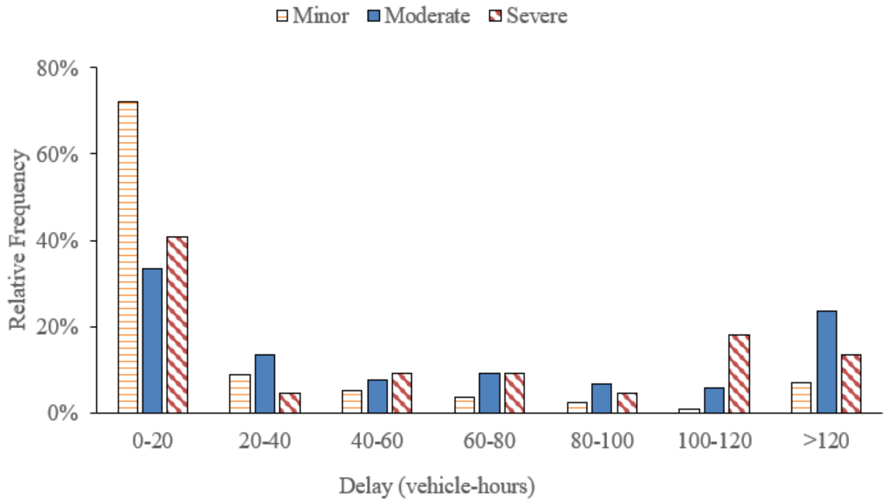
- *Speed Limit:* Figure 4-11(d) shows 72% of incidents that occurred along segments with the speed limit of 40-60 mph led to incident-related delays shorter than 20 vehicle-hours. Only 7% of incidents that occurred along roadway sections with the speed limit of 40-60 mph caused incident-related delays longer than 120 vehicle-hours. Figure 4-11(d) suggests that 63% of incidents that occurred along sections with the speed limit of 65-70 mph led to incident-related delays shorter than 20 vehicle-hours. Moreover, 13% of the traffic incidents along segments with the speed limit of 65-70 mph caused incident-related delays longer than 120 vehicle-hours.

- *Median Type:* Figure 4-12(a) shows that 65% of the incidents that occurred at locations with paved medians resulted in incident-related delays shorter than 20 vehicle-hours. About 13% of the incidents at locations with a paved median led to incident-related delays longer than 120 vehicle-hours. About 71% of the incidents that occurred at locations with vegetation on median led to incident-related delays shorter than 20 vehicle-hours. Only 7% of the incidents that occurred at locations with vegetation on median resulted in incident-related delays longer than 120 vehicle-hours.

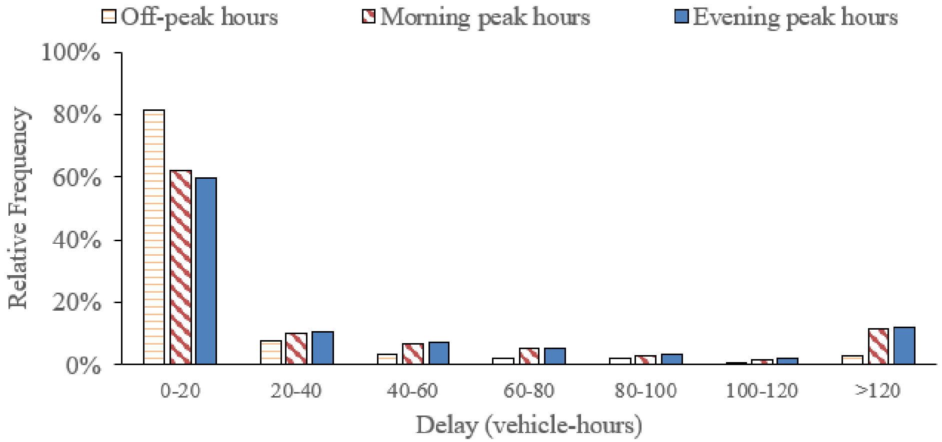
- *Horizontal and Vertical Curves:* Figure 4-12(b) shows that 71% of the incidents that occurred on straight segments led to incident-related delays shorter than 20 vehicle-hours. Only 8% of the incidents that occurred on straight segments led to incident-related delays longer than 120 vehicle-hours. Figure 4-12(b) suggests that 70% of the incidents that occurred on horizontal curves caused incident-related delays shorter than 20 vehicle-hours. About, 6% of the incidents that occurred on horizontal curves led to incident-delays longer than 120 vehicle-hours.



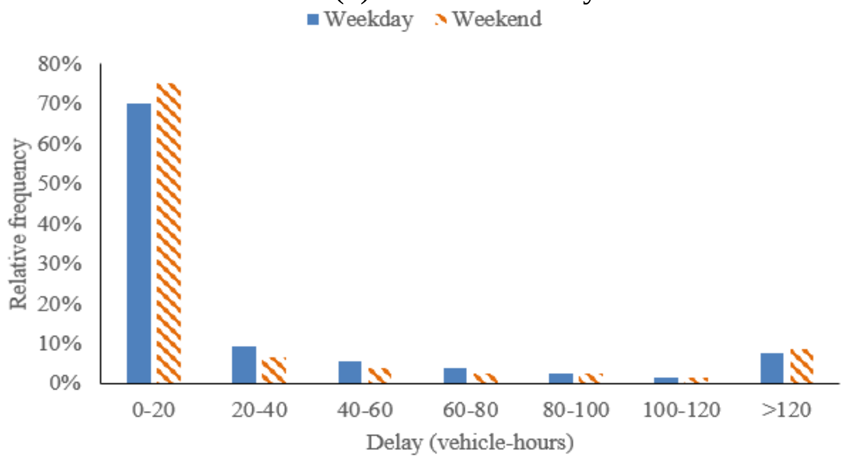
(a) Incident Type



(b) Incident Severity

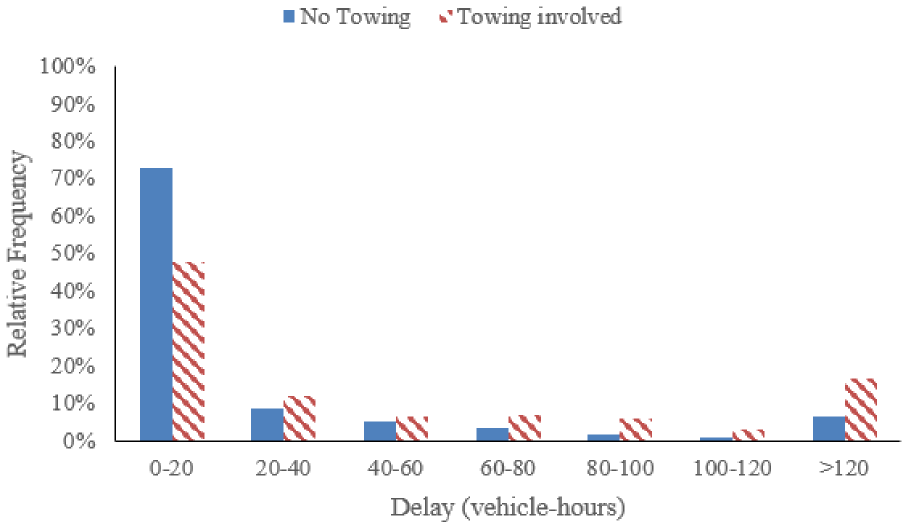


(c) Time of the Day

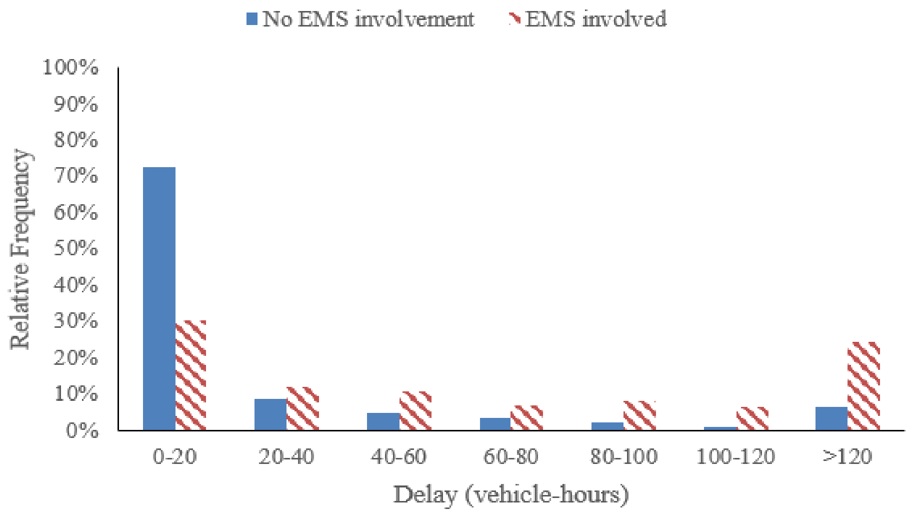


(d) Day of Week

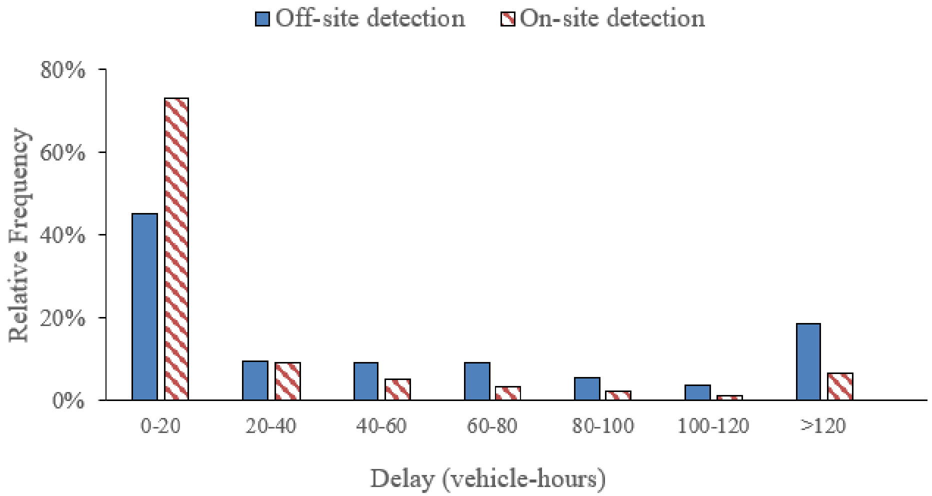
Figure 4-10: Distributions of Incident-related Delays with Respect to Various Attributes



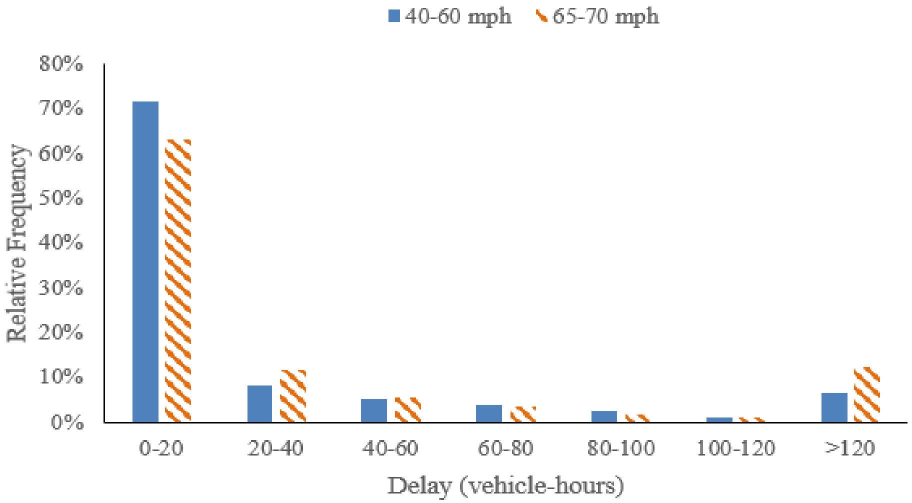
(a) Towing Services



(b) EMS Involvement

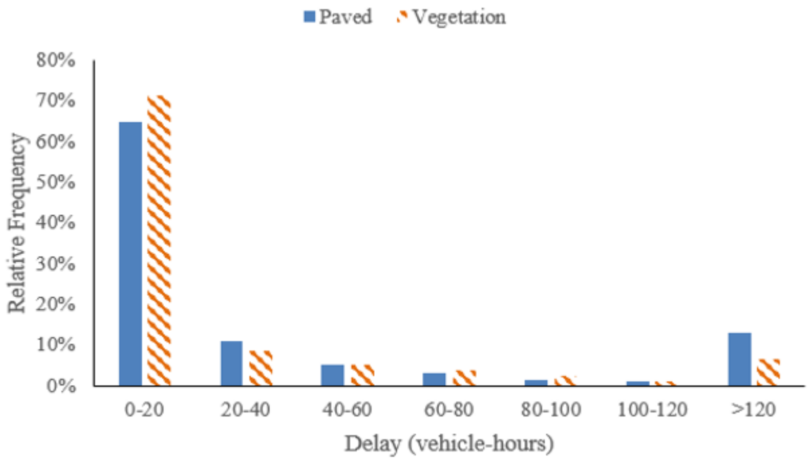


(c) Detection Method

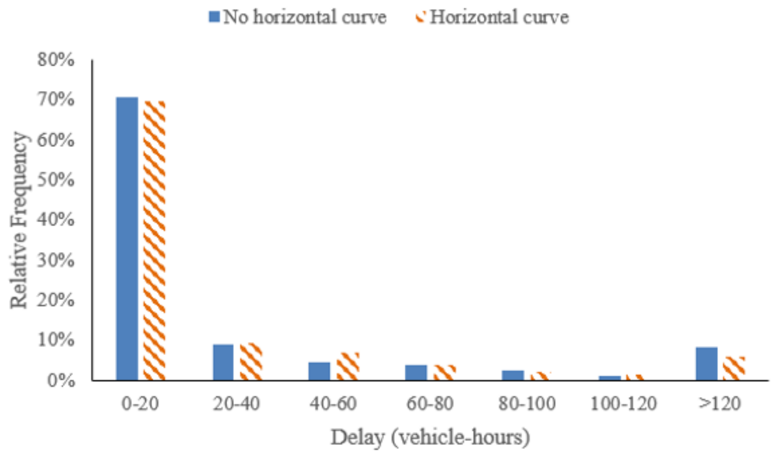


(d) Speed Limit

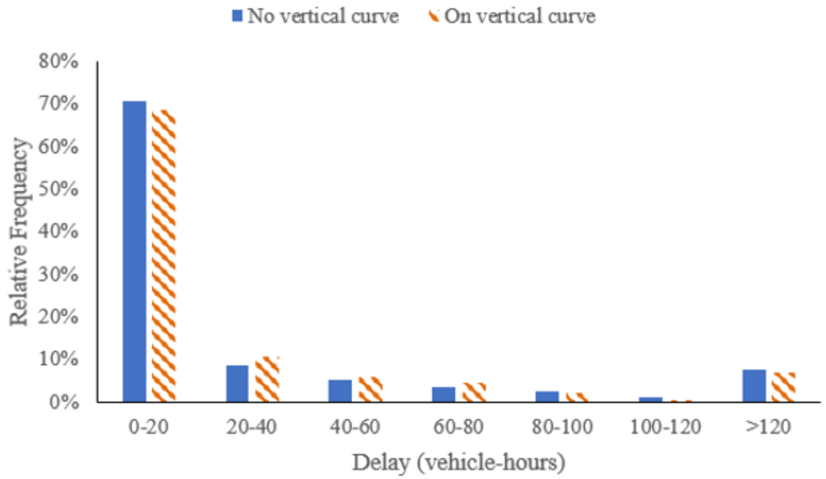
Figure 4-11: Distributions of Incident-related Delays with Respect to Various Attributes



(a) Median Type



(b) Horizontal Curve



(c) Vertical Curve

Figure 4-12: Distributions of Incident-related Delays with Respect to Various Geometric Attributes

Figure 4-12(c) shows that 71% of the incidents that did not occur on vertical curves caused incident-related delays shorter than 20 vehicle-hours, while 8% of the incidents that did not occur on vertical curves led to incident-related delays longer than 120 vehicle hours. About 69% of the incidents that occurred on vertical curves led to incident-related delays shorter than 20 vehicle-hours, while 7% of the incidents that occurred on vertical curves resulted in incident-related delays longer than 120 vehicle-hours.

4.4.4 Factors Affecting Incident-related Delays

The Accelerated Failure Time (AFT) models were developed to determine the relationship between incident characteristics, traffic conditions, roadway geometric conditions, and the estimated incident-related delays. Likelihood ratio statistic was used to select the best fit model. A model with a higher value of likelihood ratio statistic indicates improved statistical fit as compared to other models (Washington et al., 2003). The AFT model with a Weibull distribution (1,280) was selected as the best fit model compared to log-logistic (1,131), and lognormal (1,032). Table 4-2 provides the results of the AFT model with Weibull distribution. The last column (% change) in Table 4-2 shows the percent increase (or decrease) in the incident-related delays due to a change in a categorical variable from the base category or a unit change in the continuous variable.

Table 4-2: Factors Influencing Incident-related Delays

		AFT model (Weibull distribution)				
Variables	**Categories**	**Estimates**	**Std. Error**	***z*-value**	***p*-value**	**% change**
Incident attributes						
Incident type	Hazards					
	Crashes	**2.374**	**0.106**	**22.30**	**0.000**	**974**
	Vehicle problems	**0.779**	**0.101**	**7.73**	**0.000**	**118**
Incident severity	Minor					
	Moderate	**0.493**	**0.170**	**2.89**	**0.004**	**64**
	Severe	0.140	0.370	0.37	0.705	15
Temporal and roadway geometric attributes						
Time of the day	Off-peak					
	Morning peak	**0.639**	**0.067**	**9.59**	**0.000**	**90**
	Evening peak	**0.766**	**0.073**	**10.50**	**0.000**	**115**
Day of week	Weekday					
	Weekend	**-0.562**	**0.113**	**-4.99**	**0.000**	**-43**
Median type	Paved					
	Vegetation	-0.121	0.193	-0.62	0.531	-11
Median width*	Not applicable	**-0.011**	**0.002**	**-5.00**	**0.000**	**-1**
Speed limit (mph)	40-60 mph					
	65-70 mph	-0.063	0.186	-0.33	0.738	-6
Horizontal curve	No					
	Yes	-0.075	0.061	-1.21	0.224	-7
Vertical curve	No					
	Yes	**0.201**	**0.096**	**2.07**	**0.037**	**22**
Agency operations attributes						
Towing involved	No					
	Yes	0.124	0.103	1.20	0.227	13
EMS involved	No					
	Yes	**0.519**	**0.242**	**2.14**	**0.032**	**68**
Fire Department involved	No					
	Yes	-0.009	0.245	-0.03	0.970	-1
Detection method	Off-site					
	On-site	**-0.322**	**0.098**	**-3.29**	**0.001**	**-28**

Note: * Continuous variable; Bold values represent significant estimates at 95% confidence interval.

Out of the 13 variables, the following eight variables were significant at 95% confidence interval.

- *Incident Type:* As shown in Table 4-2, when compared to hazards, crashes led to approximately 10 times longer delays. This was expected because crashes are associated with longer incident clearance durations (Zhang et al., 2012), implying that the traffic upstream of a crash takes longer to dissipate compared to hazards. Also, it can be presumed that crashes affect traffic characteristics, e.g., travel speeds, more than hazards. Vehicle problems (e.g., disabled vehicles, abandoned vehicles, etc.) led to incident-related delays that were 118% longer than hazards. The incident-related delays due to vehicle problems were not as high compared to the incident-related delays caused by crashes because of the difference in the magnitude of impacts on traffic flow characteristics (e.g., the percentage of lane closure) that are associated with the two incident types. Figure 4-13(a) shows the impact of incident type on the estimated incident-related delays. Crashes have higher probabilities of having longer delays compared to hazards and vehicle problems. For example, the probability of having incident-related delays longer than 10 vehicle-hours was approximately 0.2, 0.1, and 0.05 for crashes, vehicle problems, and hazards, respectively.

- *Incident Severity:* Both moderate and severe incidents were associated with longer delays than minor incidents. Results in Table 4-2 suggest that moderate incidents caused 64% longer incident-related delays than minor incidents. Moderate incidents include those involving a high percentage of lane closure while minor incidents might only involve shoulder blockage, if at all. Note that the traffic upstream of the incident is directly affected by the extent and duration of the lane closure at the incident location. Figure 4-13(b) shows the impact of incident severity on the estimated incident-related delays. The likelihood of minor and moderate incidents to cause incident-related delays longer than 10 vehicle-hours was approximately 0.06 and 0.1, respectively. The effect of severe incidents was not significant at the 95% confidence interval, and this observation requires further investigation.

- *Time of the Day:* The positive estimates on the time of the day categories in Table 4-2 suggest longer incident-related delays during peak hours (morning peak and evening peak) than off-peak hours. There was a 90% increase in the incident-related delays during morning peak hours than off-peak hours. Likewise, the evening peak hours had 110% longer incident-related delays compared to off-peak hours. This was expected as there is more traffic on the highways during peak hours than off-peak hours (Angel et al., 2014). However, Table 4-2 shows that the difference in the increase in incident-related delays during the evening peak hours was higher than the increase in incident-related delays during the morning peak hours. Figure 4-13(c) suggests that incidents during evening peak hours had slightly higher probabilities of causing longer delays than incidents during morning peak hours. This could be attributed to the fact that the traffic pattern during evening peak hours is more volatile than during morning peak hours and off-peak hours. Moreover, Nam and Mannering (2000) observed longer incident response times during evening peak hours than morning peak hours.

- *Day of Week:* Table 4-2 shows that incidents that occurred on weekends had 43% shorter incident-related delays than incidents on weekdays. Figure 4-13(d) shows that the probabilities of longer incident-related delays were higher during weekdays than weekends. For example, the probability of having incident-related delays longer than

10 vehicle-hours was approximately 0.05 on weekdays and 0.03 on weekends. An intuitive reason could be less traffic volume on the roadways during weekends compared to weekdays. Although weekends are associated with longer clearance durations, the traffic volume affected by the incident could be low to cause significant traffic delays on weekends.

- *Median Width:* It can be inferred from Table 4-2 that a unit increase in the median width led to a significant 1% decrease in incident-related delays. Wider medians provide a clear area away from the traffic lanes for incident-responding agencies to station and operate. Moreover, wider medians allow responders to quickly clear (i.e., move) the vehicles involved in an incident from the roadway and ensure normal traffic flow while attending to the incident on the median.

- *Vertical Curves:* Compared to level sections, presence of vertical curves on segments resulted in longer incident-related delays. Table 4-2 shows that there was a 22% increase in incident-related delays on segments with vertical curves, compared to the level sections. In Florida, which is predominantly a level terrain, vertical curves are usually found in the vicinity of bridges. Since bridges have very little right-of-way, it takes longer to clear incidents on bridges, increasing the delays associated with these incidents.

- *EMS Involvement:* Table 4-2 shows that incidents that involved EMS were associated with 68% longer incident-related delays than incidents that did not involve EMS. The EMS are commonly associated with severe incidents involving injuries or fatalities. These are obviously expected to have a higher impact on the traffic flow and, hence, longer delays. Figure 4-13(e) shows that the likelihood of having longer incident-related delays was greater when EMS was involved as compared to when EMS was not involved.

- *Detection Method:* Detection of incidents on-site led to shorter incident-related delays compared to off-site detection. Figure 4-13(f) shows that the probabilities of having longer incident-related delays were higher when incidents were detected using the off-site method than the on-site method. Because the on-site detection directly involves some of the response agencies, e.g., Road Rangers, the management of an incident scene starts immediately after detection. Quick response to an incident and prompt management of the incident can avoid traffic bottlenecks. Moreover, most of the hazards and disabled vehicles were detected by the on-site services, e.g., Road Rangers, FHP, etc., and were observed to cause shorter delays.

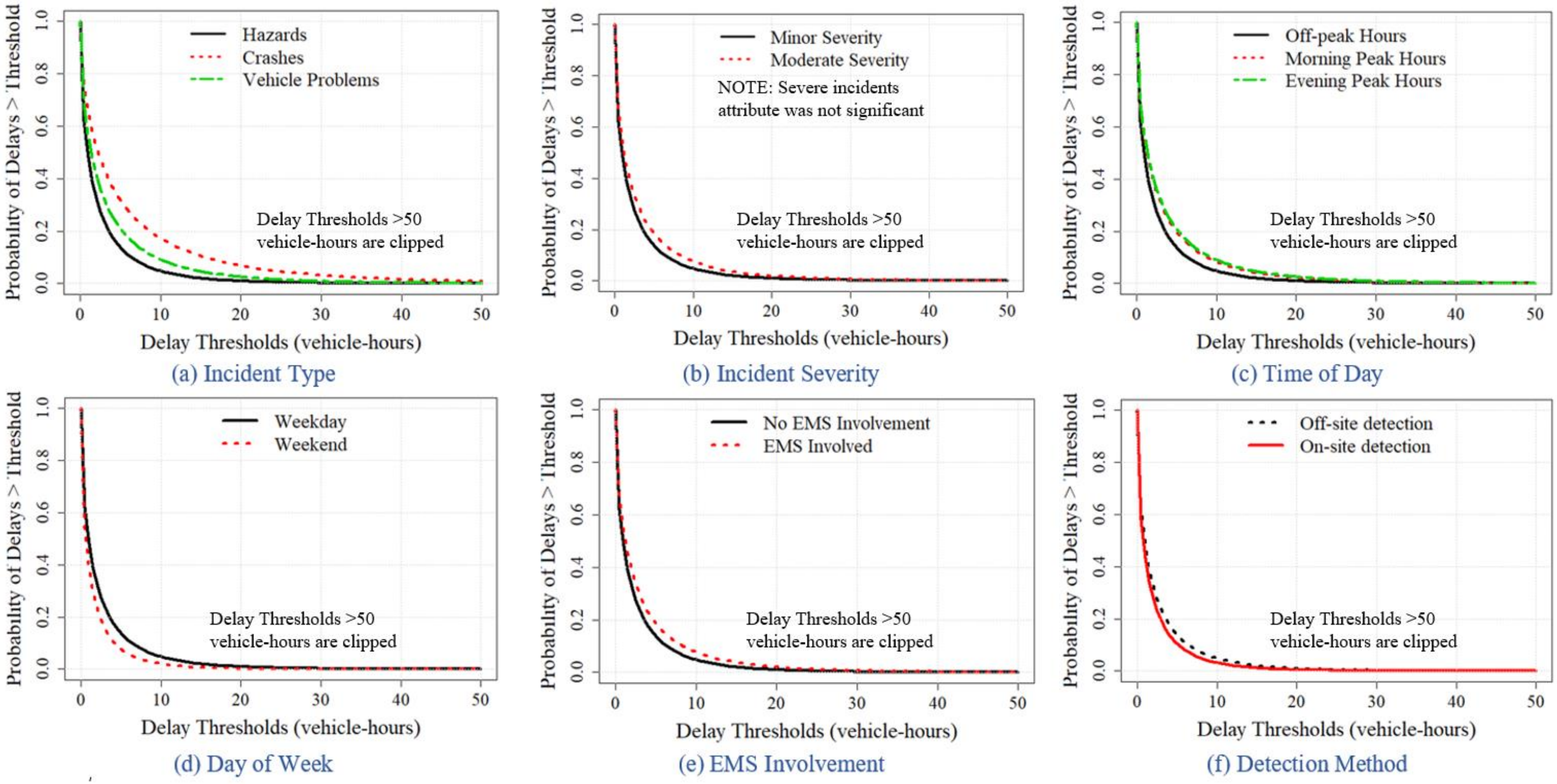


Figure 4-13: Impact of Various Attributes on Incident-related Delays

4.5 Summary

This chapter focused on estimating and analyzing incident-related delays on freeways using a data-driven approach. The analysis was based on 3,383 incidents that occurred along I-95, I-295, and I-10 in Jacksonville, Florida, from 2015-2017. A data-driven methodology was first developed and applied to estimate the incident-related delays. The approach took advantage of the vast network of traffic sensors along the freeway corridors. The analysis used data extracted from both the BlueToad® and RITIS devices. These devices enabled the identification of the dynamic spatial and temporal extent of the incidents. The developed approach used real-time traffic flow characteristics, e.g., speed, travel time, and volume, to estimate the actual delays caused by traffic incidents.

Results indicated that approximately 100%, 82%, and 48% of hazards, vehicle problems and crashes, respectively, had incident-related delays shorter than 20 vehicle-hours. Only 7%, 24%, and 14% of minor, moderate, and severe incidents, respectively, led to incident-related delays longer than 120 vehicle-hours. The distribution of incident-related delays during morning- and evening-peak hours showed a similar trend, where both had lower percentage (approximately 61%) of incident-related delays shorter than 20 vehicle-hours than incidents during off-peak hours (81%). Moreover, 70% of incident-related delays on weekdays and 75% of the incident-related delays on weekends were shorter than 20 vehicle-hours. About 48% of the incidents that involved towing services caused incident-related delays shorter than 20 vehicle hours. Only 6% of the incidents detected using on-site detection methods led to incident-related delays longer than 120 vehicle-hours while 18% of the incidents detected using off-site detection methods caused incident-related delays longer than 120 vehicle-hours.

Once the incident-related delays were estimated, the factors affecting these delays were investigated using hazard-based models. Since delays dissipate after a certain time, hazard-based models were suitable because of their duration dependence properties. Both the parametric and the semi-parametric hazard models were estimated, and the best fit model was selected by using the likelihood ratio statistics. The AFT model with Weibull distribution was selected as the best fit model.

Results indicated that the following eight variables had significant influence on the incident-related delays at the 95% confidence interval:

- incident type (i.e., crashes, vehicle problems, and hazards),
- incident severity (i.e., minor, moderate, and severe),
- time of the day (i.e., off-peak hours, morning peak hours, and evening peak hours),
- day of week,
- median width,
- vertical curvature (i.e., presence or absence),
- EMS involvement (i.e., involved or not involved), and
- detection method (i.e., on-site detection and off-site detection).

Crashes, vehicle problems, moderate incident severity, presence of vertical curves, EMS involvement, and off-site detection methods were found to cause longer incident-related delays. As suggested in the study findings, incident-related delays were longer when an incident was a crash. Enhancements to crash response and dissemination of crash information to the traffic upstream of the crash has the potential to reduce the delays caused by crashes. Further investigation is required to identify factors contributing to longer incident-related delays during evening peak hours than morning peak hours. Presence of vertical curves was associated with bridges, and was found to have significant longer incident-related delays. There is a need for special incident management procedures for such locations to minimize the incident-related delays. A spatial analysis of incident-related delays can identify the areas with the likelihood of having longer delays and help incident response agencies develop plans to cater to these locations.

CHAPTER 5
SECONDARY CRASHES

Traffic incidents have a greater propensity to result in additional incidents, commonly called secondary crashes (SCs). As such, minimizing the occurrence of SCs is one of the major focus areas for transportation agencies, in particular TMCs. This chapter focuses on identifying SCs and analyzing the risk factors influencing the occurrence of these crashes.

5.1 Secondary Crash Definition

Traffic incidents frequently affect traffic operations, accounting for more than a half of all urban traffic delays and almost all rural traffic delays (Baykal-Gürsoy et al., 2009). Furthermore, traffic incidents expose other vehicles to the risk of becoming involved in a SC (Owens et al., 2010). SCs are generally considered to occur at the boundaries or within the congested spatiotemporal region that builds up as a result of a prior incident, commonly referred to as a primary incident (PI). While most studies (Zhan et al., 2008; Moore et al., 2004) have identified SCs upstream of the direction of travel similar to the vehicles in PI, it is possible for SCs to occur in the opposite direction of the PI as a result of the rubbernecking phenomenon (Yang et al., 2014a). Figure 5-1 explains SCs using a hypothetical example.

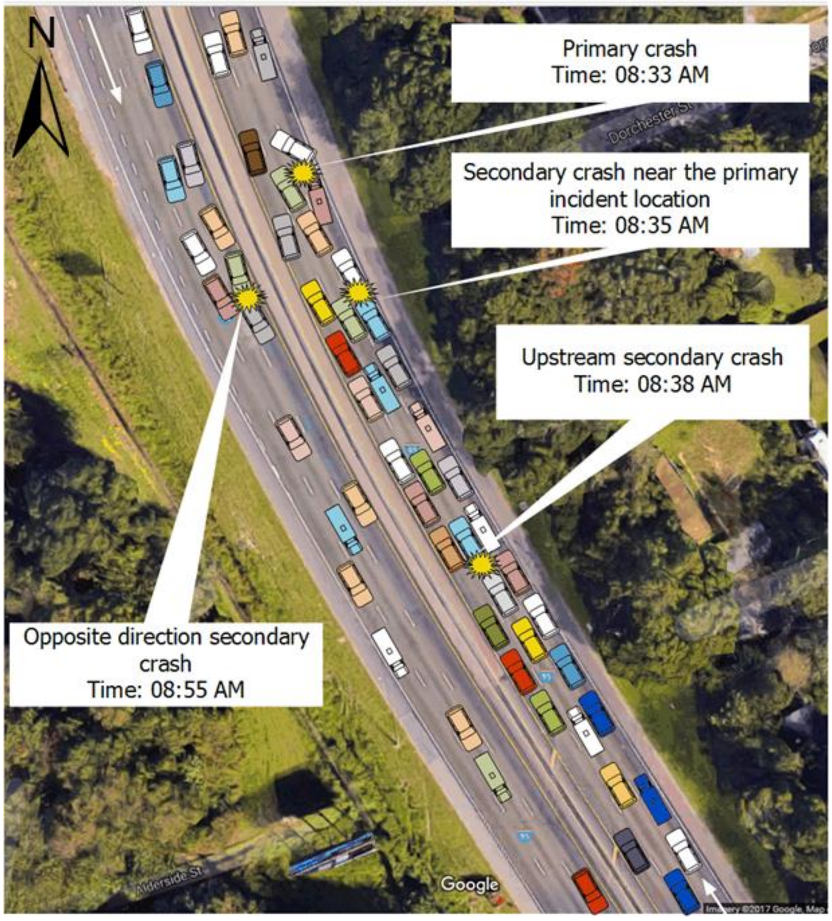


Figure 5-1: Definition of a Secondary Crash

In this example, a prior traffic incident (crash) occurred on NB lanes at 8:33 AM. This crash, categorized as a primary crash, resulted in a queue backup upstream of the crash location. Two crashes, one near the primary crash location and the other upstream of the primary crash location, occurred at 8:35 AM and 8:38 AM, respectively. Another crash also occurred in the opposite direction (i.e., on SB lanes) at 8:55 AM. While the first crash that occurred at 8:33 AM is considered as the PI, the remaining three crashes are considered as SCs which occurred as a result of the PI. In summary, a traffic incident is considered as a SC if it occurs: (a) at the scene of the PI (Zhang and Khattak, 2010); or (b) within the queue upstream of the PI (Owens et al., 2010; Zhang and Khattak, 2010; Zhan et al., 2008; Moore et al., 2004); or (c) within the queue in the opposite direction of the PI caused due to driver distraction (i.e., rubbernecking effect) (Yang et al., 2014a).

SCs have increasingly been recognized as a major problem leading to reduced capacity, additional traffic delays, and increased fuel consumption and emissions. SCs are non-recurring in nature; not only do they affect the traffic operations, but they also impose risk on safety of road users. Statistics indicate that up to 15% of reported crashes are partly or entirely due to PIs (Raub, 1997). In a more recent study, Owens et al. (2010) determined that SCs account for 20% of all crashes and 18% of all fatalities on freeways. Further, compared to PIs, SCs have significant impact on traffic management resource allocation (Vlahogianni et al., 2012; Karlaftis et al., 1999). For these reasons, prevention of SCs has been highlighted as a high priority task for traffic incident managers (NCHRP 2014; O'Laughlin and Smith, 2002). In fact, FHWA uses the reduction of SCs as one of the performance measures for state incident management systems (Owens et al., 2010). As such, several state agencies, including Florida, are considering SC identification and mitigation strategies in allocating funding for on-road help services (e.g., Road Rangers) and the development of TIM programs (NCHRP 2014). Consequently, minimizing the occurrence of SCs is one of the major focus areas for transportation agencies, in particular TMCs (Owens et al., 2010). Nonetheless, the limited knowledge on the nature and characteristics of SCs has largely impeded their mitigation strategies. The main objectives of this study include:

1. Developing an enhanced algorithm to identify SCs using real-time BlueToad pairs travel speed data.
2. Examining the relationship between the PI and its respective SC.
3. Developing a reliable SC risk prediction model using real-time traffic flow variables.

5.2 Literature Synthesis

Existing literature on SCs has mainly focused on three aspects: methods to identify SCs; characteristics of SCs; and factors that influence the occurrence of SCs. This section is therefore divided into three subsections based on the aforementioned three topics.

5.2.1 Existing Methods to Identify SCs

As mentioned earlier, SCs are traffic incidents that occur within the spatial and temporal impact range of the PIs. Unlike other traffic incidents which are easily identified by incident responders, detection of SCs is not a straightforward procedure since the definition itself is subjective. Even incident responders on-site or the TMC personnel, who observe traffic through the CCTV, cannot accurately identify SCs. This is because the process of identifying SCs varies depending on the spatial and temporal influence area of the PI. It is difficult to determine visually, either directly at the crash site or through the CCTV camera, if the crash is a result of the backup caused by another incident. Thus, accurate detection of SCs depends on the reliability of the spatial and temporal information of the prior incident. With that, the first step in identifying SCs is to define the impact area of the prior incident, i.e., its spatiotemporal boundaries.

Three major approaches have been used to define the spatiotemporal thresholds of PIs: (1) manual method where personnel visually identify SCs; (2) static method that uses predefined spatiotemporal thresholds; and (3) dynamic approach that uses varying spatiotemporal thresholds based on PI characteristics and prevailing traffic flow conditions. An extensive review of literature indicated that tremendous efforts have been conducted to identify SCs. Comprehensive reviews of the static and dynamic methods can be found in Yang et al. (2018). The following subsections provide more details about these three methods.

Manual Method

As the name “manual” indicates, in this method, SCs are manually identified by either TMC personnel or incident responders. Identifying SCs on a CCTV camera is considered an off-site approach; while identifying SCs at the incident scene by the incident responders including police, Road Rangers, etc., is considered an on-site approach. In Florida, SCs are recorded at the incident scene via a check box in the electronic crash form shown in Figure 5-2. The TMC operations personnel also often link a secondary event to a primary event and note it as being secondary to the first (i.e., primary) event in the SunGuide® database.

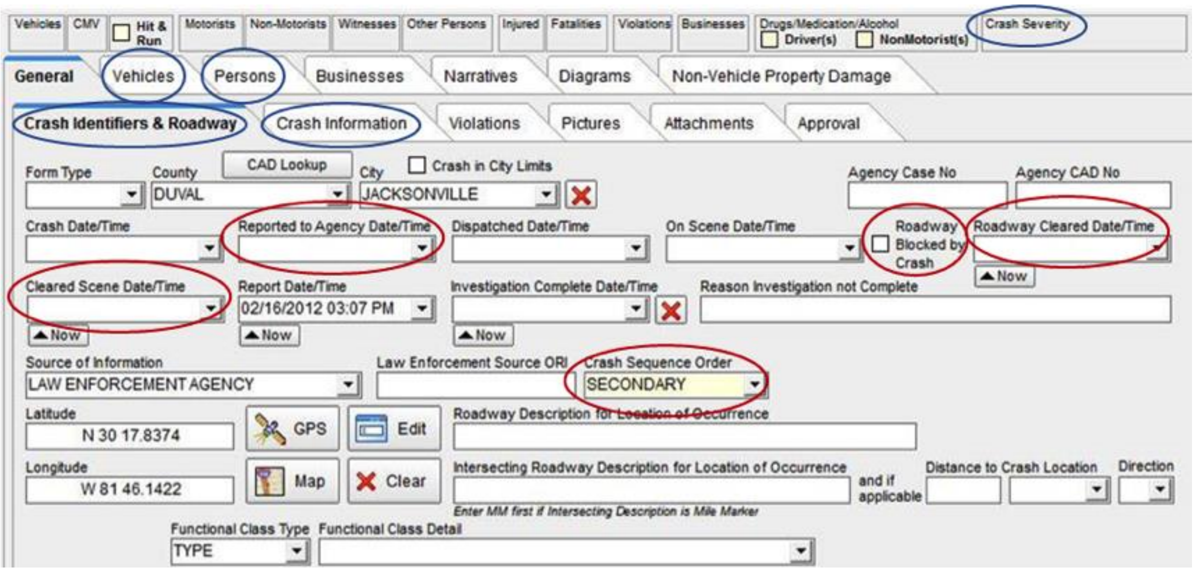


Figure 5-2: Traffic Incident Management Performance Data Elements on the FHP Electronic Crash Form (NCHRP 2014)

The manual method has traditionally been used by agencies to identify SCs. It is simple and does not require any data processing. However, despite being the most commonly used method, it is subjective, unreliable, inconsistent, and random.

Static Method

The static method identifies SCs based on some fixed spatial and temporal criteria. Crashes that occurred within the spatial and temporal impact range of a PI are identified as SCs. For SCs occurring upstream of the PI, the spatial and temporal thresholds employed by previous studies range from 1 to 2 miles and 15 minutes to 2 hours, respectively (Zhan et al., 2008; Moore et al., 2004; Karlaftis et al., 1999; Raub, 1997). On the other hand, SCs occurring in the opposite direction of the PI were identified using different thresholds. Table 5-1 summarizes some of studies that used the static method to identify SCs. For example, Chang and Rochon (2011) identified SCs using 30-minutes-0.5-mile threshold in the opposite direction of the PI. In the current study, the temporal and spatial thresholds of 2 hours and 2 miles were adopted while identifying SCs on the upstream direction; while, SCs in the opposite direction were identified using a spatial threshold of 0.5 miles and temporal threshold of incident clearance duration of the PI.

Table 5-1: Summary of Literature on Static Secondary Crash Identification Methods

Study	Data	Fixed Spatiotemporal Criteria Used
Raub (1997) and Karlaftis et al. (1999)	Incident data	Clearance time + 15 minutes 1 mile
Latoski et al. (1999)	Incident data	Clearance time + 15 minutes 3 miles upstream
Zhan et al. (2008)	Incident data	Clearance time + 15 minutes 2 miles upstream, lane closure
Hirunyanitiwattana and Mattingly (2006)	Crash data	2 hours 2 miles
Khattak et al. (2009)	Incident data	actual duration 1 mile upstream
Moore et al. (2004); Kopitch and Saphores (2011)	Incident data	2 hours 2 miles (both directions)
Chang and Rochon (2011)	Incident data	2 hours, 2 miles; 0.5 hours, 0.5 miles (opposite direction)
Green et al. (2012)	Crash data	80 minutes 6,000 ft; 1,000 ft (opposite direction)

Unlike the manual method, static method is more reliable simply because it is a function of predefined spatiotemporal parameters. This approach can be more efficient by automating it using Visual Basic for Application (VBA), or similar applications. However, the fixed spatiotemporal thresholds used in the static method are subjective and arbitrary. The method incorrectly assumes that all incident types that occur at different traffic conditions such as congested and free-flow states, have the same impacts on the upstream traffic flow. In fact, incidents occurring during free-flow conditions might not have a long lasting and far reaching effect compared to the incidents occurring during congested conditions. In addition, severe incidents tend to lead to longer incident response and clearance times compared to minor incidents. To accurately identify SCs, both spatial and temporal thresholds should vary based on traffic conditions, geometric characteristics, and certainly incident characteristics.

Dynamic Method

To overcome the limitations associated with the static approach, recent studies have focused on detecting SCs based on traffic flow conditions. In this case, spatiotemporal thresholds are flexibly selected based on the impact of the PI on traffic flow parameters hence the name dynamic methods. Sun and Chilukuri (2006) proposed the use of an incident progression curve, a method that uses incident duration to estimate the queue length and hence identify SCs that occurred within the queue. The incident progression curve method indicated a 30% improvement in the SC identification accuracy compared to the static method. Nonetheless, queuing model-based approaches are limited in the establishment of the reliable queuing model. In other words, different roadway segments are subject to different queuing formation processes because of their unique traffic, geometry, and incident characteristics.

Several researchers have estimated flexible spatiotemporal thresholds based on the PI influence area using other dynamic methods such as speed contour, automatic tracking of moving jams, vehicle probe data, shock wave principles, etc. (Park and Haghani 2016; Wang et al., 2016a; Yang et al., 2014a; Mishra et al., 2016). These approaches take the advantage of the traffic data retrieved from infrastructure-based traffic sensors. Use of traffic sensor data enables capturing the effects of traffic characteristics (e.g., flow, speed, and density) that change over time and space, and affect the queue formation as a result of the PI. Table 5-2 summarizes some of the studies that used the dynamic approaches to identify SCs.

Table 5-2: Summary of Literature on Dynamic Secondary Crash Identification Methods

Study	Data	Method Used
Zhan et al. (2009)	Incident data	Maximum queuing model
Sun and Chilukuri (2006, 2010)	Incident data	Incident progression curves
Zhang and Khattak (2010)	Incident data	Deterministic queuing model
Haghani et al. (2006) and Chou and Miller-Hooks (2010)	Incident and simulated traffic data	Simulated speed contour map
Vlahogianni et al. (2010, 2012)	Incident, monitor and sensor data	Automatic Staudynamikanalyse model
Yang et al. (2013, 2014b, 2014c)	Crash and sensor data	Speed contour map
Imprialou et al. (2013)	Detectors data	Automatic Staudynamikanalyse model and the cumulative plots method
Park and Haghani (2016)	Probe data	Speed contour map
Sarker et al. (2015, 2017) and Mishra et al. (2016)	Detector data	Queuing shockwave-based model

The results from these studies indicate that the proposed dynamic methods provide better accuracy in identifying SCs than conventional static methods. Compared to static or manual method, dynamic method is a more advanced and reliable method since it identifies SCs based on traffic flow characteristics. However, the implementation of the current approach depends on the availability of real-time traffic data. The detectors for capturing real-time traffic flow data are mostly available on limited access facilities, and hence, the use of dynamic method is limited to only these locations. Moreover, this method is resource and data intensive.

5.2.2 Secondary Crash Characteristics

Carrick et al. (2015) compared roadway, environmental, and vehicle characteristics of secondary and normal crashes. SCs were observed to be more likely to occur on freeways and in rainy weather conditions. Another study by Zhang et al. (2015) used a microscopic simulation tool to study the queuing delays associated with SCs. SCs were found to result in longer incident impact duration than normal incidents. Further, the time gap and distance between a PI and its SC were observed to significantly affect the total delays. Mishra et al. (2016) concluded that SCs on freeways are more likely to occur during the morning and evening peaks, while the SCs on arterials are more common during the evening peak.

A number of studies have also been conducted to investigate the relationship between the likelihood of SCs and various contributing factors including PI characteristics, weather conditions, geometric conditions, traffic volumes, and roadway functional classification (Wang et al., 2016a; Wang et al., 2016b; Yang et al., 2013; Khattak, et al., 2012; Zhang and Khattak, 2010; Khattak, et al., 2009). In general, factors contributing to SCs were observed to be: number of vehicles involved in PIs, PI impact duration, number of lanes blocked, traffic volume, and posted speed limit (Wang et al., 2016a; Wang et al., 2016b; Xu et al., 2016; Chimba et al., 2014; Khattak et al., 2012; 2009). Traffic incidents that occurred during the off-peak hours and on weekends are less likely to induce SCs (Khattak et al., 2009; 2012; Yang et al., 2014a).

Further, adverse weather conditions such as rain and snow were found to significantly increase the risks of SCs (Wang et al., 2016a; Wang et al., 2016b; Khattak et al., 2012). One common theme among most SCs studies is that they all associate the occurrence of SCs with the PI impact duration. Thus, examining the PI impact duration is crucial in developing SC occurrence prediction models.

5.2.3 Secondary Crash Risk Prediction Models

As discussed in earlier sections, identifying SCs is the first and the most critical step. The next important step is calculating the probability of SCs. Only a few studies have examined risk factors that influence the occurrence of SCs. Table 5-3 presents some of the previous studies that have identified SC risk factors. Most of these studies have analyzed the likelihood of SCs using either non-parametric or parametric models. Several non-parametric models such as neural networks and decision trees have been used to model SC risk. Vlahogianni et al. (2010) developed a Bayesian network for the probabilistic estimation of different influence areas for SCs with respect to various incident and traffic characteristics. Traffic conditions at the time of an incident and incident clearance duration were observed to be the most significant determinants in defining the upstream influence of a crash. Later, Vlahogianni et al. (2012) developed a neural network model with enhanced explanatory power. The study reported that traffic speed, duration of the PI, hourly volume, rainfall intensity, and number of vehicles involved in the primary crash as the most significant determinants associated with SC likelihood.

Other studies developed decision tree models to explore contributing factors based on the prediction results of artificial neural networks algorithm. For example, by identifying SCs based on the binary speed contour plot map using probe vehicles data, Park and Haghani (2016) predicted the likelihood of SCs using Bayesian neural networks model and extracted rules to generate gradient-based decision trees. In turn, the main determinants that influence the occurrence of SCs were shown based on the decision tree. Apart from directly modeling the SC occurrence risk, Wang et al. (2018) used two machine learning algorithms (back-propagation neural network and a least square support vector machine) to model the spatial and temporal gaps between the primary and secondary incidents. It was reported that both algorithms failed to predict the spatial threshold while the back-propagation neural network algorithm outperformed the least square support vector machine algorithm in temporal threshold prediction.

Most of the studies that developed parametric models used either logit or probit models to analyze the likelihood of SCs (Mishra et al., 2016; Wang et al., 2016a; Wang et al., 2016b; Yang et al., 2013; Khattak et al., 2012; 2009; Zhan et al., 2009). Both logit and probit models are symmetrical in nature, i.e., the likelihood of SC occurrence is presumed to rise up to a probability of 0.5, then decrease toward the asymptote at one (1). In other words, in SC likelihood prediction, symmetric models such as logit or probit models are applicable only when the proportion of normal incidents (~50%) is equal to the proportion of PIs (~50%). However, SCs account for less than 20% (Owens et al., 2010) of total incidents, meaning that the proportion of PIs is much less than the proportion of normal incidents (i.e., the PI and the normal incidents are asymmetrically distributed). Thus, a model which is asymmetrical around the inflection point is considered to be more reliable in predicting the likelihood of SCs. With this situation at hand, a complementary log-log model (cloglog), which is used as an alternative prediction model over the conventional logit and probit models would be a better model.

Table 5-3: Summary of Literature on Secondary Crash Risk Factors

Study	Models and Statistical Tests	Explanatory Variables	Findings
Junhua et al. (2016)	Logistic Regression Model	Crash severity, Violation category, Weather, Tow away indicator, Road surface, Lighting, Traffic volume, Duration, Shock waves	• Crash processing duration was found to significantly affect SC occurrence. • Unsafe speed of the PC was found to negatively affect SC occurrence. • Decrease in speed and increase in lane volume were found to lead to an increase in the probability of SC occurrence.
Xu et al. (2016)	Bayesian Random Effect Logit Model (BLM)	Crash severity, Sideswipe, Day of week, Road surface, Lane, AADT, Average speed, Detector occupancy, Difference in traffic volume between adjacent lanes	• Likelihood of SC was found to be higher on weekends, roadways with fewer lanes, and during morning peak periods. • Compared to several different crash types, sideswipe PC were found to be less likely to cause SC. • Difference in traffic volume between adjacent lanes was found to have significant risk effect on SC.
Zheng et al. (2015)	Pearson's Chi-square Test (SC and other general crashes)	Day of week, Month of the year, and Hour of the day	• SC were significantly different from PC with respect to month of the year and hour of the day. • SC were found to occur mostly from 6 to 11 PM.
Park and Haghani (2016)	Bayesian Neural Network (BNN)	Different stages of clearance time	• Likelihood of secondary incidents was found to be higher when clearance time of PIs was 10 - 20 minutes, or > 75 minutes.
Sarker et al. (2017)	Generalized Ordered Response Probit (GORP) model	Speed limit, Number of lanes, Land use, Median type, Ramp, High Occupancy Vehicle indicator, AADT, Right shoulder	• About 10% increase in AADT was found to increase SC occurrences by 34.24%. • Two-lane roads were found to cause 73% more SCs compared to roads with 3 or more lanes. • Locations with raised median were found to have 267% more SCs compared to the sections without raised medians.
Xie et al. (2016)	Structural Equation Model (SEM)	Driver, Vehicle, Roadway characteristics, and Environmental condition	• 13 explanatory variables were found to contribute to the occurrence of SCs: alcohol, drugs, inattention, inexperience, sleep, control disregarded, speeding, fatigue, defective brake, pedestrian involved, defective pavement, limited view, and rain. • 16 variables were expected to increase the risk of severe injuries: presence of secondary crash, alcohol, drugs, inattention, yield, illness, control disregarded, speeding, fatigue, cell phone, defective brake, motorcycle involved, bike involved, pedestrian involved, defective pavement, and at intersection. • Likelihood of the occurrence of SCs and severe injuries was found to be higher at nighttime compared to daytime conditions.

Table 5-3 (Cont'd): Summary of Literature on Secondary Crash Risk Factors

Study	Models and Statistical Tests	Explanatory Variables	Findings
Vlahogianni et al. (2012)	Neural Network Model (NN), Gompit Model, Probit Model	Duration, Collision type, Number of lanes, Number of vehicles involved, Heavy vehicle, Average speed, Hourly volume, Rainfall, Road alignment, Upstream and downstream geometry	• Traffic speed, PC duration, hourly volume, rainfall intensity, and number of vehicles involved in PC were found to be the top five factors associated with SC likelihood. • Changes in traffic speed and volume, number of vehicles involved, blocked lanes, percentage of trucks, and upstream geometry were found to significantly influence the probability of having a secondary incident.
Mishra et al. (2016)	Multinomial Logit Model (MLM)	AADT, Roadway functional class, Number of vehicle involved, Stream flow, Incident type, Weather	• Majority of SC were found to be associated with higher upstream traffic flow. • PC with rear-end collision type was found to be the predominant factor that contributed to SC.
Zhan et al. (2008)	Binary Logistic Regression Model (BLM)	Number of vehicle involved, Number of lanes, PI duration, Rollover, Midday (9:00 to 16:00), Morning peak (6:00 to 9:00)	• Five factors that were found to have significant effect on the likelihood of secondary incident occurrence are: number of vehicles involved in the PI, number of lanes at the PI location, the PI duration, time of the day of incident occurrence, and if vehicle rollover occurred during the PI. • Incident visibility and lane blockage durations of the PIs were found to be the significant contributing factors for determining the severity of SC.
Khattak et al. (2012)	Binary Logistic Regression Model (BLM)	Time of the day, Weather, Crash location, AADT, Detection source, Number of vehicles involved, Incident type, Lanes closed, EMS, Right and left shoulder, Ramp, Predicted incident duration	• A positive significant correlation was found between SC occurrences and longer PI duration, higher AADT, PIs that occurred during peak hours.
Hirunyanitiwattana and Mattingly (2006)	Proportional Test	Area type, Time of the day, Crash severity, Collision type and factor, Roadway functional class	• Speeding was found to be the major collision factor of SC compared to PC. • PDO crashes were found to be more frequent in both PC and SC. • Risk for SC was found to be higher in urban areas compared to rural districts.
Tian et al. (2016)	t-test	Crash severity, Crash type, No improper action, Careless driving	• Careless driving was found to be the leading factor which accounts for more than 50% of the total PIs, followed by exceeding safety limit (8.13%), and no improper driving/action (4.07%). • Rear-end collision type was found to be predominant in SC.

Unlike the logit and probit models, the cloglog model is asymmetrical with a fat tail as it departs from zero (0) and sharply approaches one (1) (Kitali et al., 2017; Martin and Wu, 2017). In modeling SCs, most of the previous studies have used general roadway characteristics such as AADT and speed limit as some of the model variables (Mishra et al., 2016; Chimba et al., 2014; Khattak et al., 2012; Zhang and Khattak, 2010). These variables limit the reliability of the study findings simply because they are averages and do not reflect real traffic conditions at the time of an incident. Relatively few studies have predicted the likelihood of SCs using real-time data considering the effect of dynamic traffic flow conditions (Park and Haghani, 2016; Xu et al., 2016; Vlahogianni et al., 2012).

5.3 Data

The analysis was based on four years (2014-2017). As discussed in previous chapters, the study area includes a 35-mile section on I-95, a 21-mile section on I-10, a 61-mile section on I-295, and a 13-mile section on SR-202 located in Jacksonville, Florida. In summary, the total study area covers 130 miles. The following sub-sections discuss the data preparation efforts for identifying SCs and analyzing SCs risk factors. Notably, in-depth discussion of data sources used to implement the objectives of this study are discussed in the previous chapters, i.e., SunGuide® database in Section 2.2, BlueToad® in Section 2.3, RITIS in Section 4.2.1, and RCI in Section 4.2.2.

5.3.1 Data Requirements for Static Method

Along the study corridors, the SunGuide® database included a total of 97,106 incidents for the years 2014-2017. After excluding incidents on ramps (22,746) and incidents with missing coordinates (330), the remaining data consisted of a total of 74,030 incidents. Note that the incidents that occurred near or at ramps were not included in the analysis. Compared to mainline segments, ramps have a complex geometry that significantly affects the traffic transition states, i.e., from free-flow to breakdown, to congested, recovery and eventually back to free-flow again. For this reason, incidents occurring near or on ramps require a separate analysis approach. In addition to incident data, Interstate and State Roads polyline shapefiles were extracted from the FDOT Transportation Data and Analytics Office website. The data from these shapefiles were used to assign mileposts to the incidents.

To identify SCs using the static method, the spatial and temporal characteristics of each individual incident were identified. The Incident-First-Notified Time was used to estimate the temporal threshold, while the milepost for each incident was used to calculate the distance between the PI and the potential SCs. This approach was taken to ensure that roadway alignment characteristics, especially on curved segments, do not affect the accurate computation of the spatial relationship between a PI and a SC.

5.3.2 Data Requirements for Dynamic Method

Speed data from BlueToad® pairs and incident data from the SunGuide® database were used to detect SCs using the proposed dynamic approach. Since BlueToad® pairs have not yet been extensively deployed, the study area includes only the corridors with these devices. SR-202 does not have BlueToad® pairs, and was therefore excluded from the analysis. Further, the analysis included data from 2015-2017 because very few BlueToad® pairs were operational along the study corridors in 2014. The study location has 72 BlueToad® pairs devices placed approximately every 1.8 miles on the mainline. The posted speed limit on the entire section ranges between 55 mph and 70 mph. This study used raw data collected by each BlueToad® pair. Table 5-4 provides more information about the study corridors.

Table 5-4: Distribution of BlueToad® Pairs along the Study Corridors

Roadway	Number of BlueToad® Pairs			Length of corridor (miles)	Speed limit (mph)
	East/North	West/South	Total		
I-10	3	3	6	21	55
I-295	18	21	39	61	65
I-95	14	13	27	35	55-70

Along these study corridors, the SunGuide® database included a total of 66,756 incidents from 2015-2017. Table 5-5 provides more information about the incidents analyzed in the dynamic method.

Table 5-5: Incidents Analyzed in the Dynamic Method

Criteria	**I-10**	**I-295**	**I-95**	**Total**
Total incidents from 2015-2017	8,545	35,719	22,492	66,756
Incidents on ramps	1,927	7,862	5,941	15,730
Incidents with missing coordinates	105	0	78	183
Incidents with no matched BlueToad® pairs	3,475	6,964	551	10,990
Incidents along the section without BlueToad® pairs	2,740	17,806	12,442	32,988
Total incidents included in the analysis	298	3,087	3,480	6,865

5.3.3 Data Requirements for Modeling the Risks Associated with SCs

The objective of this study was implemented using a 35-mile corridor in I-95. The following data for the years 2015-2017 were used: speed data from BlueToad® pairs, 3,480 incidents data from SunGuide® database (Table 5-5), and real-time traffic data from RITIS. To capture the conditions of traffic prior to incident occurrence, traffic data such as speed, volume, and occupancy, were extracted from 375 RITIS (183 on NB and 192 on SB directions) detector stations along the study corridor. The average spacing between detectors is approximately half a mile. The spatiotemporal thresholds of 30-min and 1-mile radius are used to capture traffic conditions before the occurrence of the incident.

In addition to these data, geometric characteristics including median width, type of roadside barrier, and presence of horizontal curve, were extracted from the 2015 FDOT-RCI database, and included in the analysis (FDOT, 2015). The following paragraph discusses the approach employed to identify incidents affected by the horizontal curve.

All incidents that occur on horizontal curves may not necessarily cause queue-visibility problem leading to SCs. For example, the red line in Figure 5-3 shows a horizontal curve on I-95. Incidents A and B occurred on I-95 northbound (NB); while incidents C and D occurred on I-95 southbound (SB). Since Incident A occurred at the beginning of the horizontal curve on I-95 NB, it does not cause queue-visibility problem leading to a SC. On the other hand, Incident B on I-95 NB lanes occurred at the end of the horizontal curve, and may cause queue-visibility problem leading to a SC.

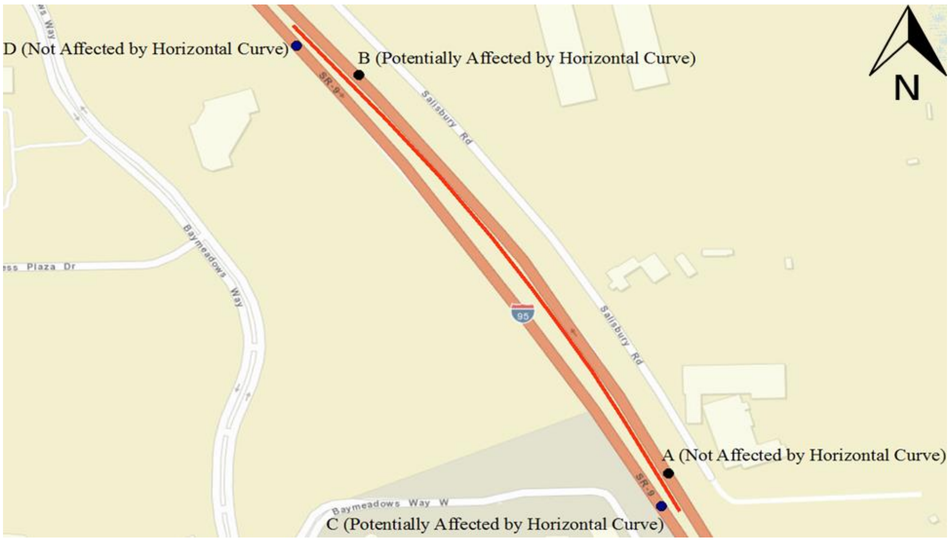


Figure 5-3: Identification of Incidents Affected by the Presence of Horizontal Curve

Similarly, on I-95 SB lanes, Incident D does not cause queue-visibility problem while Incident C may cause queue-visibility problem. Incidents on horizontal curves were identified using this approach. Tables 5-6 and 5-7 provide the descriptive statistics of the categorical and continuous variables considered in this study, respectively.

Table 5-6: Descriptive Statistics of Categorical Variables

Parameter	Factor	Count	Percent (%)
Roadway alignment	Straight	1,857	75.61
	Curved	599	24.39
Incident occurrence time	Off-peak	1,196	48.70
	Peak	1,260	51.30
Incident type	Hazards	130	5.29
	Vehicle-related	1,280	52.12
	Crash	1,046	42.59
EMS involved	No	2,266	92.26
	Yes	190	7.74
Towing involved	No	2,077	84.57
	Yes	379	15.43
Number of responding agencies	1	1,208	49.19
	2-3	965	39.29
	> 3	283	11.52
Percent lane closed (%)	≤ 25	2,098	85.42
	> 25	358	14.58
Shoulder blocked	No	1,052	42.83
	Yes	1,404	57.17
PI severity	Minor	2,424	98.70
	Moderate/severe	32	1.30
Detection method[a]	On-site	2,121	86.36
	Off-site	335	13.64
Roadside barrier	Guard rail	1,238	50.41
	Barrier wall	1,218	49.59
Lighting condition	Daytime	2,274	92.59
	Nighttime	182	7.41

Note: [a] Identifying SCs on a CCTV camera at a TMC is considered an off-site approach; while identifying SCs on site by the incident responders including police, road rangers, etc. is considered an on-site approach.

Table 5-7: Descriptive Statistics of Continuous Variables

Variable	Minimum	Mean	Median	SD	Maximum
PI impact duration (min)[1]	30	97	75	87	855
Incident clearance duration (min)	0	44	27	46	417
Average vehicle speed (mph)	5	56	61	15	78
SD of vehicle speed (mph)	0	9	7	6	35
Average EHV (veh/hour)	0	38	32	39	624
SD of EHV (veh/hour)	0	17	11	36	465
Average detector occupancy (%)	0	10	7	7	47
SD of detector occupancy (%)	0	5	3	3	20
Median width (ft)	16	39	40	28	150

Note: SD = standard deviation, EHV = Equivalent hourly volume. [1]Time taken for the traffic to return back to normal after the occurrence of the PI.

5.4 Methodology

5.4.1 Static Model to Identify SCs

Static method uses fixed spatiotemporal thresholds to identify SCs. ArcGIS, a mainstream Geographical Information System (GIS) software, was used to assign mileposts to all incidents. Next, the process of detecting SCs using static method was automated by implementing the algorithm in the VBA programming language. As mentioned earlier, SCs can occur either in the upstream direction of the PI or in the opposite direction of the PI. In this study, using the static method, SCs in the upstream and opposite direction were identified separately.

Identification of Upstream Secondary Crashes

Figure 5-4 shows SCs that occurred in the upstream direction of the PI. Figure 5-5 summarizes the steps followed in the VBA script to identify SCs upstream of the PI.

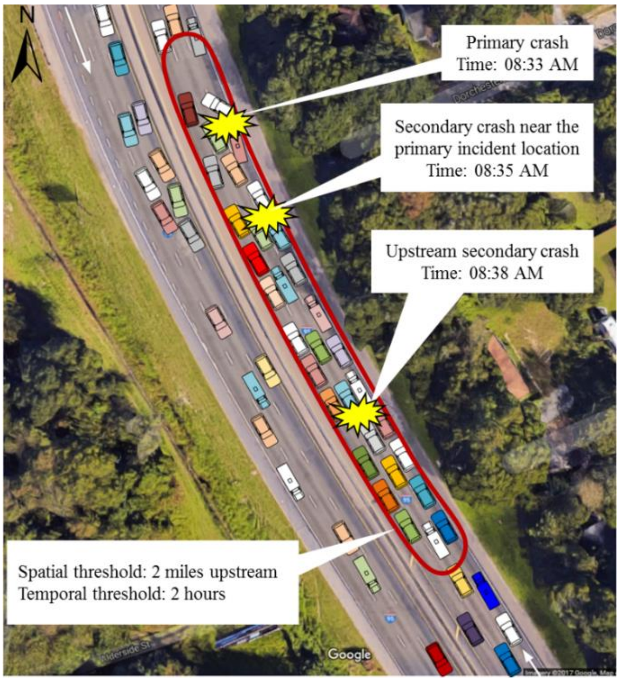
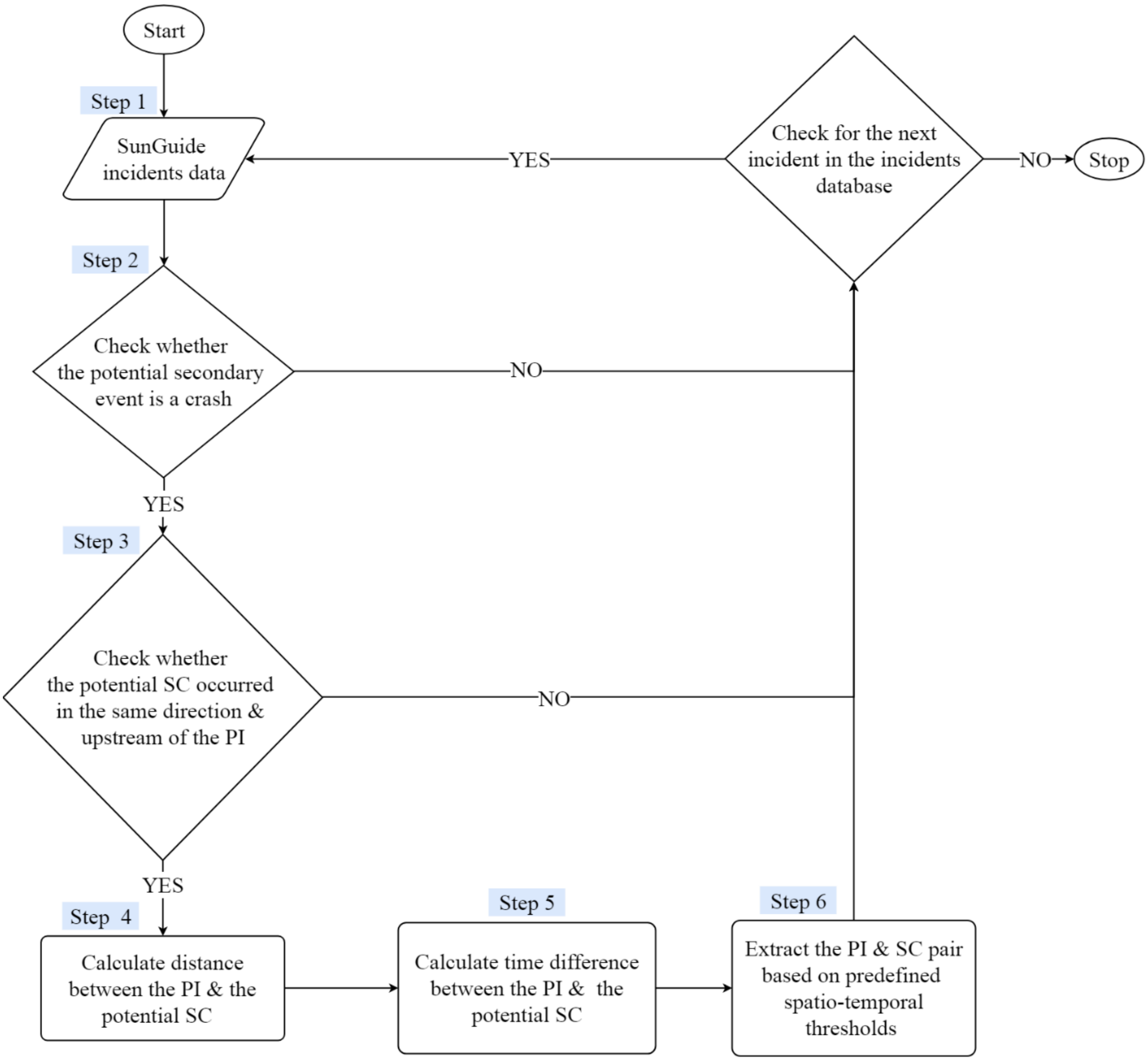


Figure 5-4: SCs in the Upstream Direction

- *Step 1 - Assign Mileposts to Incidents:* Traffic incidents are mapped in GIS using the corresponding coordinates (latitude and longitude) in the dataset. Next, mileposts are assigned to each individual traffic incident using a linear referencing tool in ArcGIS. This process is implemented using the Interstate and State Roads polyline shapefiles retrieved from FDOT Transportation Data and Analytics Office website.

- *Step 2 - Identify Potential Secondary Incidents that are Crashes:* While the primary event could be any incident and not necessarily a crash, this method focuses on identifying only SCs (and not secondary incidents). Thus, as one of the initial steps, the potential secondary incidents are checked to make sure they are in fact *crashes*.



Note: PI = Primary Incident, SC = Secondary Crash
This process was repeated for each incident in the incident database

Figure 5-5: Algorithm to Identify Upstream SCs Using Static Method

- *Step 3 - Identify Upstream Potential SCs:* The occurrence of a PI is expected to result in a queue backup in the upstream direction (and not in the downstream direction). Therefore, SCs that occurred only in the direction and upstream of the PI are identified by comparing the milepost of the PI with the milepost of the potential SCs.

- *Step 4 - Calculate Distance (Spatial Threshold):* The mileposts of the PI and the potential SCs are used to compute the distance between the two.

- *Step 5 - Calculate Time Difference (Temporal Threshold):* The time difference between the PI and the potential SC is calculated.

- *Step 6 - Extract PI-SC Pair:* Following the identification of the spatiotemporal relationship between the PI and the potential SC (in Steps 4 and 5), the respective PI-SC pairs are extracted based on the set spatiotemporal criteria.

- *Step 7 - Store the Identified Secondary Crash:* The extracted SCs are stored, and the process is repeated for the rest of the incidents in the SunGuide® database. It is worth noting that one PI can result in more than one SC. Further, an identified SC can also result in another crash, commonly referred to as tertiary crashes.

Identification of Secondary Crashes in the Opposite Direction

Figure 5-6 identifies SCs that occurred in the opposite direction of the PI. Half a mile was used as the spatial threshold, while incident clearance duration of the PI was used as the temporal threshold to identify SCs in the opposite direction.

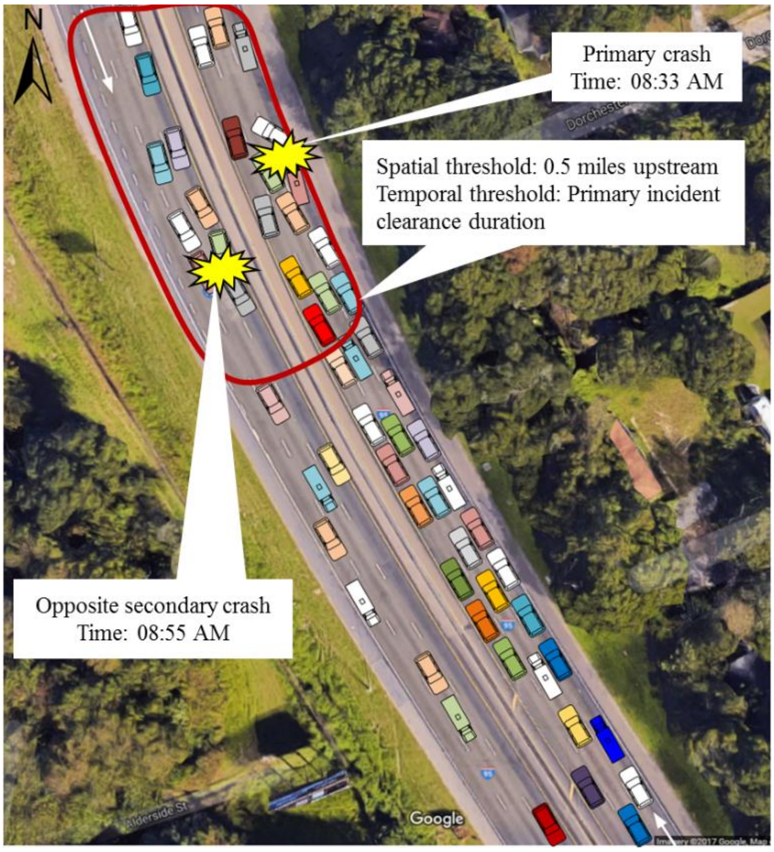
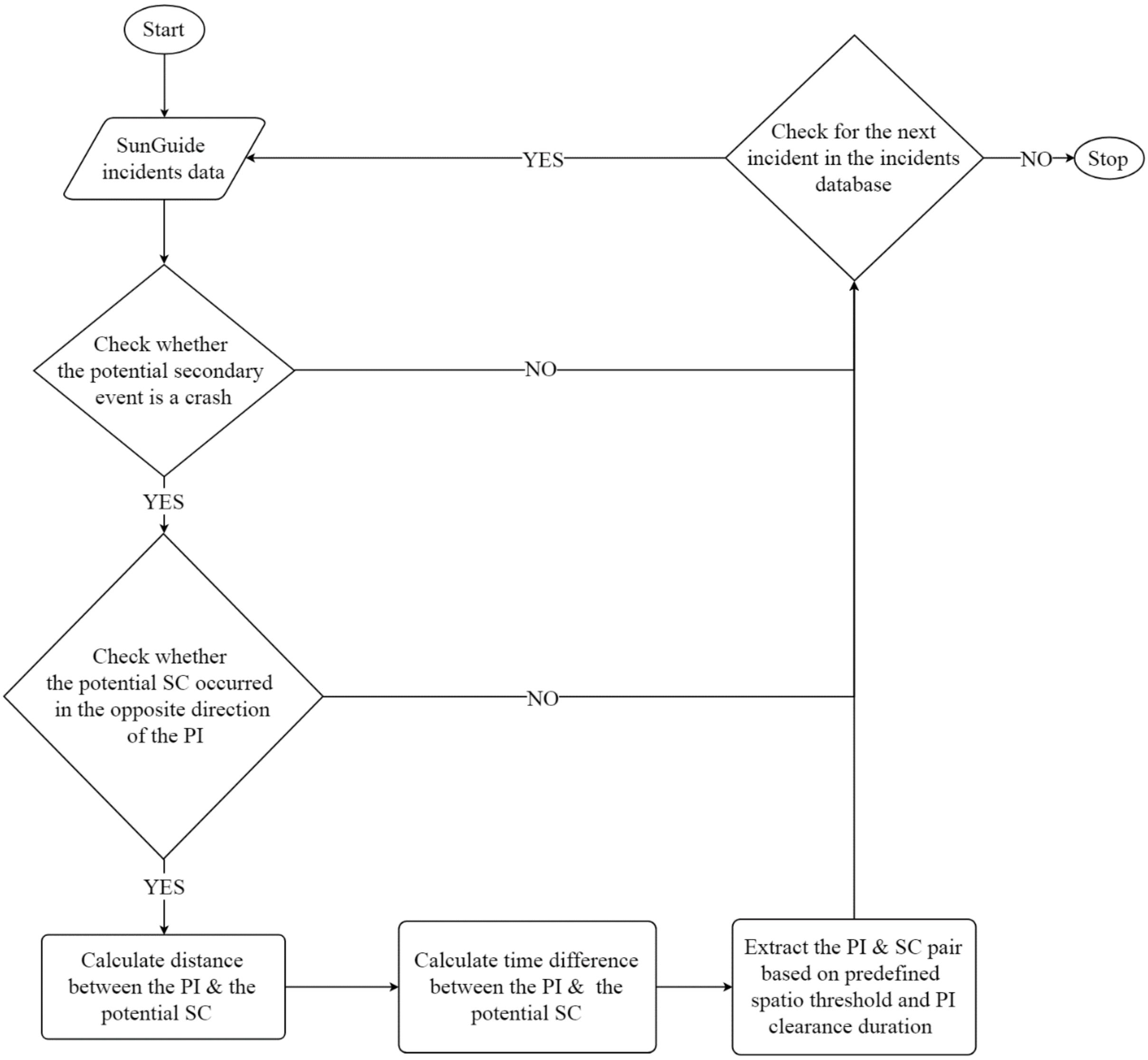


Figure 5-6: Secondary Crashes in the Opposite Direction

Steps one through seven with the exception of Step 3 that were used to identify the upstream SCs are repeated. Note that SCs in the opposite direction can occur both on the upstream and downstream of the PI. Figure 5-7 summarizes the steps followed to identify SCs in the opposite direction of the PI.



Note: PI = Primary Incident, SC = Secondary Crash
This process was repeated for each incident in the incident database

Figure 5-7: Algorithm to Identify Secondary Crashes in the Opposite Direction Using Static Method

An Example Illustrating Static Method

This section explains the static approach using an example. In this example the PI is a crash that blocked one left lane on I-95 SB in Jacksonville, Florida. This incident was recorded on November 21, 2016, at 5:52 AM. This PI resulted in one SC; 0.59-mile upstream of the primary crash and 41 minutes after the primary crash was reported. Figure 5-8 illustrates this example.

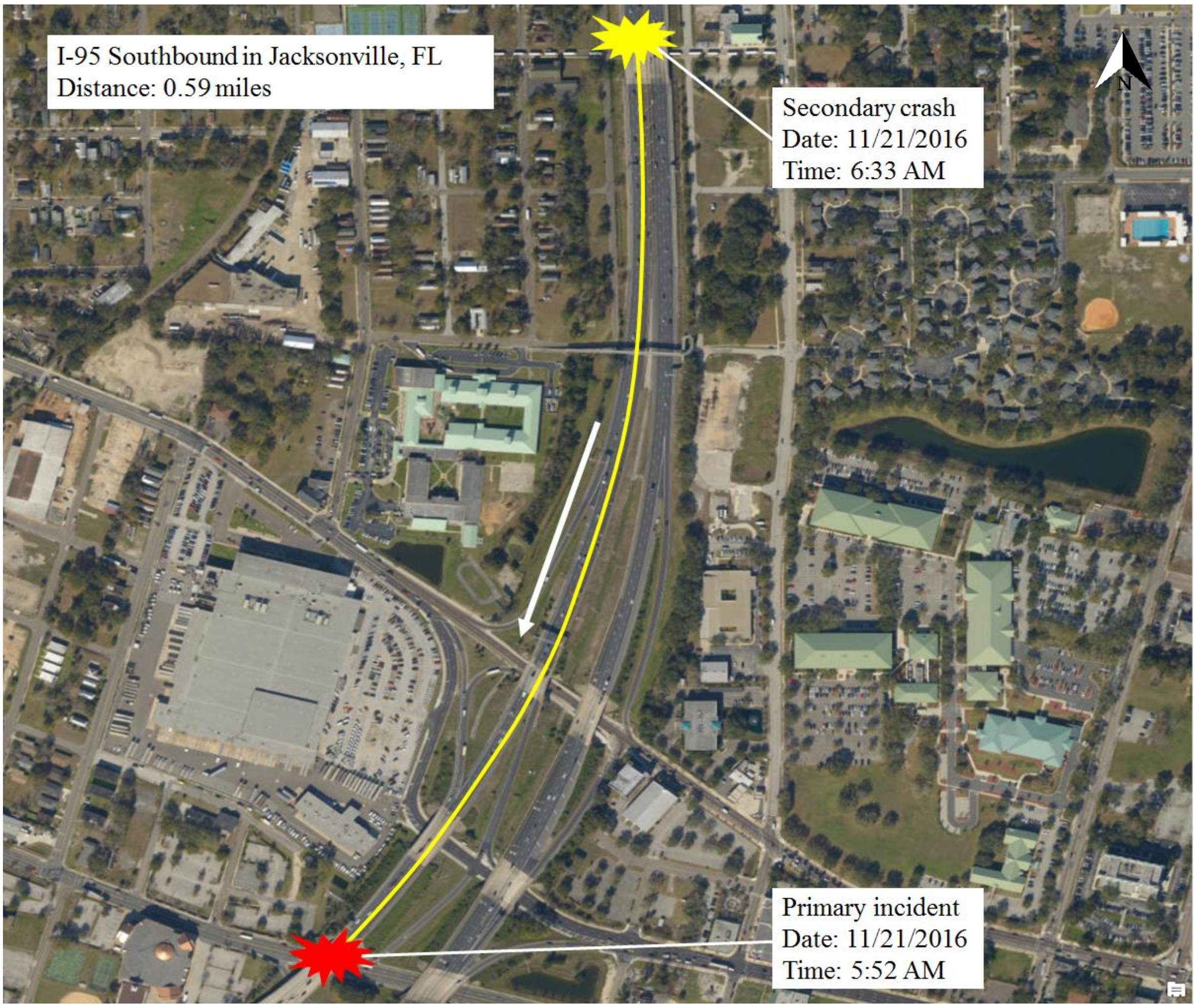


Figure 5-8: An Example Illustrating Static Method

5.4.2 Dynamic Model to Identify SCs

The dynamic method adopted in this study focuses on identifying the impact range of the PI using speed data archived by the BlueToad® pairs and identifying SCs occurring within the impact range of the PI. This method aims to better capture the effects of traffic flow characteristics, such as speed, that change over space and time and affect the queue formation as a result of a PI. The following discussion summarizes the steps followed to identify SCs using BlueToad® pairs speed data.

- *Step 1 - Prepare Speed Data:* The speed data from BlueToad® pairs are extracted and aggregated in 15-min intervals. The summary statistics for the speed data are computed for each corresponding BlueToad® pair.

- *Step 2 - Prepare Incident Data:* Each incident is first matched to a specific BlueToad® pair located along the roadway segment based on geographic coordinates (i.e., latitude and longitude). The speed data at the time of each incident are retrieved from the matched BlueToad® pair. Historical speed data for the BlueToad® pairs with matched incidents are used to establish recurrent speed profile of the section under normal traffic conditions. Average speed in 15-min intervals is used to establish the speed profiles. Additionally, a

CI of one standard deviation is established to define the upper and lower bounds of the speed profile (i.e., speed bandwidth) to account for recurrent speed variations.

- *Step 3 - Compute Incident Impact Duration:* The incident impact duration is computed for incidents that are successfully matched to the devices. This process is achieved by tracking the BlueToad® pair reported speeds at the segment of the incident occurrence from the time of the incident detection to the time when the traffic flow returned to normal. In-depth discussion of the procedure used to estimate the incident impact duration is discussed in Chapter 3.

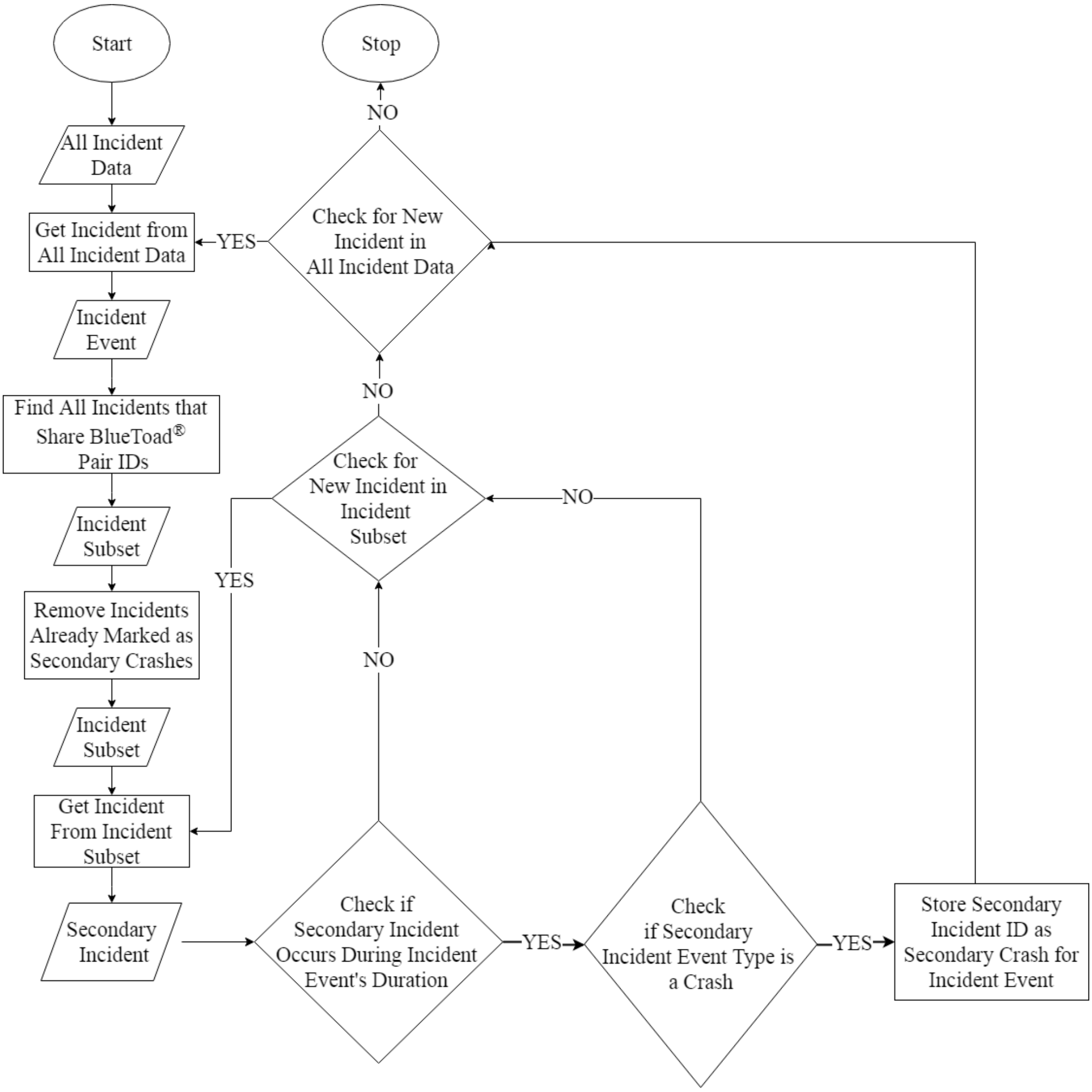


Figure 5-9: Algorithm to Identify Secondary Crashes Using Speed Data

- *Step 4 - Identify Incident Subset:* Following the establishment of recurrent speed profile for each of the incident-related BlueToad® pairs, speed data from the time of the incident occurrence are collected and aggregated in 15-min intervals to identify other BlueToad® pairs affected by the incident. For each of the incident subsets, the retrieved vehicle speeds since the incident reported time are compared with the recurrent speeds of the respective pairs (Figure 5-9). The incident subset in Figure 5-9 refers to a set of incidents that occurred within a similar BlueToad® pairs. This process is implemented both on the upstream direction and the opposite direction of the prior incident to identify BlueToad® pairs affected by the occurrence of the incident.

- *Step 5 - Identify Secondary Crashes:* A BlueToad® pair is considered to be affected by an incident when the speeds from the incident reporting time are lower than the earlier identified boundary of recurrent speeds. Once all the BlueToad® pairs affected by the incident subset (on both directions) are identified, the BlueToad® pairs are then checked to identify whether there was another incident occurring within the affected BlueToad® pairs. All incidents identified within the affected BlueToad® pairs are checked to determine whether they occurred within the time that the current speed drops below the average speed of the respective BlueToad® pair. Next, all identified incidents within the incident duration of the prior incident are checked and all incidents that are crashes are considered as SCs and are retrieved. A crash is identified as "secondary" if it occurred within the spatial and temporal impact area of the PI. This applies to crashes occurring both on the upstream and the opposite direction of the PI. This procedure was implemented in the open source statistical software "*R*".

An Example Illustrating Dynamic Method

Figure 5-10 describes the example of incidents that occurred on Monday, August 29th, 2016, along I-95 NB in 15-min speed intervals. On this particular day, ten incidents that occurred along the study corridor resulted in significant congestion, i.e., average speeds dropped below the recurring speeds along this corridor. Three of these ten incidents were identified as SCs. The first SC (S1) occurred within the incident impact duration of the first primary incident (P1). This primary incident (P1) occurred at 2:51 PM and affected eight BlueToad® pairs on the upstream direction (8.5 miles). It can be observed that the speed along the BlueToad® pair #6 came back to normal much earlier than the rest of the pairs. Due to congestion caused by the primary incident (P1), drivers might have detoured to other parallel routes (e.g., I-295). BlueToad® pair #6 is the only pair with an exit in the middle of two Bluetooth devices. A SC (S1) occurred 16 minutes later and 7.8 miles upstream of the primary incident. The SC, S1, resulted in a significant drop in speeds on the pair that it occurred (#5) plus two other pairs (#3 and #4) on its upstream direction.

Thirty-six minutes later, the same primary incident (P1) resulted in another SC (S3) at about 7.01 miles upstream of P1. This incident resulted in a significant non-recurring congestion on the pair that it occurred (#4) and three other pairs on the upstream direction (#1, #2, and #3). Incident S1 turned out to be a tertiary crash, meaning that it is a SC that became a primary incident (P2) to another SC (S2), representing cascading events. Incident P2, which occurred at 3:07 PM along BlueToad® pair #3 affected one additional pair #2, on the upstream direction. Secondary crash S2 occurred on the same pair (#5) as its primary incident 85 minutes later and affected one pair in the upstream direction (#4). It can be inferred from this observation that apart from resulting in non-recurring congestion, SCs can also lead to additional crashes, herein referred to as tertiary crashes. Six of the incidents in Figure 5-10 are normal incidents, meaning that they did not result in SCs. For example, the normal incident N1, occurred at 7:57 PM on pair #8 and resulted in a significant drop in speed along two additional pairs (#6 and #7) on the upstream direction.

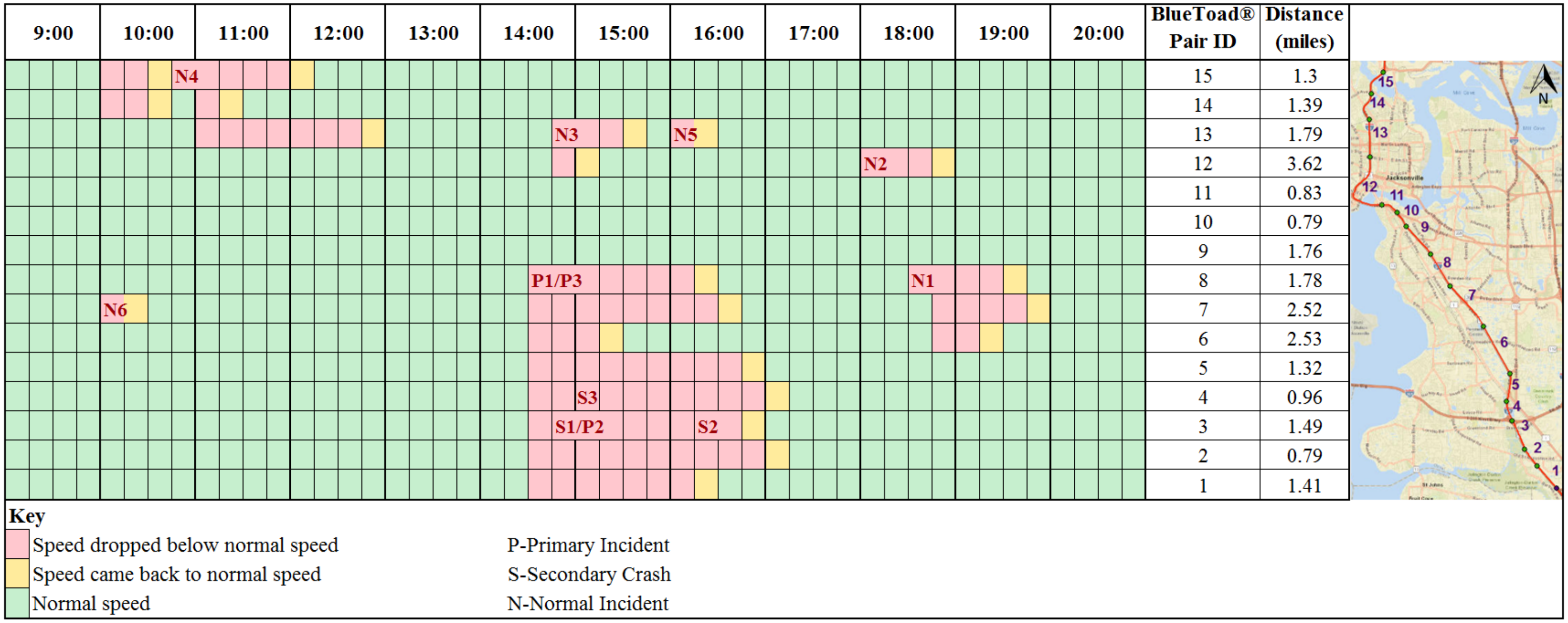


Figure 5-10: Detection of Secondary Crashes Using BlueToad® Pair Speed Data

5.4.3 SC Risk Prediction Model

A SC risk prediction model was developed based on real-time traffic flow conditions. Potential SCs were first identified using real-time speed data from BlueToad® pairs. Most important variables contributing to SCs were next screened using Random Forests (RFs) approach. Finally, the Bayesian random effect cloglog model was used to predict the probability of SCs. The following sections discuss the study methodology in detail.

Random Forests Approach to Select Important Variables

The Random Forests (RF) model is a non-parametric statistical method that is based on decision-trees (Breiman, 2001). More recently, traffic safety researchers are increasingly using the RF approach to select the important variables before applying other statistical models (Theofilatos, 2017; Haleem et al., 2015; Ahmed et al., 2012b; Abdel-Aty and Haleem, 2011). Unlike the classification and regression tree models, RF models can provide unbiased error estimates and does not require a cross-validation test (Breiman, 2001). During the tree-growing process, one-third of the training cases are left out and not used in the growing of the tree, conventionally referred to as out-of-bag (OOB) data. In this study, the RF algorithm is used to estimate prediction performance and quantify variable importance based on the OOB error.

RF use OOB samples to measure the prediction strength of each variable by constructing a different variable-importance measure. These values are in turn used to generate the accuracy plot that test to see how worse the model would perform without each variable. The use of OOB randomization to compute the variable importance using mean decrease accuracy plot tends to spread the importance more uniformly (Hastie et al., 2008). Note that several other studies have employed similar plots to identify important variables (Theofilatos, 2017; Yu and Abdel-Aty, 2014). Thus, the mean decrease accuracy (MDA) plot provided by the *R* package "randomForest" was used to select the important variables (Liaw and Wiener, 2015). A higher accuracy value represents a higher variable importance.

Bayesian Framework to Model SCs

The Bayesian random-effect cloglog model was used to predict the probability of SCs. Specifically, this model was used to develop a SC risk prediction model, in which the likelihood of SCs was linked with real-time traffic variables, PI characteristics, environmental conditions, and geometric characteristics. It is worth noting that, unlike previous studies which used the conventional logit and probit model (symmetrical models), this study uses the cloglog model to account for the asymmetric distribution of the response variable (only 8.0% of all crashes are SCs). The normal random effect parameter was included to account for the heterogeneity caused by the unobserved factors such as work zones, design features, and pavement conditions, among other factors. Failure to account for the unobserved variation in the data may lead to inconsistent and biased parameter estimates (Xu et al., 2016).

In this study, the response variable is binary in nature, i.e., y_i represents the SC indicator (1 indicates a SC is induced by a PI (i), and 0 indicates that no SC crash occurred). π_n denotes the probability of a SC induced by a PI; **X** denotes the vector of explanatory variables used in the study, $\boldsymbol{\beta}$ is the coefficients vector for explanatory variables $\mathbf{X}$. ε_i is the normal random effect variable representing the incident level random error in the model. The random-effect cloglog model can be presented using Equations 5-1 and 5-2.

$$\mathrm{y_i} \sim \mathrm{Binomial}(\pi_\mathrm{i}) \tag{5-1}$$

$$\mathrm{cloglog}(\pi_\mathrm{i}) = \log\big(-\log(1-\pi_\mathrm{i})\big) = \boldsymbol{\beta}\mathbf{X} + \varepsilon_\mathrm{i} \tag{5-2}$$

The Bayesian inference for cloglog regression follows the usual procedure for all Bayesian analysis. In Bayesian inference, a prior distribution for all unknown parameters has to be defined. Normally, two categories of priors are used in the Bayesian approach; informative and non-informative priors. Informative priors are based on the literature, expert knowledge, or information retrieved explicitly from a previous data analysis (Ahmed et al., 2012a). On the other hand, non-informative priors, also called "vague" priors, are often used in the absence of reliable prior information regarding model parameters (Huang et al., 2008; Kitali et al., 2017). For this study, there is no prior knowledge of the expected effect; hence, non-informative priors are used. The most commonly used priors are normal distributions with a zero mean, expressing the prior doubt of the relationship between the predictor variable and the response variable, and large variance. Thus, the coefficients of the predictor variables were set up with non-informative priors following normal distributions with a zero mean and a variance of one, i.e., Normal (mean = 0, SD = 1) for predictor parameters, intercept, and random parameter. The first 10,000 iterations were discarded as burn-in sample and 4 chains of 20,000 iterations were set up. The specification of the priors is then followed by estimation of the likelihood function. The likelihood function for the cloglog regression can be expressed using Equation 5-3.

$$\mathrm{Likelihood} = \prod_{i=1}^{n} \left[\pi(\mathrm{x_i})^{\mathrm{y_i}}\big(1-\pi(\mathrm{x_i})\big)^{(1-\mathrm{y_i})}\right] \tag{5-3}$$

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

The priors and the likelihood function are then used to estimate the posterior distribution of the study parameters (Equation 5-4). The Bayes theorem is normally applied while estimating the posterior distribution of all parameters.

$$\mathrm{Posterior} = \ \mathrm{Prior} \times \mathrm{Likelihood} \tag{5-4}$$

The proposed model was implemented through Rstanarm, an open source "*R*" package. The ratios of the Monte Carlo (MC) errors relative to standard deviations of the estimates, trace, density, and autocorrelation plots were monitored to achieve parameter estimation convergence. As a rule of thumb, the MC error was maintained at less than 5% of the posterior standard deviation for a parameter to converge (Huang et al., 2008). The 95% Bayesian Credible Interval (BCI) was used to determine the significance of the predictor variables, which provides probability interpretations with normality assumptions that the true parameter is inside the region with measured probability (Huang et al., 2008).

5.5 Results from Static and Dynamic Methods

5.5.1 Static Method Results

Static method was used to identify SCs for the years 2014-2017. A spatiotemporal window of 2-miles-2-hours was chosen as it is the most common threshold used in previous studies (Chang and Rochon, 2011; Kopitch and Saphores, 2011; Moore et al., 2004). Out of 74,030 incidents in the study area, 3,400 incidents were identified as SCs (5%). Figure 5-11 summarizes the proportion of SCs identified along the four study corridors. As can be observed from the figure, I-95 experienced the highest proportion of SCs (8%) and an overall increasing trend in the proportion of SCs.

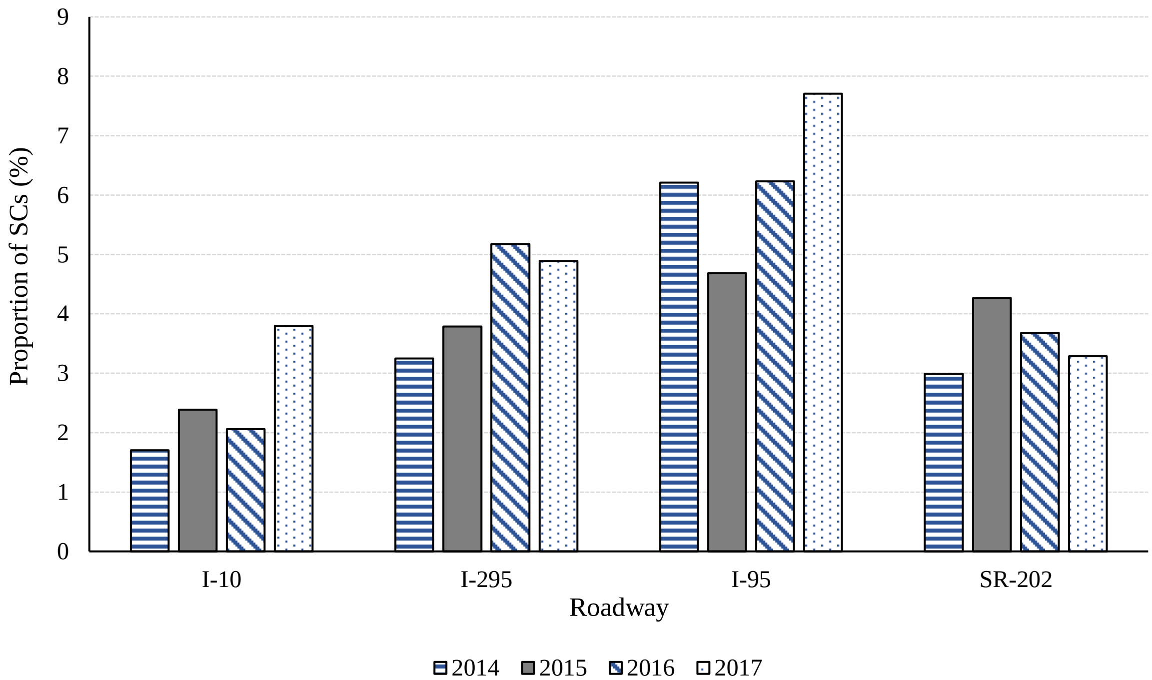


Figure 5-11: Proportion of Secondary Crashes Identified Using Static Method

SCs that occurred in the upstream direction constituted 88% of the total detected SCs, while the remaining 12% occurred in the opposite direction. Table 5-8 summarizes the number of upstream and opposite SCs identified using the static method.

Table 5-8: Upstream and Opposite Secondary Crashes Identified Using Static Method

Roadway	Upstream SCs				Opposite SCs				Total SCs				Grand Total
	2014	2015	2016	2017	2014	2015	2016	2017	2014	2015	2016	2017	
I-10	28	41	39	91	2	4	2	9	30	45	41	100	216
I-295	276	204	323	368	37	28	52	56	313	232	375	424	1,344
I-95	274	316	428	400	35	45	52	43	309	361	480	443	1,593
SR-202	48	75	56	37	3	9	9	10	51	84	65	47	247

5.5.2 Dynamic Method Results

Dynamic method was used to identify SCs for the years 2015-2017. This approach used traffic incident data from the SunGuide® database and real-time speed data from the BlueToad® pairs. Unlike the static method, SCs using dynamic method could be identified only along the corridors with BlueToad® pairs. SR-202 does not have BlueToad® pairs, and was therefore excluded from the analysis. Overall, 518 SCs were identified from 425 PIs. The identified SCs account for 8% of the 6,865 incidents used in the analysis. Figure 5-12 summarizes the distribution of SCs identified using the dynamic method. The 425 PIs that induced SCs represented 7% of all normal incidents (6,865 – 425 = 6,440). These results indicate that approximately one in every twelve normal incidents was associated with a SC. Each PI caused an average of 1.2 SCs. Out of 518 incidents that were identified as SCs, 47 crashes resulting in additional crashes (40 resulted in an additional SC, and 7 resulted to multiple additional crashes).

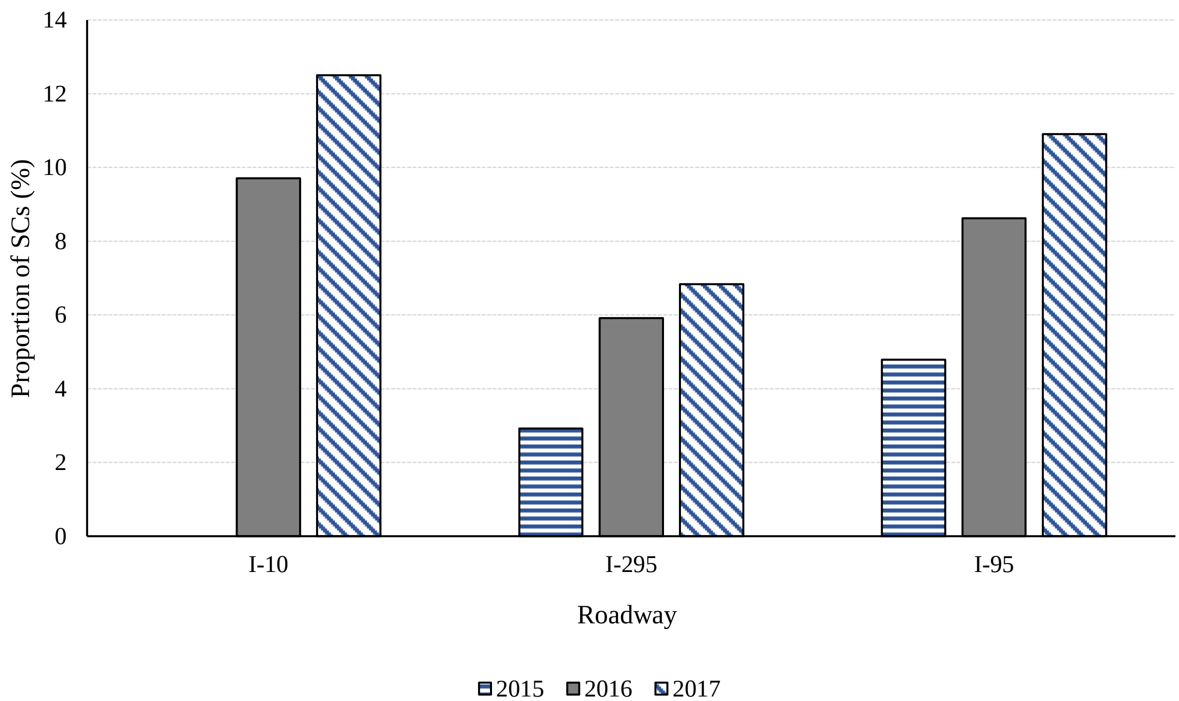


Figure 5-12: Proportion of Secondary Crashes Identified Using Dynamic Method

SCs that occurred in the upstream direction constituted 87% of the total SCs, while the remaining 13% occurred in the opposite direction. Table 5-9 summarizes the number of upstream and opposite SCs identified using the dynamic method.

Table 5-9: Upstream and Opposite Secondary Crashes Identified Using Dynamic Method

Roadway	Upstream SCs			Opposite SCs			Total SCs			Grand Total
	2015	2016	2017	2015	2016	2017	2015	2016	2017	
I-10	0	10	24	0	0	0	0	10	24	34
I-295	5	81	91	0	5	9	5	86	100	191
I-95	40	113	101	0	21	18	40	134	119	293

5.5.3 Comparison of Results from Static and Dynamic Methods Using Descriptive Statistics

Applying the same dataset used in the dynamic method, which has 6,865 traffic incidents, SCs were also identified using the static method for comparison purpose. Figure 5-13 provides a Venn diagram that compares the SCs identified using static and dynamic methods.

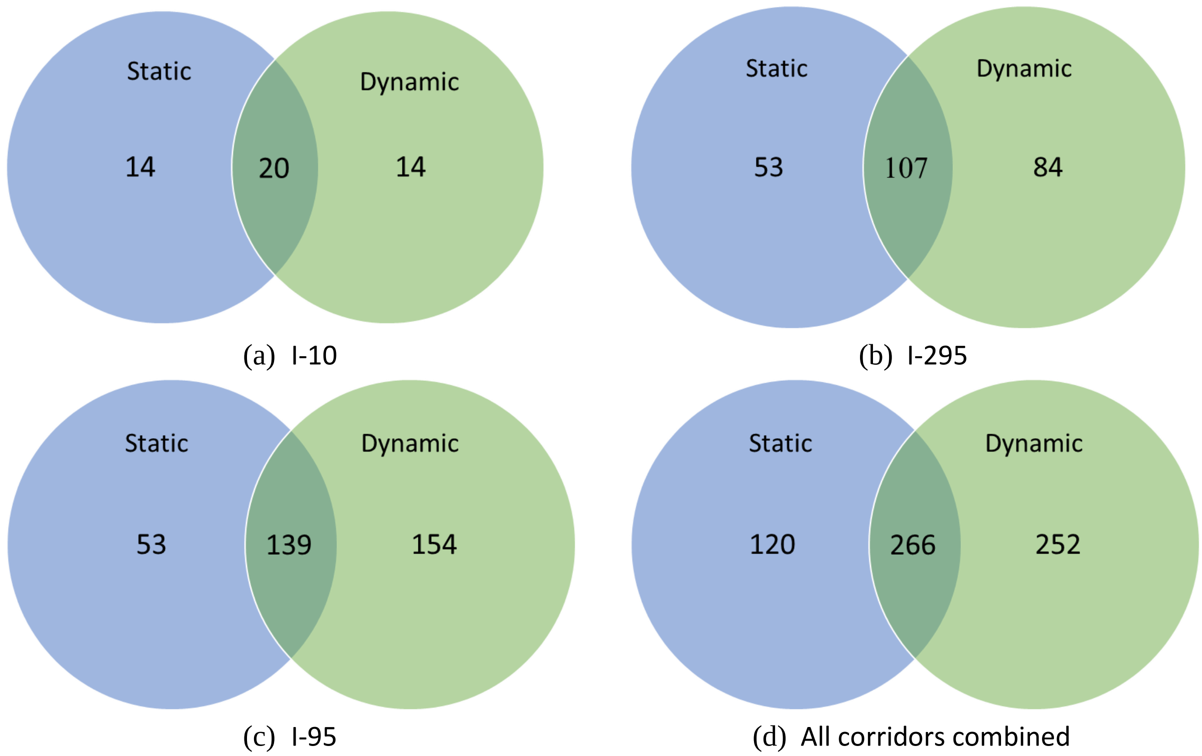
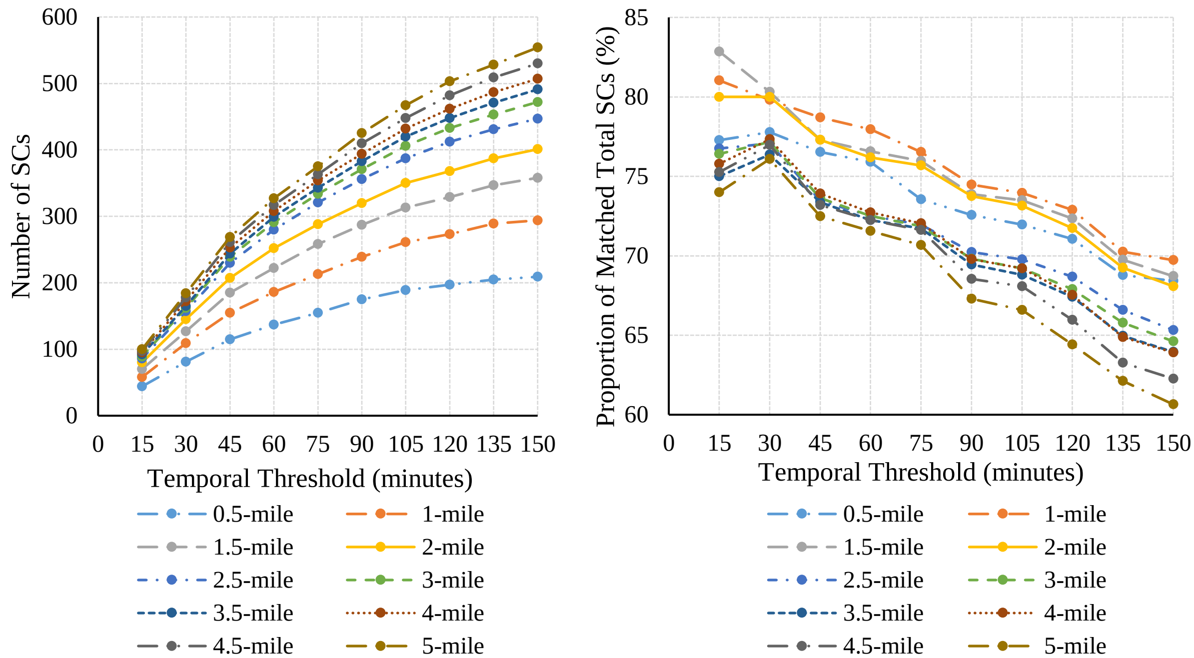


Figure 5-13: Venn Diagrams Comparing Results from Static and Dynamic Methods

Using the 2-mile-2-hour spatiotemporal threshold, a total of 386 SCs were identified from 341 PIs. On the other hand, the dynamic approach identified 518 SCs. The number of SCs identified using the static method is about half of the number of SCs identified using the dynamic method. In other words, the static method was found to underestimate the number of SCs compared to the dynamic method. It can be inferred from Figure 5-13(d) that 266 SCs were identified using both the static and the dynamic methods. I-10 was found to have the fewest number of SCs, essentially because it is the shortest segment compared the other corridors and also had the fewest number of BlueToad® pairs.

5.5.4 Comparison of Results from Static and Dynamic Methods Using Sensitivity Analysis

Using the static method, sensitivity of spatiotemporal thresholds was also conducted to determine the extent of under/overestimation of SCs when compared to the dynamic method. Since 90% of SCs detected by the dynamic method were found to occur within 2.5-hour and 5-mile spatiotemporal thresholds, these thresholds were adopted to detect SCs on the upstream direction of the PI. More specifically, 15-minute temporal thresholds (i.e., 15, 30, … 150-min) were used along with the 0.5-mile spatial thresholds (i.e., 0.5, 1, …, 5-mile). Meanwhile, SCs on the opposite direction were identified based on 0.5-mile spatial threshold and PI clearance duration as the temporal threshold. Figure 5-14(a) depicts the frequency of SCs identified using the static method. Based on the adopted spatiotemporal thresholds, 554 SCs were identified using the static method. As expected, the number of SCs increase with the increase in spatial and temporal thresholds. It can be inferred from Figure 5-14(a) that the static method begins to overestimate the SCs beyond the 4.5-mile and 150-min thresholds, when compared to the dynamic method that identified 518 SCs. Further, the rate of change of frequency of SCs is sparser within the 2.5-mile threshold and denser beyond the 2.5-mile threshold.



(a) SCs identified using static method

(b) Proportion of SCs identified using static method that were matched with the SCs identified using dynamic method

Figure 5-14: SCs Identified Using Static Method

Notably, the use of longer thresholds does not necessarily mean that all the detected SCs are accurately identified (i.e., there are no false positives). This scenario is further explained in Figure 5-14(b) where the proportion of SCs identified by the static method and the dynamic method decrease with the increase in the spatiotemporal thresholds. In Figure 5-14(b), SCs detected within 1-mile have an overall highest proportion of matched SCs (76%) compared to the rest of the spatial thresholds. Meanwhile, SCs detected using a 5-mile spatial threshold had the least proportion of matched SC-frequencies (69%). Further, the proportion of SCs detected using a spatial threshold of 0.5-mile significantly dropped beyond 60-min. The highest proportion of PIs (17%) was observed at 7:00, while the highest proportion of SCs (15%) occurred one hour later, i.e., at 8:00 AM. The other peak times for the PIs (12%) and SCs (13%) were found to be at 4:00 PM and 5:00 PM, respectively. The corresponding normal incidents were also at their highest during these particular hours, resulting in 60% of all normal incidents.

In summary, more than three-quarter of detected SCs (78%) occurred during congested traffic state (Table 5-10). This could be attributed to the fact that congested traffic is characterized with smaller gaps between vehicles providing drivers with lesser maneuvering room to avoid a crash. Similarly, 60% of normal incidents occurred during congested traffic state. During traffic congestion, SCs were found to occur within 1.4-1.7 miles and 50.7-51.3 minutes. Meanwhile, under free-flow traffic conditions, SCs occurred within 1.5-2.6 miles and 64.5-84.0 minutes.

Table 5-10: Impact of Prevailing Traffic Condition on Incident Occurrence

Incident Category	Prevailing Traffic Condition			
	Congested		Free-flow	
	6:00 - 9:00	15:00 - 18:00	9:01 - 14:59	18:01 - 05:59
Normal Incidents (%)	30	30	32	8
Primary Incidents (%)	38	37	17	8
Secondary Crashes (%)	38	40	14	8
Distance (mile)	1.4	1.7	1.5	2.6
Time (min)	50.7	51.3	64.5	84.0

Figure 5-15 shows the impact areas for PIs that resulted in SCs within a spatiotemporal threshold of 1-mile and 60-min. These impact areas refer to incidents that occurred when the prevailing traffic condition is under congested state and when it is under free-flow state. There is a significant dispersion with respect to the impact areas during congested and free-flow traffic flow conditions. It could be inferred from Figure 5-15 that prevailing traffic conditions is one of the major factors that influence the spatial and temporal locations of SCs. In other words, prevailing traffic flow characteristics were found to affect the manner in which the disturbance caused by the PI propagate on the upstream direction.

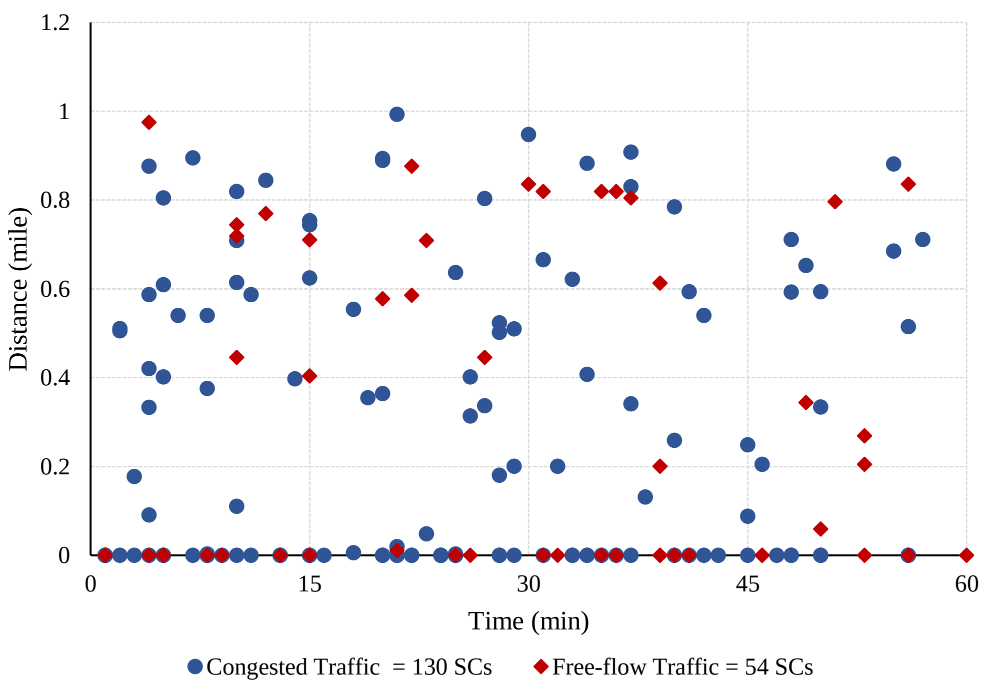
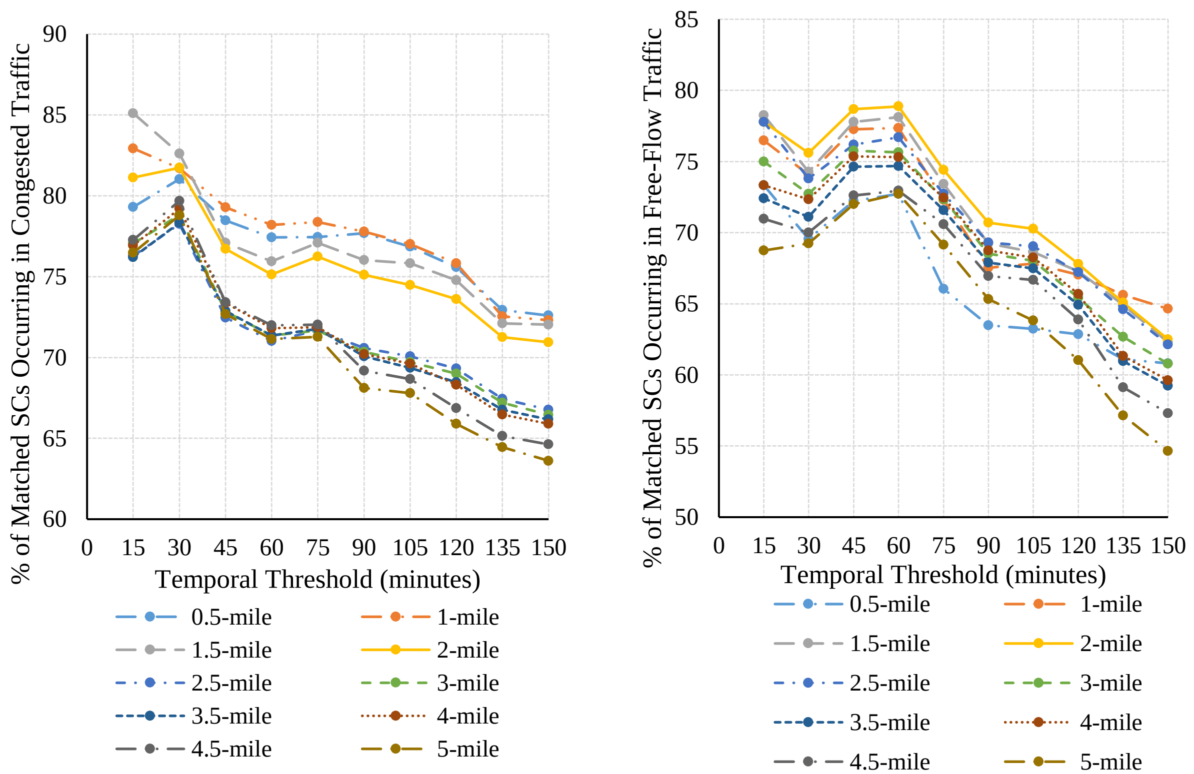


Figure 5-15: Spatiotemporal Extent of SCs from Their Respective PIs

Considering the influence of prevailing traffic conditions on the occurrence of SCs, the number of SCs identified using the static method were also compared to the number of SCs identified using the dynamic method based on traffic flow characteristics, i.e., during free-flow (off-peak hours) and congested (peak hours) conditions. Figures 5-16 (a) and (b) show the proportion of SCs identified by both the static and dynamic methods during congested and free-flow conditions, respectively. There is a clear demarcation between the proportion of matched SCs that occurred within 2-mile and beyond 2-mile during congested traffic conditions. Compared to free-flow traffic conditions, there is a higher match of SCs occurring on congested traffic within 0.5-mile from the PI. While the greatest match of SCs on congested traffic is within 1-mile (83%), the greatest match during free-flow traffic conditions is within 2-mile (78%). These results indicate that there is a distinct difference in the PI impact area under free-flow and congested traffic conditions. Therefore, using fixed spatiotemporal thresholds to detect SCs during congested and free-flow conditions could result in inaccurate results.



(a) In congested traffic (b) In free-flow traffic

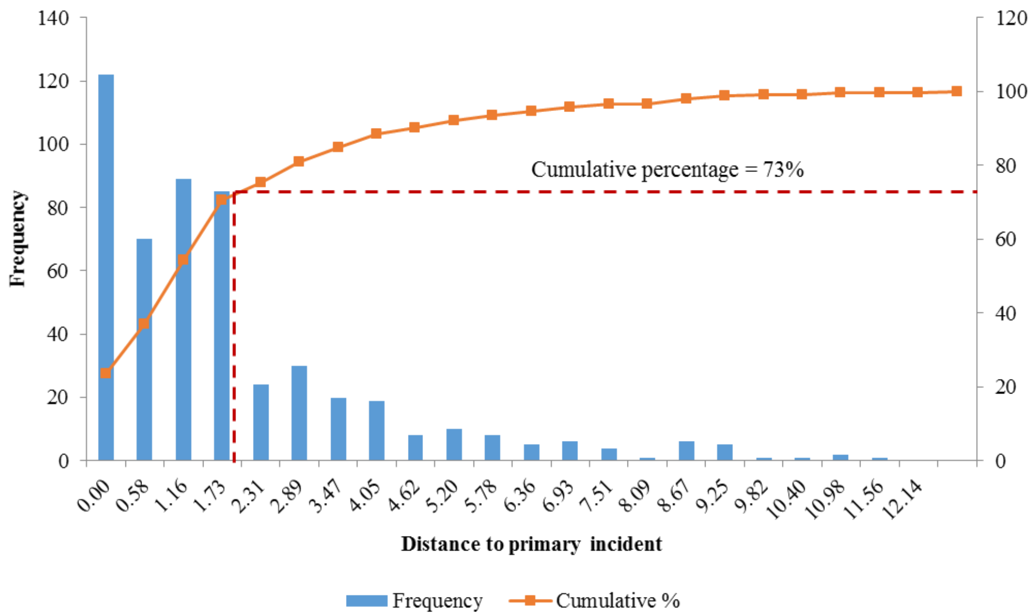
Figure 5-16: Proportion of SCs Identified Using Static Method That Were Matched with the SCs Identified Using Dynamic Method in Congested and Free-Flow Traffic Conditions

5.6 In-depth Descriptive Analysis of SCs

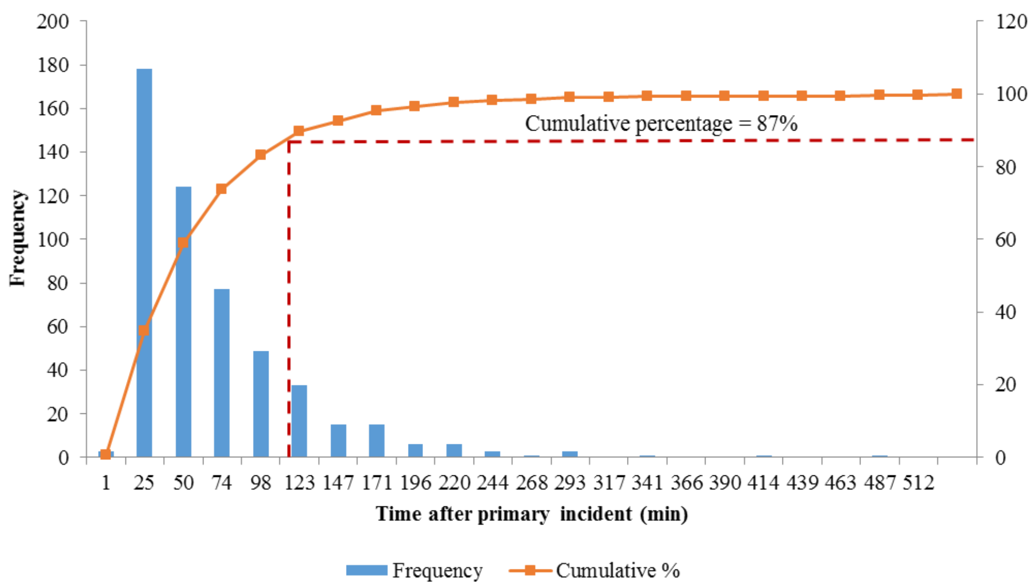
The following subsections examine the critical characteristics of SCs identified using the dynamic method.

Spatiotemporal Distribution

Figure 5-17 shows the temporal and spatial characteristics of SCs in relation to PIs. Temporally, approximately 87% of the SCs were found to occur within two hours after the occurrence of PIs. Spatially, 73% of the SCs were found to occur within two miles from the PI. Overall, 66% of SCs occurred within two hours of the onset of a PI and within two miles upstream of the PI. About 34% of SCs occurred beyond the most commonly used 2-mile-2-hour spatiotemporal threshold. These statistics confirm that the proposed dynamic approach identified more SCs than the traditional static method.



(a) Spatial Distribution



(b) Temporal Distribution

Figure 5-17: Spatiotemporal Distribution of SCs in Relation to Primary Incidents

Time of the Day and Day of Week Distribution

Figure 5-18 shows the distribution of the 518 SCs, 425 PIs, and 6,347 normal incidents by different periods. It can be deduced from the plot that only 1% of SCs occurred between 0:00 and 5:00 whereas 80% occurred during peak hours, i.e., morning peak, 6:00 AM to 9:00 AM and evening peak, 3:00 PM and 6:00 PM. Specifically, 38% of SCs occurred during morning peak while the remaining 42% occurred during evening peak.

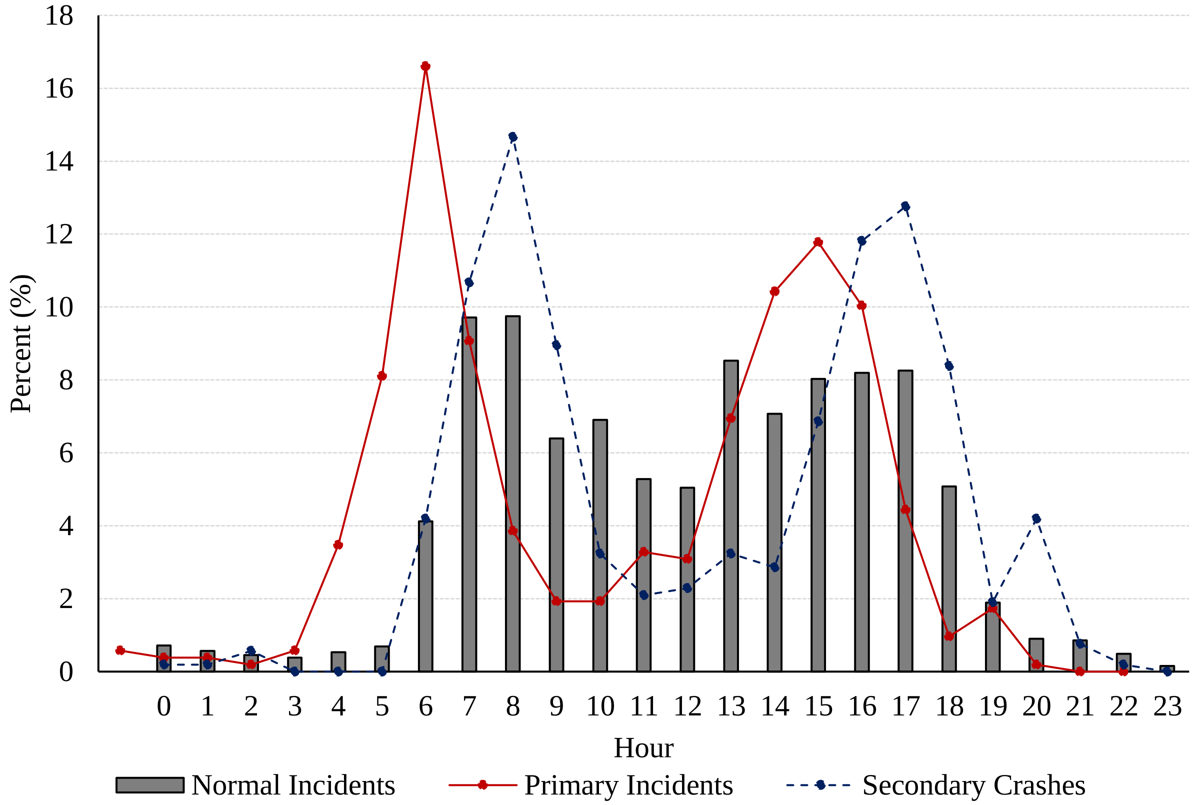


Figure 5-18: Dynamic Traffic Incidents Distribution by Time of the Day

The highest proportion of PIs (17%) was observed at 7:00 AM, while the highest proportion of SCs (15%) occurred two hours after the PI, i.e., at 9:00 AM. The other peak times for the PIs (12%) and SCs (18%) were found to be at 4:00 PM and 6:00 PM, respectively. The corresponding normal incidents were also at their highest during these particular hours, resulting in 61% of all normal incidents. As can be observed from Table 5-11, half of normal incidents occurred during peak hours while the remaining half occurred during off-peak hours.

Table 5-11: Incident Distribution by Time of the Day

Incident Characteristic	Category	Incident Category (%)		
		Normal Incidents	Primary Incident	Secondary Crashes
Time of the Day	Peak hours	50	65	66
	Off-peak hours	50	35	34

About 65% of PIs and eventually 66% of SCs occurred during peak hours. Compared to off-peak hours, peak-hour traffic flow characteristics were found to contribute more to the occurrence of SCs. Congested traffic is characterized with smaller gaps between vehicles providing drivers with lesser maneuvering room to avoid a crash.

Figure 5-19 presents the distribution of incidents by day of week. It can be inferred from the figure that the number of normal incidents and SCs is much higher on weekdays than on weekends. While SCs were found to frequently occur on Mondays and Fridays, normal incidents were found to frequently occur on weekdays (i.e., Monday through Friday).

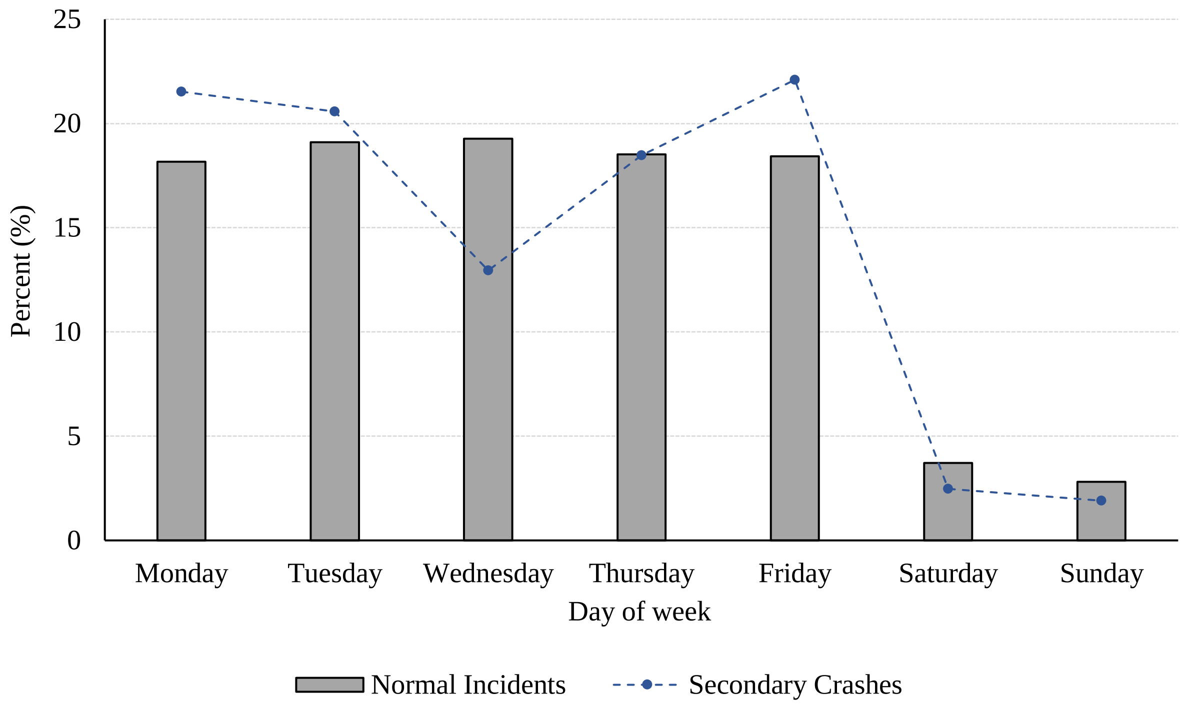


Figure 5-19: Distribution of Normal Incidents and Secondary Crashes by Day of Week

Incident Characteristics

Figure 5-20 provides the distribution of the incident clearance duration for towing-involved and no-towing involved incidents. Table 5-20 summarizes the incident responders' characteristics for normal incidents, PIs, and SCs. From the figure, it can be inferred that 90% of traffic incidents that did not involve towing were cleared within 90 minutes while only 66% of traffic incidents that involved towing were cleared within 90 minutes. As expected, towing involved incidents resulted in longer incident durations as they tend to require more time to be cleared. As indicated in previous studies, the likelihood of SCs increases with increase in incident clearance duration. This is evident from the data as 25% of PIs required towing, while only 13% of normal incidents required towing. Similarly, higher percentage of incidents involving emergency service resulted in SCs (16%). Further, while 46% of normal incidents involved more than one responding agency, 61% of PIs and 68% of SCs involved more than one responding agency. These statistics suggest that incidents involving more number of responding agencies increase the likelihood of the occurrence of SCs.

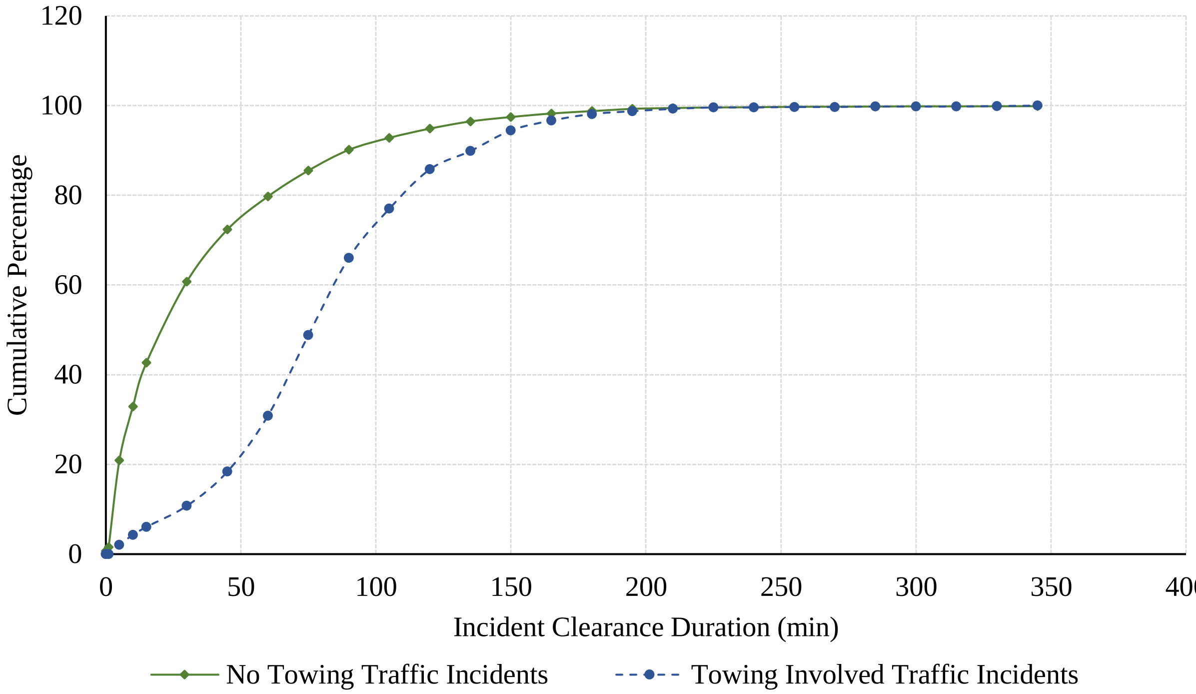


Figure 5-20: Distribution of Incident Clearance Duration for Towing-Involved and No-Towing Involved Incidents

Table 5-12: Incident Distribution Based on Responders' Characteristics

Incident Characteristics	Category	Incident Category (%)		
		Normal Incidents	Primary Incidents	Secondary Crashes
Towing Involved	No	87	75	84
	Yes	13	25	16
Emergency Involved	No	95	84	89
	Yes	5	16	11
Number of Responding Agencies	1	54	32	39
	2	30	27	32
	3	8	15	13
	4	3	8	7
	5	2	8	5
	6	2	6	3
	7	1	3	2
	8	0	0	1

As can be observed from Table 5-13, 88% of normal incidents did not result in lane closure, while 33% of PIs resulted in lane closure. The percent of lanes closed is an indicator of the severity of the PI as severe incidents tend to result in an increased number of lanes closed. About 18% of PIs were moderate/severe while only 5% of normal incidents were moderate/severe. Only 34% of normal incidents were crashes, while 74% of PIs were crashes. In other words, the probability of SCs was found to be higher when PIs were crashes.

Table 5-13: Incident Characteristics

Incident Characteristics	Category	Incident Category (%)		
		Normal Incidents	Primary Incidents	Secondary Crashes
Percentage of Lanes Closed	0	88	67	78
	25	2	4	2
	33	7	19	13
	50	2	4	3
	67	1	5	3
	75	0	1	0
	100	0	1	1
Incident Severity	Minor	95	82	90
	Moderate	4	12	7
	Severe	1	6	3
Incident Type	Crash	34	74	Not Applicable
	Debris on Roadway	10	2	
	Disabled Vehicle	54	22	
	Emergency Vehicles	1	1	
	Flooding	0	1	
	Other	0	0	
	Police Activity	0	0	
	Vehicle Fire	0	0	

Figure 5-21 shows the distribution of the incident clearance duration for normal incidents and the identified PIs. Overall, normal incidents were cleared more quickly than PIs; approximately 89% of the normal incidents were cleared within 90 minutes, while only 68% of the PIs were cleared within 90 minutes. The longer clearance time of the PIs could be considered as one of the factors that may have contributed to the occurrence of SCs.

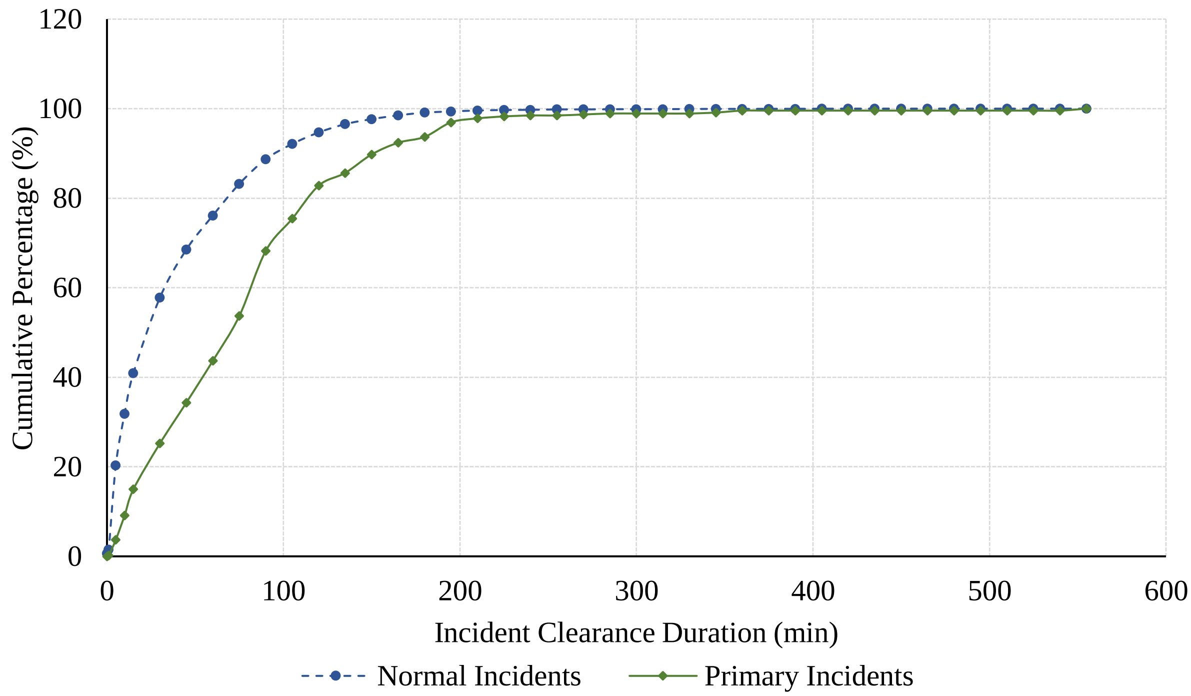


Figure 5-21: Distribution of Incident Clearance Duration for Normal and Primary Incidents

Figure 5-22 presents the distribution of the incident clearance duration for the identified PIs and SCs. The figure shows that, overall, SCs were cleared more quickly than PIs. For instance, approximately 75% of the SCs were cleared within 90 minutes, while only approximately 68% of the PIs were cleared within 90 minutes. The shorter clearance duration of SCs could be attributed to the fact that SCs are often less severe.

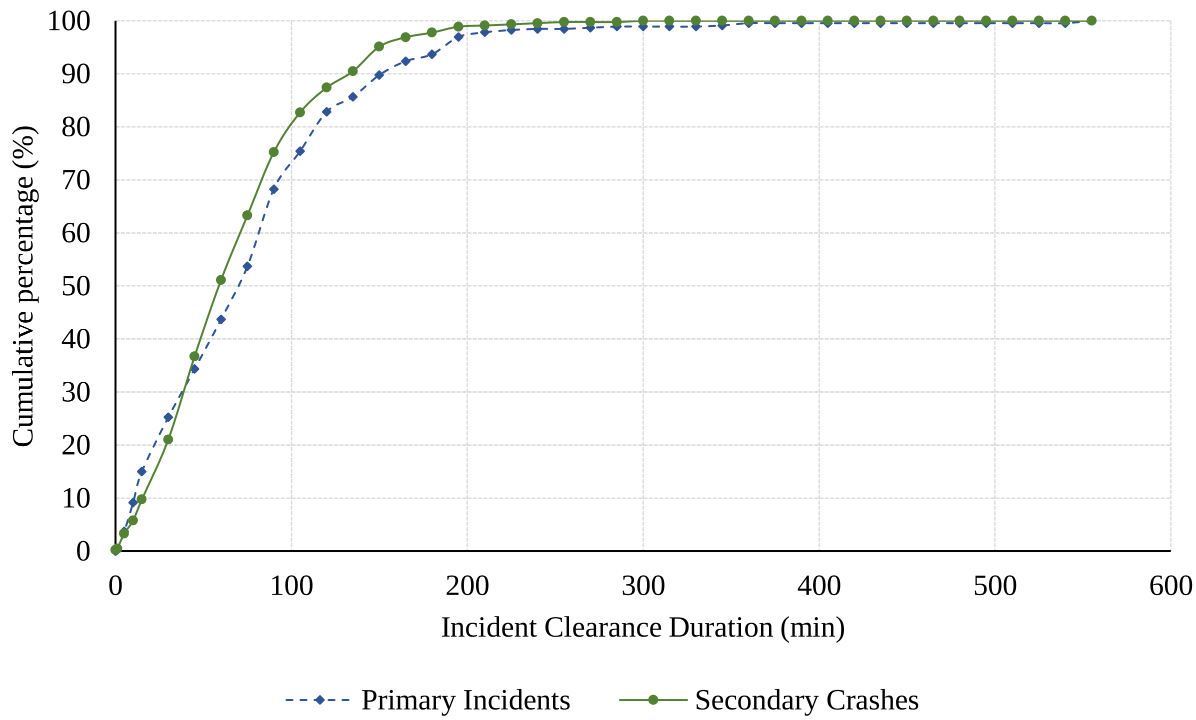


Figure 5-22: Distribution of Incident Clearance Duration for Primary Incidents and Secondary Crashes

5.7 Factors Influencing the Occurrence of SCs

5.7.1 Variable Importance

RF algorithm was used to estimate the importance of each of the predictor variable by monitoring the change in the prediction error when OOB data for the respective variables are permuted while all other remaining variables are left unchanged (Liaw and Wiener, 2015). Forests were grown using 1,200 trees and by randomly selecting six predictor variables at each node for splitting, since these combinations yield stable results with minimum OOB error rate of 0.025. Figure 5-23 shows the final results of the variable importance ranking where the MDA was used as the selection criterion. The cut-off value of 10 for the MDA was chosen to identify the important variables that yield meaningful parameter estimates. The following 16 variables were identified as important, and were included in the model: incident impact duration, incident clearance time, standard deviation of EHV, mean of occupancy, incident type, standard deviation of occupancy, mean of EHV, mean of speed, standard deviation of speed, number of responding agencies, incident severity, towing involved, median width, percent lane closed, EMS involved, and incident time.

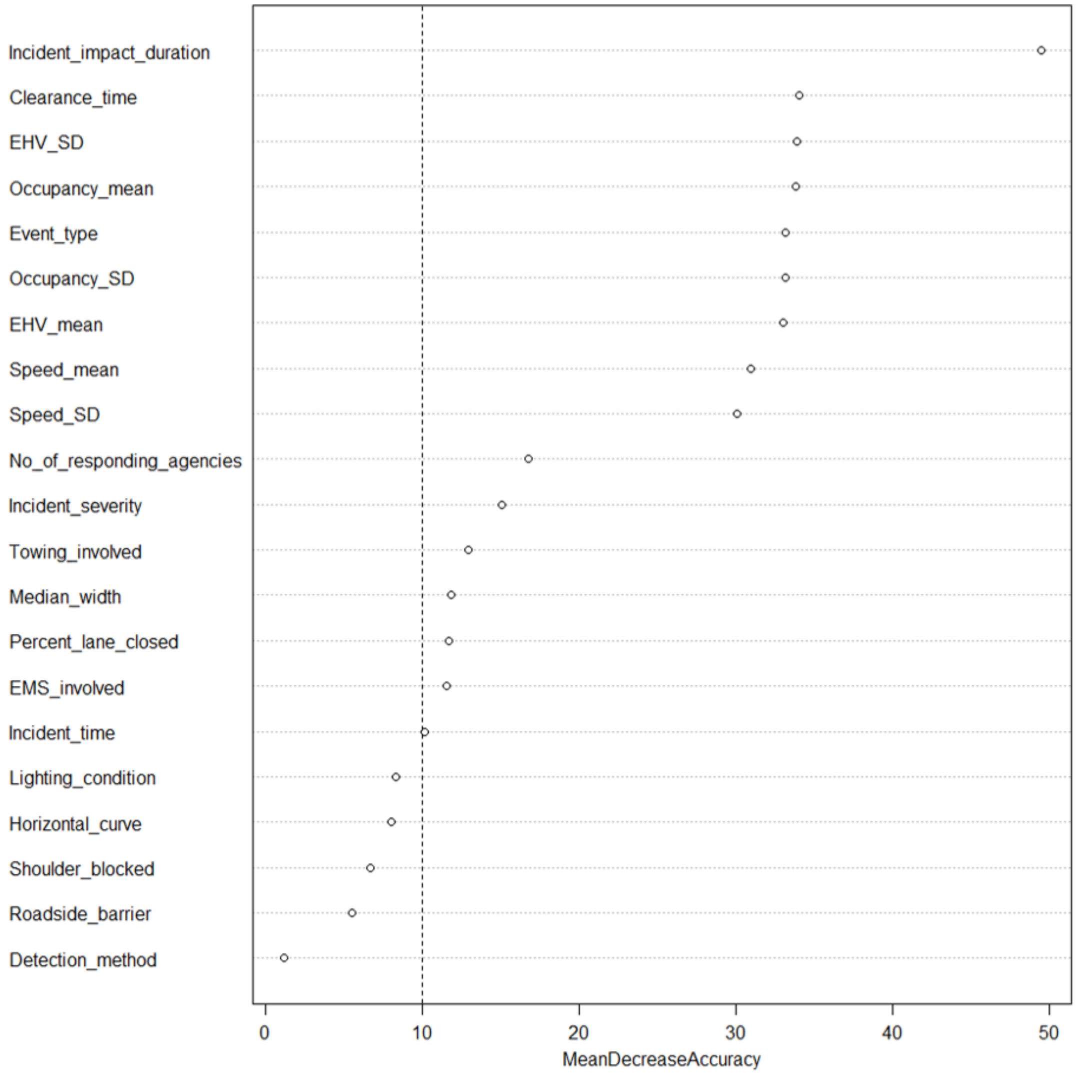


Figure 5-23: Variable Importance Ranking Using Random Forests Technique

5.7.2 Variable Correlation

At least some of the variables (e.g., traffic-related variables) identified by the RF technique are considered to be correlated. Using Pearson correlation, a correlation matrix was built to identify and exclude highly correlated variables. A correlation threshold of 0.5 was used to identify highly correlated variables (Dissanayake and Roy, 2013; Kobelo et al., 2008). The standard deviation of occupancy variable was dropped from the analysis since it is highly correlated with two variables, mean of occupancy (0.8) and mean of speed (-0.7). Furthermore, the mean of EHV was also removed from further analysis since it is also correlated with the standard deviation of EHV variable (0.9) and mean of occupancy (0.4). Finally, the following 13 variables were used as input variables in modeling the SC likelihood: incident impact duration, incident clearance time, standard deviation of EHV, mean of occupancy, incident type, standard deviation of speed, number of responding agencies, incident severity, towing involved, median width, percent lane closed, EMS involved, and incident time.

5.7.3 SC Risk Prediction Model Results

Table 5-14 summarizes the findings of the final Bayesian cloglog model with a random parameter. Of the 13 variables, seven variables were significant at the 95% BCI. Note that the predictor variable in the model is considered to be significant at the 95% BCI when the values of the 2.5% and 97.5% percentiles do not include zero (0), i.e., they are both either negative or positive. The significant variables include average occupancy, incident severity, percent of lanes closed, incident type, incident clearance duration, incident impact duration, and incident occurrence time.

Table 5-14: Posterior Estimates of Bayesian cloglog Regression Model

Parameter	Factor	Mean	Median	SD	BCI (%)	
					2.5	97.5
Intercept		-7.432	-7.324	1.205	-10.070	-5.367
Geometric characteristics						
Median width (ft)		-0.002	-0.002	0.003	-0.009	0.004
Traffic flow characteristics						
Occupancy mean		**0.084**	**0.083**	**0.017**	**0.054**	**0.121**
EHV SD (veh/hr)		-0.007	-0.007	0.005	-0.020	0.001
Speed SD (mph)		-0.025	-0.025	0.015	-0.055	0.003
Primary/normal incident characteristics						
Incident severity	Minor					
	Moderate/severe	**1.099**	**1.076**	**0.552**	**0.092**	**2.257**
Percent lane closed (%)	0-25					
	>25	**1.133**	**1.119**	**0.282**	**0.615**	**1.727**
Number of responding agencies	1					
	2-3	-0.067	-0.067	0.232	-0.518	0.395
	>3	-0.117	-0.113	0.426	-0.983	0.711
Towing involved	No					
	Yes	0.180	0.179	0.265	-0.328	0.713
Emergency Medical Services (EMS) involved	No					
	Yes	-0.616	-0.612	0.366	-1.353	0.088
Incident type	Hazard					
	Vehicle related	0.870	0.818	0.805	-0.529	2.613
	Crash	**2.461**	**2.398**	**0.807**	**1.079**	**4.241**
Incident clearance duration (min)		**0.007**	**0.007**	**0.002**	**0.003**	**0.011**
Incident occurrence time	Off-peak					
	Peak	**0.639**	**0.630**	**0.209**	**0.252**	**1.074**
Incident impact duration (min)		**0.008**	**0.008**	**0.001**	**0.005**	**0.011**

Note: variables in bold are significant, EHV = Equivalent hourly volume, SD = Standard Deviation, BCI = Bayesian Credible Interval.

As shown in Table 5-14, compared to incidents that occurred during off-peak hours, incidents that occurred during peak hours are observed to have a higher likelihood of resulting in SCs (mean =

0.639, 95% BCI (0.252, 1.074)). This observation implies that incidents occurring during congested time periods are more likely to induce traffic. Similar findings were also found by (Mishra et al., 2016; Hirunyanitiwattana and Mattingly, 2006). Congested traffic is characterized with smaller gaps between vehicles providing drivers with lesser space for maneuvering to avoid a crash. Accordingly, similar to the travel time messages posted on Dynamic Message Signs (DMSs), safety messages about the risk of SCs can also be posted based on different levels of prevailing traffic congestion, especially during peak hours. This scenario is also supported by the positive parameter of the average occupancy represented by occupancy mean parameter (mean = 0.084, 95% BCI (0.054, 0.121)). Increase in average occupancy represents an increase in traffic density, traffic volatility, and queue formation. The disturbances induced by the PIs are easier to propagate in this queuing traffic conditions, leading to a higher risk of SCs. According to the data shown in Table 5-14, the more the segments upstream of the prior incident is occupied, the longer it will take for the traffic flow to return back to normal. In this case, occupancy can also be used as one of the input parameters used to display the real-time information about the risk of SCs on DMSs and on connected vehicles. This situation is further explained by the positive parameter of time taken for speed to return back to normal, represented by the PI impact duration, (mean = 0.005, 95% BCI (0.003, 0.007)), which indicates that the risk of having a SC increases with PI impact duration.

Similarly, the positive parameter of the incident clearance duration indicates that the risks of SCs increase with an increase in incident clearance time (mean = 0.008, 95% BCI (0.005, 0.011)). As expected, the percentage of lanes closed is also identified as one of the significant predictor variables that influence the risk of SCs. More specifically, incidents resulting in more than 25% of lane closure have a higher likelihood of resulting in SCs (mean = 1.133, 95% BCI (0.615, 1.727)) compared to incidents involving less than 25% of lane closure. Note that the percentage of lanes closed was used instead of the number of lanes closed since it is a more representative variable. The percent of lanes closed is an indicator of the severity of the PI as severe incidents tend to result in an increased number of lanes closed. This fact is proven by the positive value of the PI severity coefficient (mean = 1.099, 95% BCI (0.092, 2.257)). Incident type is also a statistically significant predictor of the likelihood of the occurrence of SCs; incidents that are crashes have a higher likelihood of resulting in SCs (mean = 2.461, 95% BCI (1.079, 1.727)) compared to those involving hazards such as debris on roadway.

5.8 Summary

Proper identification of SCs is pivotal to accurate reporting of the effectiveness of the programs deployed to mitigate SCs. Nonetheless, the limited knowledge on the nature and characteristics of SCs has largely impeded their mitigation strategies. This study focused on identifying SCs using static and dynamic methods, and analyzing the risk factors influencing the occurrence of these crashes. A dynamic method that uses speed profiles derived from BlueToad® pairs was first developed and applied to identify SCs. For comparison purposes, the study also developed a Visual Basic for Applications (VBA) script that statically identifies SCs based on fixed spatiotemporal threshold. Once the SCs were identified using the dynamic method, Bayesian random effect complementary log-log (cloglog) model was used to analyze the risk factors influencing the occurrence of these crashes.

5.8.1 Static Method Results

The study area included a 35-mile section on I-95, a 21-mile section on I-10, a 61-mile section on I-295, and a 13-mile section on SR-202 located in Jacksonville, Florida. SCs were identified using a 2-mile-2-hour spatiotemporal threshold. Out of 74,030 incidents that occurred along the study corridors for the years 2014-2017, 3,400 incidents were marked as SCs (5%). I-95 experienced the highest proportion of SCs (8%) and an overall annual increasing trend in the proportion of SCs. SCs that occurred in the upstream direction constituted 88% of the total detected SCs, while the remaining 12% occurred in the opposite direction.

5.8.2 Dynamic Method Results

Dynamic approach based on speed profile data was used to identify SCs. Unlike the static method, SCs using dynamic method could be identified only along the corridors with BlueToad® pairs, i.e., I-10, I-95, and I-295. The analysis was based on 6,865 traffic incidents that occurred along the study corridors for the years 2015-2017. Overall, 518 SCs were identified from 425 PIs. The identified SCs account for 8% of the 6,865 incidents used in the analysis. The 425 PIs that induced SCs represented 7% of all normal incidents. These results indicate that approximately one in every twelve normal incidents resulted in a SC. Similar to the results from the static method, SCs that occurred in the upstream direction constituted 87% of the total SCs, while the remaining 13% occurred in the opposite direction of the PI.

Descriptive statistics of the SCs identified using the dynamic method indicated that 87% of the SCs occurred within two hours after the occurrence of PIs. Spatially, 73% of the SCs occurred within two miles from the PI. Overall, 66% of SCs occurred within two hours of the onset of a PI and within two miles upstream of the PI. About 34% of SCs occurred beyond the most commonly used 2-mile-2-hour spatiotemporal threshold. These statistics confirm that the proposed dynamic approach identified more SCs than the traditional static method.

The following are some of the key characteristics of the PIs and SCs identified using the dynamic approach:

- Only 1% of SCs occurred between 12:00 AM and 5:00 PM, whereas 80% occurred during peak hours, i.e., morning peak, 6:00 AM to 9:00 AM and evening peak, 3:00 PM and 6:00 PM. Specifically, 38% of SCs occurred during morning peak while the remaining 42% occurred during evening peak.

- The highest proportion of PIs (17%) occurred at 7:00 AM, while the highest proportion of SCs (15%) occurred two hours after the PI, i.e., at 9:00 AM.

- While SCs were found to occur on Mondays and Fridays, normal incidents were found to occur on weekdays (i.e., Monday through Friday). Only 5% of SCs were found to occur on weekends.

- Approximately 89% of normal incidents were cleared within 90 minutes, while only 68% of PIs were cleared within 90 minutes. The longer clearance time of the PIs could be considered as one of the factors that may have contributed to the occurrence of SCs.

- Approximately 75% of SCs were cleared within 90 minutes, while only approximately 68% of PIs were cleared within 90 minutes. The shorter clearance duration of SCs may be attributed to the fact that SCs are often less severe.

- The severity of PIs was found to be one of the factors that influence the occurrence of SCs. About 18% of PIs were moderate/severe while only 5% of normal incidents were moderate/severe. Besides the severity of PIs, percent of lanes closed, incident type, and incidents required towing were also considered to be good indicators of incident severity. About 12% of normal incidents resulted in a lane closure, while 33% of PIs resulted in a lane closure. Only 34% of normal incidents were identified as crashes, while 74% of PIs were crashes. About 13% of normal incidents required towing, while 25% of PIs required towing. These statistics indicate that the severity of PIs influence the occurrence of SCs.

5.8.3 SC Risk Prediction Model Results

SCs are crashes that occur within the spatial and temporal impact range of a PI. This study investigated the effect of real-time traffic, incident, environmental, and geometric related variables on the likelihood of SCs. As a first step toward achieving the study objective, potential SCs were identified using real-time speed data from BlueToad® pairs. This method was able to identify the spatial and temporal impact ranges of PIs, while accounting for the effects of traffic flow characteristics, both on the upstream and opposite directions. Random forests technique was next used to screen for the important variables. Highly correlated variables were then identified and excluded from further analysis. Finally, Bayesian random effect complementary log-log (cloglog) model was used to link the probability of SC occurrence with the real-time traffic flow variables, PI characteristics, environmental, and geometric characteristics.

The results indicated that several PI characteristics and real-time traffic variables influence the occurrence of SCs. The following seven variables were found to be significant at the 95% Bayesian credible interval (BCI): time taken for the traffic flow speed to return back to normal (incident impact duration), incident clearance duration, incident occurrence time, average occupancy, incident severity, percent of lanes closed, and incident type.

As can be inferred from the study findings, prevention of SCs is a function of PI severity, how quickly the PI is cleared, and how quickly information about the occurrence and location of traffic incidents is disseminated to the upstream drivers. To prevent the risk of SC occurrence, traffic management strategies should be developed to accelerate the dissipation of queue upstream of the PI.

CHAPTER 6
SUMMARY AND CONCLUSIONS

Transportation management centers (TMCs) serve as the hub of most freeway systems. A total of eleven regional TMCs (RTMCs) and two satellite TMCs are currently operational in the state of Florida. In November 2015, a new RTMC became operational in Jacksonville, Florida. This new facility replaced the old RTMC that was housed in the Florida Department of Transportation (FDOT) District 2 Urban Office building. The new facility has FDOT staff, TMC operators, local agency traffic signal operators, traffic monitoring consultants, and the Florida Highway Patrol (FHP) personnel under one roof. The presence of these incident management stakeholders under one roof is expected to improve traffic incident management (TIM) on the interstate system. As such, this research had two main goals:

1. evaluate the performance of the new RTMC in Jacksonville, FL; and

2. quantify the impact of incidents on the operational and safety performance of the freeway network.

The study goals were achieved through the following objectives:

- compare the performance of the new RTMC in Jacksonville where multiple response agencies are physically co-located in the RTMC building with the performance of the old RTMC where multiple incident response agencies except the FDOT and traffic monitoring consultant staff were housed at their respective agency locations;

- estimate the delays caused by incidents on freeways, and determine the factors affecting these delays; and

- develop a reliable approach to identify secondary crashes (SCs), and determine the risk factors associated with SCs.

To achieve the study goals and objectives, the following five performance measures of the RTMC were investigated:

1. incident verification duration,
2. incident response duration,
3. incident impact duration,
4. incident-related delays, and
5. SCs.

6.1 Incident Verification Duration

Incident verification duration is the time between an incident being reported and the incident being confirmed by the TMC. Verification duration is critical to the entire incident management process; it helps determine accurate and detailed information which enables the dispatch of the most appropriate personnel and resources to the scene. In this study, a before-and-after analysis of the incident verification duration was conducted to evaluate the performance of the new RTMC where multiple response agencies are physically co-located in the TMC building. The new RTMC became operational in November 2015. The before-period comprised 36,594 incidents that occurred from January 2014 to June 2015. The after-period included 36,654 incidents that occurred between January 2016 and June 2017.

In general, descriptive statistics indicated shorter average incident verification durations in the after-period than in the before-period. Crashes were verified quicker in the after-period than in the before-period. Incidents that occurred during peak hours in the after-period showed shorter verification durations than incidents in the before-period.

Hazard-based models were developed to identify the factors influencing incident verification duration before and after co-location of response agencies. The model results suggested that the following eight variables significantly affect incident verification duration both before and after co-location:

1. Incident type: incident verification duration was longer for crashes compared to hazards. However, the verification of vehicle problems was quicker than the verification of hazards, which include all objects on the roadway with the potential of causing crashes, e.g., debris on roadway, flooding, wildlife, etc.

2. Lane closure: incident verification duration was quicker when the lane closure was more than 25%. The verification duration of incidents with lane closure more than 25% was 29% and 28% quicker than the verification duration of incidents with lane closure ≤ 25% before and after co-location, respectively.

3. Incident severity: severe and moderate incidents had quicker verification durations than minor incidents. Moderate incidents had 26% and 19% quicker verification durations than minor incidents before and after co-location, respectively. Similarly, severe incidents had 21% and 26% quicker verification durations than minor incidents before and after co-location, respectively.

4. Roadway: incidents that occurred on I-95, I-295, SR-202 had shorter verification durations compared to the incidents that occurred on I-10. Incidents that occurred on I-75 had longer verification durations than those that occurred on I-10.

5. Traffic volume: an increase in the roadway AADT was associated with shorter incident verification duration. An increase in the AADT was associated with 8% and 9% decrease in the incident verification duration before and after co-location, respectively.

6. Time of the day: incidents that occurred during peak hours had shorter verification durations compared to incidents during off-peak hours. Incidents during peak hours were verified 4% and 2% quicker than incidents during off-peak hours before and after co-location, respectively.

7. Day of week: incidents that occurred on weekends had longer verification durations compared to incidents that occurred on weekdays. Incidents that occurred on weekends had 88% and 73% longer verification durations than incidents that occurred on weekdays before and after co-location, respectively.

8. Detection method: incidents that were detected by off-site detection methods had shorter verification durations than incidents detected by on-site detection methods.

6.2 Incident Response Duration

Incident response duration is measured from the time incident response team was notified of an incident to when they arrived at the incident scene. Response time includes dispatch duration and travel time to the incident scene. In general, crashes had longer average response duration than other types of incidents.

Hazard-based models were again developed to identify the factors influencing response durations before and after co-location of response agencies. The model results suggested that the following six variables significantly affect incident response duration both before and after co-location:

1. Incident type: crashes had 111% and 126% longer response durations than hazards before and after co-location, respectively.

2. Lane closure: incident response duration was longer when the lane blockage was more than 25% both before and after co-location. It was associated with 21% and 16% increase in the response duration before and after co-location, respectively.

3. Roadway: incidents that occurred on I-295 and SR-202 had quicker response durations compared to incidents that occurred on I-10 before and after co-location, respectively.

4. Day of week: incidents that occurred on weekends had significantly longer response durations compared to incidents that occurred on weekdays. Incidents that occurred on weekends had 156% and 102% longer response durations than incidents that occurred on weekdays before and after co-location, respectively.

5. Detection method: incidents detected by off-site detection methods had significantly longer response durations than incidents detected by on-site detection methods both before and after co-location.
6. Traffic volume: an increase in the AADT was associated with 4% and 7% increase in incident response durations both before and after co-location, respectively.

In addition to the afore-mentioned variables, ramp involvement was significant in the before-period, while incident severity was significant in the after-period. Prior to co-location of response agencies, incidents that were associated with ramps had relatively quicker response durations than those that were not associated with ramps. Moderate incident severity was associated with significantly longer incident response durations than minor incidents after co-location of response agencies.

6.3 Incident Impact Duration

Most agencies use incident clearance duration to measure the effectiveness of their incident management strategies. Incident clearance duration is the time between first recordable awareness of incident by a responsible agency and time at which the last responder has left the scene. However, it does not include the time it takes to restore normal traffic conditions after the incident is cleared, commonly known as the incident recovery duration.

While most previous studies have focused on analyzing the incident clearance duration, little has been done to examine the incident recovery duration. This study introduced a measure, referred to as the incident impact duration, which includes the total time the traffic is impacted by an incident. In other words, it includes the time taken since the incident occurred to when the affected operational characteristics (i.e., speed and travel time) of a roadway segment return to normal. Depending on the type of incident and prevailing traffic conditions, the incident impact duration could be shorter or longer than the incident clearance duration.

Incident impact duration, one of the most important performance measures, is challenging to measure at the time of the incident, especially because the time it takes for traffic to return to normal after an incident is difficult to record. This study developed a method to estimate the incident impact duration, and investigate the effects of various factors on the incident impact and clearance durations. The study proposed a technique that uses historical traffic speed data to estimate the incident impact duration. The method uses the speed data reported by the BlueToad® devices to create a bandwidth of mean speed profiles within one standard deviation for the times when there were no incidents. In the event of an incident, the algorithm checks if the speeds drop below the lower bound (i.e., one standard deviation below the historical mean) and tracks the traffic flow speed until it returns to within the one standard deviation bandwidth. The incident impact duration is computed as the time elapsed from the speed dropping below the bandwidth to the time it returns to normal (i.e., within one standard deviation from the historical mean).

The factors affecting the incident impact duration were identified using hazard-based models. The model results suggested that the following five variables significantly affect incident impact duration.

1. Incident type: Crashes had longer incident impact durations than hazards.

2. Incident severity: Moderate and severe incidents had longer incident impact durations than minor incidents.

3. Lane closure: Incidents resulting in lane closure of more than 25% caused longer incident impact durations than those resulting in a lane closure of less than 25%.

4. Time of the day: Incidents during peak hours had shorter incident impact durations.

5. Co-location of response agencies: Operations of the TMC facility after co-location of response agencies led to shorter incident impact durations.

6.4 Incident-related Delays

Traffic incidents are one of the major causes of traffic delays on freeways. This study aimed at estimating incident-related delays on freeways using real-time traffic flow data, and also evaluated the impact of incident characteristics, traffic conditions, and roadway geometric conditions on the extent of the incident-related delays.

The analysis was based on 3,383 incidents that occurred along I-95, I-295, and I-10 in Jacksonville, Florida, from 2015-2017. A data-driven methodology was first developed and applied to estimate the incident-related delays. The approach took advantage of the vast network of traffic sensors along the freeway corridors. The study used data extracted from both the BlueToad® and Regional Integrated Transportation Information System (RITIS) devices. These devices enabled the identification of the dynamic spatial and temporal extent of the incidents. The developed approach used real-time traffic flow characteristics, e.g., speed, travel time, and volume, to estimate the actual delays caused by traffic incidents.

Results indicated that approximately 100%, 82%, and 48% of hazards, vehicle problems, and crashes, respectively, had incident-related delays shorter than 20 vehicle-hours. Only 7%, 24%, and 14% of minor, moderate, and severe incidents, respectively, led to incident-related delays longer than 120 vehicle-hours. The distribution of incident-related delays during morning- and evening-peak hours showed a similar trend, where both had lower percentage (approximately 61%) of incident-related delays shorter than 20 vehicle-hours than incidents during off-peak hours (81%). Moreover, 70% of incident-related delays on weekdays and 75% of the incident-related delays on weekends were shorter than 20 vehicle-hours. About 48% of incidents that involved towing services caused incident-related delays shorter than 20 vehicle hours. Only 6% of incidents detected using on-site detection methods led to incident-related delays longer than 120 vehicle-hours while 18% of the incidents detected using off-site detection methods caused incident-related delays longer than 120 vehicle-hours.

Once the incident-related delays were estimated, the factors affecting these delays were investigated using hazard-based models. The results indicated that the following eight variables had significant influence on the incident-related delays at the 95% confidence interval:

1. incident type (i.e., crashes, vehicle problems, and hazards),
2. incident severity (i.e., minor, moderate, and severe),
3. time of the day (i.e., off-peak hours, morning peak hours, and evening peak hours),
4. day of week,
5. median width,
6. vertical curvature (i.e., presence or absence),
7. EMS involvement (i.e., involved or not involved), and
8. detection method (i.e., on-site detection and off-site detection).

Crashes, vehicle problems, moderate incident severity, presence of vertical curves, EMS involvement, and off-site detection methods were found to cause longer incident-related delays. As suggested in the study findings, incident-related delays were longer when an incident was a crash. Enhancements to crash response and dissemination of crash information to the traffic upstream of the crash has the potential to reduce the delays caused by crashes. Further investigation is required to identify factors contributing to longer incident-related delays during evening peak hours than morning peak hours. Presence of vertical curves was associated with bridges, and was found to have significant longer incident-related delays. There is a need for special incident management procedures for such locations to minimize the incident-related delays. A spatial analysis of incident-related delays can identify the areas with the likelihood of having longer delays and help incident response agencies develop plans to cater to these locations.

Despite the efforts in improving the analysis of incident-related delays, this study was limited by the spatial distribution of traffic sensors. For example, BlueToad® devices were not available on the entire freeway network, and even when available, some of the devices were inactive, or the devices were not closely spaced. Likewise, some locations did not have the RITIS devices to collect traffic volume data during incidents. Advances in the network of the traffic sensors would improve the analysis of incident-related delays and lead to more accurate results.

6.5 Secondary Crashes

Proper identification of SCs is pivotal to accurate reporting of the effectiveness of the programs deployed to mitigate SCs. Nonetheless, the limited knowledge on the nature and characteristics of SCs has largely impeded their mitigation strategies. This study focused on identifying SCs using static and dynamic methods, and analyzing the risk factors influencing the occurrence of these crashes. A dynamic method that uses speed profiles derived from BlueToad® pairs was first developed and applied to identify SCs. The proposed method identifies a crash as a SC if it occurred within the impact range of the primary incident (PI). For comparison purposes, the study also developed a Visual Basic for Applications (VBA) script that statically identifies SCs based on fixed spatiotemporal threshold. Once the SCs were identified using the dynamic method, Bayesian random effect complementary log-log model was used to analyze the risk factors influencing the occurrence of these crashes.

6.5.1 Identification of SCs

SCs were identified using both the static and the dynamic methods. The study area for the static method included a 35-mile section on I-95, a 21-mile section on I-10, a 61-mile section on I-295, and a 13-mile section on SR-202 located in Jacksonville, Florida. SCs were identified using a 2-mile-2-hour spatiotemporal threshold. Out of 74,030 incidents that occurred along the study corridors for the years 2014-2017, 3,400 incidents (5%) were identified as SCs. SCs that occurred in the upstream direction constituted 88% of the total detected SCs, while the remaining 12% occurred in the opposite direction.

Dynamic approach based on speed profile data was also used to identify SCs. Unlike the static method, SCs using dynamic method could be identified only along the corridors with BlueToad® pairs, i.e., I-10, I-95, and I-295. The analysis was based on 6,865 traffic incidents that occurred along the study corridors for the years 2015-2017. Overall, 518 SCs were identified from 425 PIs. The identified SCs account for 8% of the 6,865 incidents used in the analysis. The 425 PIs that induced SCs represented 7% of all normal incidents. These results indicate that approximately one in every twelve normal incidents resulted in a SC. Similar to the results from the static method, SCs that occurred in the upstream direction constituted 87% of the total SCs, while the remaining 13% occurred in the opposite direction of the PI.

Descriptive statistics of the SCs identified using the dynamic method indicated that 87% of the SCs occurred within two hours after the occurrence of PIs. Spatially, 73% of the SCs occurred within two miles from the PI. Overall, 66% of SCs occurred within two hours of the onset of a PI and within two miles upstream of the PI. About 34% of SCs occurred beyond the most commonly used 2-mile-2-hour spatiotemporal threshold. These statistics confirm that the proposed dynamic approach identified more SCs than the traditional static method.

The following are some of the key characteristics of the PIs and SCs identified using the dynamic approach:

- Only 1% of SCs occurred between 12:00 AM and 5:00 AM, whereas 80% occurred during peak hours. Specifically, 38% of SCs occurred during morning peak while the remaining 42% occurred during evening peak.

- The highest proportion of PIs (17%) occurred at 7:00 AM, while the highest proportion of SCs (15%) occurred two hours after the PI, i.e., at 9:00 AM.

- While SCs occurred on Mondays and Fridays, normal incidents occurred on weekdays (i.e., Monday through Friday). Only 5% of SCs occurred on weekends.

- Approximately 89% of normal incidents were cleared within 90 minutes, while only 68% of PIs were cleared within 90 minutes. The longer clearance time of the PIs could be considered as one of the factors that may have contributed to the occurrence of SCs.

- Approximately 75% of SCs were cleared within 90 minutes, while only approximately 68% of PIs were cleared within 90 minutes. The shorter clearance duration of SCs may be attributed to the fact that SCs are often less severe.

- The severity of PIs was found to be one of the factors that influence the occurrence of SCs. About 18% of PIs were moderate/severe while only 5% of normal incidents were moderate/severe. Besides the severity of PIs, percent of lanes closed, incident type, and incidents required towing were also considered to be good indicators of incident severity. About 12% of normal incidents resulted in a lane closure, while 33% of PIs resulted in a lane closure. Only 34% of normal incidents were identified as crashes, while 74% of PIs were crashes. About 13% of normal incidents required towing, while 25% of PIs required towing. These statistics indicate that the severity of PIs influence the occurrence of SCs.

6.5.2 Factors Affecting the Likelihood of SCs

The effect of real-time traffic, incident, environmental, and geometric related variables on the likelihood of SCs was modeled. Random forests technique was first used to screen for the important variables. Highly correlated variables were then identified and excluded from further analysis. Finally, Bayesian random effect complementary log-log model was used to link the probability of SC occurrence with the real-time traffic flow variables, PI characteristics, environmental, and geometric characteristics.

The results indicated that several PI characteristics and real-time traffic variables influence the occurrence of SCs. The following seven variables were found to be significant at the 95% Bayesian credible interval (BCI):

1. Average detector occupancy: the risk of SCs increased with the increase in the average detector occupancy.

2. Incident severity: compared to moderate or minor PIs, severe PIs were observed to increase the likelihood of SCs.

3. Lane closure: incidents resulting in more than 25% of lane closure were found to have a higher risk of resulting in SCs compared to incidents involving less than 25% of lane closure.

4. Incident type: crashes were found to have a higher likelihood of resulting in SCs compared to those involving other incident types such as debris on roadway.

5. Incident clearance duration: increase in incident clearance time was accompanied with the increase in the risk of SCs.

6. Incident impact duration: the positive parameter of time taken for speed to return back to normal indicates that the risk of having a SC increases with PI impact duration.

7. Incident occurrence time: compared to incidents that occurred during off-peak hours, incidents that occurred during peak hours were observed to have a higher likelihood of resulting in SCs.

As can be inferred from the study findings, prevention of SCs is a function of PI severity, how quickly the PI is cleared, and how quickly information about the occurrence and location of traffic incidents is disseminated to the upstream drivers. To prevent the risk of SC occurrence, traffic management strategies should be developed to accelerate the dissipation of queue upstream of the PI. The likelihood of a SC occurrence can be estimated using real-time traffic data in combination with PI characteristics. Warnings can be sent to drivers approaching a primary crash scene in real-time through various means including DMSs, information sharing technologies such as *WAZE* application, and the emerging technologies such as connected vehicles, giving them an opportunity to take necessary precautions (such as detour and/or drive with caution) to avoid being involved in a crash. Furthermore, when the conditions associated with a high likelihood of SCs prevail, responding agencies such as highway patrol, EMS, towing agencies, etc. could be better prepared to respond to SCs, if they were to occur. These strategies will help to potentially reduce the frequency and severity of SCs.

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