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Estimation of the Mobility Benefits of Ramp Metering

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ESTIMATION OF THE MOBILITY BENEFITS OF RAMP METERING

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by

Henrick Joseph Haule

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

This dissertation, written by Henrick Joseph Haule, and entitled Estimation of the Mobility Benefits of Ramp Metering, having been approved in respect to style and intellectual content, is referred to you for judgment.

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

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The dissertation of Henrick Joseph Haule is approved.

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Florida International University, 2021

DEDICATION

To my beloved parents, Joseph Haule and Eleonora Mkundi,

and my siblings Anna, Veronica, Hellen, and Flora for their endless love, support, and encouragement.

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ABSTRACT OF THE DISSERTATION

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Professor Priyanka Alluri, Major Professor

Transportation agencies are implementing traffic management strategies to improve mobility and safety on freeways. Ramp metering is a traffic management strategy deployed to mitigate congestion on freeways using traffic signals installed at entrance ramps to control and regulate vehicle entry onto the freeway mainline. Estimating the mobility benefits of ramp metering is critical to determine the strategy's effectiveness and inform the decision-making process regarding its deployment.

However, the extent of the impact of ramp metering on recurrent congestion varies across studies. Among the reasons for the inconsistencies are the limitations of conventional methods for evaluating benefits, including the before-and-after approach, shutdown experiment, and traffic simulation. In addition to alleviating recurrent congestion, ramp metering has the potential of improving traffic conditions during non-recurrent congestion. Few agencies have used ramp metering to reduce non-recurrent congestion resulting from traffic incidents and adverse weather. Nonetheless, the ramp benefits during non-recurrent congestion are not well researched.

This research aimed to estimate the mobility benefits of ramp metering during recurrent and non-recurrent congestion. To achieve the research goal, the study evaluated

the effects of ramp metering on travel time reliability, the impact of ramp metering on traffic conditions upstream of a crash location, and the effects of ramp metering on traffic conditions during rainy weather. The research used data collected when ramp metering signals (RMSs) are activated and during unintentional RMSs' downtime to account for the limitations of the conventional methods for estimating benefits.

Results of the analysis focusing on recurrent congestion showed that ramp metering significantly improves travel time reliability. It was estimated that ramp metering increased travel time reliability by 23% during moderate recurrent congestion and by 28% during severe recurrent congestion.

The analysis during non-recurrent congestion showed that ramp metering has varying impacts on traffic conditions upstream of a crash location. Ramp metering significantly affected traffic conditions upstream of a crash location during peak periods and daytime off-peak periods. Activating RMSs during rain in daytime off-peak periods and peak periods positively affected traffic conditions downstream of the entrance ramps. Based on the estimated benefits, agencies could establish criteria for selecting when and which RMSs to be activated to alleviate non-recurrent congestion. The estimated benefits could also be used when assessing the cost-effectiveness of future deployment of RMSs.

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LIST OF ACRONYMS

AIMSUN	Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks
ALINEA	Asservissement Linéaire d'Entrée Autoroutière
ATMS	Advanced Traffic Management System
BI	Buffer Index
CCTV	Closed-Circuit Television
CI	Confidence Interval
CTOD	Central Time of Day
dBZ	Decibel relative to Z (Reflectivity)
FCT	Floating Car Technique
FDOT	Florida Department of Transportation
FFS	Free-Flow Speed
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
GOLM	Generalized Ordered Logit Model
GPL	General- Purpose Lane
HCM	Highway Capacity Manual
HOV	High-occupancy Vehicle
KDOT	Kansas Department of Transportation
LASSO	Least Absolute Shrinkage and Selection Operator
LOS	Level of Service
LTOD	Local Time of Day

MoDOT	Missouri Department of Transportation
NB	Northbound
NEXRAD	Next Generation Weather Radar
NOAA	National Oceanic and Atmospheric Administration
OR	Odds Ratio
POOM	Proportional-Odds Ordered Model
PPOM	Partial Proportional-Odds Ordered Model
PSL	Posted Speed Limit
RCI	Roadway Characteristics Inventory
RITIS	Regional Integrated Transportation Information System
RMS	Ramp Metering Signal
RMSE	Root Mean-Squared Error
RSS	Residual Sum of Squares
RTMC	Regional Transportation Management Center
SB	Southbound
SWARM	System-wide Adaptive Ramp Metering
TSM&O	Transportation Systems Management and Operations
TTI	Travel Time Index
USDOT	United States Department of Transportation
VHT	Vehicle-Hours-Travelled
VISSIM	Verkehr In Städten – SIMulations
VMT	Vehicle-Miles-Traveled
vphpl	Vehicles per Hour per Lane

CHAPTER 1

INTRODUCTION

1.1 Background

Traffic congestion continues to increase each year on the urban roadway networks in the United States (U.S.). In 2017, Americans lost nearly nine billion hours due to congestion (Schrank et al., 2019). Regrettably, traditional solutions, such as adding lanes, are no longer considered feasible because the urban road capacity is already built out, and there is limited funding for road widening projects (Grant et al., 2017). Agencies are, therefore, implementing Transportation Systems Management and Operations (TSM&O) strategies to reduce traffic congestion. TSM&O strategies focus on optimizing the capacity of the existing and planned transportation infrastructure for all modes of transportation to improve safety and reduce congestion (Clark et al., 2017). Freeways are an integral part of the urban roadway network where traffic conditions could be improved using TSM&O strategies, including ramp metering, dynamic message signs, and variable speed limits.

Ramp metering is a TSM&O strategy that utilizes signals installed at freeway entry ramps to dynamically manage traffic entering the freeway. Ramp metering operates by stopping and releasing vehicles traveling from the adjacent arterials to the freeway mainline through the entrance ramp at a metered rate (Jacobson et al., 2006). As illustrated in Figure 1-1, a typical ramp metering configuration shows an entrance ramp stop line where vehicles are stopped and released onto the mainline at a rate that depends on the prevailing mainline traffic conditions. The three main objectives of ramp metering include: (1) controlling the number of vehicles entering the freeway to ensure traffic volume on the freeway section is below capacity (Balke, 2009; Piotrowicz and Robinson, 1995), (2) reducing the freeway demand, and (3) breaking up platoons of vehicles released from upstream signals from entering the freeway mainline (Balke, 2009; Gan et al., 2011; Piotrowicz and Robinson, 1995).

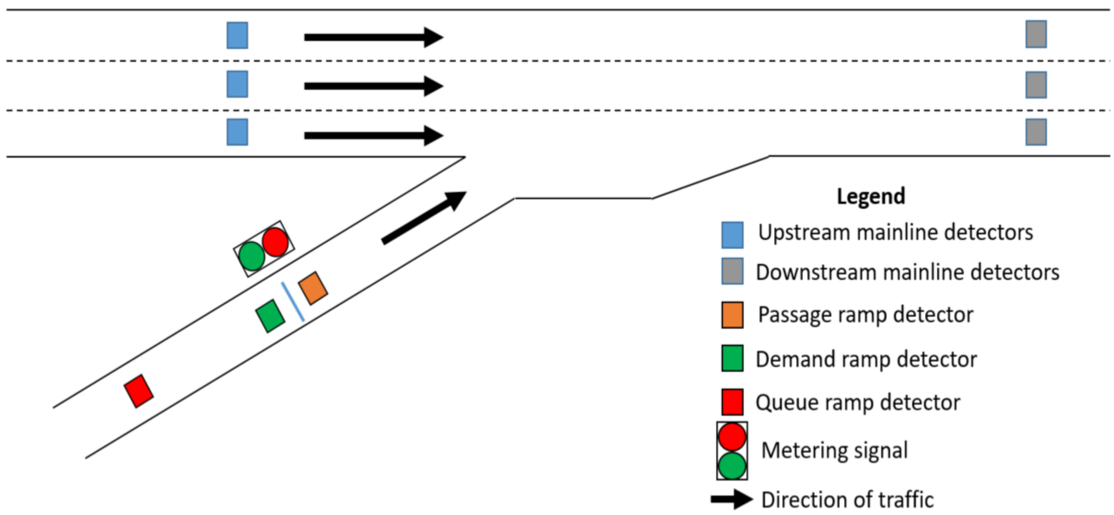


Figure 1-1: Schematic Diagram of Ramp Metering Configuration

Ramp metering is intended to improve mobility, reliability, safety, and the environment while preserving freeway capacity at a lower cost than traditional capacity improvement projects (Mizuta et al., 2014). Most agencies use ramp metering during recurrent congestion resulting from variations in traffic demand (Hallenbeck et al., 2003). In other cases, ramp metering is used to manage traffic during non-recurrent congestion due to unplanned temporary events, including traffic incidents and adverse weather conditions (Hallenbeck et al., 2003). Ramp metering helps relieve traffic congestion by keeping the freeway density close to, but below, the critical density value (Hadi et al., 2017, Mizuta et al., 2014). In addition to mobility benefits, ramp metering improves traffic safety by reducing the turbulence and speed variability associated with the risk of rear-end and sideswipe crashes in merging zones (Lee et al., 2006). By eliminating stop-and-go conditions, ramp metering reduces vehicle emissions and fuel consumption on the freeway mainline (Mizuta et al., 2014).

Several state and local agencies deploy ramp metering with the expectation of reducing congestion on urban freeways (Drakopoulos et al., 2004; Mizuta et al., 2014). Other agencies use the experience from the already deployed ramp metering systems to assess its effectiveness and viability for future implementation. However, there are conflicting opinions among stakeholders regarding the deployment of ramp metering signals (RMSs), despite their potential benefits (Cambridge Systematics Inc., 2001; Mizuta et al., 2014). Ramp metering improves freeway operations, but affects short trips involving motorists living in areas near the ramps by favoring through traffic and suburban traffic (Bertini et al., 2004). As a result, oftentimes the public opposes ramp metering due to long waiting times at the entrance ramps and the perceived lack of consistency between waiting times and level of freeway congestion (Cambridge Systematics Inc., 2001). Therefore, evaluating the benefits of ramp metering is critical to determine the effectiveness and support decision-making regarding ramp metering programs (Bertini et al., 2004). The estimated benefits can help agencies gain greater public acceptance, attract funding for ramp metering facility investments, and make changes to ramp metering operations (Jacobs Engineering Group Inc., 2013).

1.2 Problem Statement

Ramp metering is traditionally used to improve traffic conditions during recurrent congestion. Researchers have evaluated the benefits of ramp metering during recurrent congestion using several measures, including travel time, travel time reliability, traffic speed, and level of service (LOS). However, the extent of the impact of ramp metering on recurrent congestion varies across studies. Among reasons for the inconsistencies are the limitations of conventional methods for evaluating benefits, including the before-and-after approach, shutdown experiments, and traffic simulation (Ahn et al., 2007; Bertini et al., 2004; Cambridge Systematics Inc., 2001; Kansas Department of Transportation [KDOT] and Missouri Department of Transportation [MoDOT], 2011). The before-and-after approach involves measuring the performance of the freeway in the period prior to and following deployment of RMSs. One of the drawbacks of this approach is the failure to separate the effect of other changes implemented along the study corridors within the study period (Hauer, 2015). These changes may include, but not limited to, the deployment of different traffic management strategies (e.g., express lanes, dynamic message signs), construction works, and changes in the geometric characteristics.

Shutdown experiments involve the deliberate turning off of the RMSs for a certain period for data collection purposes (Bertini et al., 2004). However, shutdown experiments are prone to either underestimation or overestimation of benefits. The main reason being the behavioral changes in drivers following the deactivation of ramp signals increase the likelihood of traffic pattern change (Cambridge Systematics Inc., 2001). Moreover, only a few days of data are typically collected from the shutdown experiments because of the costs associated with turning off the RMSs (Ahn et al., 2007; Bertini et al., 2004). A few days of data, potentially affected by other factors, such as seasonal changes, are less likely to provide a complete and comprehensive understanding of the impact of ramp metering.

Traffic simulations, to an extent, can help avoid some of the challenges associated with the before-and-after approach and shutdown experiments. Traffic simulation allows controlling other factors that might influence traffic conditions, apart from ramp metering (Scariza, 2003). The simulation can include or exclude these factors (e.g., construction works, incidents) depending on the objective. The flexibility provided by traffic simulation allows placing detectors at any location of the study corridor (Scariza, 2003). However, the downside of traffic simulation is that it is difficult to mimic all of the actual field conditions and characteristics, which can lead to questionable accuracy (Hourdakis and Michalopoulos, 2007). The extent of the network also limits traffic simulation, and depending on the complexity of the simulation software, it can be time-consuming when trying to match the field conditions with the simulated network (Horowitz et al., 2004). Therefore, a different approach that addresses the aforementioned limitations could be used to estimate the benefits of ramp metering when there are constraints using the conventional methods.

In addition to relieving recurrent congestion, ramp metering has the potential of improving traffic conditions during non-recurrent congestion. Agencies have used or considered using ramp metering to reduce non-recurrent congestion due to traffic incidents and adverse weather (Fartash, 2017; Jacobs Engineering Group Inc., 2013; Zhu et al., 2010). However, depending on the agency's needs, varying criteria must be considered before activating ramp metering during non-recurrent congestion. Most agencies activate RMSs during unplanned events based on the operators' judgment (Fartash, 2017; Jacobs

Engineering Group Inc., 2013; Zhu et al., 2010). Other agencies consider the reduced freeway capacity as a result of the event (Hadi et al., 2017; Zhu et al., 2010). Even though few agencies use ramp metering during non-recurrent congestion, the associated benefits are not well recognized. As such, some agencies activate RMSs following a traffic incident, while other agencies require the signals to be deactivated right after a traffic incident occurs (Athey Creek Consultants, 2019; Zhu et al., 2010). Inconsistencies in the criteria for ramp metering activation during unplanned events make it challenging to evaluate the benefits of ramp metering during non-recurrent congestion. Moreover, the time-variant attributes of the unplanned events, such as traffic incident duration, also make it difficult to estimate the benefits of ramp metering during the non-recurrent congestion (Wang, 1994). Considering the potential of ramp metering in reducing non-recurrent congestion, it is essential to estimate the ramp metering benefits. Understanding the benefits of ramp metering during non-recurrent congestion may also help agencies establish criteria for activating the signals during non-recurrent congestion.

1.3 Research Goal and Objectives

The goal of this research is to estimate the mobility benefits of ramp metering on freeways. The traditional methods for evaluating the benefits include the before-and-after approach, shutdown experiment, and traffic simulation. As discussed in Section 1.2, the existing conventional methods used to estimate the mobility benefits of ramp metering are fraught with limitations and biases. This study therefore focuses on using the unintentional RMSs downtime to quantify the mobility benefits. Considering that each approach offers some advantages depending on the situation, the approach developed and adopted in this research complements the existing methods to quantify the benefits of ramp metering during recurrent congestion. Also, the study focuses on using high-resolution data to evaluate the effect of ramp metering in alleviating non-recurrent congestion. The impact of ramp metering during traffic conditions affected by crashes and adverse weather condition (e.g., rain) can help agencies justify activating RMSs to alleviate non-recurrent congestion. Therefore, the specific objectives of this research are:

- Estimate the effect of ramp metering during recurrent congestion.
- Evaluate the impact of ramp metering on non-recurrent congestion caused by crashes.
- Evaluate the impact of ramp metering on non-recurrent congestion due to rain.

1.4 Dissertation Organization

This dissertation is comprised of six chapters, organized as follows:

- Chapter 2 presents a comprehensive review of existing literature regarding the measures of the mobility benefits of ramp metering on freeways during recurrent and non-recurrent congestion. The chapter discusses the methods used to quantify the impact of ramp metering on traffic operations. It also describes the effects of traffic incidents and rain on traffic conditions.
- Chapter 3 explains the data used to achieve the study objectives. It describes the study area, data types, data sources, data collection, and data preparation.
- Chapter 4 discusses the methodologies adopted to achieve the study objectives. It describes in detail the study design and the statistical approaches applied in the study.

- Chapter 5 presents the analyses and discusses the results of the study. The benefits of ramp metering during recurrent and non-recurrent congestion are provided in this chapter.
- Chapter 6 concludes the dissertation by summarizing the contributions of this research and providing recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

The goal of this research is to quantify the mobility benefits of ramp metering during recurrent and non-recurrent congestion. This chapter presents a synthesis of previous studies on the operations and benefits of ramp metering. The effects of incidents and rain on the traffic conditions are also discussed. The chapter further discusses the methods used to estimate the benefits of ramp metering.

2.1 Ramp Metering Strategies

Ramp metering strategies differ depending on the infrastructure, constraints, and objectives of the deployment (Mizuta et al., 2014). The ramp metering strategies are classified by considering the extent, mode, activation strategy, and the algorithm of ramp metering control (Hadi, 2017).

2.1.1 Extent of Ramp Metering Control

The extent of ramp metering control is categorized into two broad groups depending on the number of ramps being monitored: local and system-wide (Hadi et al., 2017; Scariza, 2003). The local ramp metering is deployed on a single or an isolated ramp to improve the traffic conditions in the vicinity of that ramp (Mizuta et al., 2014; Scariza, 2003). The metering rate at the single ramp does account for the conditions at other upstream or downstream ramps (Scariza, 2003). The local ramp metering control utilizes detectors that are only located around the subject ramp and the corresponding freeway section (Kristelet, 2014).

The system-wide ramp metering involves deployment on multiple ramps along a segment or an area to improve the traffic conditions of an area (Scariza, 2003). The system-wide ramp metering considers other RMSs as a system in the estimation of the metering rates on each ramp (Scariza, 2003). The objective of the system-wide ramp metering is to optimize the rate of each ramp so as to improve the traffic conditions along the entire corridor (Mizuta et al., 2014). The system-wide ramp metering control uses traffic detectors located on the ramps and along the metered section. It is thus considered effective than the local ramp metering control (Fartash, 2017).

2.1.2 Mode of Ramp Metering Rate Selection

The ramp metering strategies are categorized into three groups based on the method of selecting the metering rate. These groups include static, adaptive, and proactive selection modes (Hadi et al., 2017). The static mode is based on the historical data assuming that traffic patterns along the freeway and the ramps do not change over time (Kristelet, 2014). Conversely, the adaptive mode selects the metering rate based on the prevailing traffic conditions on the ramp and the freeway mainline (Kristelet, 2014). The proactive model estimates the metering rate based on real-time data to prevent oversaturated conditions and traffic breakdown (Hadi et al., 2017).

2.1.3 Activation Strategies of Ramp Metering

The activation strategies of ramp metering include schedule, manual, and traffic responsive (Fartash, 2017). The schedule activation is based on a pre-determined fixed time (Simpson et al., 2013). The manual method involves an operator observing the traffic conditions on a closed-circuit television (CCTV) and activating based on their judgment

(Fartash, 2017). The traffic responsive strategy automatically activates ramp metering control based on the measurements of the existing or predicted traffic conditions (Fartash, 2017). The predicted traffic conditions are considered such that to prevent breakdown, congestion, or non-recurrent conditions caused by incidents or weather impacts (Fartash, 2017).

2.1.4 Algorithms of Ramp Metering Control

Ramp metering algorithms depend on the extent of ramp control. The algorithms for local ramp metering control include but are not limited to the demand-capacity algorithm, percent-occupancy algorithm, and the Asservissement Linéaire d'Entrée Autoroutière (ALINEA) algorithm (Fartash, 2017; Karim, 2015; Mizuta et al., 2014). The algorithms for the system-wide control include but are not limited to the Denver,Colorado Helper algorithm, Linked Ramp algorithm, FLOW algorithm, System-wide Adaptive Ramp Metering (SWARM) algorithm, Seattle Bottleneck algorithm, Model Predictive Control algorithm, and the Fuzzy Logic algorithm (Fartash, 2017; Karim, 2015; Mizuta et al., 2014). Table 2-1 summarizes ramp metering algorithms and the metering rate calculation methods.

2.2 Ramp Metering Benefits during Recurrent Congestion

Several studies estimated the mobility benefits of ramp metering on freeways. The mobility performance measures used in these studies include: travel time, travel time reliability, traffic speeds, traffic delays, LOS, traffic volume, and traffic throughput. The following sections discuss these measures in detail.

Table 2-1: Summary of Algorithms for Estimating Ramp Metering Rates

Algorithm	**Control Type**	**Metering Rate Calculation Method**
Demand-Capacity	Local	Based on: • Difference between upstream mainline flow and downstream capacity, or • Difference between upstream mainline occupancy and desired occupancy
Percent-Occupancy	Local	Based on the difference between upstream occupancy and occupancy at capacity
ALINEA	Local	Based on the difference between downstream freeway occupancy and desired occupancy
Denver, Colorado Helper	System-wide	Based on upstream occupancy of the critical ramp
Linked Ramp	System-wide	Based on the difference between upstream mainline flow and target flow
FLOW	System-wide	Calculates local and bottleneck metering rates and select the more restrictive • Local metering rate is based on occupancy • Bottleneck metering rate is based on ramp distance from the bottleneck and historical ramp volume
SWARM	System-wide	Calculates both local and system-wide metering rates and selects the more restrictive rate: • Local metering rate is based on upstream density • System-wide metering rate is based on the difference between real-time density and predefined threshold
Seattle Bottleneck	System-wide	Calculates both local and system-wide metering rates and selects the more restrictive rate: • Local metering rate is based on upstream occupancy • System-wide metering rate is based on the difference between the downstream volume and bottleneck capacity
Model Predictive Control	System-wide	Based on the optimization process of the objective function and predicted traffic parameters of predefined time
Fuzzy Logic	System-wide	Based on local speed, occupancy, flow, queue occupancy, downstream speed and predefined linguistic rules

2.2.1 Travel Time

Several studies have used travel time to quantify the mobility benefits of ramp metering (Cohen et al., 2017; Karim, 2015; KDOT and MoDOT, 2011). The travel time data along the study corridors were usually collected using the floating car technique or traffic detectors (Cambridge Systematics Inc., 2001; Cohen et al., 2017; KDOT and

MoDOT, 2011). The floating car technique (FCT) involves driving a vehicle within a traffic stream, passing as many vehicles as passed it and recording its travel time as the average condition of the segment (KDOT and MoDOT, 2011). On the other hand, traffic detectors include loop detectors and other sensors that utilize technologies such as Bluetooth or microwaves to collect traffic data.

KDOT and MoDOT (2011) collected travel time data using the FCT during the morning and afternoon peak periods on fourteen segments of I-435 in Kansas and Missouri. The travel times were collected in a one-year period before ramp meters were installed and in a two-year period after the ramp meters were operational. The traffic along the corridor experienced an increase in travel time for some segments and a decrease for others. Overall the segments experienced significant improvements in travel time during the morning peak periods. The improvements were considered as a net effect of segments that experienced shorter travel times and those experienced longer travel times (KDOT and MoDOT, 2011).

Karim (2015) used Verkehr In Städten – SIMulations (VISSIM) model, a microscopic simulation software, to explore the effectiveness of ramp metering on the average travel time of a 3000-ft freeway segment adjacent to the ramp as the measure of freeway efficiency. Karim (2015) found that ramp meters improved the efficiency of the freeway if the percentage decrease in the average travel time was at least 5%. Results suggested that ramp metering efficiency depended on the traffic volume on both the entrance ramp and freeway, RMS timing scenarios, and the geometric configuration of the entrance ramp. Overall, ramp metering was observed to be beneficial for a single lane entrance ramp during the peak periods or when the ramp traffic volume is ≥ 800 vehicles per hour per lane (vphpl), and the freeway traffic volume is ≥ 1,250 vphpl (Karim, 2015).

Travel times that were derived from loop detector measurements (i.e., flow, occupancy, and speed) on a 40-mile section of the A25 roadway linking Socx and Lille in France were used to quantify the impact of ramp metering (Cohen et al., 2017). The estimated travel times were validated based on the data collected using the FCT. Travel times were collected on weekdays during May, June, October, and November of 2015 when ramp meters were not operational, and for 11 days in February and March of 2016 when ramp meters were operational. Although data were collected for the entire day on each specified day, the analysis focused on the morning peak periods (6:30 AM to 10:30 AM). Descriptive statistics were used to compare the travel times, and results indicated that the average travel time when ramp meters were *activated* was 95 seconds less than the average travel time when *deactivated*.

2.2.2 Travel Time Reliability

Travel time reliability has recently been used by numerous agencies to assess transportation improvement deployments. Travel time reliability shows the consistency of travel time and reflect the user's experience in commuting (Kidando et al., 2019). Travel time reliability is preferred to average travel time due to the accuracy of predictable travel times although it requires extensive data collection (Cambridge Systematics Inc., 2001; Kidando et al., 2019). There is no single metric to measure the travel time reliability of a segment, and can be grouped into three major groups: variation metrics, probabilistic measures, and percentile index (Kidando et al., 2019). The variation metrics are mainly based on the measures of the central tendency in statistics, which include standard deviation, variance, mean, median, coefficient of variation, and kurtosis (Lomax et al., 2003). The probabilistic measures include misery index, congestion frequency, and percentage of on-time arrivals. The percentile index uses percentiles (e.g., 10^{th}, 50^{th}, 90^{th}, and 95^{th} percentile) of travel time distributions to estimate metrics such as buffer index, planning time index, travel time index, and the skew statistic (Lomax et al., 2003).

Cohen et al. (2017) used the variance of travel times as a reliability metric to show the impact of ramp metering on the A25 roadway connecting Socx to Lille in France during morning peak period (6:30 a.m. to 10:30 a.m.). The *F*-test was used to test the hypothesis of equal variances of travel time when ramp metering was *activated* and *deactivated*. Results indicated that travel time on segment varied more when ramp meters were *deactivated*. Levinson and Zhang (2006) analyzed the operations of freeways based on the standard deviation of travel time when ramp meters were *activated* and *deactivated* during the afternoon peak period. In the study, the standard deviation of travel time was estimated for two scenarios, inter-day and intra-day. The inter-day travel time variation was estimated from trips that were made across different days, while intra-day travel time variation was estimated from trips that occurred only on a specific day (Levinson and Zhang, 2006). Results indicated that inter-day travel time variability was reduced because of the operations of the ramp metering system. It was also observed that ramp metering significantly reduced the intra-day travel time reliability for long trips.

Xie et al. (2012) used conventional travel time reliability measures, including travel time index (TTI) and buffer index (BI). TTI is the ratio of actual travel time to the travel time under free-flow speed (FFS) or posted speed limit (PSL) conditions (Xie et al., 2012). The TTI shows the amount of extra time required to travel during the peak period relative to during free-flow conditions. Xie et al. (2012) calculated TTI as:

$$TTI = \frac{Actual\ travel\ time}{Travel\ time\ under\ FFS\ or\ PSL\ conditions} \tag{2-1}$$

Conversely, the BI represents the extra time needed to ensure on-time arrival in 95% of trips. The BI was calculated using:

$$BI = \frac{95th\ percentile\ travel\ time - \ Average\ travel\ time}{Average\ travel\ time} \tag{2-2}$$

The comparison between TTIs and BIs before and after activation of ramp metering indicated significant travel time reliability improvements in the study section. KDOT and MoDOT (2011) assessed the effectiveness of the ramp metering system using TTI as a reliability measure. The TTI for the freeway section was calculated using the weighted average of travel times using vehicle-miles-traveled (VMT). Results indicated that the TTIs before were greater than the TTIs after deployment of the RMSs, indicating more reliable travel times along the study corridor as a result of ramp metering.

2.2.3 Traffic Speed

Studies have used traffic speeds to show the impact of ramp metering on the operational performance of freeways. KDOT and MoDOT (2011) compared the traffic speeds on fourteen segments of I-435 in Kansas and Missouri before and after the ramp metering system became operational. Results indicated that traffic speeds increased for some sections of the study corridor. This improvement was observed during both morning and evening peak periods. Similarly, the evaluation of ramp metering benefits in the Twin Cities (Minneapolis – St. Paul), MN compared traffic speeds when ramp signals were *activated* and *deactivated* (Cambridge Systematics Inc., 2001). Results indicated an average 14% increase in the traffic speeds when RMSs were *activated* along all segments in the analysis. The most significant improvement in traffic speed (26%) was observed when going southbound on I-35E in St. Paul, MN. Hourdakis and Michalopoulos (2007) used traffic simulation to analyze ramp metering impact in the Twin Cities (Minneapolis – St. Paul), MN. Two sites were selected to represent the Twin Cities freeway network. Results indicated a 17% to 26% mainline speed improvement on the 12-mile section of the Trunk Highway 169. Also, an increase of 13% to 20% in the mainline speed on an 11-mile section along I-94.

Traffic speeds were used to show the benefits of the Fuzzy Logic algorithm before its large-scale implementation in Washington State (Trinh, 2000). Results indicated that ramp metering increased the traffic speed by 7 to 20 mph. Xie et al. (2012) used average speed, standard deviation of speed, and interquartile range of speed to show the impact of ramp metering along the study corridor that has high occupancy vehicle (HOV) lanes. Results indicated an increase in the average speeds, a decrease in the standard deviation of speeds, and a decrease in the interquartile speed range along the general-purpose lanes. The average speed of HOV lanes did not show significant improvements, but the standard deviation and the interquartile range were reduced.

2.2.4 Traffic Delays

The reduction in traffic delays show the benefits of the ramp metering operations on the freeway mainline. Traffic delay is defined as the excess travel time on a trip, facility, or freeway segment beyond what would occur in ideal conditions (Cambridge Systematics Inc., 2001; Sun et al., 2013). Sun et al. (2013) evaluated the effectiveness of ramp metering at work zones in Columbia, Missouri using traffic delays. This study used traffic simulation because the traffic demand observed on the mainline and ramps at the study locations was not consistently high enough for the ramp meters to have a sustained effect on mobility. The analyzed scenario involved a two-to-one lane work zone with an entrance ramp located upstream of the work zone. Three different traffic volumes (900 vph, 1,240 vph, and 1,754 vph) and two truck percentage levels (10% and 40%) were evaluated, and VISSIM models were developed for the five work zone scenarios for metered and unmetered ramp conditions. The models were calibrated using field data collected at the congested work zone sites. The total vehicular delay which considered the delay caused by both the mainline and ramp traffic, was used to measure the impact of ramp metering. Results suggested that ramp metering decreased traffic delays in work zones when traffic volume exceeded capacity. On average, a 24% decrease in delay with low truck percentage and a 19% decrease in delay with significant truck percentage conditions resulted from metering ramps near work zones operating above capacity. Ramp metering was not recommended for flows below capacity in work zones because it increased total delays.

2.2.5 Traffic Volume and Throughput

Cambridge Systematics Inc. (2001) estimated the impact of ramp metering operations on traffic volume. The study collected traffic volume data on selected freeways (I-494, I-94, I-35E, I-35W) in Twin Cities (Minneapolis – St. Paul), MN. The traffic volume data was collected during morning and afternoon peak periods when RMSs were *activated* and *deactivated* for five weeks each. An average of 9% reduction in the traffic volume along freeways was observed when ramp meters were turned off. It was presumed that the reduced traffic diverted to earlier or later times and to local streets that were not within the study area. Also, the freeway throughput during peak traffic conditions that were measured by VMT declined by 14% when ramp meters were turned off. The reduction was associated with the decrease in average speed, increase in speed variability, and poor merging conditions of ramp traffic when ramp signals were turned off. Mainline throughput calculated in terms of vehicle-hours-travelled (VHT) and VMT were used to assess the effectiveness of ramp metering on weekends (Bertini et al., 2004). The study estimated VHT and VMT on weekends when RMSs are *deactivated* and weekends when RMSs are *activated*. Results indicated a 5.8% increase in the VHT and a 0.7% increase in the VMT on Saturday due to ramp metering operations. Slight improvements on both VHT (1.8%) and VMT (1.0%) were observed as a result of ramp metering operations on Sunday.

2.2.6 Level of Service

The LOS for the freeway mainline is based on density and speed. In their study, Cohen et al. (2017) collected and used traffic flow, occupancy, and speed to estimate LOS. Additional data were also collected to give further insights into conditions with and without ramp metering. The data included incidents, planned construction work, and adverse weather conditions. LOS was estimated using fundamental traffic flow diagrams to assess the mobility improvements due to ramp metering operations and the combination of ramp metering and variable speed limit (VSL) (Cohen et al., 2017). The study reported insignificant changes but indicated that LOS gains are limited to the regulated section and have no impact on downstream sections.

2.3 Ramp Metering Benefits during Non-recurrent Congestion due to Incidents

Traffic incidents are a major cause of non-recurrent congestion (Waller et al., 2007). It is estimated that about 25% of non-recurrent congestion on the U.S. roadways could be attributed to traffic incidents (FHWA, 2017). Activation of ramp metering or adjustment of ramp metering rate could mitigate traffic congestion caused by incidents (Zhu et al., 2010). The goal of ramp treatment strategies is to improve traffic conditions on freeways rather than affecting the actual incident (Waller et al., 2007). It is therefore important to understand the effect of incidents on traffic conditions. Several studies have shown the impact of traffic incidents on traffic conditions using traffic delays and freeway capacity.

The extent of delays caused by incidents depend on the clearance duration and the prevailing traffic volume (Waller et al., 2007). Incidents with longer clearance duration or that occur during heavier traffic flow are expected to cause more delays. However, estimation of traffic delays is challenging because of the stochastic and dynamic nature of incidents and traffic conditions. Also, the spatial extent of incident delay is not static. Some incidents may form longer queues than others because of several incident-related factors, e.g., incident occurrence time, incident severity, and roadway facility type. However, studies have applied the deterministic and shock-wave methods, which assume static demand to estimate delays caused by incidents (Khattak et al., 2012; Morales, 1987; Sullivan, 1997).

As established in previous studies, incidents cause reduced freeway capacity (Addison et al., 2020; Fartash, 2017; Transportation Research Board, 2016). The Highway Capacity Manual (HCM) associated the capacity reduction with the incident severity (measured using number of lanes blocked) and the directional number of lanes in a facility. The capacity reduction ranged from 50% to 7%. Studies improved the capacity reduction estimates due to incidents by considering the time-variant characteristics of incidents such as arrival of incident responding agencies at the incident scene (Addison et al., 2020; Hadi et al., 2011).

Research on the impact of ramp metering on traffic conditions during traffic incidents is scarce despite its potential in reducing the effects of incidents. Relatively few agencies have used ramp metering to manage traffic during traffic incidents (Hadi et al., 2017; Zhu et al., 2010). Moreover, inconstancies in considerations for activating the RMSs during traffic incidents limit the estimation of the ramp metering benefits.

2.4 Ramp Metering Benefits during Non-recurrent Congestion due to Adverse Weather

Ramp metering could influence the traffic conditions affected by the adverse weather. The Florida's ramp metering standard operating guidelines suggest activating RMSs during rain if the average speed of at the adjacent detector on the freeway is lower than 45 mph (FDOT, 2020). Hadi (2017) explored the need to activate system-wide ramp metering during adverse weather using traffic simulation. It was observed that all RMSs in the study corridor needed to be *activated* during medium and heavy rain. Considering that ramp metering directly affect the traffic stream, it is important to understand the impact of adverse weather on traffic conditions.

Adverse weather conditions are known to affect traffic flow characteristics including speed, capacity, and travel time (Agarwal et al., 2005; Hranac et al., 2006). In order to take account for the effect of inclement weather on roadway facilities, the HCM provides speed adjustment factors for estimating LOS (Transportation Research Board, 2016). The provided factors are given in different categories of weather type such as rain, snow, and low visibility. Moreover, adjustment factors are differentiated in terms of the free flow speed of the given facility. For example, the speed adjustment factor for heavy rain ranges from 0.91 to 0.94 for facilities that have free flow speed of 75 mph and 55 mph, respectively. The heavy rain had the intensity greater than 0.25 in/h and medium rain as had the intensity between 0.10 and 0.25 in/h.

Rainy conditions were found to result in a 1.5 mph to 2.5 mph reduction in average speeds, and 2.5% to 10.7% reduction in average traffic demand (Angel et al., 2014). However, the effect of rain on traffic speeds on freeways differs with rain intensity and the level of congestion. A study in Florida observed a 6% and 12% decrease in speed during light rain and heavy rain conditions, respectively (Li et al., 2014). The light rain which was estimated to have the intensity of 0.0039 in/hr resulted in the decrease in free-flow speed ranging from 2% to 3% (Hranac et al., 2006). The speed at capacity was estimated to decrease by 8% to 10% in light rain (Hranac et al., 2006). Unrau and Andrey (2006) evaluated the effect of light rain volume-occupancy and speed-volume relationships. Results indicated that, during daytime rainfall, speeds were substantially reduced when traffic volume is high. Also, light rain during congested conditions was associated with reduced speeds but did not influence any changes in traffic volume. In addition to the intensity, the effect of rain on traffic speeds varies with vehicle classification. Rain resulted in a 3% reduction in the speed of heavy-duty vehicles and 5% decrease in the speed of light-duty vehicles (Rakha et al., 2012). Higher rain intensity up to 0.5 in/hr resulted to a

4.5% and 8.5% decrease in the speeds of the heavy-duty and light-duty vehicles, respectively (Rakha et al., 2012).

The HCM also provides capacity adjustment factors according to weather type and FFS for estimating the LOS (Transportation Research Board, 2016). The capacity adjustment factor for heavy rain ranges from 0.82 to 0.89 for facilities that have free flow speed of 75 mph and 55 mph respectively. Moreover, light rain (0.0039 in/hr) was estimated to reduce the capacity of a freeway by 10% to 11% but the capacity was not affected by the increasing rainfall intensity at the intensity range of 0 to 1.7 in/hr (Hranac et al., 2006). In their study, Agarwal et al. (2005) observed a statistically significant reduction in capacity of 5% - 10% and 10% - 17% for light and heavy rain condition, respectively.

2.5 Methods for Estimating Ramp Metering Benefits

Three major approaches have been applied to quantify the mobility benefits of ramp metering: before-and-after approach, shutdown experiment, and traffic simulation. The before-and-after approach involves analyzing the conditions of the facility in the period pre- and post-installation of the intervention, in this case, ramp metering. Shutdown experiment involves deliberate turning off the RMS over a certain period for data collection purposes. Traffic simulation involves the use of computer software to model the behavior of traffic systems and enable the analysis and evaluation of different scenarios in the system. The existing literature on these three methods for estimating the ramp metering benefits is discussed in the following sections.

2.5.1 Before-and-After Approach

The before-and-after approach is a frequently used approach to analyze the effectiveness of operational improvement strategies including ramp metering (Xie et al., 2012). Data collected prior to the RMSs becoming operational are compared to the data collected once the RMSs become operational. The difference between the data in the two periods is used to indicate the benefits or detriments of ramp metering. Trinh (2000) compared travel time and speed data collected manually by drivers before and after the start of nine ramp meters along I-405 in Bellevue, WA. The KDOT and MoDOT compared the travel time, speeds, and travel time reliability on a section of I-435 before and after operations of ramp metering (KDOT and MoDOT, 2011). The study collected data for a 12-month period after the ramp metering system became operational and for 24 months before the ramp metering system became operational. Horowitz et al. (2004) used data collected before and after deployment of seven ramp meters on the southbound of US 45 in Milwaukee County, WI. Data related to traffic flow were collected on six weekdays before deployment and six weekdays after deployment (Horowitz et al., 2004). Xie et al. (2012) evaluated the benefits of ramp meters by collecting data for two months before and after ramp meters were *activated* on US 95 in Las Vegas, NV (Xie et al., 2012). The analysis used metrics derived from the collected speed and travel time data along the corridor before and after the start of the ramp metering operations.

Despite its wide application, the before-and-after approach has some limitations. The before-and-after approach depends on the availability of data in both the before- and the after- periods. It is not feasible to adopt the before-and-after approach when the data before the ramp metering system became operational is not available. This is specific for cases where the ramp metering started operating when the corridor did not have the capability for real-time traffic data collection. Also, a before-and-after approach may not produce reliable results when the evaluation of ramp metering has to take place right after the ramp metering system became operational. The traffic conditions just after the ramp metering system became operational might not reflect the true impact because road users need time for acclimation to newly installed systems. The before-and-after approach is also associated with difficulties in separating the impact of other factors (e.g., construction works) that might influence the traffic conditions during the study period from the impact of ramp metering. In spite of these limitations, the before-and-after approach allows for a long study period as compared to the shutdown experiment. The study period in the before-and-after approach can range from weeks to years, thus providing a better representation of the impacts of ramp metering along a corridor over a long period.

2.5.2 Ramp Metering Shutdown Experiment

Several studies have used the shutdown experiment to estimate the mobility benefits of ramp metering. Data collected when ramp meters were deliberately turned off were compared with the data when ramp meters were turned on (Ahn et al., 2007; Bertini and Horowitz, 2008; Cambridge Systematics Inc., 2001; Levinson and Zhang, 2006). Cambridge Systematics Inc. (2001) collected data for five weeks when RMSs were turned off and when ramp meters were operational. Collecting data when RMSs were shutdown involved system-wide deactivation of the RMSs in Twin Cities (Minneapolis – St. Paul), MN for the 5-weeks period. Although all RMSs were *deactivated*, the study collected data from a few specific corridors in the area, which include I-494, I-94, I-35W, and I-35E.

Traffic data was also collected from specific adjacent arterials when ramp meters were *deactivated* and *activated* (Cambridge Systematics Inc., 2001).

Bertini et al. (2004) conducted a shutdown experiment to evaluate the effectiveness of weekend metering operations in Portland, OR. System-wide RMSs were turned off during one weekend for data collection. Data used for comparison was then collected on another weekend when RMSs were turned back on. The collected data include vehicle count, occupancy, and speed at each lane on the freeway mainline and ramp aggregated at 20-second intervals (Bertini et al., 2004). Similarly, Ahn et al. (2007) evaluated the effectiveness of SWARM as compared to a pre-timed system in Portland, OR. Data including vehicle counts, occupancy, and speed were collected for five days when the SWARM system was turned off and RMSs were operated using pre-timed rates. The comparison data was then collected in other five days when the SWARM system was operational (Ahn et al., 2007).

One advantage of the shutdown experiment is its flexibility when selecting the analysis period. Contrary to the before-and-after approach, the shutdown experiment is not constrained by the collection and availability of data in the period before the RMSs became operational. The shutdown experiment could be conducted at any time since the RMS became operational. Also, the shutdown experiment allows controlling of other factors that might influence the impact of ramp metering on traffic conditions by selecting a study period that is not affected by those factors. For example, the shutdown experiment could take place in a period without construction work along the study corridor. Despite its usefulness, the shutdown experiment is practical for a short study period (e.g., days, weeks, and months) and not feasible for a long study period (e.g., years). Other major drawbacks of shutdown experiments include high cost and time-consumed in getting consent from various stakeholders including traffic management agencies and road users to deliberately turn off the RMSs.

2.5.3 Traffic Simulation

Several studies have used traffic simulations to evaluate the benefits of ramp metering. Scariza (2003) used traffic simulation to compare the effectiveness of coordinated and local ramp metering algorithms. The algorithms were compared by testing different scenarios on the M27 Motorway network in Southampton, UK and on a generic network. The scenarios analyzed were based on variables including total demand, ramp spacing, the proportion of traffic using ramps, and traffic distribution among ramps. The study observed that ramp metering was only effective during high demand levels and the coordinated algorithms were more effective than local algorithms when the volume was extremely high (Scariza, 2003).

Horowitz et al. (2004) evaluated the impact of ramp metering using microscopic simulation software, Paramics. The analysis involved two simulations, one for the period before ramp metering operations and one for the period after the ramp metering system became operational. The comparison of the two simulations indicated better traffic conditions when ramp metering was operational (Horowitz et al., 2004). Although the simulations considered the delays at the meters and along the mainline, the analysis did not involve platoons originating from the upstream signalized intersections. Hourdakis and Michalopoulos (2007) used a simulation software AIMSUN to evaluate the ramp and freeway system benefits of ramp metering. The simulation models were developed for two testing sites selected from the freeway network in Twin Cities (Minneapolis – St. Paul), MN.

Karim (2015) used VISSIM to explore the effectiveness of ramp metering on the operational efficiency of the freeway. The study analyzed the impact of different geometric configurations of ramp-freeway junctions on the ramp metering operations. The study used the average speed in the ramp influence area and the average travel time on a 3000-ft freeway segment adjacent to the ramp as the measure of freeway efficiency. Karim (2015) considered that ramp meters improved the efficiency of the freeway if the percentage decrease in the average travel time was equal to or greater than 5%. Results suggested that ramp metering efficiency depended on the traffic volume on both the entrance ramp and freeway, signal timing scenarios, and the geometric configuration of the entrance ramp. For example, ramp metering was observed to be beneficial for a single lane entrance ramp during the peak periods or when the ramp traffic volume is ≥ 800 vphpl, and the freeway traffic volume is ≥ 1,250 vphpl.

Traffic simulation allows for the control of other factors that might influence the traffic conditions apart from ramp metering (Scariza, 2003). Traffic simulation can include or exclude these factors (e.g., construction works or incidents) depending on the objective of the study. The flexibility provided by traffic simulation allows placing detectors at any location of the study corridor (Scariza, 2003). The downside of traffic simulation, however, is it is difficult to mimic all of the actual field conditions and characteristics, which can lead to questionable accuracy (Hourdakis and Michalopoulos, 2007). Traffic simulation is also limited by the extent of the network and depending on the complexity of the simulation software, it can be time-consuming when trying to match the field conditions with the simulated network (Horowitz et al., 2004).

2.6 Summary

Estimation of the ramp metering benefits is crucial for agencies with the system in place and for those potentially looking to implement it to mitigate traffic congestion. Quantifying the benefits of ramp metering requires an understanding of the strategy, the state-of-practice evaluation of methodologies and measures of the benefits. Ramp metering can be implemented at a local or system-wide level. The local ramp metering is deployed on a single or an isolated ramp to improve the traffic conditions near the ramp while system-wide ramp metering involves deployment on multiple ramps along a segment or in an area. Apart from the extent, ramp metering is categorized into three groups based on the mode of selecting the metering rate including static, adaptive, and proactive. The static mode is based on the historical data, the adaptive mode selects the metering rate based on the prevailing traffic conditions, and the proactive model is based on real-time data to prevent oversaturated conditions and traffic breakdown. Moreover, activation of the ramp metering system is done using a schedule, manually, or automatically as a response to traffic conditions. The schedule activation is based on a pre-determined fixed time. The manual method involves an operator observing the traffic conditions and making changes accordingly, while the traffic responsive automatically activates ramp metering control based on existing or predicted traffic conditions.

The evaluation of ramp metering benefits during recurrent congestion has previously involved numerous measures. Table 2-2 summarizes the reviewed measures of the mobility benefits of ramp metering on the freeway mainline. Few studies explored the impact of ramp metering during non-recurrent congestion. Results indicated that ramp metering can improve traffic conditions during traffic incidents and rain.

Table 2-2: Measures of Mobility Benefits of Ramp Metering in Previous Studies

Measure	Reference	Findings
Travel Time	KDOT and MoDOT (2011)	Overall travel time improvements
	Cohen et al. (2017)	Average travel time 95 seconds less when RMSs were activated
Travel Time Reliability	Levinson and Zhang (2006)	Reduced travel time variability due to RMSs operations
	KDOT and MoDOT (2011)	Improved after RMSs operations
	Xie et al. (2012)	Improved after RMSs operations
	Cohen et al. (2017)	Varied more when RMSs deactivated
Traffic Speed	Trinh (2000)	7 to 20 mph increase in traffic speeds
	Cambridge Systematics Inc. (2001)	Average 14% traffic speeds increase in the study segments
	KDOT and MoDOT (2011)	Increased average traffic speeds on few segments
	Xie et al. (2012)	Increased traffic speeds on general purpose lanes (GPL)
Traffic Delays	Sun et al. (2013)	Decreased delays when traffic volume exceeded capacity
Traffic Volume/Throughput	Cambridge Systematics, Inc. (2001)	Average 9% reduction in traffic volume on freeways when RMSs were deactivated 14% decrease in VMT when RMSs were deactivated
	Bertini et al. (2004)	5.8% increase in VHT when RMSs were activated on a Saturday
		0.7% increase in VMT when RMSs were activated on a Saturday
LOS	Cohen et al. (2017)	Combination of ramp metering and variable speed improves LOS

Past research used the following three conventional approaches for quantifying the mobility benefits of ramp metering: before-and-after approach, the shutdown experiments, and traffic simulation. The before-and-after approach involves analyzing the conditions of the facility in the period prior to and following ramp meters becoming operational. Turn-off experiments involve deliberate shutting down of the ramp metering systems over a certain period for data collection purposes. Data collected when ramp meters are off are then compared with the traffic data when ramp meters are on. The traffic simulation involves the use of software to mimic the field conditions and change the status of ramp meters while collecting the simulation data. The collected data are then used to estimate the benefits of ramp metering. Table 2-3 summarizes the methods and their corresponding study period used to evaluate the mobility benefits of ramp metering in previous studies.

Table 2-3: Study Designs for Estimating the Mobility Benefits of Ramp Metering

Study design	Reference	Study period
Before-and-After Approach	Trinh (2000)	14 days before & 3 days after
	Neel and Gibbens (2001)	4-weeks before & 4-weeks after
	Horowitz et al.(2004)	6 weekdays before & 6 weekdays after
	KDOT and MoDOT (2011)	1-year period before & 2-year period after
	Xie et al. (2012)	2 months before & 2 months after
Shutdown Experiment	Cambridge Systematics, Inc. (2001)	5 weeks when off & 5 weeks when on
	Drakopoulos at al. (2004)	6 days when off & 6 days when off
	Bertini et al. (2004)	1 weekend when off and when on
	Levinson and Zhang (2006)	8 weeks when off & 8 weeks when on
	Zhang (2007)	3 months when off & 3 months when on
	Ahn et al. (2007)	5 days when off & 5 days when on
Traffic Simulation	Scariza (2003)	Not Applicable
	Horowitz et al.(2004)	
	Hourdakis and Michalopoulos (2007)	
	Sun et al. (2013)	
	Karim (2015)	

The conventional approaches have some limitations even though are widely applied when estimating ramp metering benefits. The before-and-after approach hinge on the availability of data in the before- and the after- periods and changes that may affect traffic during the study period. The shutdown experiment is associated with relatively shorter study periods and changes in the traffic pattern. Traffic simulation, is to some extent, difficult to mimic the field conditions depending on the complexity of the network. In spite of these limitations, the conventional approaches provided means to estimate the benefits of ramp metering on various situations based on resources available to the agencies.

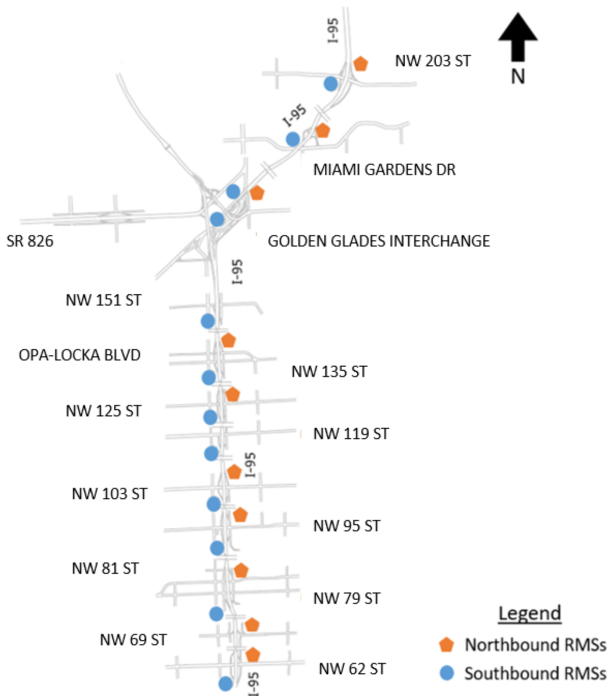
CHAPTER 3

DATA

This research has three main objectives: (1) estimate the effect of ramp metering during recurrent congestion; (2) evaluate the impact of ramp metering on non-recurrent congestion caused by crashes; and (3) evaluate the impact of ramp metering on non-recurrent congestion due to rain. This chapter discusses the study area and the data required to achieve the research objectives. The chapter is divided into three sections: study area, data requirements, and summary. The study corridor and ramp metering operations along the corridor are described in the Study Area section. The Data Requirements section discusses the types and sources of the data used in this research. The final section summarizes the data needs.

3.1 Study Area

A section along I-95 in Miami-Dade County, Florida was selected to estimate the mobility benefits of the ramp metering during recurrent and non-recurrent congestion. This approximately 10-mile section of I-95 has 22 RMSs stretching between Ives Dairy Road and NW 62nd Street in both travel directions. The RMSs along the corridor started operating in 2009 and are located at each of the 10 entrance ramps along I-95 northbound (NB) and 12 entrance ramps along I-95 southbound (SB) (Zhu et al., 2010). The ramp metering system along the corridor is operated and managed by the Florida Department of Transportation (FDOT) District Six office. The RMSs are *activated* during the morning peak period for the SB direction and the afternoon peak period for the NB direction. The morning peak period for this corridor is usually between 6:00 AM and 10:30 AM while the afternoon peak period is between 3:00 PM and 7:00 PM. However, the RMSs are not necessarily *activated* or *deactivated* at the same time. The RMSs in the study corridor are also used for traffic management during non-recurrent congestion due to crashes, adverse weather, and special events (e.g., Superbowl). Figure 3-1 shows the locations of the existing RMSs along the corridor.



Number	I-95 Direction	Location
1	Northbound	NW 62 Street
2		NW 69 Street
3		NW 79 Street
4		NW 95 Street
5		NW 103 Street
6		NW 125 Street
7		NW 135 Street
8		NW 2 Ave
9		Miami Gardens Drive
10		Ives Dairy Rd
11	Southbound	Ives Dairy Rd
12		Miami Gardens Drive
13		US 441
14		NW 167 Street
15		NW 151 Street
16		NW 135 Street
17		NW 125 Street
18		NW 119 Street
19		NW 103 Street
20		NW 95 Street
21		NW 79 Street
22		NW 62 Street

Figure 3-1: Location of Ramp Metering Signals along the Study Corridor

The number of ramp vehicles joining the freeway per given time for each ramp (i.e., ramp metering rates) on the corridor is estimated using the Washington Fuzzy Logic algorithm. This algorithm was developed by the Washington State and adopted by Florida for the ramp metering system in the study corridor (Fartash, 2017). The Fuzzy Logic algorithm is a system-wide control that is responsive to both local and corridor-wide real-time traffic conditions (Mizuta et al., 2014). The algorithm utilizes the traffic conditions upstream and downstream, and ramp queues in managing and controlling traffic on the freeway network. The Fuzzy Logic algorithm establishes the metering rates through a three-step procedure: fuzzification, activation of rules, defuzzification (i.e., generation of numerical rates). Fuzzification involves translating the numerical inputs of the segment traffic conditions, such as occupancy, into the fuzzy classes. The developed fuzzy classes are then associated with weighted rules to develop the metering rate and the degree of activation of each rule outcome. Finally, at the defuzzification stage, the developed metering rates that are represented by a set of linguistic fuzzy classes are converted to a single metering rate.

3.2 Data Requirements

The data required to achieve the research objectives include traffic data, incident data, ramp metering operations data, and contextual data. These data were collected for three years, from 2016 to 2018. The following subsections discuss in detail the data and their corresponding sources.

3.2.1 Traffic Data

The traffic data used in the analysis include speed, volume, occupancy, and travel time. Given the location of the study corridor, the main traffic data source was the Regional Integrated Transportation Information System (RITIS). 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 stores and disseminates data from several sources, including data vendors (e.g., HERE Technologies, INRIX, and TomTom) and detectors maintained by state’s transportation authorities (e.g., FDOT).

Traffic speed, volume, and occupancy data along the freeway mainline and ramps in the study corridor are available on RITIS. These data originate from detectors that are maintained by the FDOT District Six office. The data extracted from RITIS were aggregated in 5-minute intervals. The traffic detectors collect data from each lane of the freeway mainline. However, the traffic data from each lane in one location (called zone) is also aggregated to represent the overall condition at the location. This research extracted the zone traffic data on mainline detectors near the entrance ramps. The traffic data on the ramps was collected from detectors located downstream of the ramp signal's stop bar. The detectors located at this point are called passage detectors. The passage detectors collect data from vehicles entering the freeway mainline. The travel time data along the freeway were also obtained from RITIS. However, the collected travel time data originated from HERE Technologies. The travel time data were collected according to segments defined by the location of the entrance and exit ramps. Similar to other traffic data collected from RITIS, the travel time data were aggregated in 5-minute intervals.

3.2.2 Ramp Metering Operations Data

The ramp metering operations data were required to identify days and times when RMSs are *activated* and *deactivated*. The ramp metering operations data were collected from the FDOT District Six Regional Transportation Management Center (RTMC). The ramp metering operations data contained information, including operation date, RMS identification (ID), RMS activation time, RMS deactivation time, the reason for activating the RMS, and event identification (ID) in case the RMS was *activated* because of a traffic incident. The operation date indicates the day that an RMS was *activated*. Weekends and holidays are not included in the database because the RMSs in the study corridor operate only on typical weekdays. The data contains six reasons for activating RMSs, including recurrent congestion, non-recurrent congestion, incident, weather, central time of the day (CTOD), and local time of the day (LTOD). CTOD is when activation is by a fixed time that is set in the central controller of the ramp metering system at the RTMC. LTOD is when the controller in the field near the ramp meter activates the ramp metering system due to lack of communication or malfunction in the central controller.

3.2.3 Incident Data

The traffic incident data were required in the estimation of the ramp metering benefits during non-recurrent congestion. The traffic incident data were collected from SunGuide®, an Advanced Traffic Management System (ATMS) software used to process and archive incident data on Florida's transportation system. The SunGuide® incident database contains information related to incidents, including incident identification (ID), latitude and longitude of the incident, incident notification time, roadway clearance time, incident type, number and type of responding agencies, incident severity, and incident detection method.

The incident types included in the SunGuide® are crash, disabled vehicles, debris on roadway, emergency vehicles, police activity, etc. For this research, only crashes that were associated with lane blockage were included in the analysis. The lane blockage information was also obtained from the SunGuide® database. The lane blockage information specified the blockage type, including right-lane blocked, two right-lanes blocked, center-lane blocked, etc. Crashes that occurred on the ramps and those caused all lanes to be blocked were not included in the analysis. Details on the variables used in the analysis collected from the SunGuide® are provided in the next chapter (Section 4.2.3).

3.2.4 Weather Data

Weather data were extracted from the National Oceanic and Atmospheric Administration (NOAA) database. Specifically, the data were retrieved from the NOAA's Next Generation Weather Radar (NEXRAD), which detects precipitation and atmospheric movement using a network of 160 high-resolution Doppler radar sites at approximately 5-minute intervals from each site (Barr, 2015). The precipitation data are recorded as reflectivity, which is a measure of fractions of radiations reflected by a given surface expressed as a ratio of the radiant energy reflected and the total amount of energy incident on the surface (Andrew, 2019). The reflectivity data were extracted from a radar located in Miami, FL. The radar covers a 248.5-mile radius which includes the study corridor. The reflectivity data were retrieved at 5-minute intervals corresponding to the ramp metering operation hours of each RMS in the study corridor. The reflectivity values were converted to rainfall intensity using (Teegavarapu, 2012):

$$R = \left[\frac{10^{\frac{dBZ}{10}}}{250}\right]^{\frac{1}{1.2}} \tag{3-1}$$

where R is the rainfall intensity expressed in millimeters per hour (mm/hr), and dBZ is an abbreviation for decibel relative to reflectivity. The dBZ measures the strength of the energy reflected to the radar by the target surface, in this case, the roadway segment.

3.2.5 Contextual Data

The following contextual data were collected from Google Maps: the location of exit ramps, number of exit ramps, the location of entrance ramps, the distance between the entrance and exit ramps. This information was used to support the analysis. Some of the information from the contextual data were also used as variables in the analysis.

3.3 Summary

The objectives of this study are to: (1) estimate the effect of ramp metering during recurrent congestion; (2) evaluate the impact of ramp metering on non-recurrent congestion caused by crashes; and (3) evaluate the impact of ramp metering on non-recurrent congestion due to rain. The study was based on the 10-mile corridor with RMSs along I-95 in Miami, FL. Various data were collected to achieve the study objectives, including traffic data, ramp metering operations data, incident data, weather data, and contextual data. The data was collected for a three-year period from 2016 to 2018. Table 3-1 summarizes the data sources used to achieve the research objectives and sample of the available variables. The traffic data (i.e., speed, volume, occupancy, and travel time) were collected from RITIS, which is a repository of data from various sources including FDOT and data vendors, such as HERE Technologies. The traffic data aggregated in 5-minute intervals were collected from detectors on the freeway mainline and the entrance ramps.

The ramp metering operations data were obtained from the FDOT District 6 RTMC. The ramp metering operations data contained information about RMSs such as operations date, activation and deactivation time, and reason for activation. The data contained six reasons for activating RMSs, including recurrent congestion, non-recurrent congestion, incident, weather, CTOD, and LTOD. The traffic incident data were collected from SunGuide® database. Data extracted from SunGuide® database included incident type, location, extent of lane blockage, incident clearance time, incident type, number and type of responding agencies. Weather data aggregated at 5-minute intervals were retrieved from the NOAA's Next Generation Weather Radar (NEXRAD). The contextual data including the location of exit ramps, number of exit ramps, the location of entrance ramps, the distance between the entrance and exit ramps were collected from Google Maps to support data from other databases.

Table 3-1: Data Sources for Estimating the Mobility Benefits of Ramp Metering

Data	Source	Sample of available variables
Traffic data	RITIS	Volume
		Occupancy
		Speed
		Travel time
Ramp metering operations data	FDOT District Six RTMC	Days of operation
		Activation time
		Deactivation time
		Reason for activation
Incident data	SunGuide®	Incident notification time
		Incident clearance time
		Extent of lane blockage
		Incident location (longitude and latitude)
		Incident type
Weather data	NOAA	Rainfall intensity
Contextual data	Google Maps	Number of exit ramps
		Distance between entrance ramps
		Distance between exit ramps
		Location of entrance ramps
		Location of exit ramps

CHAPTER 4

METHODOLOGY

This research estimated the mobility benefits of ramp metering. Three specific objectives were identified to achieve the research goal: (1) estimating the effect of ramp metering during recurrent congestion; (2) evaluating the impact of ramp metering on non-recurrent congestion caused by crashes; and (3) evaluating the impact of ramp metering on non-recurrent congestion due to rain. This chapter presents the methodology and data preparation efforts used to achieve the research goal and objectives.

4.1 Estimation of Benefits of Ramp Metering during Recurrent Congestion

This section describes the methodology to quantify the mobility benefits of ramp metering during recurrent congestion using travel time reliability. The methodology is divided into the following four sections: the study design, estimating the travel time reliability, identifying factors influencing travel time reliability, and quantifying the effects of ramp metering on travel time reliability.

4.1.1 Study Design

The RMSs along the corridor are not *activated* or *deactivated* at the same time. Using the RMS operations data, consecutive RMSs with common activation times were grouped to segment the study corridor. As a result, the entire 10-mile study corridor was divided into six study segments. Figure 4-1 shows the segments along the study corridor defined using the common activation and deactivation times.

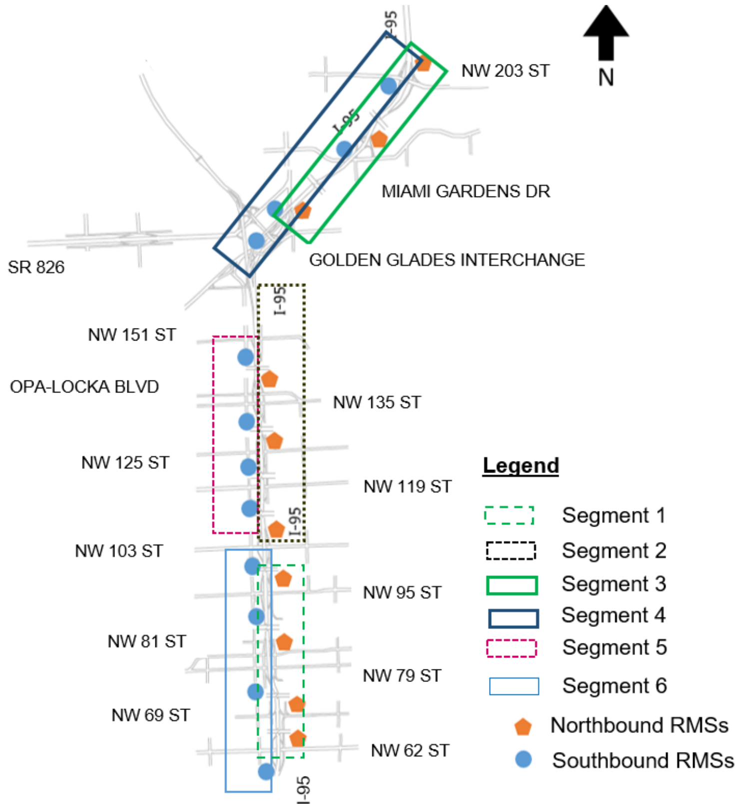


Figure 4-1: Segments along the Study Corridor (Adapted from Zhu et al. (2010))

Table 4-1 shows the most common times for activating and deactivating RMSs along each study segment, length of the segment, and number of entrance and exit ramps in the segment. Table 4-1 also shows the number of days that all RMSs on each segment were *activated*, and at least one of the RMS was *deactivated* during the common ramp metering hours.

Table 4-1: Characteristics of the Study Segments

Segment	Direction	Length (miles)	# of entrance ramps	# of exit ramps	Activation time	Deactivation time	# of days at least one RMS was deactivated in 3 years	# of days all RMSs were activated in 3 years
1	NB	2.6	4	3	2:45 PM	8:00 PM	296	74
2	NB	2.5	3	3	3:30 PM	8:00 PM	20	130
3	NB	5.3	3	3	*	*	*	*
4	SB	4.0	4	3	7:45 AM	8:00 AM	135	136
5	SB	3.0	4	2	6:30 AM	9:00 AM	52	108
6	SB	3.6	4	5	6:30 AM	10:00 AM	36	126

Note: # means number, * means there is no pattern for most common activation/deactivation times

There were very few days when all the RMSs along a segment were *deactivated*. Therefore, this research compared the BIs when all RMSs were *activated* with the BIs when at least one of the RMS was *deactivated*. Using Segment #1 as an example, the study used data collected on all days that RMSs on all four entrance ramps were *activated* between 2:45 PM and 8:00 PM and on days when at least one of the RMS was *deactivated* during the same 2:45 PM to 8:00 PM period. The analysis results hence provided the most conservative estimates of the mobility benefits of ramp metering. Note that the RMSs were *deactivated* for numerous reasons, including knock-down signal head events, controller failures, communication/fiber failures, power failures, and detector failures.

Holidays and days affected by Hurricane Irma in 2017 and Hurricane Michael in 2018 were excluded from the analysis, as well as days when RMSs were *activated* due to incidents or adverse weather. Segment #3 was excluded from the analysis due to an inconsistent operations time, while segment #4 was excluded because of a relatively short operational time. Segment #2 was also excluded from the analysis due to few RMS non-operational days (< 30 days). The remaining segments, i.e., segments #1, #5, and #6, as shown in Figure 4-2, were included in the analysis.

4.1.2 Estimate Travel Time Reliability

Several measures were previously used to measure the travel time reliability, including the buffer index (BI), travel time index (TTI), and planning time index. This research selected BI to measure the travel time reliability on the study segments. The BI was selected since it is one of the four travel time reliability measures recommended by the U.S. Department of Transportation (USDOT), and it can capture the variation of travel time at any time of the day (Texas Transportation Institute and Cambridge Systems Inc., 2017). The BI represents the percentage of extra time that travelers must add to their average time when planning trips to ensure on-time arrival at a given confidence interval (van Lint et al., 2008).

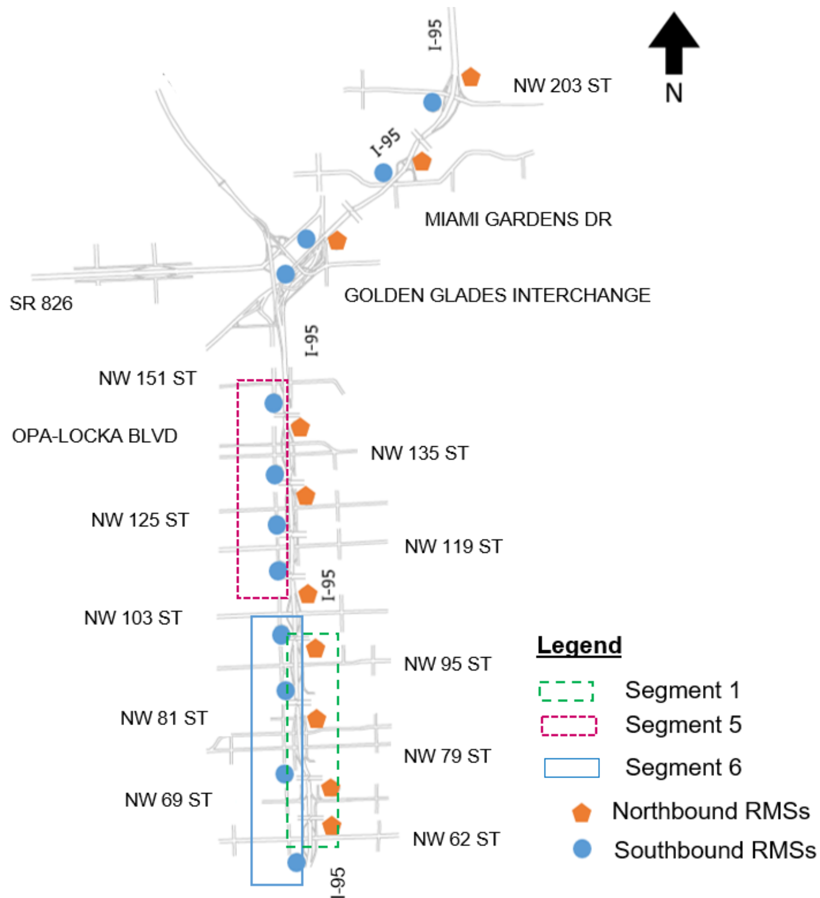


Figure 4-2: Selected Segments for Estimating the Benefits (Adapted from Zhu et al., 2010)

The BI was calculated as the ratio of the difference between the 95th percentile travel time and the average travel time to the average travel time using Equation 2-2 in Section 2.2.2. Travel time data, collected from HERE-Technologies, were used to estimate the BIs for each 5-minute interval typical RMSs' operational timeframe. For example, the average and 95th percentile of the travel times along segment #1 at 3:00 pm on each day from 2016 to 2018 were calculated. The average and 95th percentile of the travel times were then used as inputs in Equation 2-2 to estimate the BI along segment #1 at 3:00 pm. Therefore, each segment's number of observations was equal to the number of 5-minute intervals within the RMSs' operational timeframe.

4.1.3 Identify Relevant Variables

The following predictor variables were used in the model: RMS operational status (i.e., *activated* or *deactivated*), freeway mainline traffic speed, ramp traffic volume, density of entrance ramps, density of exit ramps, and mainline traffic congestion levels. The status of the RMS variable had two categories: *activated* (when RMSs are operational), and *deactivated* (when RMSs are not operational). The mainline traffic speed represented the study segment's three-year average traffic speed at the 5-minute intervals of the typical RMSs operational timeframe. Similar to mainline traffic speed, the ramp traffic volume was calculated by averaging the three-year ramp volume during the typical RMSs operational timeframe. The density of entrance ramps in a segment was computed as the number of entrance ramps per mile, while the density of exit ramps in segment was the number of exit ramps per mile.

The mainline traffic congestion levels were established based on traffic occupancy and volume data as in the previous study by Xu et al. (2012). The traffic occupancy and volume data used was the segment's three-year average at the 5-minute intervals of the typical RMSs operational timeframe. The *k*-means clustering analysis was used to categorize traffic congestion into groups. This method is a common approach used to separate data into subgroups by reducing the within-group distances and maximizing the distances between groups (Xu et al., 2012). The *k*-means clustering allocates each observation to a cluster with the nearest center point based on a pre-specified number (*k*) of clustering centers. The objective criterion of the *k*-means algorithm is the squared-error function in (Chu et al., 2012; Govender and Sivakumar, 2020; James et al., 2013):

$$J = \sum_{j=1}^{k} \sum_{i \epsilon C_j} \left\| X_i - c_j \right\|^2 \tag{4-1}$$

where

X_i	=	*i*th traffic flow observation,
c_j	=	*j*th cluster center,
k	=	number of clusters, and
C_j	=	object set of the *j*th cluster.

The symbol ‖.‖ denotes any vector norm representing the distance between the traffic flow observation and the cluster center. The *k*-means algorithm is applied following three main steps. First, the algorithm chooses *k* objects as initial cluster centers. Then, each observation is assigned to the cluster with the nearest center. Finally, the centers of the new clusters are established after calculating the mean of all observations in each cluster. The last two steps are repeated until the criterion function does not change after iteration.

The *k*-means clustering was conducted iteratively by setting the number of clusters from 2 to 12. The silhouette index, which is one of the indices to determine the optimal number of clusters in a dataset, was used to determine the number of clusters. The silhouette index combines information about within-cluster and between-cluster variation (Charrad et al., 2014; Rousseeuw, 1987). It was observed that the optimal number of clusters was two. Figure 4-3 shows the clusters identified using *k*-means algorithm, which were defined as moderate and severe congestion.

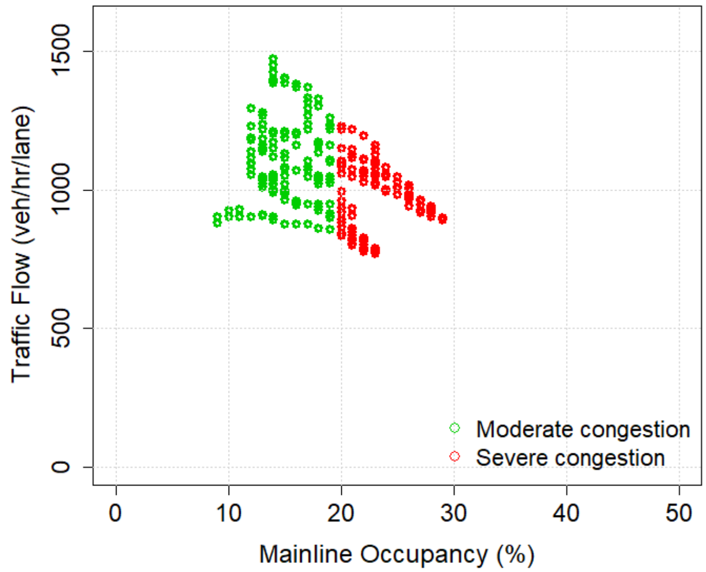


Figure 4-3: Traffic Congestion Levels during the Analysis Period

Multicollinearity between variables was assessed to avoid two or more predictor variables that are linearly related in a statistical model. Multicollinearity can increase the variance of regression coefficients leading to unstable estimation of parameter values. Multicollinearity was assessed using the Pearson correlation coefficient between each pair of predictor variables. A correlation threshold of 0.6 was used to identify highly correlated variables (Kwak and Kho, 2016). The pairs of mainline traffic speed, ramp traffic volume, and congestion levels variables had a correlation coefficient greater than 0.6. Similar to Shi et al. (2020) and Wang et al. (2019) the penalized regression model was used to account for the existing multicollinearity between the predictor variables. The penalty term in the penalized regression models forces the coefficients of redundant predictors to shrink towards zero, or set them to zero, hence addressing multicollinearity (Hastie et al., 2015; James et al., 2013; Shi et al., 2020; Tibshirani, 1996; Wang et al., 2019).

4.1.4 Identify Factors Influencing Travel Time Reliability

Penalized regression models were used to identify factors that could influence the BIs along the study corridor. The model was also used to predict BIs of the freeway mainline segment when RMSs are *activated* and *deactivated*. These models were selected due to their relatively high accuracy in cases with small sample sizes and the presence of correlated variables (Hui and Trevor, 2005; James et al., 2013). Penalized regression methods regularize (i.e., constrain) regression coefficients to enhance prediction accuracy and interpretability of a model (James et al., 2013). The imposed regularization allows the less contributive variables to have a coefficient close to or equal to zero (Kassambara, 2017), thus identifying the most influential variables. Two of the most common penalized regression methods are the ridge regression and the Least Absolute Shrinkage and Selection Operator (LASSO) regression (Kassambara, 2017). Two models were developed using these two penalized regression methods (i.e., ridge regression and LASSO regression), and the model with the best prediction accuracy was selected for predicting the BIs along the freeway mainline.

Given that the BIs are on a continuous scale, the relationship between BIs and the predictor variables was established using:

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

where

y_i = response (BI) for observation i,

β_o = constant term,

β_j = estimated model coefficients,

x_{ij} = vector of predictors *j* for observation *i*, and

ε_i = error term.

The penalized methods (ridge regression and LASSO regression) were introduced in the estimation of the coefficients β_j of the linear regression. Ridge regression coefficient estimates are the values that minimize:

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

where

λ = tuning parameter ($\lambda \geq 0$),

n = number of observations,

p = number of predictors, and

RSS = residual sum of squares.

Other variables are as defined in Equation 4-2. Ridge regression shrinks close to zero the coefficients of variables with only a minor contribution to the response variable (Kassambara, 2017). Although ridge regression shrinks coefficients towards zero it does not set the coefficients exactly to zero. The LASSO regression is an alternative that achieves variable selection by setting coefficients exactly to zero and accounts for the existing multicollinearity between variables.

The LASSO coefficient estimates are the values that minimize:

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

where all variables are as defined in Equation 4-2 and 4-3. As λ increases, the elements of β_j are continuously reduced towards zero, such that some elements will be reduced to zero and automatically deleted. Both models were developed using the BIs of the study segments as the response variable. The penalized regression models were developed using the GLMNET package in *R* (Jerome et al., 2018).

4.1.5 Quantify the Effects of Ramp Metering on Travel Time Reliability

Cross-validation was used to test the prediction accuracy of the models. Data were divided into training and testing datasets. About 80% of the data was used as the training dataset to fit the models, and the remaining 20% of the data was used for model testing. The training and testing dataset observations were selected randomly. The Root Mean Squared Errors (RMSE) between the predicted and the observed BIs from the testing dataset were used to measure the prediction accuracy of the models. A penalized regression model with better accuracy was used to predict the BIs using a fraction of the data that was not used to fit the model. The predicted BIs were used to estimate the benefits of ramp metering. The BIs were predicted The benefits of ramp metering were calculated as:

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

where $\hat{y}_{o,i}$ is the predicted BI of the *i*th 5-minute time interval assuming the RMSs are *activated*, and $\hat{y}_i$ is the BI of the i^{th} 5-minute interval assuming that RMSs are *deactivated*. The overall mobility benefits of ramp metering were calculated as:

$$Overall\ mobility\ benefits = \frac{\sum_i^n Mobility\ benefits}{n} \tag{4-6}$$

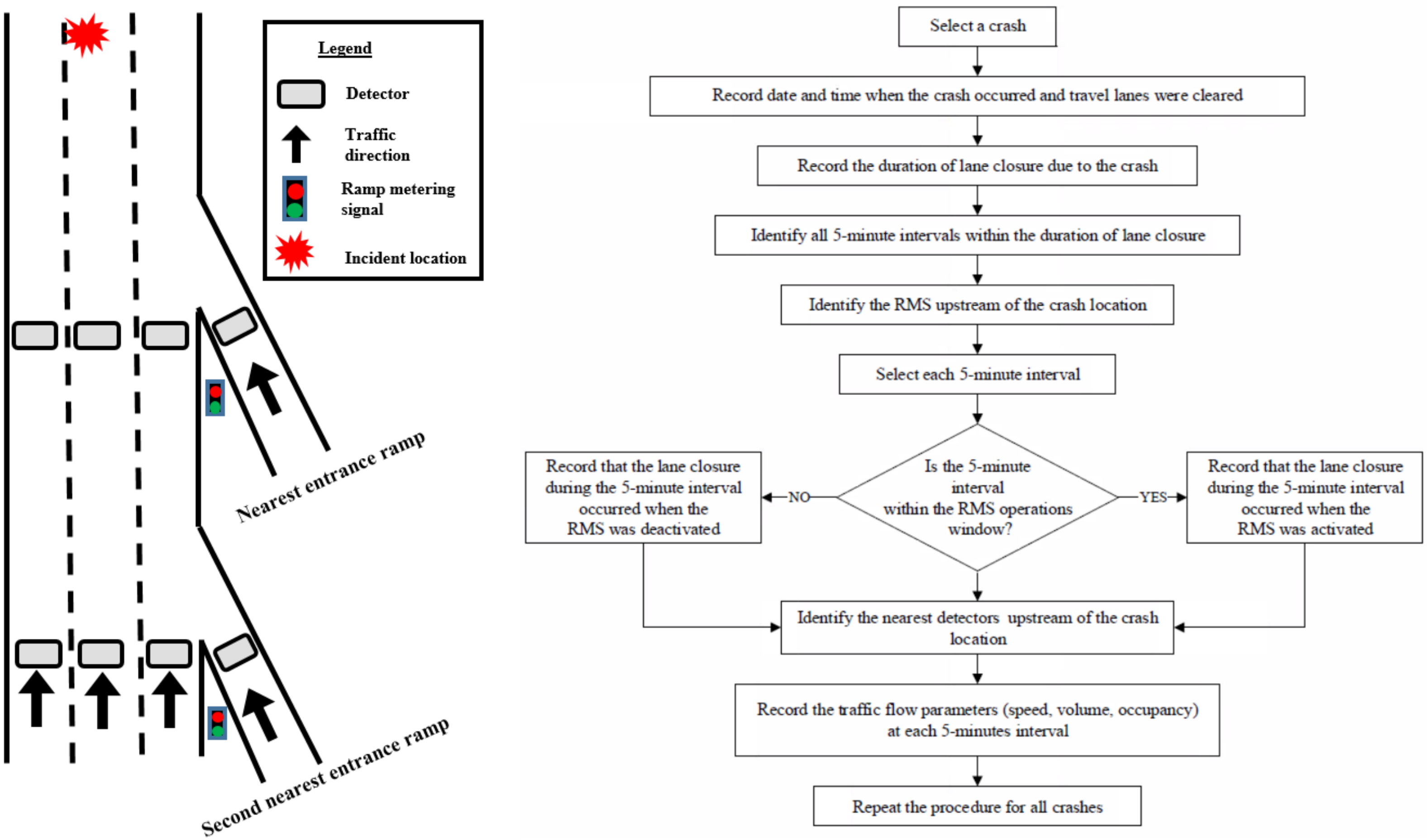
using the estimated benefits from the *i*th to the *n*th 5-minute interval.

4.2 Estimation of Benefits during Non-recurrent Congestion due to Crashes

This section describes the methodology to quantify the mobility benefits of ramp metering during non-recurrent congestion due to crashes. The methodology is divided into the following three sections: associating traffic flow parameters with the crashes, establishing traffic states upstream of the crash location, identifying factors affecting the traffic conditions upstream of the crash location. The following sections discuss the adopted methodology in detail.

4.2.1 Associate Crashes with Ramp Metering and Traffic Flow Parameters

Crash data were used to associate the lane closures with the ramp metering operations and traffic flow conditions upstream of the crash location. Traffic detectors and RMSs upstream of the crash location were identified, as shown in Figure 4-4(a) of a typical crash location along the study corridor. The 5-minute intervals traffic data were then collected from the nearest detectors upstream of the crash location. Instead of using the lane-wise data, the traffic data aggregated in a zone was collected from RITIS. Figure 4-4(b) summarizes the process used to associate the traffic flow parameters upstream of the crash location with RMSs operations. For each crash, the time and date of occurrence, the time when lanes are closed, and the time when lanes are cleared were recorded. This information was then associated with the RMS operations data to check whether the two nearest upstream RMSs were *activated* or *deactivated* during the lane closures. It is worth noting that all crashes that occurred on holidays, on weekends, and during Hurricane Irma in 2017 and Hurricane Michael in 2018 were excluded from the analysis.



(a) Typical Crash Location Scenario (b) Procedure for Associating Traffic Flow Parameters with Crashes

Figure 4-4: Summary of Data Processing

4.2.2 Establish Traffic States Upstream of the Crash Location

The data collected using the procedure described in Section 4.2.1 included three traffic flow parameters: volume, speed, and occupancy. This research used traffic occupancy and speed to establish traffic states upstream of the crash location. Traffic occupancy was used instead of density since density cannot be directly measured from detectors. The *k*-means clustering method was applied to the traffic flow data (speed and occupancy) collected at every five minutes that lanes were closed to establish the traffic states. The *k*-means clustering described in Section 4.1.3 was used to categorize the traffic flow observations (speed and occupancy). The *k*-means clustering was conducted iteratively by setting the number of clusters from 3 to 15. The minimum number of considered clusters was based on the assumption that traffic flow commonly consists of three states: uncongested, transition, and congested. The silhouette index was used to select the optimum number of clusters.

4.2.3 Identify Variables Affecting Traffic States Upstream of the Crash Location

The main variables of the models were related to the operations of RMSs upstream of the crash location. Other model variables were associated with traffic incident management, including the number of responding agencies, the involvement of fire rescue, the involvement of towing services, lane blockage, type of lane closure, and the detection method. The RMS variables had two categories: whether RMSs are *activated* or *deactivated*. The number of responding agencies was a continuous variable. The fire rescue and towing service involvement variables had two categories indicating whether or not the services were required. The lane blockage was estimated by dividing the number of closed lanes by the available lanes at the crash location. The lane blockage variable had two groups, the percentage of lane blockage ≤ 33% and percentage of lane blockage > 33%. The type of closed lanes indicated whether the closed lanes were on the right, left, or center of the freeway. The detection method was categorized into off-site and on-site detection. Off-site detection methods included CCTVs and Waze, while the on-site detection methods included Road Rangers and Florida Highway Patrol (FHP).

4.2.4 Identify Factors Influencing Traffic Conditions Upstream of the Crash Location

Based on the number of observations in clusters, the generalized ordered logit model (GOLM) or the logistic regression model was applied to identify factors that could affect traffic conditions upstream of the crash location. The GOLM is one of the ordered probability models which include other models such as the Proportional-Odds Ordered Model (POOM) and the Partial Proportional-Odds Ordered Model (PPOM). The GOLM was preferred to the other models because it assumes that none of the variables is constrained by the proportional-odds assumption that all variables had the same effect when comparing the medium class (i.e., *transition state*) with the low class (i.e., *uncongested state*) and when comparing the high class (i.e., *congested state*) with medium class (i.e., *transition state*). The GOLM was derived by defining an unobserved latent variable U as a linear function for each observation such that:

$$U = \beta X + \varepsilon \tag{4-7}$$

where

X = vector of independent variables determining a discrete ordering for each observation,

β = vector of estimable parameters, and

ε = random disturbance.

The observed traffic state y for each observation was defined using:

$$
\begin{aligned}
&y_1 = 1 \text{ (Uncongested state)} && \text{if } U \leq \mu_1 \\
&y_2 = 2 \text{ (Transition state)} && \text{if } \mu_1 < U \leq \mu_2 \\
&y_3 = 3 \text{ (Congested state)} && \text{if } U > \mu_2
\end{aligned}
\tag{4-8}
$$

where μ_1 and μ_2 are estimable thresholds that define y_1, y_2, and y_3. The study used the logit link function to fit the model. The probability of assigning an observation to traffic state in the GOLM was calculated as (Pour-Rouholamin and Zhou, 2016):

$$P(y_i > j) = \frac{\exp(X_i\beta_j - \mu_j)}{1 + \exp(X_i\beta_j - \mu_j)} \qquad j = 1, \ldots, J - 1 \tag{4-9}$$

where

y_i = traffic state of observation i,

j = traffic state level (1 = *uncongested*, 2 = *transition*, or 3 = *congested*),

J = number of traffic states (in this case J = 3),

X_i = vector of explanatory variables for observation i,

β_j = vector of parameter estimates that vary across equations for different traffic states,

μ_j = cutoff term for the thresholds defining traffic state j in the model.

Results of the GOLM were interpreted using the odds ratio (OR). An odds ratio was calculated as the exponential of the estimated mean β, exp (β). An odds ratio of 1.0 indicates a variable with no effect on the highest class (i.e., congested state). An odds ratio greater than 1.0 indicates that a change from the base level to another for the studied categorical variable would increase the odds of the highest class by 100(OR – 1) %. An odds ratio less than 1.0 indicates that a change from the base level to another for the studied categorical variable would decrease the odds of the highest class by 100(OR – 1) %.

The logistic regression model was developed to analyze the effect of variables between two traffic states. Logistic regression is a widely applied method for analyzing binary classification problems (Kitali et al., 2019; Xu et al., 2013). The response variable of the logistic regression has two classes: 0 or 1. The probability of classifying the observation *i* in class 1 is estimated as:

$$\pi_i = \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)} \tag{4-10}$$

where

x_i^T = *i*th explanatory variable vector-matrix transpose,

β = vector of unknown coefficients.

The parameters of Equation 4-10 were estimated using the log-likelihood function:

$$\ell(\beta) = \sum_{i=1}^{n} \{y_i \log(\pi_i) + (1 - y_i) \log(1 - \pi_i)\} \tag{4-11}$$

where

n = number of observations,

y_i = response variable for observation *i*, and

π_i = probability of classifying the observation *i* in class 1.

Other variables are as defined in Equation 4-10.

4.3 Estimation of Benefits during Non-recurrent Congestion due to Rain

This section describes the methodology to quantify the mobility benefits of ramp metering during non-recurrent congestion due to rain. The methodology is divided into the following three sections: associating rain with ramp metering and traffic flow parameters, establishing traffic states near the RMSs, identifying factors affecting the traffic conditions near the RMSs during rainy conditions. The following sections discuss the adopted methodology in detail.

4.3.1 Associate Rain with Ramp Metering and Traffic Flow Parameters

Rain data collected from the NOAA database were associated with the ramp metering operations and traffic flow parameters. Given that the rain data is collected in a raster format, three polygons were defined on the study corridor for data collection. The data was extracted from the polygons and was then converted to rain intensity using the formula defined in Section 3.2.4. The rain data for each time was then associated with the time when RMSs within the polygon were *activated* and *deactivated*. It was also associated with the 5-min interval traffic flow parameters from the detectors within the polygons that a located adjacent, upstream, and downstream of the entrance ramp with RMS. The traffic incident data was used to identify and exclude traffic flow observations that were affected by crashes. All observations that coincided with the lane closures near the detector were identified using the crash notification time and when travel lanes were cleared. The remaining observations were then used to establish traffic states.

4.3.2 Establish Traffic States Downstream of the Entrance Ramp

The data collected using the procedure described in Section 4.2.1 included three traffic flow parameters: volume, speed, and occupancy. This research used traffic occupancy and speed to establish traffic states downstream of the entrance ramp with RMSs. The procedure for establishing the traffic states was similar to that described in Section 4.2.2.

4.3.3 Identify Factors Influencing Traffic Conditions during Rainy Conditions

Based on the number of observations in clusters, the GOLM and the logistic regression described in Section 4.2.4 were applied to identify factors that could affect traffic conditions downstream of the entrance ramps during rainy conditions. The logistic regression was fit using the bootstrap resampling method due to the imbalance in the observations in the categories of the target variables. For example, significantly fewer observations when RMSs are *activated* during off-peak periods. Bootstrap resampling involves estimating parameters and standard errors by repeatedly and randomly sampling subsets of data from the original dataset to reduce bias caused by imbalanced data in parameter and standard errors of a model's estimates (Pei et al., 2016).

In this study, observations were divided into two datasets. The first dataset was the major dataset as it contained the majority of the observations. The second dataset was the minor dataset containing relatively fewer observations. Then, a sample of observations that amount to the number of observations in the minor dataset was randomly drawn from the major dataset in each replication. The subset was then joined with the minor group to form a balanced dataset that was used to fit a logistic regression model. The procedure of drawing samples of observations from the majority group was repeated 10,000 times, and the variables' estimates of logistic regression in each replication were recorded. The number of repetitions (i.e., 10,000) was arbitrarily selected as an optimum number to measure consistent parameters while balancing the computation time. The model results of were interpreted using the odds ratio (OR) as described in Section 4.2.4.

The main variables of the models were the operations of the nearest and the second nearest RMSs upstream of the entrance ramp. The rain category was the other variable included in the model. The rain categories were defined according to the HCM. The light rain had an intensity > 0 in/hr but ≤ 0.10 in/hr. The medium rain had an intensity > 0.10 in/hr and ≤ 0.25 in/hr. The heavy rain had an intensity > 0.25 in/hr.

4.4 Summary

This chapter described the approach used to estimate the effect of ramp metering during recurrent congestion and non-recurrent congestion due to crashes and rain. The incident data from SunGuide®, the RMS operations data from FDOT District Six, the traffic flow data from RITIS, and the contextual data from Google Maps were used to accomplish the research goal. The approach used the data collected when RMSs are *activated* and when they are *deactivated* due to unplanned events, including controller failures, communication failures, fiber failures, power failures, or detector failures.

The benefits during recurrent congestion were measured using BIs along the study segments when the RMSs are *activated* and *deactivated*. Two penalized regression methods, ridge and LASSO regressions, were used to identify factors that could predict the BIs of freeway segments with RMSs. The regression models evaluated the impact of various factors, including ramp metering operations, freeway mainline congestion levels, freeway mainline traffic speed, ramp traffic volume, and density of entrance and exit ramps. The mobility benefits were calculated as the ratio of the predicted BIs when RMSs are *activated* to when they are *deactivated*.

The study extracted traffic flow parameters (i.e., speed and occupancy) during lane closures due to crashes and used *k*-means clustering to identify the three traffic states (i.e., *uncongested, transition,* and *congested*) upstream of crash locations. A GOLM and logistic regression were then applied to identify and estimate the impact of RMSs operations and other factors on the traffic states during lane closures. The study focused on the operations of the two nearest RMSs upstream of the crash location. Two GOLMs were developed: for crashes that occurred during daytime off-peak periods and for crashes during peak periods. Logistic regression was used to evaluate the effect of RMSs on traffic conditions upstream of the crash location during the nighttime off-peak periods.

The benefits of ramp metering during rain were estimated by collecting traffic data downstream of the entrance ramps when it was raining. The *k*-means clustering was applied on speed and occupancy to group observations into different traffic states. The GOLM and logistic regression were applied to estimate the impact of ramp metering on traffic conditions affected by rain. The study focused on the operations of the two nearest RMSs upstream of the entrance ramp. The impact of rain intensity on the traffic conditions was also considered in the analysis. A bootstrap resampling method was used to account for the imbalance in the number of observations when RMSs are *activated* or *deactivated* during rain. The analysis was conducted considering the time-of-day: daytime off-peak periods, nighttime off-peak periods, and peak periods.

CHAPTER 5

RESULTS AND DISCUSSION

This chapter is divided into three major sections. The first section presents the analyses, results, and discussion of the benefits of ramp metering during recurrent congestion. The second and third section discuss the benefits of ramp metering during non-recurrent congestion due to crashes and rain, respectively. The final section provides a summary of the research findings.

5.1 Benefits of Ramp Metering during Recurrent Congestion

The first objective of this research was achieved by evaluating the effect of ramp metering on travel time reliability during recurrent congestion. The study corridor was divided into segments based on the time when consecutive RMSs are *activated* and *deactivated*. Travel time reliability, measured using BIs, was estimated for each segment using data collected over three years (i.e., 2016 – 2018). The penalized regression models were then used to evaluate the effect of ramp metering and other factors on the travel time reliability along the freeway segments. The following sections discuss the results in detail.

5.1.1 Descriptive Summary of the Analysis Variables

Travel time data collected on days that RMSs are *activated* and *deactivated* were used to estimate the BIs for every five minutes during the typical RMSs' operational timeframe. The number of estimated BIs in each segment was therefore equal to the number of 5-minute intervals within the operational RMSs timeframe. The average mainline speed and ramp volume over the three-year study period corresponding to the 5-minute BIs were calculated. Table 5-1 presents the descriptive statistics of the BIs and other variables (i.e., mainline speed and ramp volume) included in the analysis when the RMSs are *activated* and *deactivated*. The average, minimum, and maximum BIs when RMSs are *activated* were 0.385, 0.149, and 0.825, respectively. When the RMSs are *activated*, the mainline speed was ranging between 16 mph and 49 mph, with an average of 30 mph. Also, the entrance ramp volume was ranging from 18 vehicles/5 minutes to 49 vehicles/ 5 minutes.

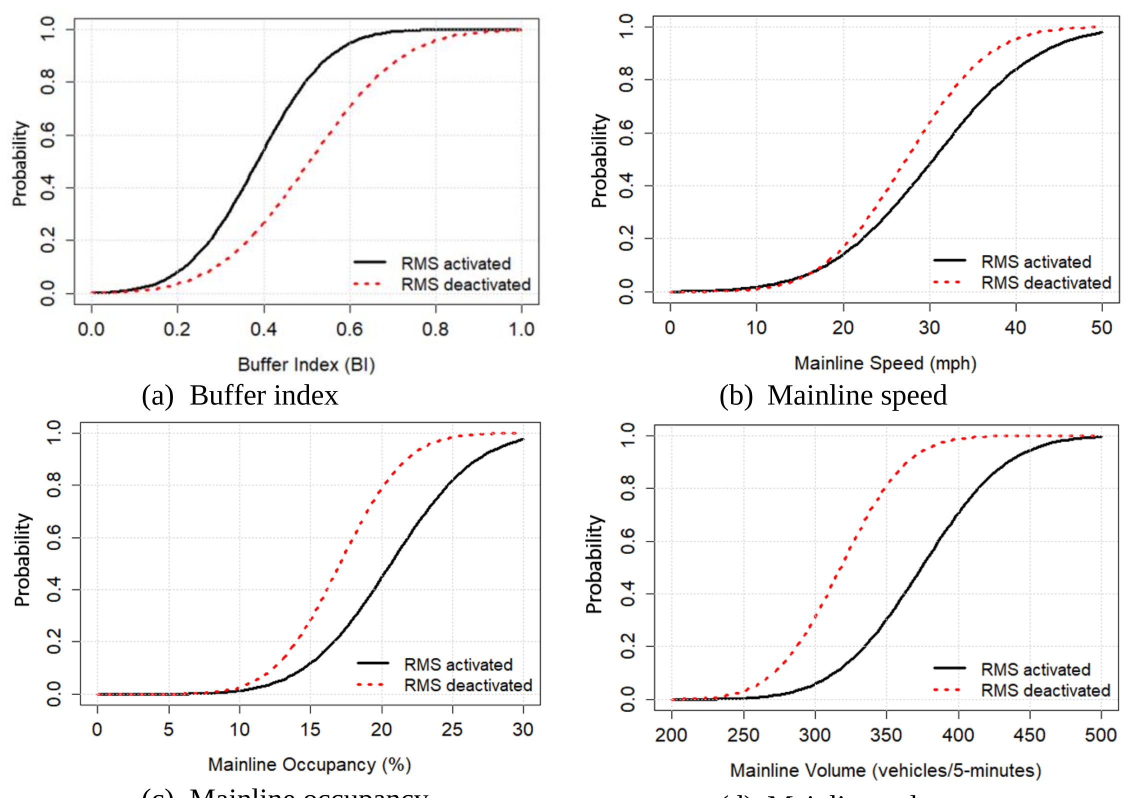
The average entrance ramp volume when the RMSs are *activated* was 31 vehicles/5 minutes. When the RMSs are *deactivated*, the average, minimum, and maximum BIs were 0.507, 0.211, and 0.885, respectively. Moreover, when the RMSs are *deactivated*, the average, minimum, and maximum mainline speeds were 27 mph, 15 mph, and 38 mph. When the RMSs are *deactivated*, the entrance ramp volume was ranging between 20 vehicles/5 minutes and 55 vehicles/5 minutes. The minimum and maximum density of entrance ramps were 1.110 ramps/mile and 1.540 ramps/mile, respectively. The minimum density of exit ramps was 0.670 ramps/mile, and the maximum was 1.390 ramps/mile.

Table 5-1: Descriptive Statistics of the Variables for the RMS

	Variable	**Average**	**S.D**	**Min.**	**Max.**
RMS Activated	Buffer Index	0.385	0.132	0.149	0.825
	Mainline Speed (mph)	30	10	16	49
	Mainline Volume (vehicles/5 mins)	374	47	298	492
	Mainline Occupancy (%)	21	5	12	29
	Ramp Volume (vehicles/5 mins)	31	10	18	49
	Density of entrance ramps (ramps/mile)	1.359	0.187	1.110	1.540
	Density of exit ramps (ramps/mile)	1.117	0.263	0.670	1.390
RMS Deactivated	Buffer Index	0.507	0.171	0.211	0.885
	Mainline Speed (mph)	27	8	15	38
	Mainline Volume (vehicles/5 mins)	318	36	410	410
	Mainline Occupancy (%)	17	4	23	23
	Ramp Volume (vehicles/5 mins)	34	10	20	55
	Density of entrance ramps (ramps/mile)	1.359	0.187	1.110	1.540
	Density of exit ramps (ramps/mile)	1.117	0.263	0.670	1.390

Note: S.D means standard deviation, Min. means minimum, Max. means maximum

Figure 5-1(a) shows the BI distributions when the RMSs are *activated* and *deactivated*. It indicates that the BIs were lower when RMSs are *activated* than when *deactivated*. For example, approximately 58% and 23% of the BIs were less than 0.4 when RMSs are *activated* and *deactivated*, respectively. A Welch two-sample *t*-test was used to test the null hypothesis that BIs when RMSs are *activated* and *deactivated* were equal. The alternative hypothesis was the BIs when RMSs are *activated* were lower than when *deactivated*. The *t*-test indicated that, at the 95% confidence interval, the BIs were significantly lower when RMSs are *activated* than when *deactivated*. It showed that travelers experience more reliable travel times when the RMSs are *activated* than when *deactivated*.



(a) Buffer index

(b) Mainline speed

(c) Mainline occupancy

(d) Mainline volume

Figure 5-1: Traffic Conditions when RMSs are Activated and Deactivated

Figure 5-1(b) shows the distributions of the average traffic speed on the freeway mainline when the RMSs are *activated* and *deactivated*. The distributions indicate that the average mainline speeds were higher when the RMSs are *activated* than when *deactivated*. For example, approximately 44% and 62% of the average traffic speeds were less than 30 mph when RMSs are *activated* and *deactivated*, respectively. A Welch two-sample *t*-test was used to test the null hypothesis that the average mainline speeds when RMSs are *activated* and *deactivated* were equal. The alternative hypothesis was the average mainline speeds were higher when the RMSs are *activated* than when *deactivated*. The *t*-test indicated that, at the 95% CI, the average mainline speeds were higher when RMSs are *activated* than when *deactivated*.

Figure 5-1(c) illustrates the distributions of the mainline occupancy when the RMSs are *activated* and *deactivated*. It shows that the average mainline occupancy values were higher when RMSs are *activated* than when *deactivated*. A Welch two-sample *t*-test was used to test the null hypothesis that the average mainline occupancy when RMSs are *activated* and *deactivated* were equal. The alternative hypothesis was the average mainline occupancy values were higher when the RMSs are *activated* than when *deactivated*. A Welch two-sample *t*-test confirmed, at the 95% CI, that the average mainline occupancy values were higher when RMSs are *activated* than when *deactivated*.

Figure 5-1(d) shows the average mainline traffic volume distributions when RMSs are *activated* and *deactivated*. It indicates that the average mainline traffic volumes were higher when RMSs are *activated* than when *deactivated*. For example, approximately 25% and 80% of the average mainline traffic volumes were less than 350 vehicles/5 minutes when RMSs are *activated* and *deactivated*, respectively. A Welch two-sample *t*-test was used to test the null hypothesis that the average mainline traffic volumes when RMSs are *activated* and *deactivated* were equal. The alternative hypothesis was the average mainline traffic volumes were higher when the RMSs are *activated* than when *deactivated*. A Welch two-sample *t*-test confirmed, at the 95% CI, that the average mainline traffic volumes were higher when RMSs are *activated* than when *deactivated*.

5.1.2 Factors Influencing Travel Time Reliability along Segments with Ramp Metering Signals

The study developed a model using the BIs when the RMSs are *activated* and *deactivated*. The model aimed at determining whether ramp metering affected the BIs along freeways. The model included other variables (i.e., congestion level, mainline speed, ramp traffic volume, and density of entrance and exit ramps) that could be used to predict the BIs. Table 5-2 shows the coefficients of the variables used in the penalized regression models. The magnitude and sign of the coefficients indicate the influence of the variables on the BIs. Results from both LASSO and ridge models were consistent in showing the relationship between the predictor variables and the BIs. Both models indicated that activating RMSs has a positive impact on the BIs of along freeway segments. The coefficients of the ramp metering indicator variable suggested that activating RMSs was associated with a decrease in the BIs. Similar to Bertini et al. (2004), this finding indicates that RMS operations increase the travel time reliability on the freeway mainline.

Table 5-2 also shows the impact of other factors that could predict the BIs. It was indicated that all variables included in the model were important in predicting the BIs. The estimates of the indicator variable for congestion level showed that severe congestion was associated with lower BIs than moderate congestion. A minor difference exists between the 95th percentile travel times and the average travel times on the freeway mainline during severe congestion. It indicates that most of the time, traffic has relatively the same travel time when traversing a segment during severe traffic congestion.

High mainline traffic speeds were associated with unreliable travel times (i.e., higher BIs). During congested times, high speeds on the freeway mainline reflect a segment that is in moderate congestion and has more traffic speed variation as compared to during severe congestion. Conversely, during severe congestion, vehicles travel at lower speeds but with more consistent travel times, which accounts for the minor difference between the 95th percentile travel times and the average travel time. High entrance ramp volumes were also associated with high BIs on the freeway mainline and are indicative of more traffic entering the freeway mainline. Vehicles can join the mainline traffic with less difficulty during moderate congestion compared to severe congestion. Therefore, high ramp volumes could predict periods when mainline traffic has a greater variation in travel times.

Table 5-2: Results of the Penalized Regression Models

Variable	**Category**	**Ridge Estimate**	**LASSO Estimate**
Intercept		-0.100	-0.641
RMS operations	No*		
	Yes	-0.112	-0.146
Congestion level	Moderate congestion*		
	Severe congestion	-0.070	-0.026
Mainline traffic speed		0.007	0.012
Ramp traffic volume		0.002	0.003
Density of exit ramps		0.069	0.171
Density of entrance ramps		0.213	0.340

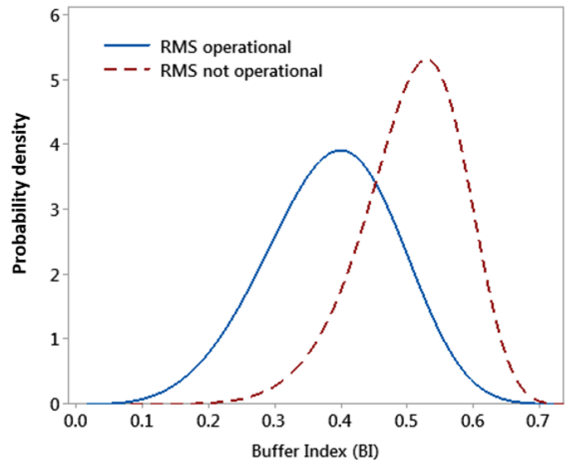
Note: * Base category

The high density of exit ramps was associated with high BIs. Traffic on exit ramps could affect the mainline when the downstream arterials receiving the traffic are congested. Therefore, many exit-ramps in a short segment may result in higher variability in travel times along a segment. Model results showed that the high density of entrance ramps was also associated with decreased reliability in travel times (i.e., high BIs). Merging locations downstream of the entrance ramps are synchronous with increased traffic turbulence and variation in traffic conditions between locations upstream and downstream of the merging area. Consequently, the high density of entrance ramps could negatively affect the travel time reliability on the freeway mainline.

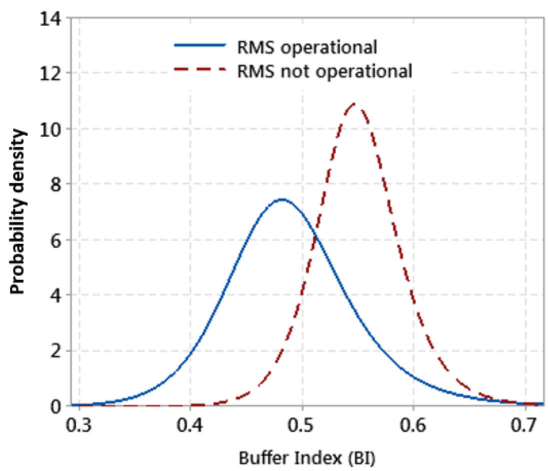
5.1.3 Prediction of Travel Time Reliability

Two penalized regression were used to analyze the BIs when RMSs are *activated+deactivated*. Results showed that the RMSE of the ridge regression model and the LASSO model were 0.108 and 0.107, respectively. It indicates that the prediction accuracy of the LASSO model was slightly better than the prediction accuracy of the ridge regression. Therefore, the LASSO model was used to predict the BIs.

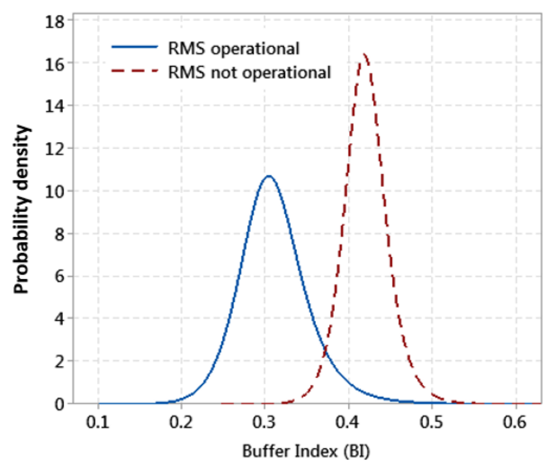
The benefits of activating RMSs were estimated using the predicted BIs from the LASSO model. The BIs were predicted considering the RMSs are *activated* and *deactivated*. Figure 5-2(a) shows the predicted BIs distributions when RMSs are *activated* and *deactivated*. The BIs distribution when the RMSs are *activated* is more to the right of the distribution when RMSs are *deactivated*. It indicates that the predicted BIs are lower when the RMSs are *activated* than when *deactivated*. Thus, ramp metering improves the travel time reliability of the freeway mainline segments.



(a) All congestion levels



(b) Moderate congestion



(c) Severe congestion

Figure 5-2: Distribution of the Predicted BIs

The predicted BIs were categorized according to the traffic congestion level to evaluate the expected benefits when RMSs were operational during moderate and severe congestion. Figures 5-2(b) and 5-2(c) show the distribution of the BIs during moderate and severe traffic congestion, respectively. The BIs' distributions when the RMSs are *activated* were right of the corresponding distributions when the RMSs are *deactivated*. It indicates that the ramp metering improves the travel time reliability on freeway segments during moderate and severe traffic congestion. It was estimated that ramp metering reduced the

BIs along a segment by approximately 23% during moderate congestion. Also, ramp metering decreased the BIs along a segment by approximately 28% during severe congestion. Results suggested that higher mobility benefits were observed at locations with severe congestion compared to areas with moderate congestion. These results were similar to the findings in Drakopolous et al. (2004), Trinh (2000), and Xie et al. (2012), which showed greater mobility improvements due to ramp metering at locations with severe recurring congestion than segments that experienced moderate congestion.

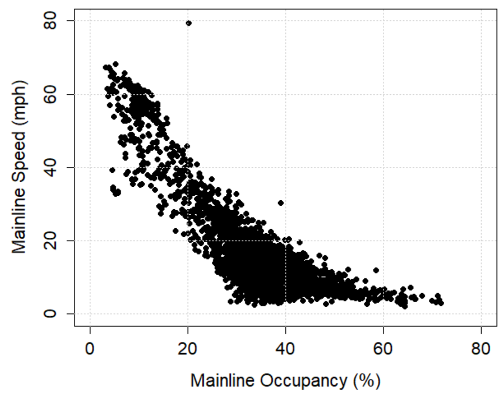
5.2 Benefits of Ramp Metering during Non-Recurrent Congestion due to Crashes

The second objective of the research was to evaluate the impact of ramp metering operations on traffic conditions upstream of the crash location. About 11,472 crashes were recorded during the three-year study period. Approximately 49.5% of the crashes were excluded from the analysis because they occurred on ramps, did not require lane closure, or involved closure of all lanes. Only 1,046 crashes out of the remaining 5,682 crashes were included in the analysis after removing crashes that occurred on weekends, holidays, and those associated with missing traffic data. About 30% of the remaining crashes occurred during peak periods. Crashes that occurred during daytime off-peak periods and nighttime off-peak periods comprised 54% and 16% of the remaining crashes, respectively. The *k*-means clustering was used to classify the traffic flow parameters (i.e., speed and occupancy) upstream of the crash locations into traffic states. Three traffic states were identified from the traffic flow parameters during the off-peak and peak periods. The GOLM and the logistic regression were then developed to show the impact of ramp metering on the traffic states during off-peak and peak periods. The following sections discuss the results in detail.

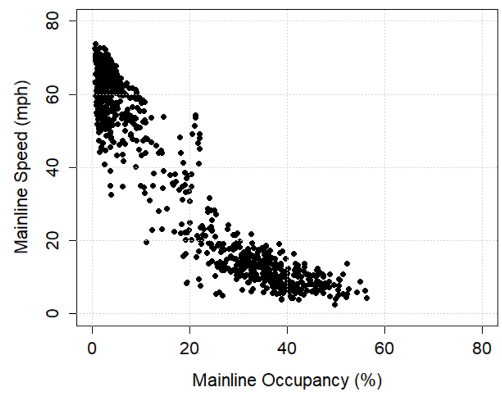
5.2.1 Traffic States Upstream of the Crash Location

The *k*-means clustering was used to classify the traffic speed and occupancy into different traffic states. The clustering method was applied to three sets of traffic speed and occupancy observations grouped according to the time-of-day: daytime off-peak periods, nighttime off-peak periods, and peak periods. The daytime off-peak periods included observations between 6:00 AM and 2:00 PM for the northbound traffic, and between 11:00 AM and 8:00 PM for the southbound traffic. The nighttime off-peak periods included observations between 8:00 PM and 6:00 AM. The peak periods included observations between 2:00 PM and 8:00 PM for the northbound traffic and between 6:00 AM and 11:00 AM for the southbound traffic. Figure 5-3 shows the traffic flow observations upstream of a crash location in all groups before clustering. During the daytime off-peak periods, the average traffic speed and occupancy were approximately 17 mph and 34%, respectively. During the nighttime off-peak periods, the average traffic speed and occupancy were approximately 39 mph and 17%, respectively. During the peak periods, the average traffic speed and occupancy were approximately 14 mph and 36%, respectively.

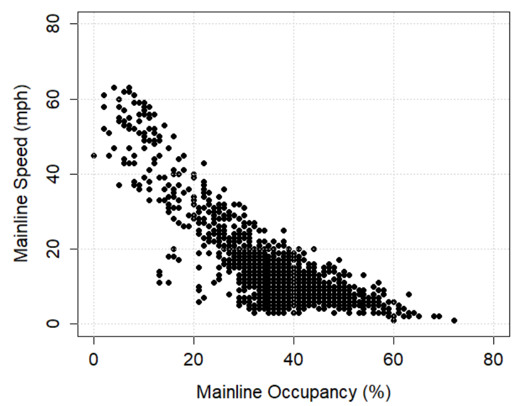
Using the silhouette index, the *k*-means clustering showed that three clusters were the optimal number of groups for traffic flow observations during daytime off-peak periods, nighttime off-peak periods, and peak periods. Based on their speed-occupancy characteristics, the clusters were named as an *uncongested*, *transition*, and *congested state*.



(a) Daytime off-peak periods



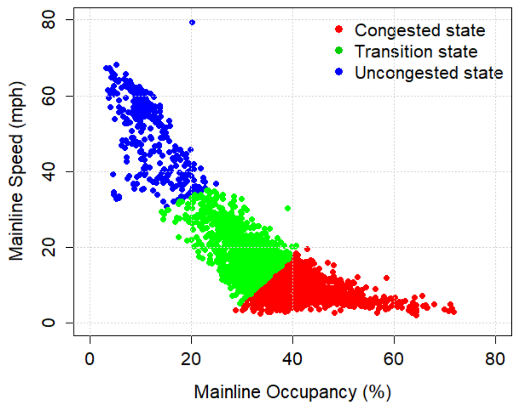
(b) Nighttime off-peak periods



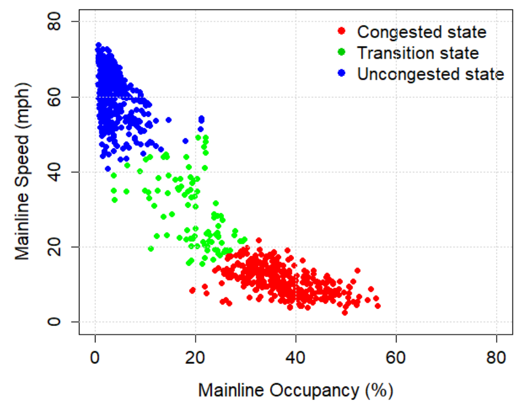
(c) Peak periods

Figure 5-3: Speed-Occupancy Diagram Upstream of Crash Locations

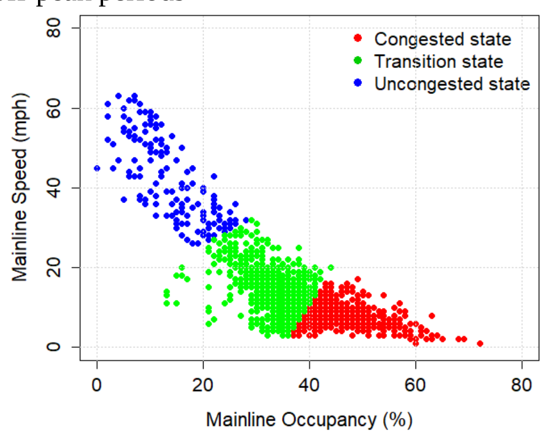
Figure 5-4 shows the speed-occupancy diagram after clustering the traffic flow observations upstream of the crash location during the daytime off-peak periods, nighttime off-peak periods, and peak periods. The *uncongested state* was characterized by the highest travel speed and lowest occupancy. The *transition state* was characterized by the moderate travel speed and moderate occupancy. On the other hand, the *congested state* was characterized by the lowest travel speed and highest occupancy.



(a) Daytime off-peak periods



(b) Nighttime off-peak periods



(c) Peak periods

Figure 5-4: Traffic States as Classified using k-means Clustering

5.2.2 Impact of Ramp Metering on Traffic Conditions affected by Crashes during Daytime Off-Peak Periods

Traffic flow observations upstream of a crash location during daytime off-peak periods were grouped into *uncongested*, *transition*, and *congested states*. Approximately 12%, 43%, and 45% of the observations were classified in the *uncongested*, *transition*, and *congested states*, respectively. The average traffic speed and occupancy in the *uncongested state* were approximately 50 mph and 12%, respectively. Also, the average traffic speed and occupancy in the *transition state* were about 18 mph and 30%, respectively. The average traffic speed and occupancy in the *congested state* were approximately 9 mph and 42%, respectively.

Table 5-3 shows the descriptive statistics of the analysis variables according to the traffic state during daytime off-peak periods. Fewer observations were classified into the *uncongested state* than the *transition* and *congested state*. The *transition* and *congested state* had the same proportions of observations when the nearest upstream RMSs are *activated*. The percentage of observations involving fire rescue was lower in the *transition* than in the *congested state*. The percentage of observations associated with lane closure ≤ 33% was higher in the *transition* than in the *congested state*. In general, the percentage of observations associated with left-lane closures were higher than the right-lane closures.

Table 5-3: Summary of Variables during Daytime Off-Peak Periods

		Uncongested State		Transition State		Congested State	
Variable	**Category**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Deactivated	318	97	1,023	87	1,071	87
	Activated	10	3	155	13	161	13
Second Nearest Upstream RMS	Deactivated	311	95	1,033	88	1,065	86
	Activated	17	5	145	12	167	14
Number of responding agencies	*	*	*	*	*	*	*
Fire rescue present	No	218	66	770	65	498	40
	Yes	110	34	408	35	734	60
Towing involved	No	293	89	1,104	94	1,101	89
	Yes	35	11	74	6	131	11
Lane blockage	≤ 33%	224	68	852	72	363	29
	> 33%	104	32	326	28	869	71
Closed lane side	Right	195	59	450	38	317	26
	Center	13	4	57	5	45	4
	Left	120	37	671	57	870	71
Detection method	On-site	110	34	356	30	382	31
	Off-site	218	66	822	70	850	69

Note: * Not applicable, Count represents number of 5-minute interval observations

Table 5-4 presents the results of the logistic regression of the traffic states during the daytime off-peak periods. The uncongested state was not included in the model due to fewer observations during the daytime off-peak periods. Activating the nearest RMS upstream of the crash location decreased the likelihood of traffic flow changing from *transition state* to *congested state* by 43%. Conversely, activating the second nearest RMS upstream of the crash did not significantly affect the traffic states changing from *uncongested state* to *transition state*. These findings suggest that activating the nearest upstream RMS can help improve traffic conditions upstream of a crash location. Also, results suggest that, during off-peak periods, it might not be necessary to activate the farther upstream RMSs to improve traffic conditions upstream of the crash location.

Table 5-4: Results of the Logistic Regression during Daytime Off-Peak Periods

		Transition vs Congested				
				90% CI		
Variable	**Category**	**Coeff.**	**S. E.**	**5%**	**95%**	**OR**
Nearest Upstream RMS	Deactivated*					
	Activated	**-0.571**	**0.317**	**-1.091**	**-0.050**	**0.57**
Second Nearest Upstream RMS	Deactivated*					
	Activated	0.176	0.322	-0.353	0.705	1.19
Number of responding agencies		**0.170**	**0.040**	**0.104**	**0.236**	**1.19**
Fire rescue present	No*					
	Yes	**0.463**	**0.117**	**0.271**	**0.655**	**1.59**
Towing involved	No*					
	Yes	0.110	0.193	-0.206	0.426	1.12
Lane blockage	≤ 33%*					
	> 33%	**1.498**	**0.101**	**1.333**	**1.664**	**4.47**
Closed lane side	Right*					
	Center	**0.880**	**0.238**	**0.490**	**1.269**	**2.41**
	Left	**0.759**	**0.106**	**0.586**	**0.933**	**2.14**
Detection method	On-site*					
	Off-site	**-0.258**	**0.102**	**-0.424**	**-0.091**	**0.77**
Constant		-1.981	0.237	-0.975	-0.026	

Note: Bold numbers show significant variables at 90% confidence interval (CI), Coeff. means coefficient, S.E. means standard error, OR means odds ratio,* means base category

The presence of fire rescue at the crash location increased the likelihood of traffic flow changing from *transition* to *congested state* by 59%. Similarly, left-lane closures, center-lane closures, increased the likelihood of *transition state* changing to *congested state*. Left-lane closures and center-lane closures were associated with 141% and 114% increase in the likelihood of traffic flow changing from *transition* to *congested state*, respectively. As expected, lane blockage >33% increased the likelihood of traffic flow changing from the *transition state* to the *congested state*. Detection of crashes using off-site methods lowered the likelihood of traffic flow changing from *transition* to *congested* state by 33%. Results also indicated that an increase in the number of responding agencies at the incident scene was associated with an increase in the likelihood of traffic conditions changing from *transition* to *congested state*.

5.2.3 Impact of Ramp Metering on Traffic Conditions affected by Crashes during Nighttime Off-Peak Periods

Traffic flow observations upstream of a crash location during nighttime off-peak periods were grouped into *uncongested, transitioned, and congested states*. Approximately 53%, 10%, and 37% of the observations were classified in the *uncongested*, *transition*, and *congested states*, respectively. The average traffic speed and occupancy in the *uncongested state* were approximately 60 mph and 3%, respectively. Also, the average traffic speed and occupancy in the *transition state* were around 29 mph and 19%, respectively. The average speed and occupancy in the *congested state* were approximately 11 mph and 37%, respectively.

Table 5-5 presents the descriptive statistics of the analysis variables according to the traffic state during the nighttime off-peak periods. None of the observations were in the *uncongested state* when the RMSs are *activated*. Approximately the same proportions of observations were in the *transition* and the *congested state* when the RMSs are *activated*. The percentage of observations involving fire rescue was higher in the *uncongested* than the *transition state*. The percentage of observations associated with lane closure ≤ 33% was higher in the *transition* than the *uncongested* or *congested state*. In the *uncongested state*, a higher percentage of observations were associated with right-lane/s closure than left-lane/s or center-lane/s closure. More observations in the *transition* and *congested state* were associated with left-lane/s closure than right- or center-lane/s closure. A higher percentage of observations in the *uncongested state* were associated with crashes detected using off-site than on-site methods.

Table 5-5: Summary of Variables during Nighttime Off-Peak Periods

		Uncongested State		Transition State		Congested State	
Variable	**Category**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Deactivated	519	100	96	97	342	95
	Activated	0	0	3	3	19	5
Second Nearest Upstream RMS	Deactivated	519	100	96	97	342	95
	Activated	0	0	3	3	19	5
Number of responding agencies	*	*	*	*	*	*	*
Fire rescue present	No	160	31	45	45	133	37
	Yes	359	69	54	55	228	63
Towing involved	No	410	79	81	82	324	90
	Yes	109	21	18	18	37	10
Lane blockage	≤ 33%	164	32	43	43	117	32
	> 33%	355	68	56	57	244	68
Closed lane side	Right	380	73	48	48	146	40
	Center	8	2	1	1	18	5
	Left	131	25	50	51	197	55
Detection method	On-site	41	18	329	85	161	45
	Off-site	190	82	58	15	200	55

Note: * Not applicable, Count represents number of 5-minute interval observations

The research analyzed the impact of ramp metering on traffic conditions in the *transition* and *congested state*. The *uncongested state* excluded in the analysis due to a lack of observations when RMSs are *activated*. Results of the logistic regression of the traffic states (i.e., *transition and congested state*) during nighttime off-peak periods are presented in Table 5-6. It was indicated that activating the nearest upstream RMSs did not influence the changes in the traffic states. Relatively few observations when the RMSs are *activated* during the nighttime off-peak periods might be the reason for this finding. The effect of activating the second nearest upstream RMS was not directly analyzed because it was linearly correlated with the nearest upstream RMS. Towing services significantly reduced the likelihood of traffic conditions changing to *congested state*. Compared to when the towing services were not involved, the probability of traffic conditions changing from the *transition* to the *congested state* was reduced by 65% when the towing services were involved.

Table 5-6: Results of the Logistic Regression during Nighttime Off-Peak Periods

		Transition vs Congested State				
				90% CI		
Variable	**Category**	**Coeff.**	**S.E.**	**5%**	**95%**	**OR**
Nearest Upstream RMS	Off*					
	On	1.046	0.647	-0.015	2.106	2.85
Number of responding agencies		0.059	0.100	-0.105	0.223	1.06
Fire rescue present	No*					
	Yes	0.474	0.310	-0.034	0.982	1.61
Towing involved	No*					
	Yes	**-1.053**	**0.411**	**-1.728**	**-0.378**	**0.35**
Lane blockage	≤ 33%*					
	> 33%	0.458	0.298	-0.031	0.946	1.58
Closed lane side	Right*					
	Center	1.631	1.065	-0.116	3.377	5.11
	Left	0.367	0.277	-0.088	0.822	1.44
Detection method	On-site*					
	Off-site	-0.069	0.246	-0.473	0.335	0.93
Constant		0.491	0.261	0.063	0.920	

Note: Coeff. means coefficient, CI means confidence interval, OR means odds ratio, and * means base category, S.E. means standard error

5.2.4 Impact of Ramp Metering on Traffic Conditions affected by Crashes during Peak Periods

Traffic flow observations upstream of an incident during peak periods were grouped into *uncongested*, *transition*, and *congested* states. Approximately 9%, 56%, and 35% of the observations were classified in the *uncongested*, *transition*, and *congested states*, respectively. The average traffic speed and occupancy in the *uncongested state* were approximately 42 mph and 14%, respectively. Also, the average traffic speed and occupancy in the *transition state* were about 14 mph and 34%, respectively. The average speed and occupancy in the *congested state* were approximately 8 mph and 46%, respectively.

Table 5-7 presents the descriptive statistics of the analysis variables according to the traffic state during peak periods. In the *uncongested state*, the percentage of observations was higher when the nearest upstream RMSs are *activated* than when *deactivated*. Conversely, the percentage of observations was lower when the second nearest upstream RMSs are *activated* than when *deactivated*. In the *transition* and *congested state*, more observations were associated with *activated* than *deactivated* RMSs. A higher percentage of observations in the *uncongested* and *transition state* were associated with fire rescue presence at the crash location. In general, fewer observations were associated with crashes involving towing services. The highest percentage of observations associated with lane blockage > 33% were in the *congested state*. The percentage of observations associated with crashes detected using off-site methods was higher than on-site methods.

Table 5-7: Summary of the Variables during Peak Periods

		Uncongested State		Transition State		Congested State	
Variable		**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Deactivated	77	45	297	29	216	33
	Activated	93	55	744	71	446	67
Second Nearest Upstream RMS	Deactivated	94	55	371	36	250	38
	Activated	76	45	670	64	412	62
Number of Responding Agencies		*	*	*	*	*	*
Fire Rescue Present	No	112	66	638	61	290	44
	Yes	58	34	403	39	372	56
Towing Involved	No	156	92	987	95	628	95
	Yes	14	8	54	5	34	5
Lane Blockage	≤ 33%	98	58	619	59	174	26
	> 33%	72	42	422	41	488	74
Type of Lane Closure	Right	75	44	348	33	201	30
	Center	1	1	44	4	36	5
	Left	94	55	649	62	425	64
Detection Method	On-site	82	48	278	27	230	35
	Off-site	88	52	763	73	432	65

Note: * Not applicable, Count represents number of 5-minute interval observations

Table 5-8 presents the results of GOLM of the traffic states during peak periods. The nearest RMSs upstream of the crash location did not significantly influence the change from *uncongested* to the *transition state*. The second nearest RMS upstream of a crash location decreased the likelihood of traffic flow changing from *uncongested state* to *transition state* by 46%. This finding suggests that ramp metering farther upstream of the crash location helps keep the traffic condition near the crash scene *uncongested*. More responding agencies at the crash scene increased the likelihood of changing from *uncongested* to *transition state*. Lane blockage > 33% was associated with a 36% decreased likelihood of traffic flow changing from *uncongested* to *transition state*. This finding was unexpected, and it requires further analysis. The off-site detection method increased the likelihood of traffic flow changing from *transition* to *congested state* by 33%.

Table 5-8: Results of the GOLM during Peak Periods

		Uncongested vs Transition State					Transition vs Congested State				
				95% CI					95% CI		
Variable	**Category**	**Coeff.**	**S. E.**	**2.5%**	**97.5%**	**OR**	**Coeff.**	**S. E.**	**2.5%**	**97.5%**	**OR**
Nearest Upstream RMS	Deactivated*										
	Activated	-0.051	0.271	-0.593	0.490	0.95	0.244	0.191	-0.137	0.625	1.28
Second Nearest Upstream RMS	Deactivated*										
	Activated	**-0.620**	**0.267**	**-1.154**	**-0.085**	**0.54**	-0.216	0.182	-0.579	0.147	0.81
Number of Responding Agencies		**0.186**	**0.062**	**0.061**	**0.311**	**1.20**	**-0.113**	**0.038**	**-0.188**	**-0.037**	**0.89**
Fire Rescue Present	No*										
	Yes	**-0.917**	**0.219**	**-1.354**	**-0.479**	**0.40**	-0.215	0.127	-0.469	0.040	0.81
Towing Involved	No*										
	Yes	-0.058	0.351	-0.761	0.644	0.94	0.411	0.248	-0.085	0.907	1.51
Lane Blockage	≤ 33%*										
	> 33%	**-0.449**	**0.181**	**-0.812**	**-0.086**	**0.64**	**-1.225**	**0.115**	**-1.455**	**-0.995**	**0.29**
Type of Lane Closure	Right*										
	Center	**-2.232**	**1.022**	**-4.276**	**-0.188**	**0.11**	**-0.841**	**0.261**	**-1.364**	**-0.318**	**0.43**
	Left	**-0.424**	**0.175**	**-0.775**	**-0.074**	**0.65**	**-0.262**	**0.115**	**-0.493**	**-0.031**	**0.77**
Detection Method	On-site*										
	Off-site	**-0.728**	**0.170**	**-1.068**	**-0.389**	**0.48**	**0.285**	**0.111**	**0.063**	**0.506**	**1.33**
Constant		-1.474	0.291	-2.349	-0.600		1.895	0.209	1.476	2.313	

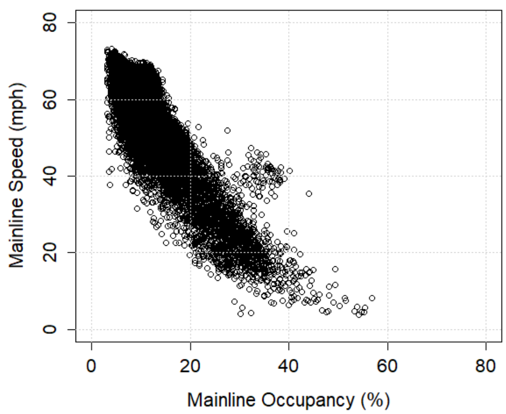
Note: Bold numbers show significant variables at 95% confidence interval (CI), Coeff. means coefficient, S.E. means standard error, OR means odds ratio, and * means base category

5.3 Benefits of Ramp Metering during Non-Recurrent Congestion due to Rain

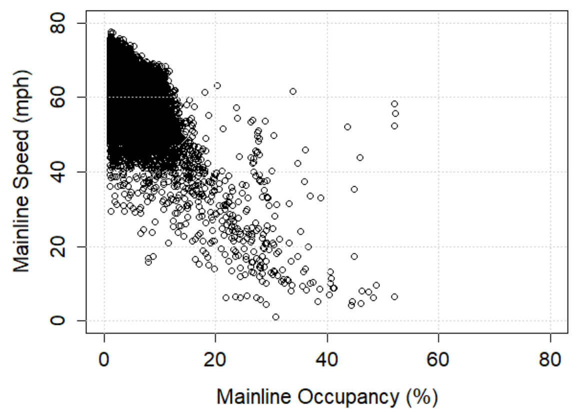
The third objective of the research was to evaluate the impact of ramp metering operations on traffic conditions during rain. Along the study corridor, it rained in about 651 days during the three-year study period (2016 - 2018). Approximately 579,696 traffic data observations were extracted on the days that it was raining. About 4% of the observations were excluded because they were collected on holidays and days associated with hurricanes. In addition, observations recorded when travel lanes were closed due to crashes were excluded from the analysis. The remaining 134,230 observations were divided according to the time-of-day: daytime off-peak periods, nighttime off-peak periods, and peak periods. The definition of the time-of-day categories was similar to that provided in Section 5.2.1. Approximately 34%, 49%, and 17% of the observations were recorded during daytime off-peak, nighttime off-peak, and peak periods, respectively. The *k*-means clustering was used to classify the traffic flow parameters (i.e., speed and occupancy) downstream of the entrance ramps into traffic states. The logistic regression model and the GOLM were used to evaluate the impact of ramp metering on the traffic conditions affected by rain during daytime off-peak, nighttime off-peak, and peak periods. The following sections discuss the results in detail.

5.3.1 Traffic States Downstream of the Entrance Ramp during Rain

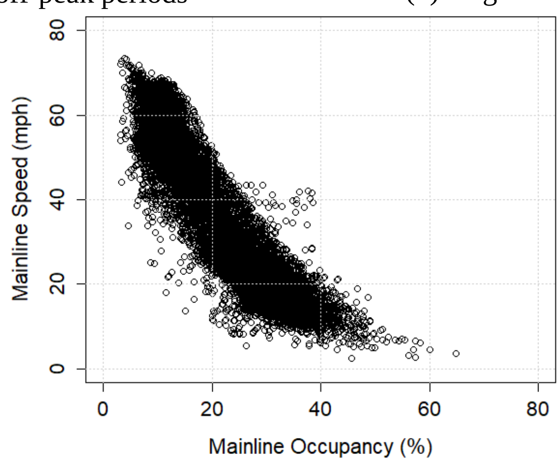
The *k*-means clustering was used to classify the traffic speed and occupancy into different traffic states. Similar to Section 5.2.1, the clustering method was applied to three sets of traffic speed and occupancy observations grouped according to the time of day. Figure 5-5 shows the traffic flow observations downstream of the entrance ramp during rain before clustering. During the daytime off-peak periods, the average traffic speed was 55 mph, and the average traffic occupancy was 12%. In contrast, during the nighttime off-peak periods, the average traffic speed was 62 mph, the average traffic occupancy was 4%. During the peak periods, the average traffic speed and occupancy were approximately 42 mph and 18%, respectively.



(a) Daytime off-peak periods



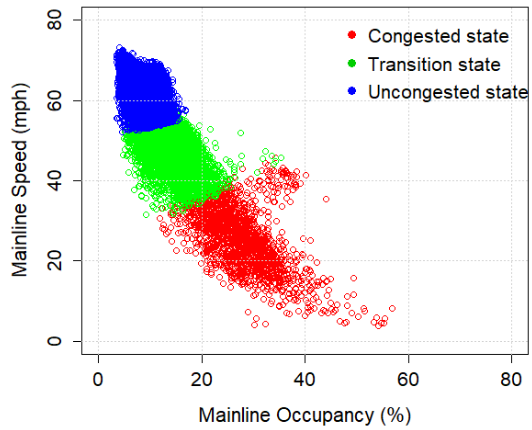
(b) Nighttime off-peak periods



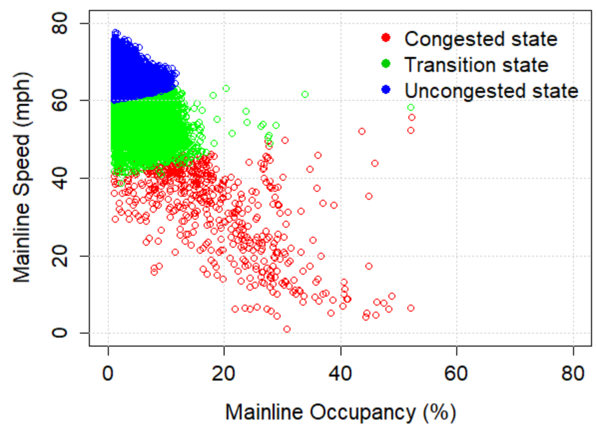
(c) Peak periods

Figure 5-5: Speed-Occupancy Diagram during Rain

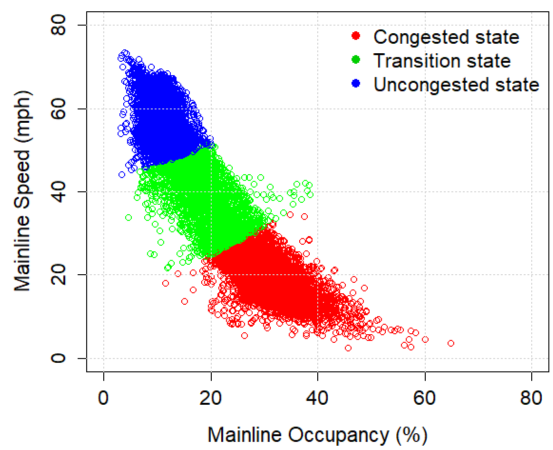
The silhouette index of the *k*-means clustering showed that three clusters were the optimal number of groups for traffic flow observations during the daytime off-peak periods, nighttime off-peak periods, and peak periods. The clusters were named an uncongested, transition, and congested state based on their speed-occupancy characteristics. Figure 5-6 shows the speed-occupancy diagram after clustering the traffic flow observations downstream of the entrance ramp during rain according to the time of day.



(a) Daytime off-peak periods



(b) Nighttime off-peak periods



(c) Peak periods

Figure 5-6: Traffic States Downstream of the Entrance Ramp During Rain

5.3.2 Impact of Ramp Metering on Traffic Conditions during Rain in Daytime Off-Peak Periods

Traffic flow observations downstream of the entrance ramp during rain in daytime off-peak periods were grouped into *uncongested*, *transition*, and *congested states*. The average traffic speed and occupancy in the *uncongested state* were approximately 60 mph and 10%, respectively. The average traffic speed and occupancy in the *transition state* were about 49 mph and 13%, respectively. Also, the average traffic speed and occupancy in the *congested state* were approximately 25 mph and 28%, respectively.

Table 5-9 shows the descriptive summary of the variables affecting the traffic conditions during rain in daytime off-peak periods according to the traffic state. Relatively more observations were classified into the *uncongested state* (64%) than the *transition* (29%) and *congested state* (7%). The *uncongested* and *transition state* had approximately the same proportions of observations when the nearest upstream RMSs are *activated*. The proportion of observations when the RMSs are *activated* was relatively higher in the *congested state* than the *uncongested* and *transition state*. The distribution of observations when the second nearest upstream RMSs are *activated* was similar to the distribution when the nearest RMSs are *activated*. The percentages of observations associated with moderate and heavy rain were higher in the *transition* and *congested state* than in the *uncongested state*.

Table 5-9: Summary of the Factors Affecting Traffic Conditions during Rain in Daytime Off-Peak Periods

		Uncongested State		**Transition State**		**Congested State**	
Variable	**Category**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Off	29,448	99	12,889	98	3,195	94
	On	176	1	262	2	200	6
Second Nearest Upstream RMS	Off	29,413	99	12,880	98	3,189	94
	On	211	1	271	2	206	6
Rain Intensity	Light	26,266	89	8,651	66	2,027	60
	Moderate &Heavy	3,358	11	4,500	34	1,368	40

Note: Count represents number of 5-minute interval observations

A logistic regression was used to analyze the factors affecting the traffic conditions downstream of the entrance ramp during rain in daytime off-peak periods. The *transition* and *congested state* observations were grouped because they were relatively fewer than observations in the *uncongested state*. Also, considering ramp metering activation was the target variable, the bootstrap resampling was used when fitting the logistic regression to account for fewer observations when RMSs are *activated* than *deactivated*. Therefore, the logistic regression model was developed 10,000 times by combining the observations when RMSs are *activated* and 10,000 bootstrapped samples from the observations when RMSs are *deactivated*. The coefficient of each variable was obtained by averaging the coefficients of the models when the variable was significant.

Table 5-10 presents the logistic regression results of the traffic states (*uncongested state* versus *transition & congested state*) during rain in daytime off-peak periods. Only, the variable for activation of the nearest RMS was found significant at the 95% CI. Other variables, including activation of the second nearest upstream RMS and rain intensity, were not significant at the 95% CI.

Table 5-10: Factors Affecting Traffic States during Rain in Daytime Off-Peak Periods

		Uncongested vs Transition & Congested State				
				95% CI		
Variable	**Category**	**Coeff.**	**S. E.**	**2.5%**	**97.5%**	**OR**
Nearest Upstream RMS	Off*					
	On	**-1.622**	**0.260**	**-2.132**	**-1.113**	**0.20**
Second Nearest Upstream RMS	No*					
	Yes	-0.212	0.229	-0.660	0.236	0.81
Rain Intensity	Light*					
	Moderate & Heavy	-0.084	0.159	-0.397	0.228	0.92
Constant		2.615	0.160	2.302	2.929	

Note: Coeff. means coefficient, CI means confidence interval, OR means odds ratio, S.E. means standard error, and * means a base category,

Figure 5-7 shows the distribution of the coefficient of the variable for activation of the nearest upstream RMS. It was indicated that, on average, activating the nearest RMSs upstream of the entrance ramp reduced the likelihood of traffic conditions changing from *uncongested* to *transition* and *congested state* by 80%. This finding suggests that ramp metering improves traffic conditions downstream of the entrance ramp during rain in daytime off-peak periods. It could therefore be suggested, the nearest upstream RMSs be *activated* during rain to prevent traffic conditions during daytime off-peak periods getting worse because of rain.

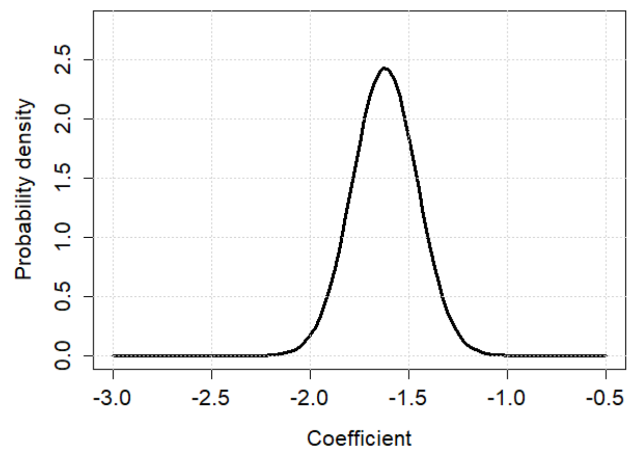


Figure 5-7: Coefficients of the Nearest Upstream RMS Variable during Daytime Off-Peak Periods

5.3.3 Impact of Ramp Metering on Traffic Conditions during Rain in Nighttime Off-Peak Periods

Traffic flow observations downstream of the entrance ramp during rain in nighttime off-peak periods were grouped into *uncongested*, *transition*, and *congested states*. The average traffic speed and occupancy in the *uncongested state* were approximately 66 mph and 3%, respectively. The average traffic speed and occupancy in the *transition state* were about 57 mph and 6%, respectively. Also, the average traffic speed and occupancy in the *congested state* were approximately 32 mph and 18%, respectively. Table 5-11 shows the descriptive summary of the variables affecting the traffic conditions during rain in nighttime off-peak periods according to the traffic state. More observations were in the *uncongested state* (58%) than the *transition* (39%) and *congested state* (3%). There were significantly fewer observations when the RMSs are *activated* than when *deactivated*. None of the observations in the *uncongested state* occurred when the upstream RMSs are *activated*. The distribution of observations when the second nearest upstream RMSs are *activated* was similar to the distribution when the nearest RMSs are *activated*. The percentages of observations associated with moderate and heavy rain were higher in the *transition* and *congested state* than in the *uncongested state*.

Table 5-11: Summary of the Factors Affecting Traffic Conditions during Rain in Nighttime Off-Peak Periods

		Uncongested State		Transition State		Congested State	
Variable	**Category**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Off	33,673	100	24,176	100	1,102	96
	On	0	0	21	0	50	4
Second Nearest Upstream RMS	Off	33,670	100	24,163	100	1,110	96
	On	3	0	34	0	42	4
Rain Intensity	Light	31,380	93	19,210	79	737	64
	Moderate &Heavy	2293	7	4987	21	415	36

Note: Count represents number of 5-minute interval observations

Logistic regression was used to analyze the factors affecting the traffic conditions downstream of the entrance ramp during rain in nighttime off-peak periods. The observations in the *uncongested state* were excluded due to a lack of observations when RMSs are *activated*. Similar to the model that was fitted when analyzing the traffic conditions during daytime off-peak periods in Section 5.3.2, the logistic regression model was fitted 10,000 times using bootstrap samples. The coefficient of each variable was obtained by averaging the coefficients of the logistic regression model when the variable was significant.

Table 5-12 presents the results of logistic regression of the traffic states (*transition* versus *congested state*) during rain in nighttime off-peak periods. The variable representing activation of the nearest RMS was found significant at the 95% CI. Other variables, including activation of the second nearest upstream RMS and rain intensity, were not significant at the 95% CI.

Table 5-12: Factors Affecting Traffic States during Rain in Nighttime Off-Peak Periods

		Transition vs Congested State				
				95% CI		
Variable	**Category**	**Coeff.**	**S. E.**	**2.5%**	**97.5%**	**OR**
Nearest Upstream RMS	Off*					
	On	**-3.868**	**0.883**	**-5.599**	**-2.137**	**0.02**
Second Nearest Upstream RMS	No*					
	Yes	-0.197	0.745	-1.264	1.658	1.22
Rain Intensity	Light*					
	Moderate & Heavy	-0.271	0.585	-1.418	0.875	0.76
Constant		3.060	13.817	-24.021	30.142	

Note: Coeff. means coefficient, CI means confidence interval, OR means odds ratio, and * means a base category, S.E. means standard error

Figure 5-8 presents the distribution of the coefficient of the variable for activation of the nearest upstream RMS. It was indicated that activating the nearest RMSs upstream of the entrance ramp significantly reduced the likelihood of traffic conditions changing from *transition* to *congested state* by 98%. This finding suggests that ramp metering improves traffic conditions downstream of entrance ramp during rain in nighttime off-peak periods. However, the effect of ramp metering depends on whether the traffic conditions are already in *transition state*.

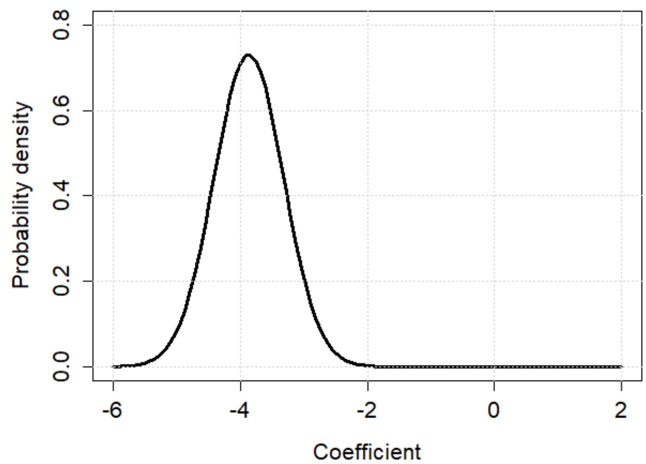


Figure 5-8: Coefficient of the Nearest Upstream RMS Variable during Nighttime Off-Peak Periods

5.3.4 Impact of Ramp Metering on Traffic Conditions during Rain in Peak Periods

Traffic flow observations during rain in peak periods were grouped into the *uncongested state* (34%), *transition state* (25%), and *congested state* (41%). The average traffic speed and occupancy in the *uncongested state* were approximately 57 mph and 11%, respectively. Also, the average traffic speed and occupancy in the *transition state* were about 39 mph and 19%, respectively. The average traffic speed and occupancy in the *congested state* were approximately 19 mph and 32%, respectively. Table 5-13 presents the descriptive statistics of the analysis variables according to the traffic state during peak periods. In the *uncongested state*, there were more observations when the nearest upstream RMSs are *deactivated* than when *activated*. In the *transition* and *congested state*, more observations were associated with *activated* RMSs than *deactivated* RMSs. A higher percentage of observations in all traffic states was associated with light rain than moderate and heavy rain.

Table 5-13: Summary of the Factors Affecting Traffic Conditions during Rain in Peak Periods

		Uncongested State		Transition State		Congested State	
Variable	**Category**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Nearest Upstream RMS	Off	5,003	67	1,823	33	2,167	24
	On	2,471	33	3,651	67	6,838	76
Second Nearest Upstream RMS	Off	4,721	63	2,078	38	2,963	33
	On	2,753	37	3,396	62	6,042	67
Rain Intensity	Light	6,218	83	3,971	73	6,703	74
	Moderate &Heavy	1,256	17	1,503	27	2,302	26

Note: Count represents number of 5-minute interval observations

Table 5-14 presents the results of GOLM of the traffic states during rain in peak periods. The nearest RMSs upstream of the entrance ramp significantly influenced the change from *uncongested* to the *transition state*. Activating the RMS decreased the likelihood of traffic conditions downstream of the entrance ramp changing from *uncongested* to *transition state* by 86%. It also reduced the likelihood of traffic conditions downstream of the entrance ramp changing from the *transition* to the *congested state* by 76%. The variable for activating the second nearest RMS was not included in the analysis because it was highly correlated with the variable for activating the nearest upstream RMS. Moreover, the results indicated that heavy rain was associated with a 45% and 22% reduced likelihood of traffic conditions downstream of the entrance changing from the *uncongested* to *transition state* and *the transition* to *congested state*, respectively.

Table 5-14: Model of Factors Affecting Traffic during Rainy Conditions in Peak Periods

		Uncongested vs Transition State					Transitions vs Congested State				
				95% CI					95% CI		
Variable	**Category**	**Coeff.**	**S.E.**	**2.5%**	**97.5%**	**OR**	**Coeff.**	**S.E.**	**2.5%**	**97.5%**	**OR**
Nearest	Off*										
Upstream RMS	On	**-1.933**	**0.052**	**-2.035**	**-1.832**	**0.14**	**-1.444**	**0.046**	**-1.533**	**-1.354**	**0.24**
Rain Intensity	Light*										
	Moderate & Heavy	**-0.606**	**0.038**	**-0.680**	**-0.531**	**0.55**	**-0.252**	**0.034**	**-0.319**	**-0.186**	**0.78**
Constant		0.331	0.023	0.285	0.377	1.39	1.179	0.027	1.127	1.231	3.25

Note: Bold numbers show significant variables at 95% confidence interval (CI), Coeff. means coefficient, S.E. means standard error, OR means odds ratio, and * means a base category

5.4 Summary

This research estimated the mobility benefits of ramp metering. To achieve the research goal, the study evaluated the effects of ramp metering during recurrent and non-recurrent congestion. The research applied an approach utilizing data collected during ramp metering operations and unplanned downtime of RMSs to achieve the research objectives. This method was selected to account for the limitations of the conventional methods for estimating ramp metering benefits.

The BI, selected as a measure of the travel time reliability, was estimated for segments along the study corridor when RMSs are *activated* and *deactivated*. Two penalized regression methods, ridge and LASSO regressions, were used to identify factors that could predict the BIs of a freeway segment with ramp metering. The regression models evaluated the impact of ramp metering and other factors, including freeway mainline congestion levels, freeway mainline traffic speed, ramp traffic volume, density of entrance ramps, and density of exit ramps. Both models indicated that all factors were important in predicting the BIs of the segments with RMSs. The LASSO regression model was selected to predict the BIs. The predicted values were used to show the overall benefit of ramp metering during different congestion levels. It was indicated that ramp metering during moderate and severe congestion reduced the BIs by 23% and 28%, respectively.

The effect of ramp metering on non-recurrent congestion due to crashes was evaluated using the traffic speed and occupancy upstream of the crash location when RMSs are *activated* and *deactivated*. The *k*-means clustering method was used to classify the traffic flow parameters upstream of the crash location into three traffic states (i.e., *uncongested, transition, and congested*). A GOLM or a logistic regression was then applied to estimate the impact of RMSs operations on the traffic states upstream of the crash location. The models were also used to identify other factors that could influence the traffic states upstream of the crash location, including the percentage of lanes blocked, type of lane closed, and the number of responding agencies. Separate analyses were done considering the time-of-day (i.e., peak periods, daytime off-peak periods, and nighttime off-peak periods). Two logistic regression models were developed: for crashes that occurred during daytime and nighttime off-peak periods. A GOLM was also developed to analyze traffic conditions upstream of the crash locations during peak periods.

It was indicated that activating the nearest RMS upstream of the crash location prevented traffic flow changing from *transition* to *congested state* during daytime off-peak periods. Conversely, ramp metering did not influence the traffic conditions upstream of the crash location during nighttime off-peak periods. Activating the second nearest RMS upstream of the crash location prevented traffic flow changing from *uncongested* to *transition state* during peak periods. In general, results suggested that ramp metering operations did not significantly impact traffic conditions upstream of the crash location when it was already in a *congested state*. Other factors, including, number of responding agencies, lane blockage, type of lane closure, and detection method, significantly affected the change of traffic states upstream of the crash location from the *transition* to the *congested state* during daytime off-peak and peak periods.

Traffic flow parameters downstream of the entrance ramp when RMSs are *activated* and *deactivated* were used to estimate the benefits of ramp metering during rain. Similar to the analysis of ramp metering during crashes, the *k*-means clustering was used to classify the traffic flow parameters downstream of the entrance ramp during rain into *uncongested*, *transition*, and *congested states*. Depending on the distribution of the data, a logistic regression that was fitted using bootstrap resampling and the GOLM were used to evaluate the effect of ramp metering on traffic conditions during rain in daytime off-peak periods, nighttime off-peak periods, and peak periods. The models were also used to evaluate the effect of rain intensity on the traffic conditions downstream of the entrance ramp.

Results indicated that, during rain in daytime off-peak periods, activating the nearest RMSs upstream of the entrance ramp significantly reduced the likelihood of downstream traffic conditions changing from *uncongested* to *transition* and *congested state*. Activating the nearest RMSs upstream of the entrance ramp during rain in nighttime off-peak periods, significantly reduced the likelihood of traffic conditions downstream changing from *transition* to *congested state.* During rain in peak periods, activating the nearest RMSs upstream of the entrance ramp decreased the likelihood of traffic conditions downstream of the entrance ramp changing from *uncongested* to *transition state* and changing from the *transition* to *congested state*. As compared to light rain, heavy rain was associated with the decreased the likelihood of traffic conditions changing to *transition* and *congested state*.

CHAPTER 6

CONCLUSIONS

The goal of this research was to estimate the benefits of ramp metering. This goal was achieved by: (1) estimating the effect of ramp metering on recurrent congestion, and (2) quantifying the impact of ramp metering on non-recurrent congestion due to crashes and rain. This chapter provides a summary of the effort, contributions, and limitations of the research. The chapter concludes by recommending future research efforts.

6.1 Summary and Conclusions

6.1.1 Benefits of Ramp Metering during Recurrent Congestion

Estimating ramp metering benefits helps agencies assess the effectiveness of ramp metering programs or plan for future deployment of RMSs. Several challenges limit the effectiveness of conventional estimation methods, including the before-and-after approach, shutdown experiments, and traffic simulation, in estimating the benefits of ramp metering. The principal task of this research was to estimate the benefits using an approach that can overcome, to an extent, the challenges of conventional estimation methods. This research applied an approach that used traffic data collected during unplanned ramp metering downtime to evaluate the benefits of ramp metering during recurrent congestion. Buffer index (BI), estimated using the 95^{th} percentile travel time and average travel time, was used as a measure of the benefits. BIs along the selected study segments were estimated when RMSs are *activated* and *deactivated*. Penalized regression methods, ridge and LASSO regressions, were used to measure the effect of ramp metering on the BIs and identify factors that could predict the BIs along the freeway segments with ramp metering.

Descriptive statistics indicated that the average BI was 0.38 when the RMSs are *activated* and 0.51 when the RMSs are *deactivated*. It was further confirmed that at a 95% confidence interval, the average BI when the RMSs are *activated* was less than when *deactivated*. The regression models indicated that ramp metering had a significant influence on the travel time reliability and is one of the factors that could predict travel time reliability. Other factors that could predict travel time reliability on segments with RMSs include freeway mainline congestion levels, freeway mainline traffic speed, ramp traffic volume, and the density of entrance and exit ramps along a segment. The prediction model also showed that ramp metering resulted in a 23% and 28% reduction in BIs during moderate and severe congestion, respectively.

In practice, the observed benefits could be used to inform future ramp metering programs and compare its effect on mobility with other alternatives. Also, the research methodology could be adopted to measure the effectiveness of ramp metering on other corridors. Agencies could utilize the prediction model to determine when it is beneficial to activate or deactivate the RMSs.

6.1.2 Benefits of Ramp Metering during Non-recurrent Congestion due to Crashes

Estimating the benefits of ramp metering is essential for agencies to rationalize using ramp metering in managing traffic during non-recurrent congestion due to incidents. However, the lack of specific criteria for activating RMSs during incidents and the time-variant attributes of incidents makes it difficult to estimate the benefits. A second research objective was to quantify the effect of ramp metering on traffic conditions upstream of the crash location. An approach using traffic flow parameters (i.e., speed and occupancy), ramp metering operations data, and crash data was used to estimate the benefits of ramp metering during non-recurrent congestion due to crashes. The traffic flow parameters were collected during crash clearance duration when ramp meters were *activated* and *deactivated*. The *k-means* clustering method was used to classify traffic conditions, using the speed and occupancy data, in three groups: *uncongested state*, *transition state*, and *congested state*. The logistic regression model and GOLM were then applied to measure the effect of ramp metering on the traffic condition classes (i.e., *uncongested state*, *transition state*, and *congested state*). The research focused on evaluating the impact of the two consecutive RMSs upstream of the crash location. Other factors that could affect the traffic conditions upstream of the crash location were also analyzed. These factors included the number of responding agencies, involvement of fire rescue, involvement of towing services, lane blockage, type of lane closure, and the detection method.

Results indicated that activating the nearest RMS upstream of the crash location prevented traffic flow changing from a *transition state* to a *congested state* during daytime off-peak periods. Activating the second nearest upstream RMS did not have an impact on traffic conditions immediately upstream of the crash location during off-peak periods. It was also indicated that activating the nearest upstream RMS did not affect traffic conditions upstream of the crash location during peak periods. Results showed that activating the second nearest RMS upstream of the crash location prevented traffic flow changing from an *uncongested state* to a *transition state* during peak periods, and decreased the likelihood of changing from *uncongested* to *transition* by 46%. Results also suggested that ramp metering operations did not have a significant impact when the traffic flow was already in a *congested state*. The model results indicated that the following factors influence traffic conditions upstream of the crash location on a segment with ramp metering: number of responding agencies, involvement of fire rescue, involvement of towing services, lane blockage, type of lane closure, and detection method.

The research findings show the extent to which ramp metering influence traffic conditions upstream of the crash location. Agencies could use the estimated benefits to rationalize the activation of ramp metering to alleviate non-recurrent congestion due to crashes. Results could further be used to prepare standard guidelines for ramp metering operators to determine the time to activate and deactivate the RMSs during non-recurrent congestion due to crashes.

6.1.3 Benefits of Ramp Metering during Non-recurrent Congestion due to Rain

Estimating the benefits of ramp metering can help agencies determine the need for activating RMSs during non-recurrent congestion caused by rain. However, the lack of reliable rain data due to spatial and temporal attributes of rain limits the estimation of benefits. The third objective of this research was to evaluate the effect of ramp metering on non-recurrent congestion due to rain. An approach using traffic flow parameters (i.e., speed and occupancy) downstream of the entrance ramp, ramp metering operations data, and crash data was used to estimate the benefits of ramp metering during non-recurrent congestion due to rain.

The traffic flow parameters during rain were collected when ramp meters are *activated* and *deactivated*. The collected traffic data was divided into three groups depending on the time-of-day: daytime off-peak periods, nighttime off-peak periods, and peak periods. For each time of the day, the *k-means* clustering classified traffic conditions in the *uncongested state*, *transition state*, and *congested state*. The logistic regression that was fitted using a bootstrap resampling was used to analyze the data during daytime off-peak periods and nighttime off-peak periods. Conversely, the GOLM was applied to evaluate the effect of ramp metering on the traffic conditions during peak periods. The research also analyzed the impact of the rain intensity on traffic conditions downstream of the entrance ramp.

Results indicated that activating the nearest upstream RMS positively affected the traffic conditions downstream of the entrance ramp. During rain in daytime off-peak periods, activating the nearest RMSs upstream of the entrance ramp reduced the likelihood of downstream traffic conditions changing from *uncongested* to *transition* and *congested state* by 80%. During rain in nighttime off-peak periods, activating the nearest RMSs upstream of the entrance ramp reduced the likelihood of traffic conditions downstream changing from *transition* to *congested state* by 98%. The second nearest RMSs upstream of the entrance ramp did not significantly impact the traffic conditions during day and nighttime off-peak periods. During rain in peak periods, activating the nearest RMSs upstream of the entrance ramp decreased the likelihood of traffic conditions downstream of the entrance ramp changing from *uncongested* to *transition state* by 86%. Activating the nearest RMSs upstream of the entrance ramp also reduced the likelihood of traffic conditions downstream of the entrance ramp changing from the *transition* to the *congested state* by 76%. Moreover, as compared to light rain, heavy rain was associated with the decreased likelihood of traffic conditions changing to *transition* and *congested state*.

The research findings show how ramp metering influences traffic conditions downstream of the entrance ramp during rain. Agencies could use the estimated benefits to justify activating the RMSs in an attempt to alleviate non-recurrent congestion due to rain. Results could help to establish standard operating guidelines of ramp metering during rain.

6.2 Research Contributions

Agencies have been deploying ramp metering to help reduce recurrent and non-recurrent congestion on the urban roadway network. Future deployment of RMSs depends on their effectiveness in reducing congestion. Estimated benefits can justify using ramp metering to alleviate non-recurrent congestion due to crashes. Agencies could also establish criteria for activating and deactivating RMSs during non-recurrent congestion based on the estimated benefits.

Although few agencies have estimated the benefits of ramp metering during recurrent congestion, there are inconsistencies stemming from the constraints of the conventional estimation methods. These constraints include failure to separate the effects of other changes implemented along study corridors after deployment of RMSs, failure to account for changes in driver behavior following a shutdown experiment, and inability to mimic field conditions in a traffic simulation. Therefore, an approach that addresses some of the limitations of conventional methods can be used complement the conventional approaches in estimating the benefits of ramp metering during recurrent congestion.

While there are some efforts to estimate ramp metering benefits during recurrent congestion, most agencies have not quantified the effects of ramp metering on non-recurrent congestion. Analyses of the benefits during non-recurrent congestion are limited by the discrepancies in criteria for activating RMSs during non-recurrent congestion and the time-variant characteristics of unplanned events (i.e., crashes or rain) causing the non-recurrent congestion. Thus, using a data-driven approach can account for the limitations of quantifying ramp metering effects during non-recurrent congestion.

This research presented the shortcomings of the conventional methods used in estimating the mobility benefits of ramp metering during recurrent and non-recurrent congestion. Then, the study recommended and demonstrated the use of data collected during the unplanned downtime of the RMSs to account for the challenges of using conventional estimation methods. Not presented in previous studies, this research estimated the benefits of ramp metering using field-collected data that accounts for changes in the study corridor and driver behavior. Moreover, the research analyzed other factors rarely considered that influence travel time reliability along segments with system-wide ramp metering, including congestion level, traffic volume on entrance ramps, and density of entrance and exit ramps.

Also, for the first time, this research estimated the benefits of system-wide ramp metering during non-recurrent congestion due to crashes. The impact of the RMS location, relative to the crash location, was also explored. This research analyzed other crash attributes that could influence the traffic conditions (i.e., speed and occupancy) upstream the crash location along a corridor with system-wide ramp metering. The crash attributes included the number of responding agencies, involvement of fire rescue, involvement of towing services, lane blockage, type of lane closure, and the incident detection method. For the first time, this research showed the impact of lane-blockage on traffic conditions along segments with ramp metering using historical traffic data.

This research evaluated the benefits of ramp metering during non-recurrent congestion due to rain. The study focused on the impact of activating the RMS on the traffic conditions downstream of the entrance ramp. The effect of ramp metering was explored depending on the time of day. Other factors, including the rain intensity and other operations of further upstream RMSs were also explored. This research showed the benefit of ramp metering operations during rain.

6.3 Study Limitations and Recommendations for Future Research

The benefits of ramp metering during non-recurrent congestion were based on crashes. Future studies could consider all other incidents such as disabled and abandoned vehicles. The research could focus on incidents that cause lane blockage along on the freeway mainline. The extent of the estimated benefits of ramp metering is reliant on the quality and availability of data. This research used the crash data from SunGuide® when evaluating the benefits during non-recurrent congestion. The location of the crash recorded in the data depends on the decision of the operator inputting the crash-related information. Instead of geographical coordinates, the crash location was defined according to the closest cross-street. Specifically, the crash location along the freeway was defined as *before*, *after*, or *at* the cross street. Future research using more detailed crash datasets can improve the accuracy of the estimated benefits during non-recurrent congestion.

The research focused on the benefits of ramp metering on the freeway mainline. It is worth noting that the overall benefits of ramp metering depend on its effect on traffic along the entrance ramps, adjacent arterials, and parallel arterials. Future studies could evaluate the benefits of ramp metering on the urban roadway network by analyzing other locations affected by ramp metering, including adjacent arterials and ramps. The analyzed study corridor is adjacent to express lanes. During the study period, operations of the express lanes may influence the traffic conditions when ramp meters are *activated* or *deactivated*. Incorporating express lane operations in the analysis could give further insight into ramp metering benefits, especially its interaction with other TSM&O strategies in alleviating congestion.

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