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Evaluating Mobility and Safety Benefits of Freeway Service Patrols: A Case Study of Florida's Road Rangers

Jimoku H. Salum
University of North Florida, jimokuhinda@yahoo.com

EVALUATING MOBILITY AND SAFETY BENEFITS OF FREEWAY SERVICE PATROLS: A CASE STUDY OF FLORIDA'S ROAD RANGERS

By

Jimoku Hinda Salum

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The thesis "Evaluating Mobility and Safety Benefits of Freeway Service Patrols: A Case Study of Florida's Road Rangers" submitted by Jimoku Hinda Salum in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering has been

Approved by the thesis committee: **Date:**

Dr. Thobias Sando,
Thesis Advisor and Committee Chairperson

Dr. Priyanka Alluri,
Committee Member

Dr. Christopher Brown,
Committee Member

Dr. O. Patrick Kreidl,
Committee Member

Accepted for the School of Engineering:

Dr. Osama Jadaan,
Director

Accepted for the College of Computing, Engineering, and Construction:

Dr. William Klostermeyer,
Interim Dean

Accepted for the University of North Florida:

Dr. John Kantner,
Dean of the Graduate School

DEDICATION

…to my oldest relative and jester: my grandfather, Gwisu Hinda, Ng'waniyuki.

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I would like to express my sincere thanks to everyone whose contribution is immensely appreciated. Just to trim that long list, not by importance;

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AFT	Accelerated Failure Time
ATMS	Advanced Traffic Management System
B/C	Benefit Cost Ratio
CCTV	Closed-Circuit Televisions
FDOT	Florida Department of Transportation
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
FL511	Florida 511 travel information system
FSPs	Freeway Service Patrols
IITD	Incident-induced Traffic Delay
ITS	Intelligent Transportation System
JSO	Jacksonville Sheriff's Office
LL	Log Likelihood
MAC	Media Access Control
MEF	Mobility Enhancement Factor
OLS	Ordinary Least Square
PI	Primary Incident

RITIS	Regional Integrated Transportation Information System
RTMC	Regional Transportation Management Center
SC	Secondary Crash
TMC	Transportation Management Center
USDOT	United States Department of Transportation

ABSTRACT

The Florida's Road Rangers monitor the freeways for incidents to minimize their adverse impacts on traffic. The objectives of this study were to evaluate the extent to which Road Rangers reduce incident clearance duration (ICD), incident-induced traffic delays (IITDs) and secondary crashes (SCs).

Since ICD distributions are often right-skewed, the study applied quantile regression to relate ICD to influencing factors. Data skewed to the right is usually a result of lower bounds in a data set being extremely low relative to the rest of the data. Data from 28,000 incidents that occurred on freeways in Jacksonville, Florida were analyzed. Of the factors analyzed, crash events, incident severity, shoulder blockage, peak hours, weekends, nighttime, number of responding agencies, and towing were found to associate with significantly longer ICDs. Road Rangers were found to reduce incident clearance duration by 25.3%. In other words, shorter incident clearance durations were observed when Road Rangers responded to incidents compared to other agencies.

On the second objective, IITDs were estimated by establishing incident-free recurrent travel time profiles as bases from which the incident-induced delays could be measured. To determine the extent to which Florida's Road Rangers can reduce IITDs, the analysis was based on the data from 4,045 incidents that occurred on freeways in Jacksonville, Florida. The parametric accelerated failure time (AFT) survival model, with Weibull distribution of IITD was used to model IITDs. The results show that significant variables affecting IITDs include incident characteristics (severity, type, towing requirements, lane and shoulder blockage, etc.), Road Rangers involvement, and prevailing traffic conditions. The findings also revealed no significant effects of median width, average detector occupancy and the day-of-the-week on IITDs. A significant and

unique contribution of this paper is that the Road Rangers program was found to shorten IITDs relative to other responding agencies by 12.6%.

To identify the potential impact of Road Rangers in lowering the likelihood of SCs, this study sought to evaluate the safety performance of the Road Rangers program. Since SCs are often rare, the study applied a complimentary log-log model. The analysis was based on incident data related to 6,088 incidents on freeways in Jacksonville, Florida. Of the factors analyzed, traffic volume, incident impact duration, moderate/severe crashes, weekdays, peak periods, percentage of lane closure, and shoulder blockage were found to significantly increase the likelihood of SCs. While vehicle speed and lighting condition showed little contribution (not significant at 95%) to SC likelihood, Road Rangers were associated with relatively lower probabilities of SC occurrence. Based on the reduction in the average incident duration, the results suggest that the Road Rangers reduce SC risk by 20.9%. Based on increased safety at incident scenes, Road Rangers reduce SC probability by 17.9%.

The results of this study can, in general, provide researchers and practitioners with an effective way for evaluating mobility and safety benefits of the Road Rangers program. The developed approaches provide practical guidance on how to quantify the mobility and safety impact of the Road Rangers program. The results can, in general, help practitioners to improve incident management plans.

Keywords: Freeway service patrols, Road Rangers, incident clearance duration, incident-induced delays, quantile regression, hazard-based models, mobility enhancement factor, secondary crashes.

CHAPTER 1

INTRODUCTION

The Need for Freeway Service Patrols

As congestion spreads and intensifies and the level of incidents, delays, and disruptions increase, the level of service and reliability of the roadway systems in many areas continues to deteriorate (FHWA, 2017). One of the main goals of today's transportation systems is to provide a safe and reliable travel experience to road users. Unfortunately, non-recurring congestion is unpredictable (Olmstead, 2004; Habtemichael et al., 2015). Non-recurring congestion resulting from 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). For instance, the toll of traffic congestion in the United States (U.S.) in 2014 was estimated to be 6.9 billion hours and 3.1 billion gallons of fuel, equivalent to approximately $160 billion. On average, a commuting motorist spent 42 additional hours during peak traffic periods in 2014 (Schrank et al., 2015). Moreover, traffic incidents expose other vehicles to the risk of a secondary crash (SC) (Karlaftis et al., 1999).

In search for an approach to reduce the effect resulting from traffic incidents on freeway operations, many states have included freeway service patrols (FSPs) in their incident management plans. As one component of incident management systems, FSPs facilitate quick removal of incidents through faster response and reduced clearance time (Karlaftis et al., 1999). FSP typically operate as follows. The freeways are divided into disjoint beats, along with a certain number of probe vehicles. These vehicles travel back and forth along the beat, stopping to clear incidents in a first-reach-first serve manner. The probe vehicles would remove the vehicles stalled in the freeways and provide services such as changing flat tires and offering a needed gallon of gasoline. If they cannot get the vehicles operational in a few minutes, they will tow them off the freeway to a designated area. Note that the way FSP systems operate is different from that of incident-response dispatch systems. FSP probe vehicles spontaneously detect, respond to and clear the incidents. In contrast, in the incident-response systems trucks are placed at certain depots, waiting for the dispatch commands (Yin, 2006).

The Florida's Road Rangers

The Road Ranger Service Patrol (simply Road Rangers) in Florida is an FSP that provides free highway assistance services to motorists. The Florida Department of Transportation (FDOT) initially used Road Rangers for the management of vehicle incidents in construction zones. This program has since expanded to respond to all type of incidents and has become one of the most effective elements of the FDOT's incident management program. The Road Rangers provide a direct service to motorists by quickly clearing travel lanes and assisting motorists. Services can include providing a limited amount of fuel, assisting with tire changing and other types of minor emergency repairs, and providing support at crash sites. Since its inception in 1999, as of 2016, the Road Rangers had offered over 5 million service assists with more occurring daily. Road Rangers are typically assigned to work along major interstate corridors and within construction areas on these interstates (FDOT, 2016).

Figure 1-1: Road Rangers at work

Study Objectives

Although Road Rangers have become an increasingly vital element of incident management strategies in Florida, the extent of their benefits is currently not well understood. This thesis evaluates both mobility and safety benefits of the program. Specifically, the objectives are;

1. To evalaute the mobility (operational) benefits of the Road Rangers using incident clearance duration as a performance metric.
2. The second objective, which is closely related to the previous objective addresses important answers to the following questions;
    a. How much delays are a result of incidents?
    b. To what extent do Road Rangers reduce incident-induced traffic delays (IITD)?
3. To evaluate safety benefits of Road Rangers using secondary crashes as a performance measure.

Thesis Organization

This thesis is thematically structured, compiling three potential stand-alone journal papers. It starts by providing a general overview of FSPs, and research objectives in chapter 1. Chapter 2 is a stand-alone journal paper that evaluates the mobility benefits of Florida's Road Rangers. Chapter 3 presents a paper on estimating incident-induced traffic delays: a quest of delay savings of Florida's Road Rangers. Chapter 4 presents a paper that evaluates the safety benefits of Road Rangers. In each individual paper, the thesis discusses the results and conclusively highlights some important findings.

CHAPTER 2

PAPER 1

Operational Evaluation of Freeway Service Patrols: A Case Study of Florida's Road Rangers

Submitted to the ASCE Journal of Transportation Engineering

INTRODUCTION

In 2014, motorists spent an additional 6.9 billion hours and 3.1 billion gallons of fuel, equivalent to approximately $160 billion, as a result of traffic congestion in the United States (U.S.). On average, a commuting motorist spent 42 additional hours during peak traffic periods in 2014 (Schrank et al., 2015). According to the Federal Highway Administration (FHWA), non-recurring congestion events account for almost half of all congestion (Amer et al., 2015). Traffic incidents, ranging from a flat tire to an overturned hazardous material truck, contribute to almost half of all non-recurring congestion events (Amer et al., 2015).

In response to the adverse impacts of non-recurring congestion, many states have included freeway service patrols (FSPs) in their incident management plans to minimize incident clearance time. FSP program names vary by state agency. For example, Florida's FSP program is referred to as the Road Rangers Service Patrol (or Road Rangers), Ohio's FSP program is called the Freeway Incident Response Service Team (FIRST), Maryland's FSP is the Coordinated Highway Action Response Team (CHART), Georgia's FSP is the Highway Emergency Response Operators (HERO) program, and both New York and Tennessee call their FSP programs the Highway Emergency Local Patrol (HELP) (Baird, 2008). The goal of such programs is to restore the freeway to full capacity as quickly as possible after an incident occurs, as well as alert motorists until the incident is cleared. FSP programs are widely used to help mitigate the effects of non-recurring congestion and have become an increasingly vital element of the incident management programs. A national survey of 19 agencies showed that the benefit-cost (B/C) ratios for FSP programs ranged from 4.6:1 to 42:1, with an average B/C ratio of 12.4:1, and a median of 9.45:1 (Baird, 2008).

The Road Rangers FSP, provided by the FDOT, offers free highway assistance services during incidents on Florida freeways. Road Rangers provide direct benefits to the public in terms of reduced delay, fuel consumption, and air pollution, as well as improved safety and security. To facilitate these objectives, Road Rangers probe vehicles monitor the freeways for road debris, traffic crashes, stranded vehicles, and other traffic incidents (Lin et al., 2012; Carrick et al., 2018; Sun et al., 2018). Since its inception in 1999, Road Rangers have assisted over 5 million motorists, as of 2016, with more service assists occurring each day (FDOT, 2016). A case study performed by Lin et al. (2012) revealed that although the contract costs for the program were about $19.9 million, the benefits in reduced delay and fuel savings, in total, were about $135.3 million. Overall, the Road Rangers program achieved a combined B/C ratio of 6.78:1 statewide in 2010.

Although Road Rangers have increasingly become one of the crucial incident management strategies in Florida, extent of the program's benefits has not yet been quantified. Very few studies, if any, have assessed the operational effectiveness and the monetary value of the program. This study evaluates the operational performance of the Road Rangers program by developing Mobility Enhancement Factors (MEFs) using incident clearance duration as a performance measure. The benefits of the program were assessed in terms of reduced incident clearance duration, with a specific emphasis on the impact of the Road Rangers program. To effectively evaluate both incident management and traffic operational improvements, the MEFs were developed based on statistical modeling of incident clearance duration. Multiple variables were included in the model to gain a broader understanding of their effects on incident clearance durations and traffic operations, and to evaluate the effectiveness of the Road Rangers program.

LITERATURE REVIEW

Despite an increasing investment in FSPs by state transportation agencies, comprehensive studies that evaluate the operational effectiveness of such programs are sparse. Several previous studies focused on evaluating the performance and overall benefits of FSPs using incident clearance duration (Lee & Fazio, 2005; Li, et al., 2017). However, the majority of previous studies focused on benefit-cost analyses to determine the programs' benefits by aggregating the delay savings in terms of reduced incident clearance duration with other performance measures, such as fuel savings (i.e., reduced fuel consumption) and reduced air pollutant emissions (Guin et al., 2007; Dougald & Demetsky, 2008; Lin et al., 2012). Nevertheless, in each study, FSPs were recognized as one of the most cost-effective incident management strategies available to transportation agencies.

Freeway incidents, such as crashes and disabled vehicles, can result in considerable non-recurring congestion. The primary goal of most FSPs is to minimize the length of time that an incident affects the freeway section, thus minimizing the resulting traffic congestion. Therefore, incident clearance duration is a primary measure of the effectiveness of an FSP, where reduced incident clearance duration implies greater effectiveness. Until recently, various methodologies have been used to estimate delays caused by incidents, and the savings in delay resulting from FSP response. However, estimating such benefits can be challenging when considering the various aspects of incidents, such as incident detection and response times, with and without FSPs; reduction in roadway capacities; travel time value; and delay estimation methods. Incident modeling and formulation used to estimate delay savings vary among previous studies. While several studies evaluated delay using empirical formulations based on simulations (Chou et al., 2009; Ma et al., 2009; Sun et al., 2017), the majority used queuing-theory-based models (Hagen et al., 2005; Guin et al., 2007; Dougald & Demetsky, 2008; Lin et al., 2012).

Dougald and Demetsky (2008) evaluated the benefits of FSPs based on incident delay savings and reduction in fuel consumption. To estimate incident-induced delay and associated delay savings attributable to FSP operations, the study employed deterministic queuing models to estimate motorist delay associated with queues that form during incident conditions. The models used capacity reduction factors in conjunction with the geometric and traffic characteristics of an FSP route, as well as the frequency and type of assisted incidents on the route. An earlier study by Guin et al. (2007) used a similar method to evaluate the benefits of FSPs based on incident delay savings, secondary crash reduction, reduction in fuel consumption, and commuter perception of motorist assistance. The study estimated incident-induced delay savings using deterministic queuing models with a specific assumption that accommodates dual-phase incidents. According to Guin et al. (2007), based on the nature of incident response operations, the number of lanes blocked by an incident varies with time. As the incident is cleared over time, progressively fewer lanes are blocked. Typically, clearance of a lane-blocking incident on a freeway has two phases (Guin et al., 2017). The first phase involves the blockage of one or more lanes by the incident or by the responders for the period of time of when the incident occurs to when the vehicles involved are moved to the shoulder. The second phase involves the blockage of the shoulder. Both Dougald & Demetsky (2008) and Guin et al. (2017) employed subjective assumptions of roadway capacities based on experience.

The current study evaluates the extent to which Road Rangers reduce incident clearance. Based on archived incident data, a statistical model is developed to relate incident clearance duration to influencing factors. The model is used to evaluate the mobility benefits of Road Rangers. It is anticipated that the MEFs developed in this study may provide researchers and practitioners with an effective way for conducting the economic appraisal of the program.

DATA

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

In this study, the response variable is the incident clearance duration, as defined in Figure 2-1. Incident clearance duration is defined as the time elapsed (in minutes) from the time an incident is reported (i.e., first notified) until all evidence of the incident has been removed from the incident scene, i.e., when the last responder leaves the scene, as shown in Figure 2-1. Incident clearance duration consists of three stages: incident verification time, incident response time, and incident clearance time.

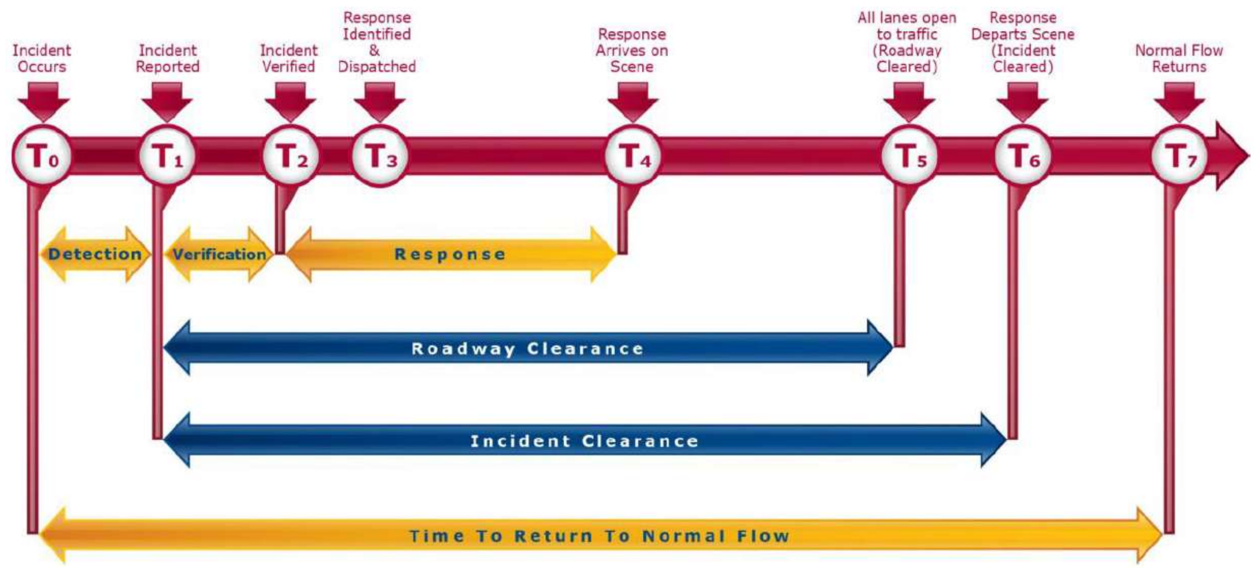


Figure 2-1: Traffic incident duration timeline (Amer et al., 2015)

Table 2-1 lists the eleven explanatory variables included in the analysis as well as general descriptive statistics. As shown in Table 2-1, the *number of responding agencies* variable was considered continuous, while the remaining ten variables, generally associated with freeway incidents, were considered categorical. *Event type* (or, *incident type*) was categorized into crashes, vehicle problems (disabled or abandoned vehicles, emergency vehicles, vehicle fire, and police activity), and traffic hazards (debris, flooding, and spillage). Two temporal variables, *time of day* and *lighting condition*, were included in the analysis. *Peak hours* included morning peak (0600 to 1000 hours) and evening peak (1530 to 1830 hours), and *lighting condition* was categorized as day or night based on sunrise and sunset times on the day of the incident. *Detection method* was divided into three categories: Road Rangers, Intelligent Transportation System (ITS) services, and on-road services (police, Florida Highway Patrol (FHP), and motorists). ITS services included the use of closed-circuit televisions (CCTV), the Florida 511 travel information system (FL511), FL511 probe vehicles, Waze, and Transportation Management Centers (TMCs).

The variable *lane closure* refers to whether an incident resulted in lane(s) closure. The percent of lanes closed is usually considered an indicator of the severity of an incident, as severe incidents tend to result in an increased number of lanes closed. In the current study, a 25% lane closure implies one lane out of four lanes of a roadway section is closed. A closure of one of three lanes will eventually mean 33.3% lane closure and 100% means all lanes are closed. Lane closure was categorized into two groups as illustrated in Table 2-1. *Shoulder blockage* was divided into two categories: No (no any shoulder is blocked) and Yes (at least one shoulder is blocked). In the same token, *towing* was divided into either no towing was involved, or towing was involved.

Table 2-1: Descriptive statistics of incident data

Categorical Variables	Factor	Code	Frequency	Share (%)
Incident Type	Crash	0	8,974	32.05
	Vehicle problems	1	17,231	61.54
	Traffic hazards	2	1,795	6.41
Detection Method	Road Rangers	0	14,790	52.82
	ITS services	1	2,649	9.46
	On-road services	2	10,561	37.72
Incident Severity	Minor	0	26,235	93.70
	Moderate	1	1,328	4.74
	Severe	2	437	1.56
Shoulder blocked	No	0	17,106	61.09
	Yes	1	10,894	38.91
Lane Closure (%)	0 – 25	0	24,216	86.49
	> 25	1	3,784	13.51
Time of day	Peak hours	0	15,475	55.27
	Off-peak hours	1	12,525	44.73
Day of the week	Weekdays	0	26,066	93.09
	Weekends	1	1,934	6.91
Lighting Condition	Day	0	24,610	87.89
	Night	1	3,390	12.11
Towing involved	No	0	24,580	87.79
	Yes	1	3,420	12.21
Responding agencies	Road Rangers	0	23,680	84.57
	Other Agencies	1	4,320	15.43
Continuous variables	**Min**	**Mean**	**Median**	**Max**
Number of Responding agencies	1	1.7	1	10
Incident Clearance Duration [a] (min)	1	36.71	20	325

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

METHODOLOGY

Quantile Regression

Previous studies have demonstrated the application of various modeling techniques to predict incident clearance durations, oftentimes resulting in skewed distributions. Such models include hazard-based models (Li et al., 2014; Haule, et al. 2018), and nested models (Ghosh, et al. 2012). Since incident clearance durations are often skewed (Figure 2-2(a)), the current study used quantile regression to fit the incident clearance distribution. Incidents that have a much shorter or longer than average durations may not be accurately predicted with other models. Theoretically, quantile regression provides better prediction accuracy since it can account for dispersed and skewed distributions of incident clearance durations. Quantile regression is a statistical technique that can relate quantiles of the incident clearance duration distribution to explanatory variables (Khattak et al., 2016).

A more complete picture of incident clearance duration distribution can be obtained through quantile regression analyses. Rather than modeling only the average incident clearance duration as in Ordinary Least Square (OLS) regression, quantile regression can model the relationship of any quantile with a set of explanatory variables (Khattak et al., 2016). In quantile regression, a sum that gives asymmetric penalties for over-prediction, $(1-q)|\varepsilon_i|$, and under-prediction, $q|\varepsilon_i|$, is minimized (Koenker, 2005). The prediction errors in quantile regression are given by:

$$\varepsilon_i^q = y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \qquad (2\text{-}1)$$

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

y_i = observed duration for ith incident in dataset (min),

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

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

x_{ij} = value of independent variable j in ith incident.

The coefficients $\hat{\beta}_0^q$ and $\hat{\beta}_j^q$ are estimated by minimizing the following objective function (Koenker, 2005):

$$\sum_{i:y_i \geq \hat{\beta}_0^q + \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij}}^{n} q \left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \right| + \sum_{i:y_i \geq \hat{\beta}_0^q + \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij}}^{n} (1-q) \left| y_i - \hat{\beta}_0^q - \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} \right| \tag{2-2}$$

In this study, quantile regression was applied to predict incident clearance duration at the 5th, 15th, 25th, …, 95th percentiles. Table 2-2 provides the regression model results for the 25th, 50th (median), 75th, and 95th percentiles.

Incident Clearance Duration Prediction

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

Location-based Prediction

This study applied a location-based prediction method to predict the incident clearance durations with quantile regressions at the 5th, 15th, 25th, …, 95th percentiles in the intervals of 10, with the assumption that traffic safety outcomes do not change dramatically in a short period (Khattak et al., 2016). Therefore, the predicted duration could be obtained at the 5th percentile regression if the observed value was less than the 10th percentile, or at the 15th percentile regression if the observed value was between the 10th and the 20th percentile, and so forth. Using the location-based prediction method, the incident clearance duration was predicted using Equation 2-3.

$$\hat{y} = \left\{ \hat{y}_m \middle| \begin{array}{c} m = 5, if \;\; q_0 < \bar{y} \leq q_{10} \\ m = 15, if \; q_{10} < \bar{y} \leq q_{20} \\ \vdots \\ \vdots \\ m = 95, if \; q_{90} < \bar{y} \leq q_{100} \end{array} \right\} \tag{2-3}$$

where; $\hat{y}$ = predicted incident clearance duration using location-based prediction method,

$\hat{y}_m$ = predicted incident clearance duration at center of interval m (i.e., percentile location),

$\bar{y}$ = average of historical incident clearance duration at particular location (e.g., bottleneck), and

q_p = pth percentile value of durations of incidents in the region.

Using the coefficients from quantile regression, the probability that an incident with a given duration will occur, resulting in a change in values of the independent variables, can be quantified using Equation 2-4a and 2-4b. Equations 2-4a and 2-4b estimate incident clearance durations when an incident is not related and related to a particular independent variable (category in case of discrete variable) respectively. This allows the prediction of the incident clearance duration given a certain value of the independent variable while holding other variables at their means.

$$y_i = \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} - \hat{\beta}_j^q x_{ij} \tag{2-4a}$$

$$y_i = \sum_{j=1}^{n} \hat{\beta}_j^q x_{ij} - \hat{\beta}_j^q x_{ij} + \hat{\beta}_j^q \tag{2-4b}$$

where, y_i is the estimated duration of ith incident in data set. All other notations are defined earlier.

Model Accuracy

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

$$\text{RMSE} = \sqrt{\frac{\sum_i^n (y_i - \hat{y}_i)^2}{n}} \tag{2-5}$$

where;

n = number of observations,

y_i = observed duration for ith incident in data set, and

$\hat{y}_i$ = predicted duration for ith incident in data set.

Mobility Enhancement Factors Definition

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

$$\mathrm{MEF}_i = \frac{\hat{y}_{r,i}}{\hat{y}_i} \qquad (2\text{-}6)$$

where $\hat{y}_{r,i}$ is the predicted incident clearance duration for *i*th incident in data set assuming Road Rangers were involved, and $\hat{y}_i$ is the predicted incident clearance duration for *i*th incident in data set assuming Road Rangers were not involved. The overall MEF for Road Rangers was calculated using Equation 7.

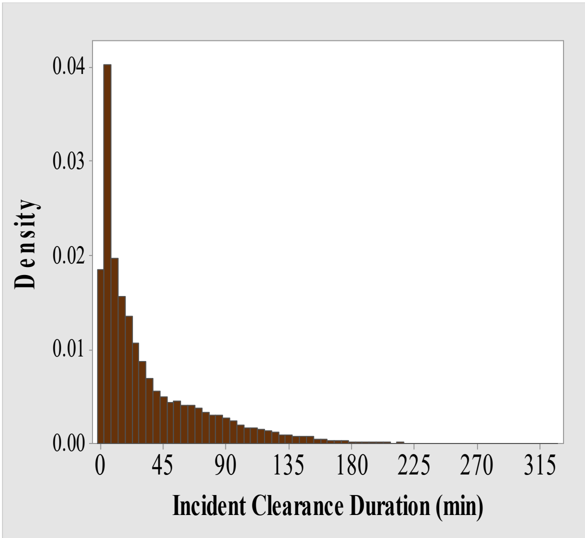
$$MEF_{Incident\ clearance\ duration}^{Road\ Rangers} = \frac{\sum_{i=1}^{n} MEF}{n} \qquad (2\text{-}7)$$

RESULTS AND DISCUSSION

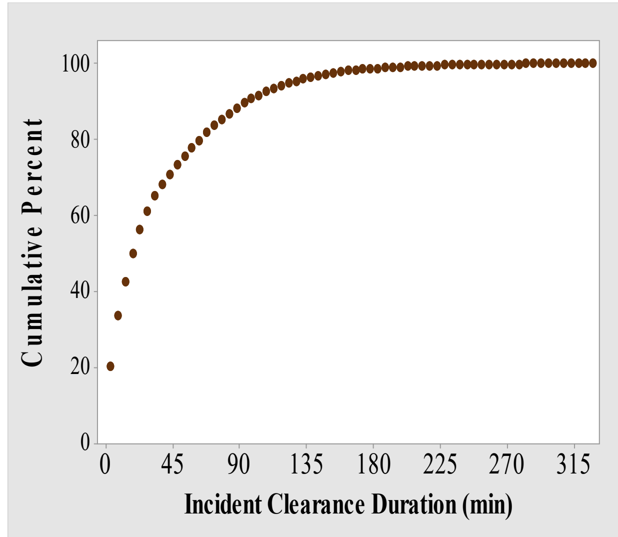
Descriptive Statistics

The analysis was based on a total of 28,000 incidents that occurred from 2015-2017 along SR-202, I-10, I-95, and I-295 in Jacksonville, Florida. Table 2-1 provides the descriptive statistics of all the variables included in the analysis. Incidents associated with vehicle problems accounted for 61.54% of incidents, while 32.05% and 6.41% were crashes and traffic hazards, respectively. Nearly half (49.05%) of the incidents analyzed were responded by only Road Rangers. Road Rangers, combined with other responding agencies, responded to 35.52% of the incidents, while other rescue services without Road Rangers responded to only 15.43% of the incidents. Collectively, Road Rangers were involved in responding to nearly 85% of all incidents.

Figure 2-2 shows the incident clearance duration distribution of the dataset. Nearly one-fourth (23.79%) of the incidents were cleared within 5 minutes (min), cumulatively 35.58% of incidents lasted 10 min or less, and 51.24% lasted 20 min or less. Overall, the vast majority of incidents (95%) lasted 125 min or less, and the maximum incident clearance duration was 325 min. The mean and median incident clearance duration were 36.71 min and 20 min, respectively. Standard deviation was 43.33 min. This dispersed distribution of incident clearance duration implies that the mean duration does not appropriately represent all the incidents.



(a) Incident clearance duration distribution



(b) Relative frequency distribution

Figure 2-2: Incident clearance duration distribution *(N = 28,000)*

As shown in Figure 2-3, for all the three incident types, the average incident clearance was considerably quicker when the responding agencies included Road Rangers. The average incident clearance duration for crashes was 66.3 min with Road Rangers involvement, 22.4% quicker than the average duration with other responding agencies. Similar results were also observed for vehicle problem and traffic hazard incident types. On average, Road Rangers resulted in shorter average incident clearance durations compared to other responding agencies by 58.0% and 69.0% for incidents involving vehicle problems and traffic hazards, respectively. Overall, the average incident clearance duration with Road Ranger assistance was 28.9 min compared to 79.3 min without Road Ranger involvement, a 63.6% reduction. These reductions in incident clearance duration translate into substantial travel time and fuel consumption savings for motorists.

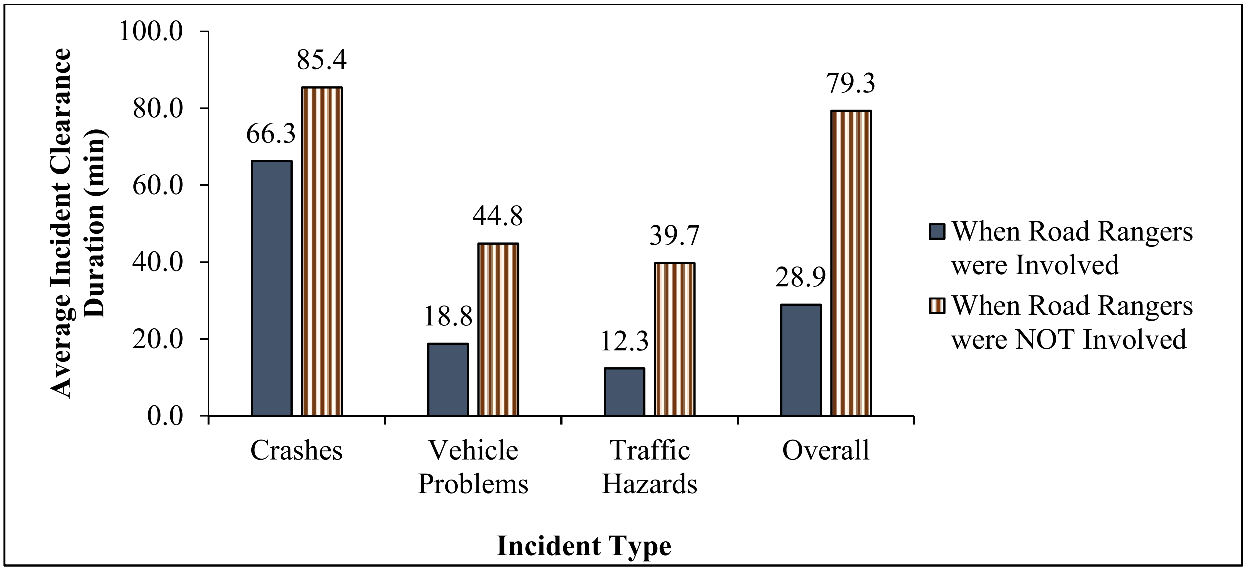


Figure 2-3: Average incident clearance duration with and without Road Rangers involvement

Model Results

Results from the quantile regression models estimated at the 25th, 50th, 75th, and 95th percentiles are presented in Table 2-2, and most variables are statistically significant at the 95% confidence level. Coefficients for each quantile regression model indicate the amount of increase or decrease in the average incident clearance duration for each unit increase in the independent variable, when other variables are held constant. For a given quantile (percentile), the interpretation of the coefficients is similar to the other regression models, i.e., the coefficients represent the change in the dependent variable (i.e., incident clearance duration) for a given quantile category, for each unit increase in the continuous independent variable and a categorical change of a discrete variable. Figure 2-4 graphically illustrates the coefficients from Table 2-2 for key factors analyzed, with all quantiles combined. Note that the quantile regression coefficients vary among the different quantiles.

Table 2-2: Quantile regression models

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

Insignificant estimates at 95% level of confidence are in italics, *RMSE = 41.14 min. The goodness-of-fit measure is calculated as pseudo-R^2*

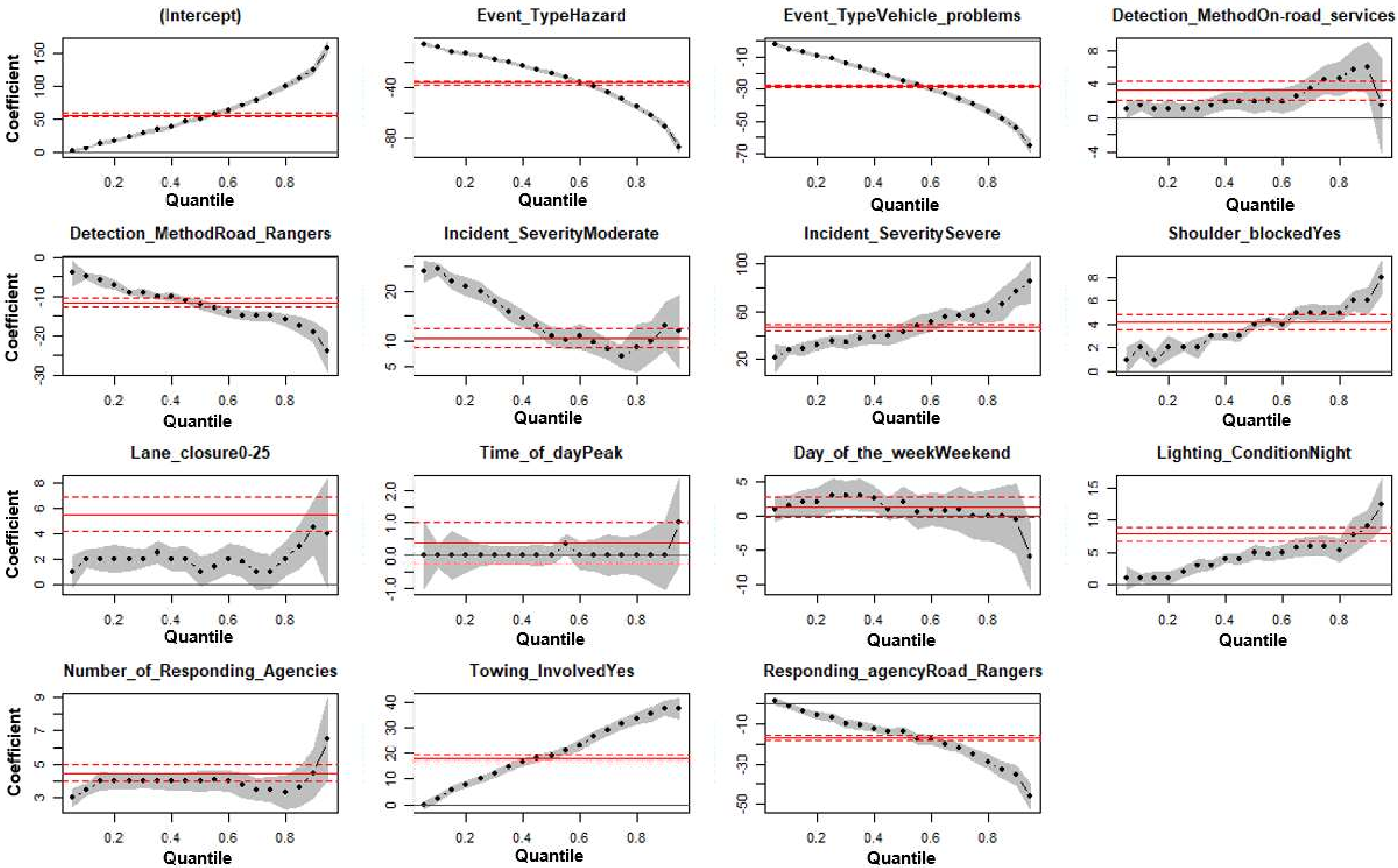


Figure 2-4: Quantile regression coefficients. The red line shows estimates from OLS regression; red broken lines show the OLS 95% confidence intervals; the black line shows estimates from quantile regression; 95% confidence intervals are shown by shaded region

Table 2-3: Estimation of incident clearance duration at means of independent variables

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

Table 2-3 provides the estimation of incident clearance duration by holding all variables at their mean values. The mean incident clearance duration is estimated as 17.46 min at the 25th percentile, 29.83 min at the 50th percentile, 48.65 min at the 75th percentile, and 87.15 min at the 95th percentile. All these numbers are close to the distributions of the 28,000 incidents. From Table 2-3, the incident clearance duration can be predicted, given a specific independent variable value while keeping other variables at their means. Changes in the probability that an incident with a given duration will occur, based on the change in values of independent variables, can be quantified.

For example, if all other factors are set to their mean values, and only the incident type can vary, the incident clearance duration at the 75th percentile can be estimated to be 48.65 + 3.14 = 51.29 min for an incident that is not related to a traffic hazard. Hence, for incidents other than traffic hazards, there is a 25% chance that the incident will last at least 51.29 min. If the incident is related to a traffic hazard, the incident clearance duration at the 75th percentile can be calculated to be 48.65 + 3.14 – 49.00 = 2.79 min, indicating a 25% chance that a traffic hazard incident will last 2.79 min or longer. Incident clearance durations with other associated factors can be interpreted in the same manner. The exact increase or decrease in probability can also be obtained by comparing estimations among the different percentiles using Equation 2-4.

Model Goodness of Fit

In order to assess the model goodness of fit, the pseudo R^2 were examined. The higher pseudo R^2, the better the model. However, this is not always achievable since many transportation-related problems and challenges involve stochastic processes that are influenced by observed and unobserved factors in unknown ways. As a result, transportation-related data are overly stochastic (Washington et al., 2011). Due to this stochasticity, some researchers (Washington et al., 2011) suggest that if the value of pseudo R^2 is more than 0.2, it indicates that the proposed model has sufficient explanatory and predictive power. As shown in Table 2-2, the model fitted the data fairly well, with pseudo R^2 values ranging 0.471 – 0.504. However, since the proportion of the total variability not explained in the model is almost half, this may be sought as a limitation of the proposed model despite performing better over the others.

Discussion

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

Incident Attributes

Analysis results reveal that crashes generally have longer incident clearance durations than the incidents involving vehicle problems and traffic hazards. As shown in Table 2-3 (50th percentile), incident clearance durations resulting from vehicle problems and traffic hazards averaged 25 min and 29 min shorter than crashes, respectively. This trend is consistent for each quantile (percentile). This finding is consistent with previous studies by Khattak et al. (2009), Zhang & Khattak (2010), Khattak et al. (2012), Hojati et al. (2013), and Haule et al. (2018).

The model coefficients for the variable *Detection Method* indicate that incidents first detected by methods other than Road Rangers resulted in longer incident clearance durations. For example, the incident clearance duration at the 50th percentile for incidents first reported by Road Rangers were 12 min and 14 min shorter, than for incidents first reported by ITS services and on-road services, respectively. Note also that incidents reported by on-road services, such as the FHP, law enforcement officials, and motorists, resulted in little bit longer durations (2 min) compared to incidents reported by ITS-services. In a nutshell, Road Rangers reveal the additional benefit of mobile-based incident identification methods.

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

Incidents resulting in blocked shoulder tended to last slightly longer compared to incidents that did not involve shoulder blockage. On average, incident clearance duration resulting from an incident that blocked a shoulder was 4 min longer (50^{th} percentile) than one with no shoulder blockage. Quantile regression results also reflect an increasing trend in incident clearance duration with quantiles for incidents associated with shoulder blockages, as shown in Table 2-3.

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

There are several potential scenarios that may account for shorter incident clearance durations when more than 25% of lanes were closed. One scenario is that partial or complete lane closures can quickly result in considerable non-recurring congestion, prompting urgent and prioritized response. Another scenario involves road debris from trucks or vehicles that can be easily removed by responders, thus clearing the lane for traffic. Road debris can also be secondary to a crash, where the vehicles involved reside in the median or along the shoulder, and the debris can be quickly removed by responders to clear the blockage. Nevertheless, more research is needed to examine the effects of lane closure on incident clearance duration.

Temporal Attributes

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

The model coefficients for the weekday incidents are significant for lower incident clearance durations (25th or lower percentile), yet insignificant for longer incident clearance durations (50th, 75th, and 95th percentiles). However, compared to the incidents on weekdays, incidents on weekends resulted in longer clearance durations. Haule et al. (2018) suggested that longer incident clearance durations on weekends may be attributed to fewer responders on duty. These findings suggest that the day of the week on which a freeway incident occurs has little influence on incident clearance duration. Similar findings were reported by Lee & Fazio (2005), Chimba et al. (2014), and Khattak et al. (2016).

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

Operational Attributes

Regression results show that the number of responding agencies is positively related to incident clearance duration and significant (Table 2-2). This may be attributed to clearance procedures, which are complex when many responding agencies are on the scene, hence, resulting in longer incident clearance durations. The minor difference in incident clearance duration for higher quantiles may be attributed to the random arrival of responding agencies at an incident scene and depends largely on the responding agencies' locations when dispatched. Some responding agencies may reach the site immediately, while others may take longer. This situation favors the reduction of incident clearance duration for incidents expected to last longer.

Quantile regression results for Road Rangers indicate considerable decrease in incident clearance duration for all four quantiles. As shown in Table 2-3 (50th percentile), incidents responded to by Road Rangers are estimated to last an average of 14 min shorter than incidents responded to by agencies other than Road Rangers. Incident clearance duration is shorter by 46.0 min at the 95th percentile, indicating a more pronounced benefit of mobile-based programs (FSPs), as further shown in Table 2-4.

Table 2-4: Road Rangers' incident clearance duration reduction rate relative to other agencies

Quantile (Percentile), qth	**Observed *qth i*ncident clearance duration when responded by agencies other than Road Rangers (min)**	**Estimated *qth* incident clearance duration saving by Road Rangers**	**Percent reduction (%)**
0.25	37	7	18.9
0.50	70	14	20.0
0.75	110	25.5	23.2
0.95	185	46	24.9

From Table 2-3, when all other factors are at their means and only the "responding agencies" variable can vary, the incident clearance duration at the 25th percentile is estimated to be 17.46 + 5.92 = 23.38 min for an incident not responded by Road Rangers. This implies a 75% chance that an incident will last at least 23.38 min, and a 25% chance that it will last at most 23.38 min, if Road Rangers are not involved. If the incident is responded by Road Rangers, the incident clearance duration at the 25th percentile can be calculated to be 17.46 + 5.92 – 7.00 = 16.38 min, indicating a 75% chance that an incident will last 16.38 min or longer. There is a 7 min (at 25th percentile) potential reduction of incident clearance duration when Road Rangers are involved. Previous studies presented similar findings (Zhang & Khattak, 2010; Lin et al., 2012; Chimba et al., 2014; Haule et al., 2018).

Regression results show that towing operations lead to significantly longer incident clearance durations. For instance, at the median (50th percentile, Table 2-2), if an incident involves towing, the incident clearance duration will be up to 19 min longer, compared to if towing operations are not involved. Similar results were observed by Khattak et al., (1995); Chimba et al., (2014); and Li et al., (2017).

Mobility Benefits of Road Rangers Program

From the quantile regression analyses, mobility enhancement factors (MEFs) were developed to evaluate the operational performance of the Road Rangers program using incident clearance duration as a performance measure. MEFs are multiplicative factors used to compute the expected mobility level after implementing a given strategy at a specific site. A factor of one (MEF = 1.0) is used as a reference, below or above which an expected increase or decrease in mobility is deduced. Table 2-5 presents the MEFs developed to quantify the operational effectiveness of Road Rangers in responding to incidents. Overall, the Road Ranger program offers a 25.3% reduction in incident clearance duration.

As shown in Table 2-5, Road Rangers involvement is expected to reduce the incident clearance duration of crashes, vehicle problems, and traffic hazards by 23.2%, 32.1% and 43.9%, respectively. Comparably, incident clearance duration reduction for crashes is less than that of other incidents. This result may be attributed to additional incident clearance procedures for crashes, which in many cases may involve multiple responding agencies.

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

Table 2-5: Mobility Enhancement Factors (MEFs) for Road Rangers

Incident Attribute	Category	MEF	95% CI Lower Limit	95% CI Upper Limit	Std. Error	% Incident Clearance Duration Reduction
Incident Type	Crash	0.768	0.766	0.770	0.001	23.2
	Vehicle problems	0.679	0.665	0.693	0.007	32.1
	Traffic Hazards	0.561	0.547	0.575	0.007	43.9
Incident Severity	Minor	0.739	0.737	0.741	0.001	26.1
	Moderate	0.776	0.770	0.782	0.003	22.4
	Severe	0.842	0.838	0.846	0.002	15.8
Time of day	Off peak	0.752	0.750	0.754	0.001	24.8
	Peak	0.738	0.734	0.742	0.002	26.2
Day of the week	Weekday	0.752	0.750	0.754	0.001	24.8
	Weekend	0.740	0.736	0.744	0.002	26.0
Lighting Condition	Daylight	0.734	0.730	0.738	0.002	26.6
	Night	0.765	0.763	0.767	0.001	23.5
Towing Involved	No	0.734	0.732	0.736	0.001	26.6
	Yes	0.812	0.808	0.816	0.002	18.8
Overall		**0.747**	**0.745**	**0.749**	**0.001**	**25.3**

Performance metric: incident clearance duration

CONCLUSIONS

This study evaluated the operational performance of the Road Rangers Service Patrol, a mobile-based program provided by FDOT to assist motorists and minimize the impacts of freeway incidents on non-recurring traffic congestion. Mobility Enhancement Factors (MEFs) were developed using incident clearance duration as a performance measure. The study examined the benefits of the Road Rangers in terms of reduced incident clearance duration, with a specific emphasis on the impact of the program.

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

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

Time of day was insignificant at a 95% confidence level, indicating that there is relatively no difference in the duration of incidents between the peak hours and the off-peak hours. However, weekend incidents were associated with longer durations, compared to weekday incidents.

Results for responding agencies consisting of Road Rangers, indicate considerable decrease in incident clearance duration. Incidents responded to by Road Rangers are estimated to last an average of 14 min shorter than incidents responded to by agencies other than Road Rangers.

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

CHAPTER 3

PAPER 2

Incident-induced Traffic Delays: Investigating Delay Savings of Florida's Road Rangers

Submitted to the Journal of Transportation Research Board

BACKGROUND

The toll of traffic congestion in the United States (U.S.) in 2014 was estimated to be 6.9 billion hours and 3.1 billion gallons of fuel, equivalent to approximately $160 billion. On average, a commuting motorist spent 42 additional hours during peak traffic periods in 2014 (Schrank et al., 2015). According to the Federal Highway Administration (FHWA), non-recurring congestion events account for almost half of all congestion (Amer et al., 2015). Traffic incidents, ranging from a flat tire to an overturned hazardous material truck, contribute to almost half of all non-recurring congestion events (Amer et al., 2015). For every minute a freeway lane is blocked due to an incident during a peak travel period, there is a 4-minute delay to the traffic using the freeway (Owens et al., 2010).

Since traffic incidents are often unpredictable, transportation agencies rely heavily on timely and appropriate responses of traffic incidents. To increase their efficiencies, many states have included freeway service patrols (FSPs) in their incident management plans (Dougald & Demetsky, 2008; Chou et al., 2010; Daneshgar & Haghani, 2016; Z. Sun et al., 2017). The Florida's Road Ranger Service Patrol (or Road Rangers) for example, responds to incidents on Florida's roadways. To facilitate these objectives, Road Rangers probe vehicles monitor the freeways for road debris, traffic crashes, stranded vehicles, and other traffic incidents (Hagen et al., 2005; Singh, 2006; Lin et al., 2012; Carrick et al., 2018; Sun et al., 2018). An efficient FSP program substantially reduces incident duration time, which, in turn, alleviates the delay attributed to non-recurring congestion, and therefore, incident-related congestion (Latoski et al., 1999).

However, one question remains: to what extent do Road Rangers affect incident-induced traffic delays? To answer this question, the first step is to accurately estimate traffic delays. Although traffic delay is simply the additional travel time required to travel between two points relative to normal travel time, its estimation is however not as simple as its definition. Researchers have used different methods to estimate traffic delays. While some have used deterministic queuing models and shock-wave theory (Khattak et al., 2012; Zhang et al., 2015), others have developed microscopic simulation models (Zhang et al., 2015). Table 3-1 summarizes the existing literature on estimating incident-induced traffic delays. As can be observed from Table 3-1, all the approaches discussed in literature have limitations. For example, queuing models assume linear traffic demand which is only achieved in uncongested traffic conditions. Shock-wave theory needs several parameters (e.g., jam-density, capacity, critical density, and free-flow speed) and detailed incident information (e.g., number of lanes blocked and vehicle arrival rate) (Habtemichael et al., 2015) which may not always be available. Microscopic simulation, on the other hand, require calibration and validation which may be challenging, data dependent, scenario dependent, cumbersome, and time-consuming (Habtemichael et al., 2015).

Table 3-1: Methods for Estimating Incident-induced Delays

Method	**Study**	**Limitation(s)**
Deterministic queuing	(Cohen & Southworth, 1999; Dougald & Demetsky, 2008; Khattak et al., 2012)	Considers static demands, which are unrealistic under peak hours or flow fluctuation situations
Shock-wave	(Chung, 2011; Zhang et al., 2015)	Requires too many parameters that must be determined beforehand
FREEVAL model	(Khattak et al., 2004)	Does not consider dynamic route diversion
Microscopic simulation	(Zhang et al., 2015)	Requires well calibration and validation
Data driven approaches	(Snelder et al., 2013; Habtemichael et al., 2015; Haule et al., 2018)	Requires real-time data which may not be available in some corridors

The main objective of this paper is to determine the extent to which Road Rangers program can reduce IITDs. To achieve this objective, firstly, the paper presents a data-driven approach for estimating IITDs. The method involves generating a recurrent (i.e., normal) incident-free travel time profile that is free of recorded incidents and their influences. Once this incident-free reference profile is established, incident-induced delay can be estimated as the difference between incident-influenced and incident-free travel time profiles. In general, this paper has two specific objectives: (a) estimate IITDs using real-time traffic data, and (b) determine the extent to which Florida's Road Rangers can reduce IITDs. The study results can, in general, improve incident management strategies and incident-induced delays estimations. The approach, results, and recommendations could also be transferable and applicable to other agencies.

RESEARCH APPROACH

The main goal of this study is to quantify the delay saving benefits of Road Rangers program. The delay savings are estimated based on the reduction in IITDs when Road Rangers were involved. The framework adopted to achieve the research goal involves estimating IITDs and evaluating whether there is an added advantage of Road Rangers relative to conventional incident responding strategies (other responding agencies). Five tasks were undertaken to develop the evaluation method; data collection, IITD estimation, variables selection, survival analysis, and inferences as detailed in Figure 3-1.

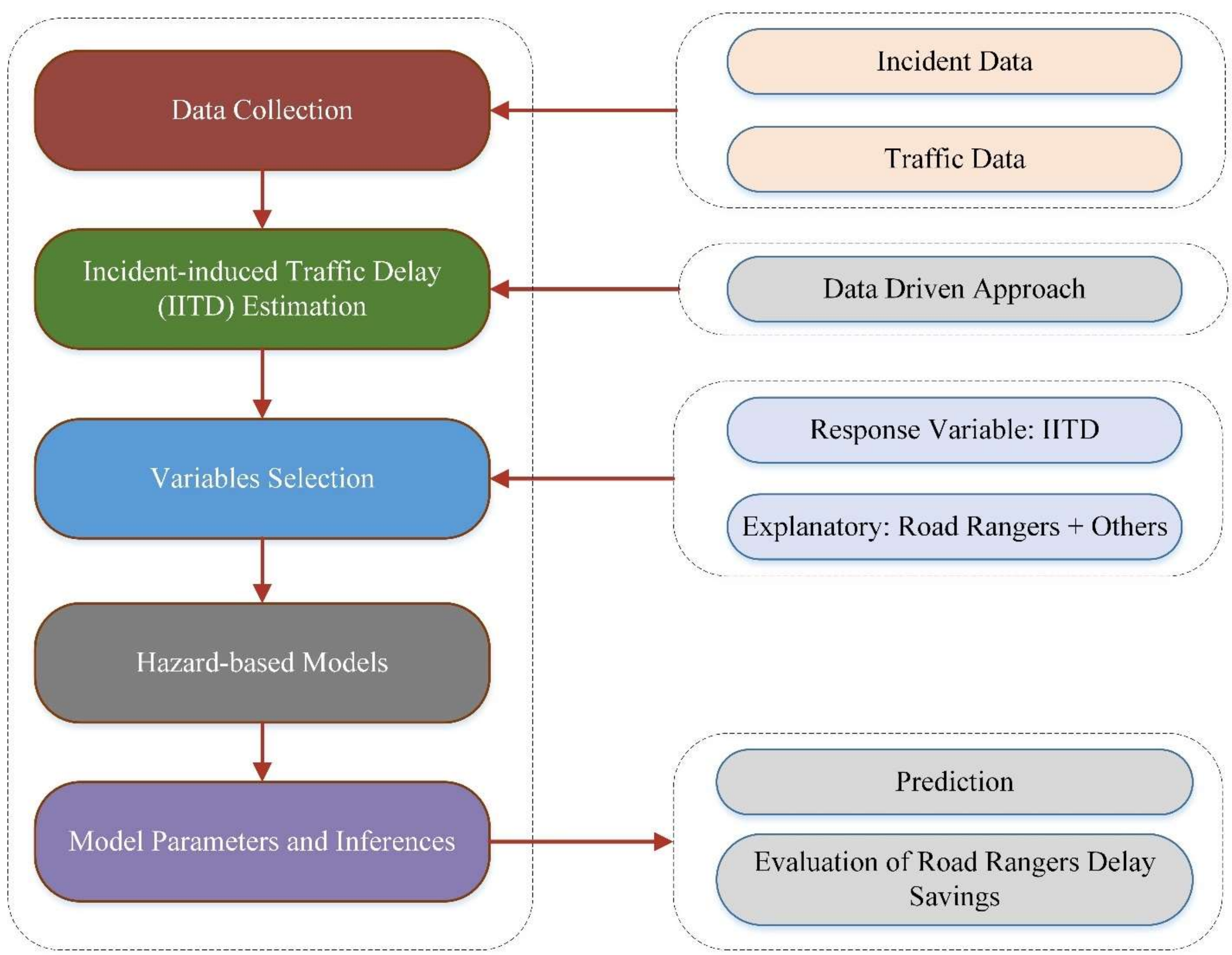


Figure 3-1: Methodological framework

Data Collection

The study area included a 35-mile section on I-95, a 21-mile section on I-10, and a 61-mile section on I-295 located in Jacksonville, Florida (see Figure 3-2). The total study area covers 117 miles. Data used in this study included travel time data from BlueToad® devices, incident data from SunGuide® database, and archived real-time traffic data from the Regional Integrated Transportation Information System (RITIS) database for the years 2015-2017.

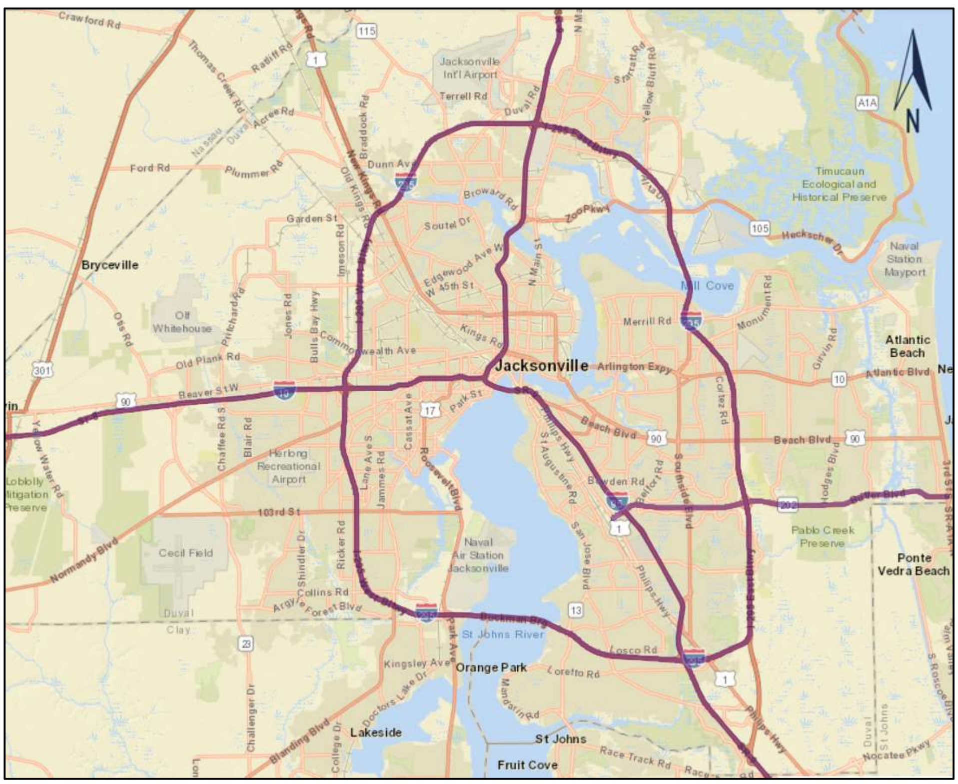


Figure 3-2: Study corridors (Street Map)

SunGuide® is an advanced traffic management system (ATMS) software that is used at all regional traffic management centers (RTMCs) in Florida. SunGuide® software offers tools like automated incident detection and assist with event management and archiving of incident data. The database stores incident attributes like; incident ID, incident timeline, incident severity, incident type, incident detection, incident location and incident responders. Along the study corridors, the SunGuide® database included a total of 66,756 incidents from 2015-2017. After excluding incidents on ramps (15,730), incidents with missing coordinates (183), incidents with no matching BlueToad® pairs (10,990), incidents along the section without BlueToad® pairs (32,988), incidents without RITIS devices (2,280), the remaining data consisted of a total of 4,045 incidents.

BlueToad® devices are Bluetooth signal receivers, which read the Media Access Control (MAC) addresses of active Bluetooth devices of vehicles passing through their area of influence. These devices record the time when a vehicle passes nearby. A pair of devices is used to estimate the vehicle travel time between the two devices by taking the difference of the recorded times. The speed is calculated from the travel time and the known path distance (not Euclidean distance) between the devices. The study location had 72 BlueToad® devices pairs, spaced approximately every 1.8 miles along the freeway corridor. The posted speed limits on the entire section range from 55 mph and 70 mph. This study used raw data collected at each BlueToad® device pair.

RITIS is an automated data sharing, dissemination, and archiving system that includes real-time data feeds and archived data analysis tools such as probe, detector, and transit data analytics. RITIS detectors provide traffic flow data in addition to speed data (volume and detector occupancy). There are 375 RITIS detector stations along the selected freeway corridor. The average spacing between detectors is approximately 0.5 miles.

Estimation of Incident-induced Traffic Delays (IITDs)

Incident-induced traffic delay (IITD) is the difference between incident-influenced and incident-free travel time profiles of a given roadway segment. To estimate the traffic delays due to incidents, this study used travel times with and without incidents and traffic volumes during incidents for the affected freeway segments. The following sections provide details on how the IITDs were estimated.

Generating Recurrent and Incident-Affected Travel Time Profiles

A recurrent travel time profile provides the travel times along any portion of the roadway at any given time. As the name suggests, it shows a typical commuting traffic travel time patterns along any portion of the roadway at any given time. This profile is used to compare with the travel time data for a given incident to determine the difference in travel time when there is an incident and typically travel time when there is no incident.

In this study, the recurrent travel time profile of each BlueToad® pair along the corridor was constructed by taking the average of travel times in 15-minute intervals. The 15-minute travel time data were used to obtain stable traffic flow rates as suggested by Smith and Ulmer (Smith & Ulmer, 2003). To consider the variations in the recurrent travel time profiles, the 95% confidence interval was used to define the upper and lower bounds. Using the known distances between the BlueToad® pairs, the corresponding recurrent travel speed profiles were established. Figure 3-3 illustrates the travel time profiles of one of the BlueToad® pairs (ID: 15484). A solid (blue) line represents an incident-free recurrent travel time profile and the dashed (red) line represents an incident-affected travel time profile. The shaded region represents the IITD. The algorithm was automated in R programming language.

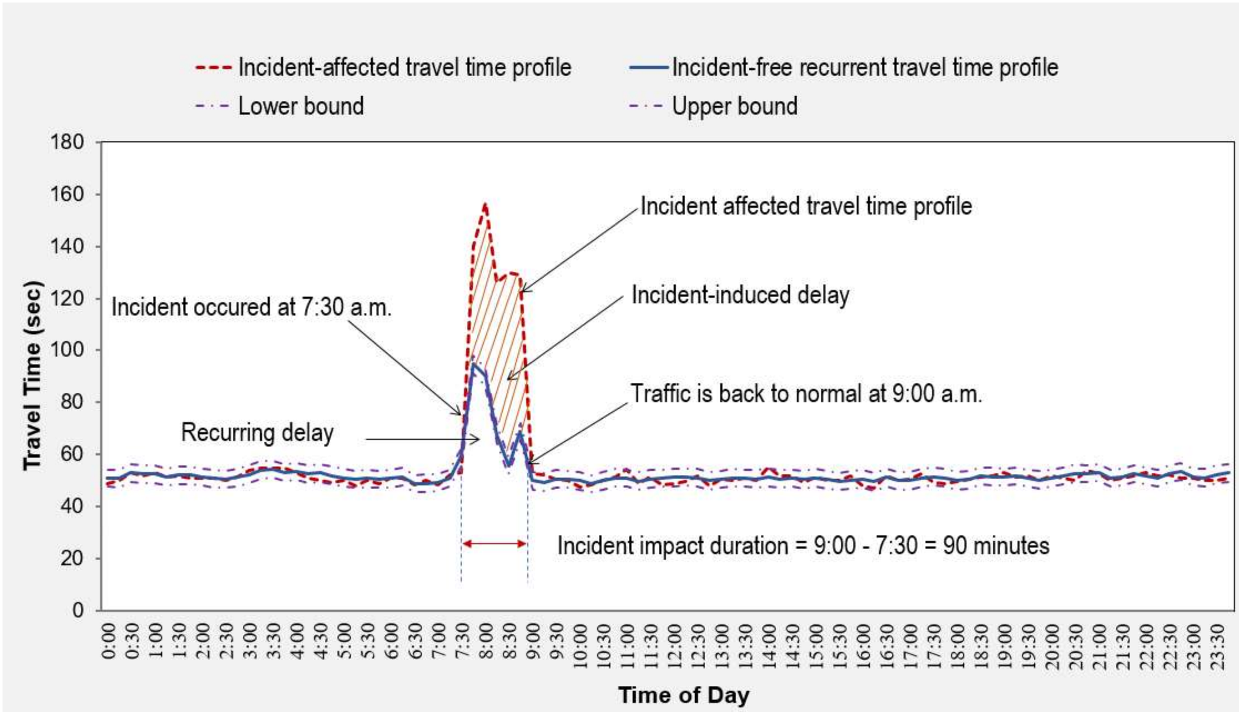


Figure 3-3: Estimation of IITD using travel time profiles

Defining Impact Zones of Incidents

To define the impact zones, incidents were first mapped onto the corresponding BlueToad® pairs using geographical coordinates. The dates and time of occurrence of the incidents were then matched with the dates and time in the travel time data from the BlueToad® pairs, and this information was used to extract the travel times during incidents. The travel times during incidents were compared to the recurrent travel time profiles from the time of incident occurrence. Travel time higher than the upper boundaries of the recurrent travel time profiles were tracked from the incidents' occurrence time to the time the travel times were lower than the upper boundaries of the recurrent travel time profiles. The duration during which the travel time were higher than the upper bound was defined as the temporal extent of an incident (i.e., incident impact duration), as shown in Figure 3-3.

The algorithm also checked for the BlueToad® pairs upstream of the incident BlueToad® pair that had higher travel times than normal. The BlueToad® pairs upstream of the incident pair that met the requirement had their travel times tracked in the same way as the BlueToad® pair along which an incident occurred. The number of the affected BlueToad® pairs upstream of the incident defined the spatial extent of the incident. Figure 3-4 illustrates the example of incident's impact zone along I-95 NB. An incident occurred at 0730 hours and affected four BlueToad® pairs on the upstream direction (4.75 miles). The travel time along the BlueToad® pair #15485 came back to normal much earlier than the rest of the pairs, the last pair, came back to normal at 0900 hours. The IITD as a result of this incident is estimated as the sum of IITDs of the four pairs.

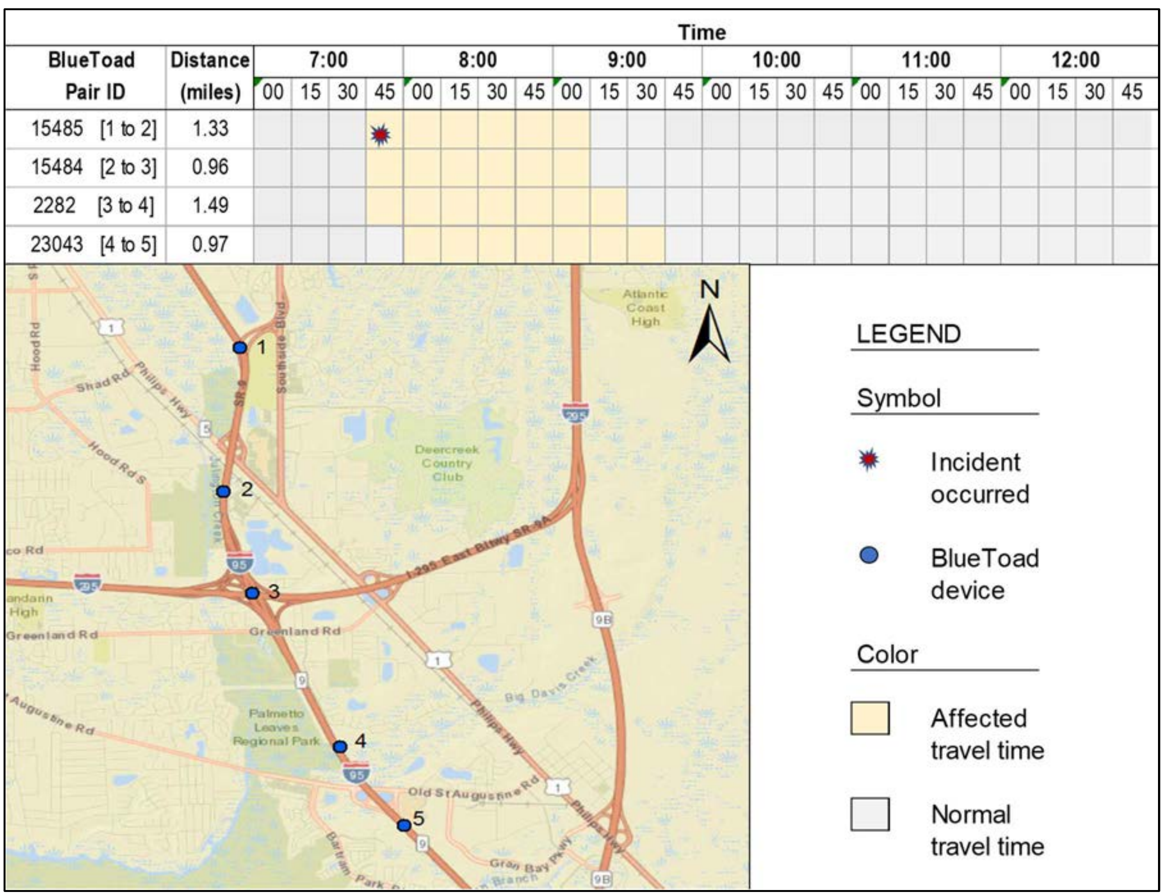


Figure 3-4: Spatial and temporal extents of an incident (not to scale)

Estimating Incident-induced Traffic Delay (IITD)

Figure 3-5 provides the framework adopted to estimate IITDs on freeway mainline. The method applies to a contiguous section of freeway with n affected BlueToad® devices' pairs herein indexed as $i = 1, \ldots, n$, whose flow (volume) and travel time measurements are averaged over 15-min windows. Thus, the delay in a specific pair i is

$$D_i = \Delta t_i * V_{ai} \qquad vehicle\ hours\ (veh - hours) \tag{3-1}$$

where Δt_i is the travel time difference between the recurrent and the incident-induced travel time profiles for the BlueToad® pair i. V_{ai} is the average traffic volume between the BlueToad® devices building the pair i.

The total delay due to an incident is therefore estimated as;

$$D_{total} = \sum_{i=1}^{n} D_i \qquad vehicle\ hours\ (veh - hours) \tag{3-2}$$

It is important to note that RITIS devices in the proximity of the affected BlueToad® pairs were used to obtain traffic volume data at 15-minute intervals. However, the absence of these devices along entry and exit ramps of some corridors posed some limitations. Due to this limitation, only the mainline IITDs were estimated. Figure 3-5 presents the IITDs estimation framework.

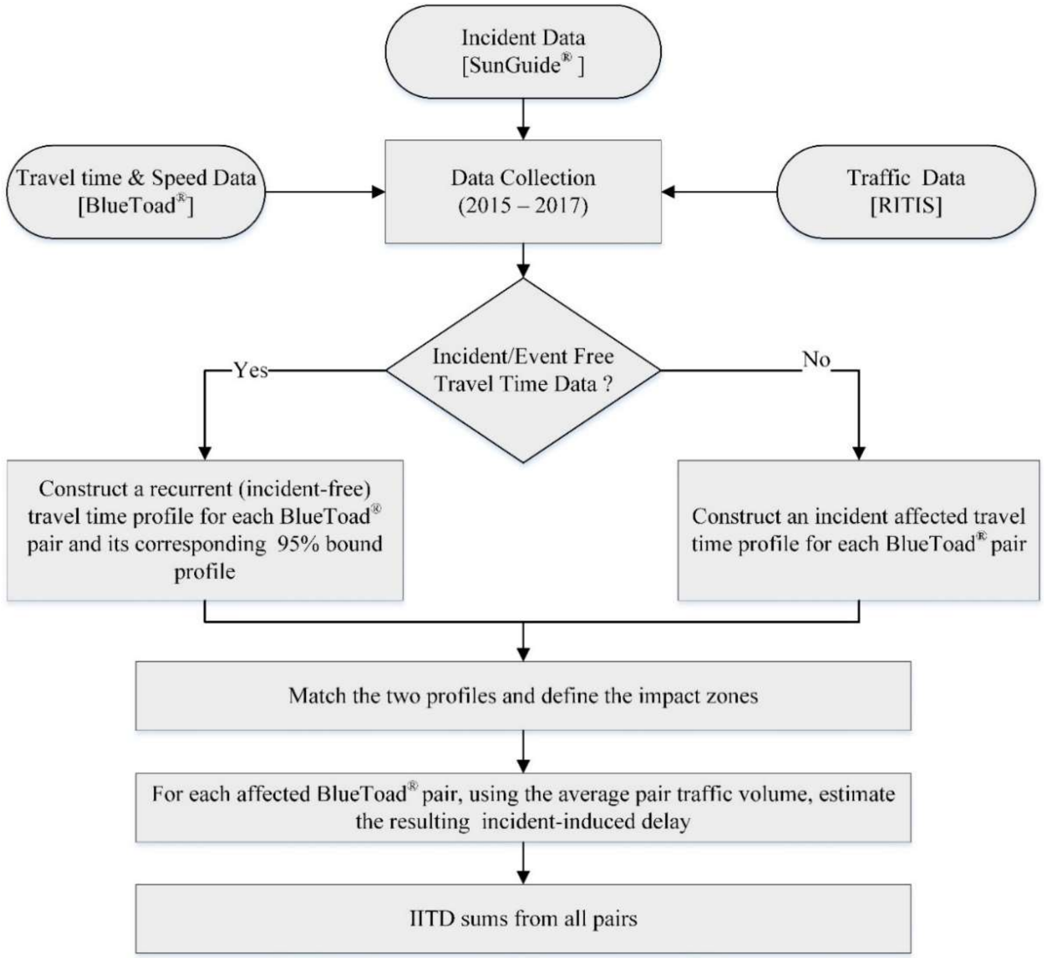


Figure 3-5: IITD estimation framework

Variable Selection

To evaluate and quantify the delay savings of Road Rangers, IITDs were first estimated and summarized against other explanatory variables in Table 3-2. As shown in Table 3-2, the *hourly traffic volume, average vehicle speed, average detector occupancy and median width* variables were considered continuous, while the remaining variables, generally associated with freeway incidents, were considered categorical. *Event type* (or, *incident type*) was categorized into crashes, vehicle problems (disabled or abandoned vehicles, emergency vehicles, vehicle fire, and police activity), and traffic hazards (debris, flooding, and spillage). Two temporal variables, *incident occurrence time* and *day-of-the-week*, were included in the analysis. *Morning (a.m.) peak* included (0600 to 1000 hours), *evening (p.m.) peak* (1530 to 1830 hours) and the *off-peak* included (all other hours not in peak). *Day-of-the-week* was categorized as weekdays and weekends (Saturday and Sunday). *Detection method* was divided into two categories: *on-site* included on-road services such as Florida Highway Patrol (FHP), Road Rangers, motorists, etc., *off-site* included the use of closed-circuit televisions (CCTV), the Florida 511 travel information system (FL511), FL511 probe vehicles, *Waze*, and Transportation Management Centers (TMCs).

The variable *lane closure* refers to whether an incident resulted in lane(s) closure. The percent of lanes closed is usually considered as an indicator of the severity of an incident, as severe incidents tend to result in an increased number of lanes closed. In this study, a 25% lane closure implies one lane out of four lanes of a roadway section is closed. A closure of one of three lanes is denoted by 33.3% lane closure and 100% means all lanes are closed. This variable was considered categorical coded as 25% or less and greater than 20% lane closure. *Shoulder blockage* was divided into two categories: No (no shoulder is blocked) and Yes (at least one shoulder is blocked). In the same token, *towing* was divided into either no towing was involved, or towing was involved. During the survival analysis process, the log transformation of the equivalent hourly traffic volume (i.e., data normalization) was applied for better results.

Table 3-2: Descriptive statistics of variables: IITDs against categorical variables

Categorical Variable	Factor	Count	Average (veh-hrs)	SD (veh-hrs)	Min (veh-hrs)	Max (veh-hrs)
Incident type	Crash	1545	187.16	431.88	0.005	4772.49
	Vehicle problems	2118	84.95	268.87	0.007	3644.10
	Traffic hazards [a]	382	42.15	230.70	0.010	3903.85
Incident severity	Minor	3832	104.43	300.52	0.005	4772.49
	Moderate	175	333.88	611.44	0.067	4474.42
	Severe	38	699.54	1045.60	0.120	4291.58
Day of the week	Weekday	3787	124.03	349.15	0.005	4772.49
	Weekend	258	60.09	203.77	0.011	2060.39
Incident occurrence time [b]	Off-peak	1702	66.76	289.44	0.005	4474.42
	a.m. peak	1355	161.83	380.09	0.013	4473.00
	p.m. peak	988	154.13	358.33	0.023	4772.49
Lane closure (%)	0-25	3574	98.53	292.60	0.005	4772.49
	> 25	471	282.45	570.95	0.067	4474.42
Shoulder blocked	Yes	2459	135.43	358.15	0.005	4772.49
	No	1586	95.94	314.13	0.005	3903.85
Towing involved	Yes	3577	105.60	316.78	0.005	4772.49
	No	468	229.59	480.83	0.052	4473.00
Road Rangers involved	Yes	3153	126.24	355.61	0.007	4772.49
	No	892	97.70	288.24	0.005	3140.31
Detection method	Off-site	428	197.60	427.85	0.030	4474.42
	On-site	3617	110.76	329.31	0.005	4772.49
Continuous variable		**Median**	**Mean**	**SD**	**Min**	**Max**
Hourly traffic volume (veh/hr)		515	593	328	31	1,667
Average vehicle speed (mph)		62.1	60.8	9.0	18.6	78.6
Average detector occupancy (%)		6.1	7.6	5.0	0.3	37.3
Median width (ft)		40	42.5	14.4	10.0	100.0
Incident-induced traffic delay (veh-hrs)[c]		9.26	119.95	342.07	0.005	4,772.49

NOTE: [a] Hazards: debris on roadway, flooding, and wildlife; [b] a.m. peak (6:00-10:00), p.m. peak (15:30-18:30), off-peak (others); [c] Response variable, Valid N = 4,045

Hazard-Based IITD Modeling

Hazard-based models are statistical procedures for data analysis for which the outcome variable of interest is time until an the event occurs (or ends) (Hojati et al., 2013). In the case of an incident occurrence, one of the key variables is IITD. Practically, IITDs are cleared with the passage of time, and they are therefore naturally like the pattern of machine's failure or end of life. For this reason, hazard-based models (also known as survival analysis) were used in this study. Hazard models are based on the survival theory, meaning, in this study, the existence of an incident on a roadway at a point in time is considered as the survival of the incident to that time. Counterintuitively, the clearance of an incident and its impact is taken as the incident's survival failure, as illustrated in Figure 3-6.

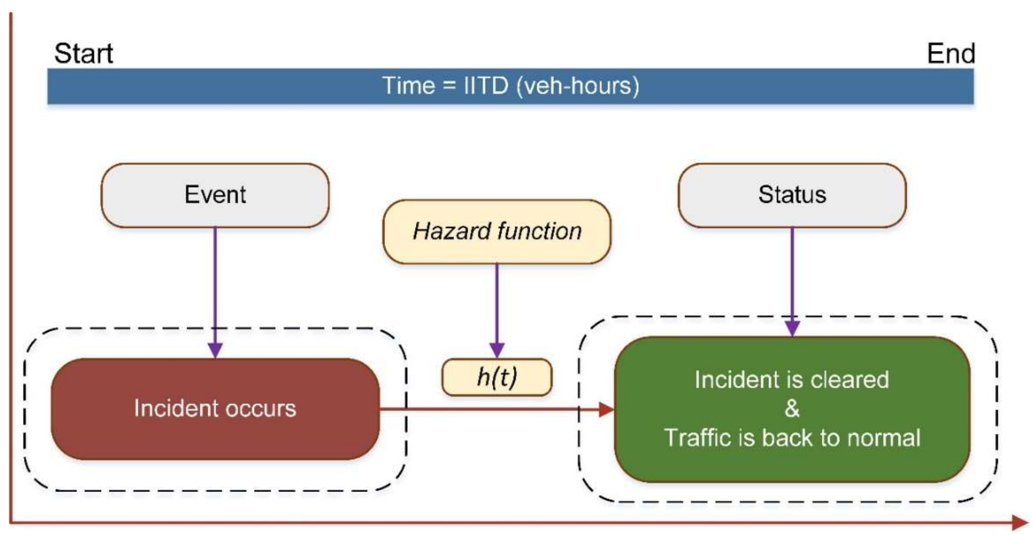


Figure 3-6: Conceptualization of hazard-based model for IITDs

The IITD, in this study, is considered as a continuous random variable T with a cumulative distribution function $F(t)$ and the probability density function $f(t)$. $F(t)$ is also known as the failure function and gives the probability of having an IITD before some specified time *t.* Conversely, the survival function, *S(t)*, is the probability of the IITD being greater than some specific time (Hojati et al., 2013).

Two types of hazard-based models were estimated, the Proportional Hazard (PH) model and Accelerated Failure Time (AFT) model. Both models are based on the cumulative density functions shown in Equation 3-3. In this equation, P denotes the probability of the delay T to end before time *t*. Equation 3-5 shows the survival function which provides the probability that a studied delay is equal to or greater than the specified time *t*. Therefore, the hazard function in Equation 3-6 gives the conditional probability that the delay will end between time t+Δt given that there has been a delay up to time *t* (Hojati et al., 2013).

$$F(t) = P(T < t) \tag{3-3}$$

$$f(t) = \frac{dF(t)}{dt} \tag{3-4}$$

$$S(t) = P(T \geq t) = (1 - P(T < t)) = 1 - F(t) \tag{3-5}$$

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - P(T < t)} = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} \tag{3-6}$$

In evaluating the effects of covariates on the hazard, the AFT model assumes that covariates rescale time directly in the survival function while the PH model assumes that the covariates act multiplicatively on the underlying hazard function (Hojati et al., 2013). Equation 3-7 is the AFT hazard model function where X is a vector of covariates and β is a vector of estimable parameters.

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 a 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 3-8 shows the formula of the 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.

Unlike the AFT model, the PH model is a semi-parametric model. PH models are considered parametric due to lack of an assumed distribution on the duration but maintain a parametric assumption on the influence of covariates on the hazard function (Washington et al. 2003). Equation 3-9 shows the hazard function for the PH model where all the notations are as explained in the previous sections. Similar to AFT models, the likelihood ratio statistics are used to compare results of the PH and the AFT models.

$$h(t|X) = h_o[tExp(\beta X)]Exp(\beta X) \tag{3-7}$$

$$X^2 = -2(LL_o - LL_{\beta C}) \tag{3-8}$$

$$h(t|X) = h_o(t)Exp(\beta X) \tag{3-9}$$

In other words, *h(t)* gives the rate at which event delays are ending at time *t* (such as the duration in an incident-free state that would end with the occurrence of an accident), given that the event delay has not ended up to time *t*.

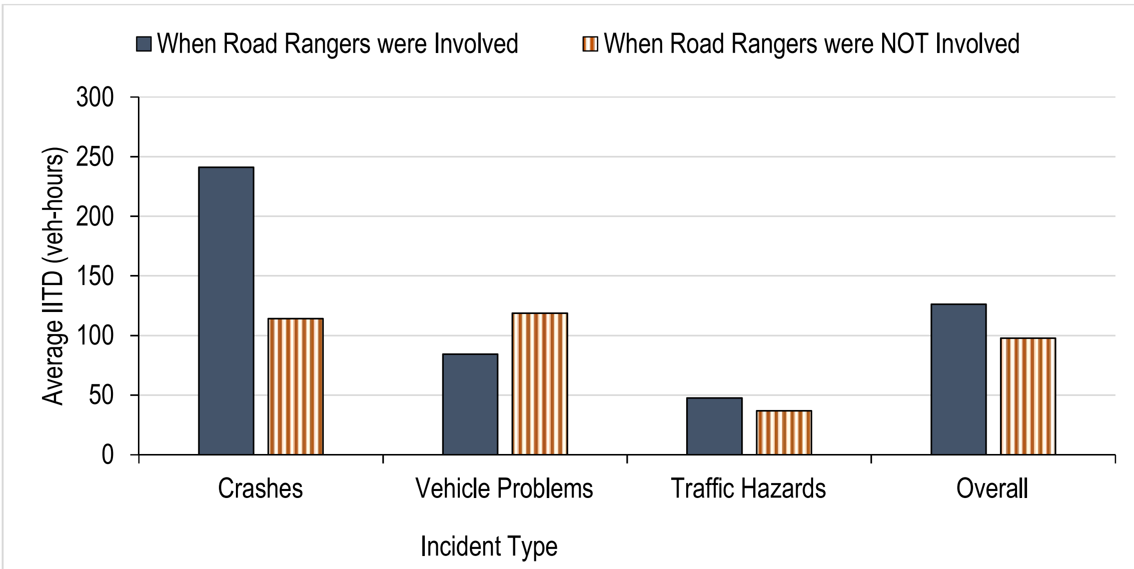
RESULTS AND DISCUSSION

Descriptive Statistics

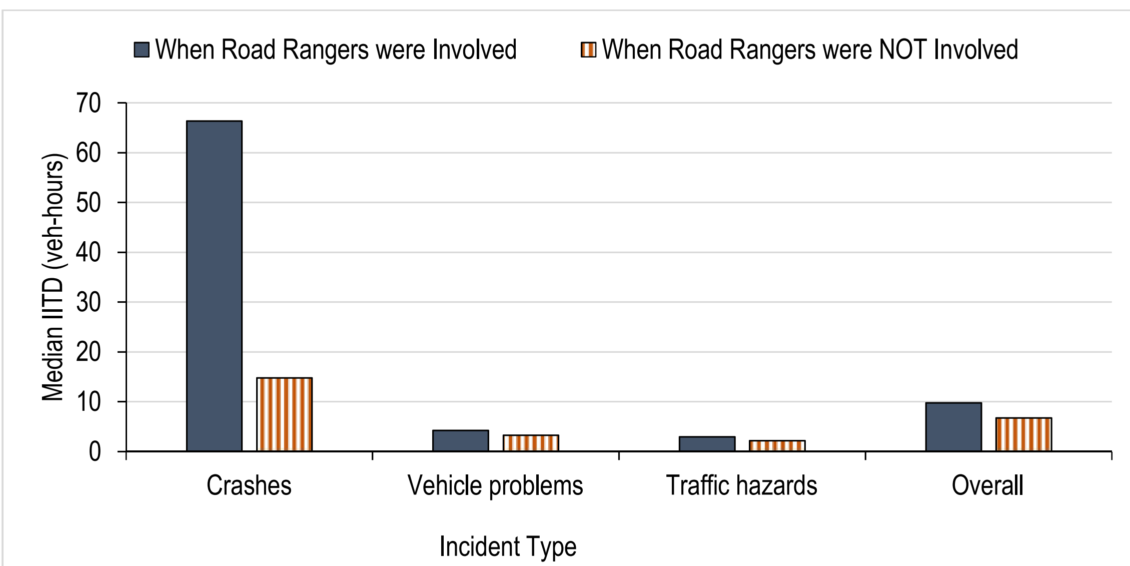
Descriptive statistics of variables selected for analysis and modeling are shown in Table 3-2 for the 4,045 valid observations (N) included in the analysis. The response variable was the incident-induced traffic delay. By definition, one vehicle-hour (veh-hour) of delay reflects one vehicle stuck in traffic for one hour. The average IITDs were 119.95 veh-hours and the maximum were 4772.49 veh-hours.

Incidents associated with vehicle problems accounted for approximately half (52.36%) of the incidents, while 38.20% and 9.44% were crashes and traffic hazards, respectively. Overall statistics showed that the mean IITDs spent on crashes, vehicle problems, and traffic hazards were 187.16, 84.95, and 42.15 veh-hours, respectively. Crashes, as expected, resulted in longer IITDs compared to vehicle problems and traffic hazards. Similarly, severe incidents resulted in longer IITDs compared to moderate and minor incidents. The average travel time on weekends and during p.m. peak hours, when affected by incidents, resulted in relatively longer delays compared to the travel times on weekdays and off-peak hours. If a lane or a shoulder or both are blocked by an incident, travel time is on the other hand longer.

Road Rangers responded to nearly three-quarters (77.94%) of all incidents. On average, 126.24 vehicle-hours were wasted due to incidents that were responded to by Road Rangers relative to 97.70 vehicle-hours of incidents responded to by other responding agencies. One possible explanation for the longer IITDs with Road Rangers may be the result of additional incident clearance procedures for crashes, which in many cases may involve multiple responding agencies plus strict police report documentation. The shorter average IITDs for incidents involved vehicle problems responded to by Road Rangers provides intuitive justification the suggested reason. Vehicle problems related incidents are usually responded by Road Rangers without additional clearance requirements.



(a) Average



(b) Median

Figure 3-7: Average and median IITDs with and without Road Rangers involvement

Model Results and Discussion

Table 3-3 presents the results of the AFT model with Weibull distribution, the model that gave a relatively best fit. All the variables except the italicized ones are statistically significant at the 95% confidence level ($\alpha = 0.05$). Note that the coefficients in Table 3-3 indicate the amount of increase or decrease in the average IITD for each unit increase in the independent variable, with other variables held constant. A positive coefficient implies longer IITDs. A negative estimated coefficient indicates that IITDs are shorter. The p-value indicates whether a change in the predictor significantly changes the IITDs at the rejection level ($\alpha = 0.05$). In the current study, the emphasis is placed on Road Rangers. The cloglog results in Table 3-3 indicate the following key points;

A unit increase in traffic volume increases IITDs by 0.7%. On the other hand, a unit increase in occupancy increases IITDs by 1.1%. One study (Kitali et al., 2018) suggested that congested traffic is characterized with lesser gaps between vehicles providing drivers with lesser room for maneuvering and increase in average occupancy represents an increase in traffic density, traffic volatility, and queue formation. Thus, at higher traffic volumes and occupancy, the disturbances induced by the incidents easily propagate in queuing traffic conditions, leading to excessive delay. Moreover, it takes longer for the heavy traffic upstream to dissipate after an incident is cleared.

Table 3-3: The Accelerated Failure Time model (Weibull distribution)

Categorical Variable	**Factor**	**Estimates**	**Std. Error**	***p*-value**	**Lower**	**Upper**	**% Change**
Intercept		9.838	0.389	0.000	9.826	9.850	1873121
Incident type	Crash						
	Vehicle problems	-0.694	0.070	0.000	-0.716	-0.673	-50.0
	Traffic hazards	-1.000	0.106	0.000	-1.032	-0.967	-63.2
Incident severity	Minor						
	Moderate	0.438	0.168	0.009	0.386	0.490	55.0
	Severe	1.095	0.292	0.000	1.005	1.185	198.9
Day of the week	*Weekday*						
	Weekend	*0.095*	*0.128*	*0.459*	*0.055*	*0.134*	*10.0*
Incident occurrence time	*Off-peak*	*-0.495*	*0.066*	*0.000*	*-0.515*	*-0.475*	*-39.0*
	a.m. peak						
	p.m. peak	*0.142*	*0.073*	*0.052*	*0.120*	*0.165*	*15.3*
At least 1 lane closed	No						
	Yes	0.518	0.112	0.000	0.484	0.553	67.9
Shoulder blocked	No						
	Yes	0.134	0.060	0.026	0.132	0.136	14.3
Towing involved	No						
	Yes	0.249	0.096	0.010	0.219	0.278	28.3
Road Rangers involved	No						
	Yes	-0.135	0.086	0.016	-0.161	-0.108	-12.6
Detection method	*Off-site*						
	On-site	*-0.016*	*0.092*	*0.865*	*-0.044*	*0.013*	*-1.6*
Continuous variable							
Ln [hourly traffic volume] (veh/hr)		0.526	0.081	0.000	0.501	0.551	69.2
Average vehicle speed (mph)		-0.154	0.006	0.000	-0.156	-0.152	-14.3
Average detector occupancy (%)		*0.011*	*0.014*	*0.421*	*0.007*	*0.016*	*1.1*
Median width (ft)		*-0.002*	*0.002*	*0.409*	*-0.003*	*-0.001*	*-0.2*

Note: Loglink (model) = -17651.7, Loglink (intercept) = -19043.4, Chisq = 2783.44, Log (scale) 0.5372, scale =1.71, italicized variables are not significant at 95% level.

Incident type and severity also significantly contribute to IITDs. Crashes result to higher IITDs compared to the incidents associated with vehicle problems and traffic hazards. Moderate and severe incidents increase the IITDs by factors of 1.55 and 3 relative to minor incidents. One possible reason is that the percent of lane closure is an indicator of the severity of an incident.

Severe incidents tend to result in an increased number of lanes closed. Thus, lane closure will increase freeway congestion, and as traffic queue length increases, thus greater IITDs as illustrated by the positive coefficients. Furthermore, additional procedures involved in crashes clearance increase the incident duration which in turn increases the IITDs.

Regarding incident detection and clearance, incidents that involve towing are in many cases severe and involve lane blockage (Haule et al., 2018). The results reveal that, it takes longer for the traffic upstream to dissipate when the incident involves towing. In addition, detection of incidents on-site is associated with shorter IITDs compared to off-site detection. Since the on-site detection 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 potentially avoid traffic bottlenecks. Quantitatively, from the model results, the negative coefficient reveals that, Road Rangers reduce the expected IITDs. From the analysis results, it could be inferred that Road Rangers reduce IITDs by 12.6% compared to other responding agencies.

CONCLUSIONS AND RECOMMENDATIONS

This paper evaluated the benefits of the Road Rangers in terms of reduced IITDs. The study developed a model to predict IITDs with data from I-10, I-95, and I-295 in Jacksonville, Florida. Data used include; speed data from BlueToad® devices, incident data from SunGuide® database, and real-time traffic data from RITIS for the years 2015-2017. Incident induced traffic delays (IITDs) were estimated by establishing reference incident-free recurrent travel time profiles from which the IITDs were calculated. The hazard-based models were used to model the association between IITDs and the predictor variables. The findings can be summarized as follows:

Of the hazard-based models considered, the parametric accelerated failure time (AFT) survival models, with Weibull distribution of IITDs came up with a best fit. The results show that significant variables affecting IITDs include characteristics of the incidents (severity, type, towing involvements, lane and shoulder blockage etc.), Road Rangers involvement, and traffic characteristics of the incident. Moreover, the findings reveal no significant effects of median width, average detector occupancy and the day of the week on which an incident occurred. A significant and unique contribution of this paper is that the Road Rangers shorten IITDs relative to other responding agencies by 12.6%. The results can, in general, help incident managers on improving incident management strategies and IITDs estimations.

It is worth mentioning that this study used traffic volume data from RITIS devices to estimate IITDs. RITIS devices in the proximity of the affected BlueToad® pairs were used to obtain the 15-minute intervals traffic volume data. However, the absence of these devices along entry and exit ramps of some corridors posed some limitations. Due to this limitation, only the mainline IITDs were estimated. In addition, on evaluating the Road Rangers mobility benefits, the evaluation did not account for disaggregate-level operational details of the program (e.g., day-to-day or seasonal variations in Road Rangers activities, fleet sizes, beat lengths and probe vehicle types, pickup versus tow trucks). Future studies may seek to expand this study to microscopic level of Road Rangers (or any other FSP program) operations.

CHAPTER 4

PAPER 3

Do Road Rangers Help in Preventing Secondary Crashes?

Submitted to the Journal of Transportation Research Board

INTRODUCTION

Traffic incidents 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 increase the likelihood of secondary crashes (SCs) (Karlaftis et al., 1999). For every minute a freeway lane is blocked due to an incident during a peak travel period, there is a 4-minute delay to the traffic using the freeway and a 2.8% chance of a SC occurrence (Owens et al., 2010). A crash is considered secondary if it occurs either: (a) at the scene of the primary incident (PI), or (b) within the queue upstream of the PI, or (c) within the queue in the opposite direction of the PI caused by driver distraction known as rubbernecking effect (Khattak et al., 2009; Zhan et al., 2009).

SCs have increasingly been recognized as a major problem leading to reduced capacity, additional traffic delays, and increased fuel consumption and emissions, especially on freeways. SCs are non-recurring in nature; not only do affect the traffic operations, but also impose safety risk to road users and traffic incident responders. The USDOT estimated that SCs alone account for approximately 18% of all freeway traffic fatalities and 20% of all traffic crashes (Owens et al., 2010). Compared to PIs, SCs have a significant impact on traffic management resource allocation (Karlaftis et al., 1999). In fact, traffic incident managers use the reduction of SCs as one of the performance measures for state incident management systems (Owens et al., 2010).

Since the likelihood of SCs increases with the increase in the duration of the PI (Khattak et al., 2009), transportation agencies are exploring several strategies to clear incidents as quickly as possible. Freeway service patrols (FSPs) are one such strategies that have been known to reduce incident response and clearance time (Karlaftis et al., 1999). This reduction can help alleviate the delay due to nonrecurring-incident related congestion, as well as lowering the chance of SCs.

However, one question remains: to what extent do FSPs reduce the likelihood of SC occurrence? While much work has been done in identifying the benefits stemming from the delay savings, fuel savings, and emission reduction (Guin et al., 2007; Dougald & Demetsky, 2008; Lin et al., 2012), little information is available in literature on the potential impact of FSPs in lowering the likelihood of SCs.

This research investigates the extent to which the Florida's FSP (Road Rangers) reduce(s) the SC likelihood. The study provides an approach to account for SC reduction benefit of FSP (Road Rangers) in addition to other benefits. More specifically, the study first uses a data-driven approach to identify SCs; it uses a dynamic approach to account for varying spatiotemporal thresholds based on prevailing traffic conditions. Once SCs are identified, then, the impact of Road Rangers in reducing the likelihood of SC occurrence is evaluated using a complementary log-log model. Structurally, the paper starts by discussing how SCs are related to FSPs and continues by documenting previous efforts in estimating the safety benefits of FSPs. The data sources are briefly explained, followed by a discussion on the study approach. Finally, the paper presents and discusses the results and conclusively highlights some important findings.

PREVIOUS STUDIES

Freeway service patrols (FSPs), in general, serve as a key component within any comprehensive incident management framework (Latoski et al., 1999). An efficient FSP substantially reduces incident duration time, which, in turn, alleviates the delay attributed to nonrecurring, incident-related congestion and lowers the risk of SCs (Karlaftis et al., 1999). FSPs, by the nature of their role are often in a position to arrive at an incident scene quickly to enable advance safety protection and traffic control, which helps to prevent occurrence of another related incident. An FSP, by virtue of its roving presence on the freeways, can substantially reduce the time it takes to detect and to respond to an incident. The flashing lights on the patrol vehicles on the other hand, warn motorists to exercise caution in the vicinity of assisted incidents. Furthermore, these programs create a sense of security for motorists in addition to improving public relations (Karlaftis et al., 1999; Guin et al., 2007).

In the U.S., a national survey of 19 agencies showed that the benefit-cost ratios for FSP programs ranged from 4.6:1 to 42:1 (Baird, 2008). While the costs included contractual and operating costs, the benefits stemmed from the delay savings, fuel savings, emission reductions, and motorist assistance (Ma et al., 2009; Dougald & Demetsky, 2008; Lin et al., 2012; Z. Sun et al., 2017). SC reduction may represent another significant benefit of FSP, but little has been done to identify the potential savings from lowering the likelihood of SC. In fact, these programs reduce primary incident duration, which is a significant contributor to SCs occurrence (Karlaftis et al., 1999; Olmstead, 2004; Guin et al., 2007; Kitali et al., 2018).

The existing studies which considered SCs as one of FSP benefits (performance measures) differ in the way they identified SCs. While some used predefined spatial-temporal thresholds (Karlaftis et al., 1999), others assumed a fixed proportion (say 15%) out of all incidents as SCs (Chang et al., 2003; Guin et al., 2007; Chou et al., 2010). The later studies acknowledge that it is difficult to estimate savings in SCs, because such savings can only be determined by estimating the amount of crashes that did not occur, which may not be accurately computed. Thus, to estimate such savings, authors assumed that incident duration and total delay resulting from the PIs would be proxies for SCs. Although these studies developed a modestly detailed framework for considering SCs, one limiting consideration in all these studies is the approach used to identify SCs. These approaches are subject to underrepresentation or over representation of SCs. The choice of the predefined spatial-temporal thresholds and proportions are subjective in the sense that they are arbitrary.

This study investigates the extent to which the Florida's Road Rangers reduce SCs. The study gives details to account for SC reduction benefit of Road Rangers in addition to other benefits. Moreover, instead of using predefined spatial-temporal thresholds or fixed proportions the study uses a data-driven approach to identify SCs. This dynamic approach accounts for the varying spatiotemporal thresholds based on prevailing traffic conditions. The study can, in general, help incident managers assess the effectiveness of the program in improving safety.

DATA SOURCES

The study area included a 35-mile section on I-95, a 21-mile section on I-10, and a 61-mile section on I-295 located in Jacksonville, Florida. The total study area covers 117 miles. Figure 4-1 shows the study area. Data used in this study included speed data from BlueToad® devices, incident data from SunGuide® database, and real-time traffic data from the Regional Integrated Transportation Information System (RITIS) for the years 2015-2017. The following sections provide further details of the aforementioned data sources.

SunGuide®

SunGuide® is an advanced traffic management system (ATMS) software that is used at all regional traffic management centers (RTMCs) within Florida. SunGuide® software offers tools like automated incident detection and assisting with event management and archiving of incident data. The database stores incident attributes like; incident ID, incident timeline, incident severity, incident type, incident detection, incident location and incident responders. Along the study corridors, the SunGuide® database included a total of 66,756 incidents from 2015-2017. After excluding incidents on ramps (15,730), incidents with missing coordinates (183), incidents with no matched BlueToad® pairs (10,990), incidents along the section without BlueToad® pairs (32,988), the remaining data consisted of a total of 6,865 incidents.

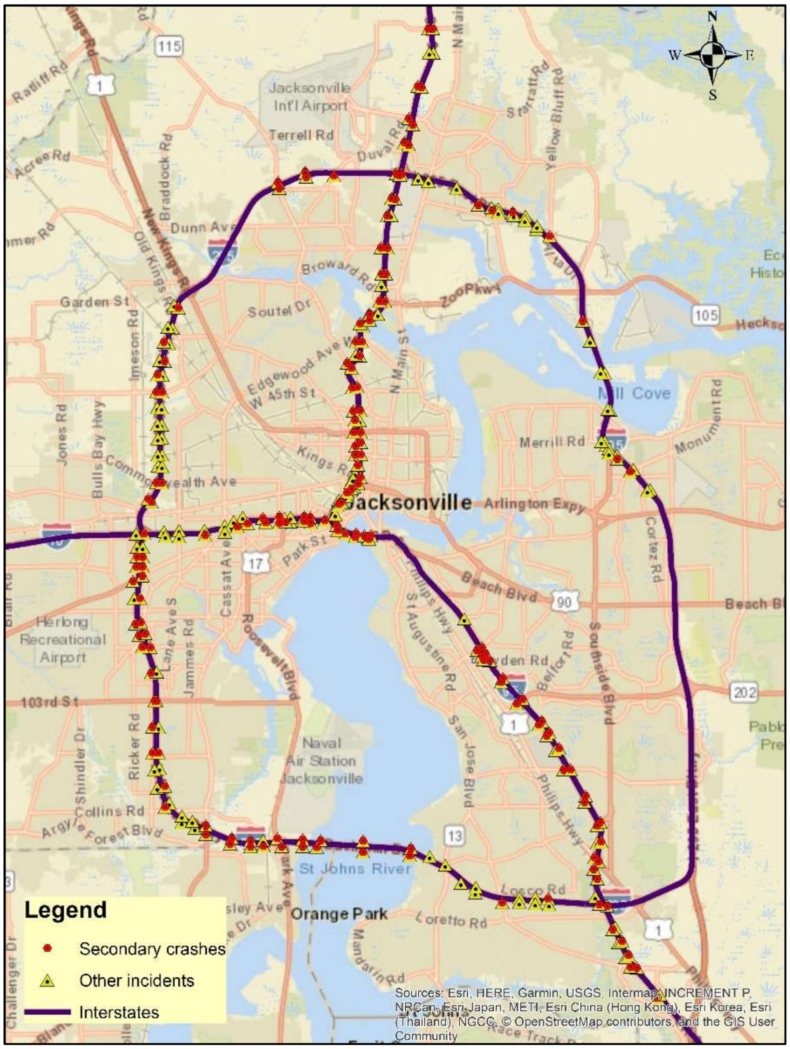


Figure 4-1: Study corridor

BlueToad® Devices

BlueToad® devices are Bluetooth signal receivers, which read the Media Access Control (MAC) addresses of active Bluetooth devices of vehicles passing through their area of influence. These devices record the time when a vehicle passes nearby. A pair of devices is used to estimate the vehicle travel time between the two devices by taking the difference of the recorded times. The speed is calculated from the travel time and the known path distance (not Euclidean distance) between the devices. The study location had 72 BlueToad® devices pairs, spaced approximately every 1.8 miles along the freeway corridor. The posted speed limits on the entire section range between 55 mph and 70 mph. This study used raw data collected at each BlueToad® device pair.

RITIS

RITIS is an online 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. RITIS provides traffic flow data in addition to speed data (volume and detector occupancy). These high-resolution raw traffic data from RITIS were included in the likelihood model as possible factors that may influence the risk of SCs. There are 375 detectors along the selected freeway corridors. The average spacing between these detectors is approximately 0.5 miles. It is worth noting that traffic data just before the incident occurrence may account for potential inaccuracies in the reported incident time. Therefore, in this study, 15-min aggregated traffic characteristics were collected 5-min before the incident's first notified time and within 1-mile upstream and downstream of each incident to minimize the inaccuracies.

METHODOLOGY

The primary objective of this study is to evaluate the safety benefits of Road Rangers based on real-time traffic flow conditions. The objective was achieved through the following steps: (i) identification of SCs; (ii) identification of SC contributing factors; and finally, (iii) prediction of the probability of SCs and estimation of the safety benefits of Road Rangers. Figure 4-2 provides the framework for Road Rangers safety benefits evaluation adopted in this study.

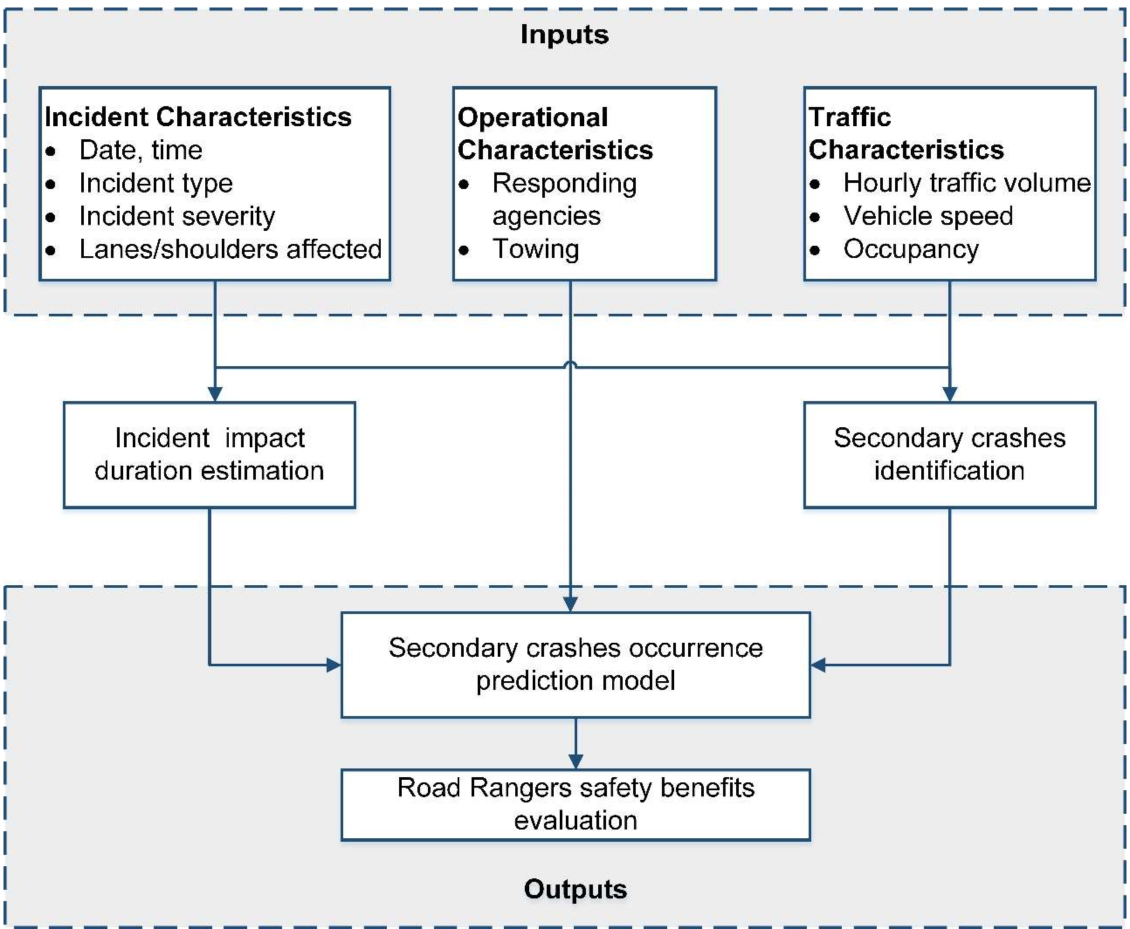


Figure 4-2: Framework for Road Rangers safety benefits evaluation

Identification of Secondary Crashes

SCs result from a change in traffic characteristics caused by a PI. Researchers have traditionally been using static and dynamic approaches to identify SCs. Previous studies (Zheng et al., 2014; Goodall, 2017; Kitali et al., 2018; Yang et al., 2018) provide more details about these methods. In this study, SCs were identified by the method developed by Kitali et al. (Kitali et al., 2018) where the spatiotemporal impact ranges of the PIs were identified dynamically using archived BlueToad® speed data. This method captures the effects of traffic flow characteristics, such as speed, that change over space and time and affect the queue formation as a result of a PI. It overcomes the challenges of predefining the impact range thresholds or considering the deterministic queues of PIs that occur within observed queues from empirical measurements. The developed SC identification algorithm was automated in the R programming language. The analysis identified 537 SCs resulting from 377 primary incidents, as presented in Table 4-1.

By definition, a primary incident (PI) is an incident which is directly associated with a SC. A normal incident (NI) on the other hand, is an incident not associated to a SC.

Table 4-1: Secondary crash distribution by freeway corridors (2015-2017)

Freeway	Normal Incidents	Primary Incidents	Secondary Crashes	Total Incidents	Secondary Crashes Share (%)
I-10 E	133	16	20	169	11.83
I-10 W	105	9	15	129	11.63
I-95 N	1581	110	174	1865	9.33
I-95 S	1387	95	133	1615	8.24
I-295 E	555	13	15	583	2.57
I-295 W	2190	134	180	2504	7.19
Total	**5951**	**377**	**537**	**6865**	**7.82**

Complementary Log-Log Analysis

The response variable (SC likelihood) is binary, taking a value of 0 for NIs (incidents not linked to SCs) and 1 for PIs (incidents associated with SCs). From the descriptive statistics provided in Table 4-2, PIs constitute 5.9% of all incidents. This means that the proportion of PIs is much less than the proportion of NIs, i.e., the PIs and the NIs are asymmetrically distributed. Thus, a complementary log-log model (cloglog) is applied to associate the relationship between the probability of SC and predictors. The model analyzes the relationships between the PI characteristics and the possibility of SC occurrence. Practically, a complementary log-log model, being asymmetrical around the inflection point, provides a more reliable prediction of SCs likelihood (Kitali et al., 2018). The cloglog model is asymmetrical with a fat tail as it departs from zero (0) and sharply approaches one (1) (Kitali et al., 2018). The cloglog model is presented using Equations. (4-1) and (4-2)

$$y_i = Binomial(n_i, \pi_i) \tag{4-1}$$

$$cloglog(\pi_i) = \log(-\log(1 - \pi_i)) = \beta X + \alpha \tag{4-2}$$

where;

π_i denotes the probability of a SC induced by a primary incident;

X denotes the vector of explanatory variables

β is the coefficients vector for explanatory variables X

α is the specific constant term

The likelihood function for the cloglog regression can be expressed using Eq. (4-3).

$$Likelihood = \prod_{i=1}^{n}[\pi(x_i)^{y_i}(1 - \pi(x_i)^{(1-y_i)}]$$
(4-3)

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

Potential Explanatory Variables

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

Incident Characteristics

- *Incident impact duration*: refers to time taken for the traffic flow speed to return to normal. This was estimated using the approach developed by Haule et al., 2018. It is generally assumed that the SC likelihood increases as incident impact duration increases (Karlaftis et al., 1999; Haule et al., 2018).
- *Incident type*: it is logical to anticipate that the probability of SC occurrence differs with incident type. This variable was considered categorical and included; crashes, vehicle problems (disabled or abandoned vehicles, emergency vehicles, vehicle fire and police activity), and traffic hazards (debris, flooding, spillage and pedestrian crossing).
- *Incident severity*: incident severity may influence the clearance time of an incident resulting in a higher chance of SC occurrence. The variable was considered bivariate coded as minor, and moderate/severe.

- *Lane closure*: refers to whether an incident blocked lane(s). The percent of lanes closed is usually considered an indicator of the severity of an incident, as severe incidents tend to result in an increased number of lanes closed. In the current study, a 25% lane closure implies one out of four lanes of a roadway section is closed. A closure of one of three lanes would result to 33.3% lane closure and 100% means all lanes are closed. It is logical to anticipate that the probability of SC occurrence increases with increase in percent of lanes closed. This variable was considered categorical coded as 25% or less and greater than 20% lane closure.
- *Shoulder blockage*: refers to whether an incident blocked a shoulder. Similarly, it is logical to anticipate that the probability of SC occurrence increases when a shoulder is blocked. The variable was divided into two categories: No (no shoulder is blocked) and Yes (at least one shoulder is blocked).
- *Incident occurrence time*: time factors are good indicators of traffic conditions, driver alertness, and familiarity with the route (Zhan et al., 2009). The variable was categorized as peak (a.m. 0600 to 1000 hours and p.m. 1530 to 1830 hours) and off-peak (other times of day).
- *Day of the week*: a proxy for activity variability. The variable was coded as weekdays and weekends. Weekends were Saturday and Sundays.
- *Lighting condition*: a proxy for lighting variability. The variable was coded as day light and night with respect to sunrises and sunsets.

Traffic Characteristics

- *Hourly traffic volume*: It is logical to anticipate that the probability of SC occurrence increases with increase in traffic volume. 15-min aggregated traffic volumes were collected 5-min before the incident's first notified time and within 1-mile upstream and downstream of an incident. The variable was considered continuous.
- *Vehicle speed*: 15-min aggregated vehicle speeds were collected 5-min before the incident's first notified time and within 1-mile upstream and downstream of an incident.
- *Occupancy*: refers to the percent time that the sensor (detector) is occupied by a vehicle, usually at 30-sec intervals. 15-min aggregated detector occupancy were collected 5-min before the incident's first notified time and within 1-mile upstream and downstream of an incident.

Operational Characteristics

- *Responding agencies*: bivariate coded as Road Rangers involved and other agencies involved. Other agencies included but not limited to Florida Highway Patrol (FHP), Jacksonville Sherriff's Office (JSO), Emergency Medical, Fire Department, and Safety Tow. Of the variables, this is a central variable.
- *Towing:* refers to whether an incident involved towing or not. Towing is usually considered an indicator of the severity of an incident, as severe incidents tend to involve towing. This variable was divided into either no towing was involved, or towing was involved.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 4-2 provides the descriptive statistics of all the variables selected for analysis and modeling. The statistics are provided for 6,088 valid observations (*N*) that were included in the analysis. Of the 6,685 observations presented in Table 4-1, a total of 537 were SCs, 18 PIs and 222 NIs had some missing information and therefore were excluded from the analysis. Of the valid observations, PIs and NIs accounted for nearly 6.0% and 94.0%, respectively. Incidents associated with vehicle problems accounted for 53.07% of all incidents, while 36.84% and 10.09% were crashes and traffic hazards, respectively.

Overall, statistics showed that nearly three-quarters (76.94%) of incidents analyzed were responded to by the Road Rangers. Despite responding to such a significant proportion, 270 (5.2%) of incidents were PIs, which resulted to 321 (6.2%) SCs relative to 107 (6.4%) of incidents responded to by other agencies, which resulted to 216 (12.9%), as illustrated in Table 4-3. Furthermore, the table presents the incident impact duration distributions against incident responding agencies. In all cases, Road Rangers were associated with shorter average durations than other responding agencies. Since there exists a relationship between incident duration and SCs (Khattak et al., 2009), these reductions in incident impact duration can translate into substantial travel time and fuel consumption savings for motorists and reduced SCs.

Table 4-2: Descriptive statistics of variables

Categorical Variable	**Factor**	**Frequency**	**Share (%)**
Incident	Normal incidents	5,729	94.10
	Primary incidents	359	5.90
Incident type	Crash	2,243	36.84
	Vehicle problems	3,231	53.07
	Traffic hazards	614	10.09
Incident severity	Minor	5,731	94.14
	Moderate/Severe	357	5.86
Day of the week	Weekday	5,702	93.66
	Weekend	386	6.34
Incident occurrence time	Peak	3,350	55.03
	Off-peak	2,738	44.97
Lighting condition	Daylight	5,419	89.01
	Night	669	10.99
Lane closure (%)	0 - 25	5,254	86.30
	> 25	834	13.70
Shoulder blocked	Yes	3,468	56.96
	No	2,620	43.04
Towing involved	Yes	826	13.57
	No	5,262	86.43
Responding agencies	Road Rangers	4,684	76.94
	Other agencies	1,404	23.06

Continuous variable	**Min**	**Mean**	**Median**	**Max**	**SD**
Hourly traffic volume (veh/hr)	8	192	186	1564	93.47
Average vehicle speed (mph)	6.08	63.23	65.74	85.14	9.00
Average detector occupancy	0.24	7.69	6.88	48.29	4.37
Incident impact duration (min)	15	86.93	75	285	60.00

Valid N = 6,088

Table 4-3: Descriptive statistics of incident impact duration with respect to responding agencies

Responding agencies / Incident level	Mean (min)	Median (min)	N	Min	Max	Std. Dev. (min)
Other agencies	*99.19*	*82.4*	*1672*	*15*	*285*	*64.45*
Normal incidents	92.13	75	1349	15	285	62.51
Primary incidents	154.68	150	107	30	285	62.63
Secondary crashes	118.06	105	216	30	285	61.44
Road Rangers	*83.04*	*66.4*	*5193*	*15*	*285*	*57.99*
Normal incidents	77.67	60	4602	15	285	54.59
Primary incidents	143.87	135	270	30	285	62.29
Secondary crashes	112.25	105	321	30	285	65.54
All incidents	*86.93*	*70.5*	*6865*	*15*	*285*	*60.00*

Figure 4-3 presents the relative frequencies of Road Rangers responses versus other agencies responses. The four plots show that Road Rangers respond to vehicle problems and minor incidents more frequently than other agencies. Their responses are much more evident on weekdays and during peak hours.

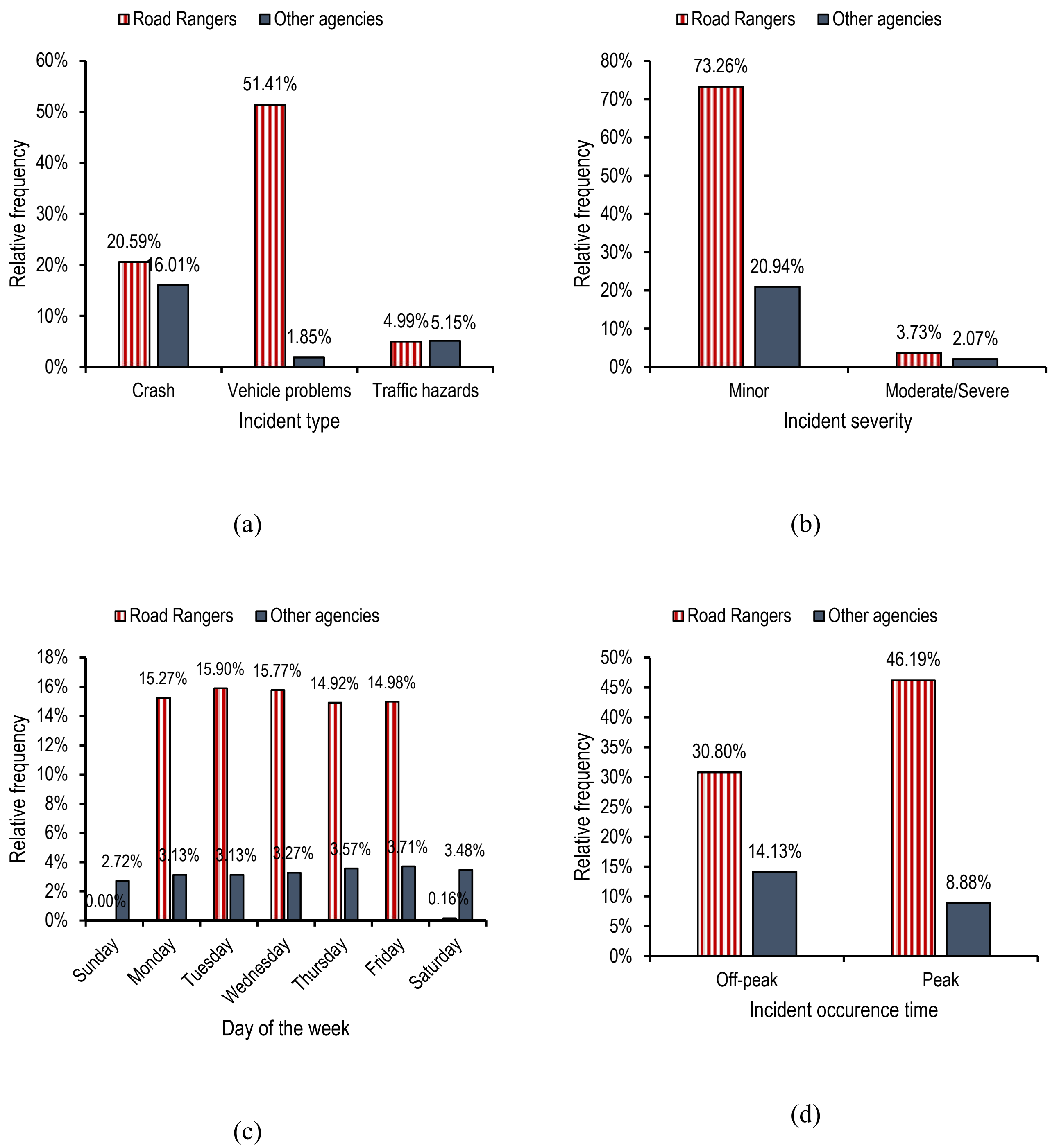


Figure 4-3: Road Rangers versus other agencies assists relative frequencies (a) incident type, (b) incident severity, (c) day of the week and (d) incident occurrence time

Secondary Crash Occurrence Likelihood Model

The regression results are presented in Table 4-4, and most variables are statistically significant at the 95% confidence level ($\alpha = 0.05$). All the factors elaborated in the previous section were included in the model. The results can be useful in explaining how various factors affect SC occurrence. Estimated coefficients measure the change in the SC likelihood due to a change in the predictor variable while keeping the other predictor variables constant. A positively estimated coefficient implies an increase in the SC likelihood. A negative estimated coefficient indicates that there is less SC likelihood. P-value indicates whether a change in the predictor significantly changes the SC likelihood ($\alpha = 0.05$). Hazard ratio measures the instantaneous strength of association between predictors and the probability of SC occurrence. In the current study, the emphasis is placed on Road Rangers. The cloglog results in Table 4-4 indicate the following key points;

A unit increase in traffic volume increases the SCs likelihood by 0.1%. On the other hand, a unit increase in occupancy increases the risk by 0.9%. One study (Kitali et al., 2018) suggested that congested traffic is characterized with lesser gaps between vehicles providing drivers with lesser room for maneuver and increase in average occupancy represents an increase in traffic density, traffic volatility, and queue formation. Thus, at higher traffic volumes and occupancy, the disturbances induced by the PIs easily propagate in queuing traffic conditions, leading to a higher risk of SCs. Similarly, when all other factors are fixed, the SCs likelihood is higher during the peak hours than during other time periods. The coefficient of the peak hours' variable is positive suggesting that the possibility of SCs occurrence is higher during peak hours.

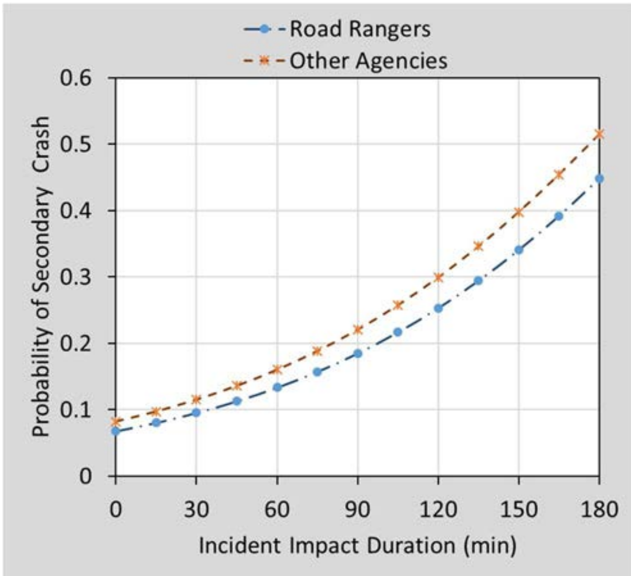
Incident type and severity also significantly contribute to the SC likelihood. Crashes have a higher likelihood of resulting in SCs compared to the incidents associated with vehicle problems and traffic hazards. Moderate/severe incidents increase the risk by 4.7% relative to minor incidents. One possible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

For responding agencies, the negative coefficient of Road Rangers indicates a decrease in SCs occurrence likelihood. Probabilities of SCs occurrence are illustrated in Figure 4-4 for (a) a crash, (b) vehicle problem and (c) traffic hazard as PIs. Illustratively, suppose a moderate/severe crash occurred during a weekday afternoon peak, blocked both a shoulder and a lane and impacted the traffic for 90 min. The traffic was moderate (750 veh/h) at a mean speed of 60 mi/h and occupancy of 7.68. The probability of SC occurrence can be estimated as 18.5% when Road Rangers were involved compared to 21.2% when Road Rangers were not involved. This means that there is a 2.7% reduced risk of SC occurrence due to Road Rangers involvement.

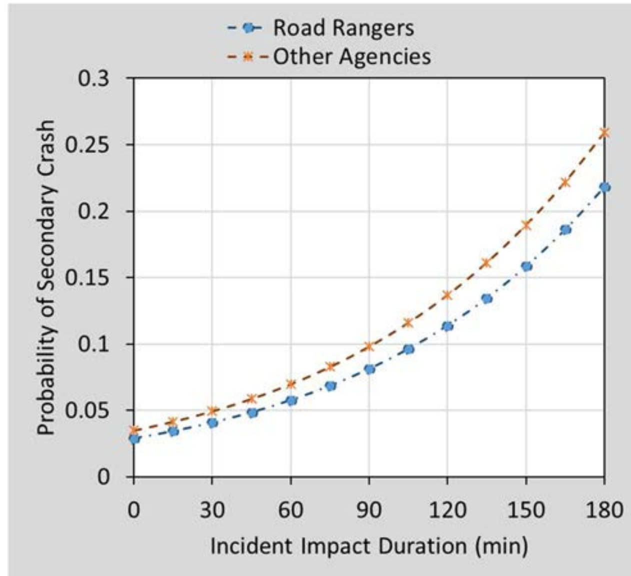
Table 4-4: Model results

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

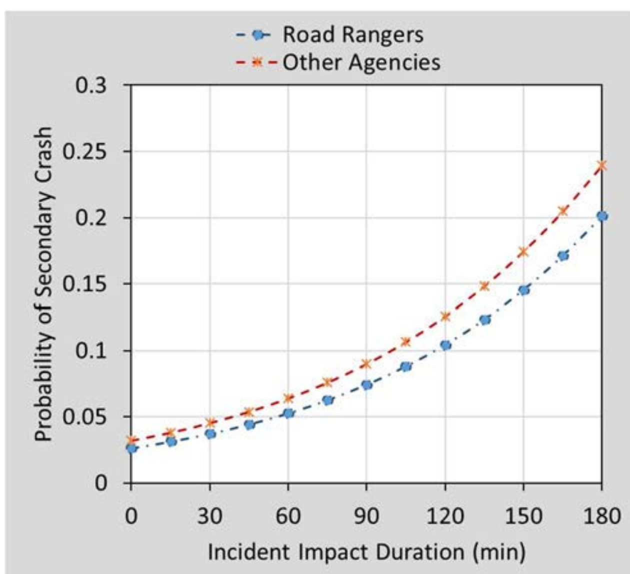
Note: *AIC: 2364.9, Null deviance: 2729.4, Residual deviance: 1312.5, pseudo R2: 0.42, italicized variables are not significant at 95% level*



(a) Probability of SC occurrence when a PI is a crash



(b) Probability of SC occurrence when a PI is vehicle problems related



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

Figure 4-4: Probability of SC occurrence against incident impact duration

Road Rangers Safety Benefits

As discussed earlier, the assumption exists that FSPs can help with reducing SCs because one of their duties is to provide traffic control (guide) at incident scenes, and the better the traffic control, the more apt you are to reduce SCs. On the other hand, FSPs by the nature of their role are often able to arrive at an incident scene quickly to enable early safety protection and traffic control which helps to prevent another related incident. In this study, two safety scenarios of Road Rangers are discussed. The first being the benefit delivered from reduced incident duration and the second from the traffic control (increased safety at incident scene).

Incident duration reduction

The hazard ratios in Table 4-4 assist in quantifying the effect of predictors on the likelihood of SC occurrence. Hazard ratio measures the instantaneous strength of association between predictors and the probability of SC occurrence. For example, in Table 4-4 the hazard ratio of incident impact duration is 1.012. This suggests that each additional minute of incident impact duration increases the likelihood of a SC by 1.2%. Figure 4-5 shows that the probability of a SC occurrence increases with incident impact duration implying that reducing incident impact duration would translate into reduced SCs.

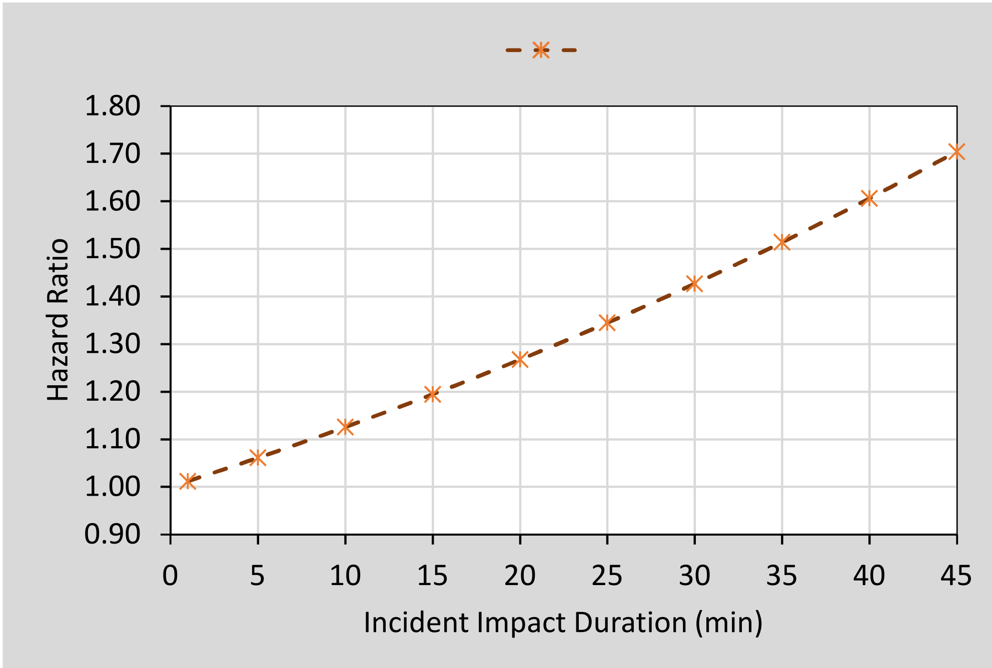


Figure 4-5: Probability of a secondary crash occurrence

Since Road Rangers reduce incident duration by offering faster incident detection and response, there is an expected reduction in SCs. For example, if Road Rangers reduce incident duration by an average of 10 min, based on Figure 4-5 (or Table 4-5), the likelihood of a SC decreases by 12.6%. Based on Table 4-3, the average incident impact duration is 83.04 minutes with Road Rangers involvement, which is 16 minutes less than the median duration with other responding agencies (99.19 min). According to Table 4-5, a 16 minutes duration corresponds to a hazard ratio of 1.209, indicating that Road Rangers may help reduce SC likelihood by 20.9%. Therefore, traffic management strategies, Road Rangers in particular, that clear roadway blockages as quickly as possible have a significant impact on reducing the probability of SCs.

Table 4-5: Estimation of reduction of probability of secondary crash occurrence

Incident impact duration reduction (min)	Hazard Ratio	Safety Effectiveness	Probability of secondary crash reduction (%)		
			Estimate	95% confidence interval	
				Lower bound	Upper bound
0	1.000	1.000	0.0	0.0	0.0
5	1.061	0.939	6.1	6.1	6.1
10	1.126	0.874	12.6	12.6	12.6
15	1.195	0.805	19.5	19.4	19.5
20	1.267	0.733	26.7	26.7	26.8
25	1.345	0.655	34.5	34.4	34.5
30	1.427	0.573	42.7	42.6	42.8
35	1.514	0.486	51.4	51.3	51.5
40	1.606	0.394	60.6	60.5	60.8
45	1.704	0.296	70.4	70.3	70.6

Traffic control

Based on the model results presented in Table 4-4, Road Rangers reduce the probability of SCs by 17.9% (mean 17.9%, 95% CI: 17.6 - 18.2). This reduction could be associated with how quickly Road Rangers respond to incidents. Also, features like the flashing lights on the patrol vehicles warn motorists to exercise caution in the vicinity of assisted incidents.

CONCLUSIONS AND RECOMMENDATIONS

This study evaluated the safety performance of the Road Rangers Service Patrol, a mobile-based program administered by FDOT to assist motorists and minimize the impacts of freeway incidents on non-recurring traffic congestion. Specifically, this study examined the benefits of the Road Rangers in reducing the risk SCs occurrence. The study developed a model to predict SCs probabilities with data from I-10, I-95, and I-295 in Jacksonville, Florida. Data used include; speed data from BlueToad® devices, incident data from SunGuide® database, and real-time traffic data from RITIS for the years 2015-2017.

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

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

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

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VITA

JIMOKU HINDA SALUM

Professional Summary

My experience extends from transportation systems planning and designing, traffic operations and safety analysis, simulation, to traffic data collection and modeling. I have applied statistical models such as parametric, non-parametric, and machine learning models in my research. I have also participated in real-time data collection that can be used in intelligent transportation systems.

Education

Master of Science: Civil Engineering
University of North Florida - Jacksonville, FL 32224 08/2018 - 12/2019

- Member of Institute of Transportation Engineers (ITE) student chapter
- Major in Transportation Engineering

Bachelor of Science: Civil Engineering
University of Dar Es Salaam - Tanzania 10/2013 - 11/2017

- Graduated magna cum laude
- Member of Institution of Engineers in Tanzania (IET) student chapter

Related Work History

Graduate Research Assistant
University of North Florida - Jacksonville, FL 32224 08/2018 – 12/2019

- Investigated the performance of Florida's Road Rangers onto both traffic mobility and safety

Conferences Attended

- Attended the Florida Section ITE (FSITE) annual meeting in Fort Lauderdale, FL 33067 USA on October 29, 2018 - October 31, 2018
- Attended the Florida Automated Vehicles (FAV) summit in Tampa, FL 33067 USA on November 2018
- Attended the 98th Transportation Research Board (TRB) annual meeting in Washington DC, on January 13, 2019 - January 16, 2019
- Attended the Florida's i3 transportation Showcase in Orlando, on June 23-26, 2019

Publications

Journal Papers Under Review

1. **Salum, J. H.**, Sando, T., Alluri, P., and Kitali, A. (2019). "Incident-induced Traffic Delays: Investigating Delay Savings of Florida's Road Rangers". *Transportation Research Record: Journal of the Transportation Research Board.*
2. **Salum, J. H.**, Sando, T., and Alluri, P. (2019). "Do Road Rangers Help in Preventing Secondary Crashes?". *Transportation Research Record: Journal of the Transportation Research Board.*
3. **Salum, J. H.**, Mcharo, R., and Sando, T. (2019). "Parking Ratios for Malls and Supermarkets in Dra es Salaam, Tanzania". *Transportation Research Record: Journal of the Transportation Research Board.*
4. **Salum, J. H.**, Sando, T., and Alluri, P. (2019). "Operational Evaluation of Freeway Service Patrols: A Case Study of Florida's Road Rangers". *Journal of Transportation Engineering: Part A systems.*
5. Andrew, L., **Salum, J. H.**, Sando, T., and Richardson, R. (2019). "Investigating the Effects of Rainfall on Traffic Operations on Florida Freeways". *Transportation Research Record: Journal of the Transportation Research Board.*

Refereed Journal Papers

1. **Salum, J. H.**, Kitali, A., Bwire, H., Sando, T., and Alluri, P. (2019). "Severity of motorcycle crashes in Dar es Salaam, Tanzania", Traffic Injury Prevention, 20:2, 189-195, DOI: 10.1080/15389588.2018.1544706

Full-Paper Refereed Proceedings

1. Kitali, A., Kidando, E., Alluri, P., Sando, T., and **Salum, J. H.** (2019). "Using a Dirichlet Multinomial Logit Model to Investigate Factors Influencing the Severity of Motorcycle Crashes in Tanzania," Proceedings of the 98th Annual Meeting of the Transportation Research Board, Washington, DC.

2. **Salum, J. H.**, Kitali, A., Bwire, H., Sando, T., and Alluri, P. (2018). "Factors Influencing the Severity of Motorcycle Crashes in Dar es Salaam" Proceedings of the 97th Annual Meeting of the Transportation Research Board, Washington, DC.

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