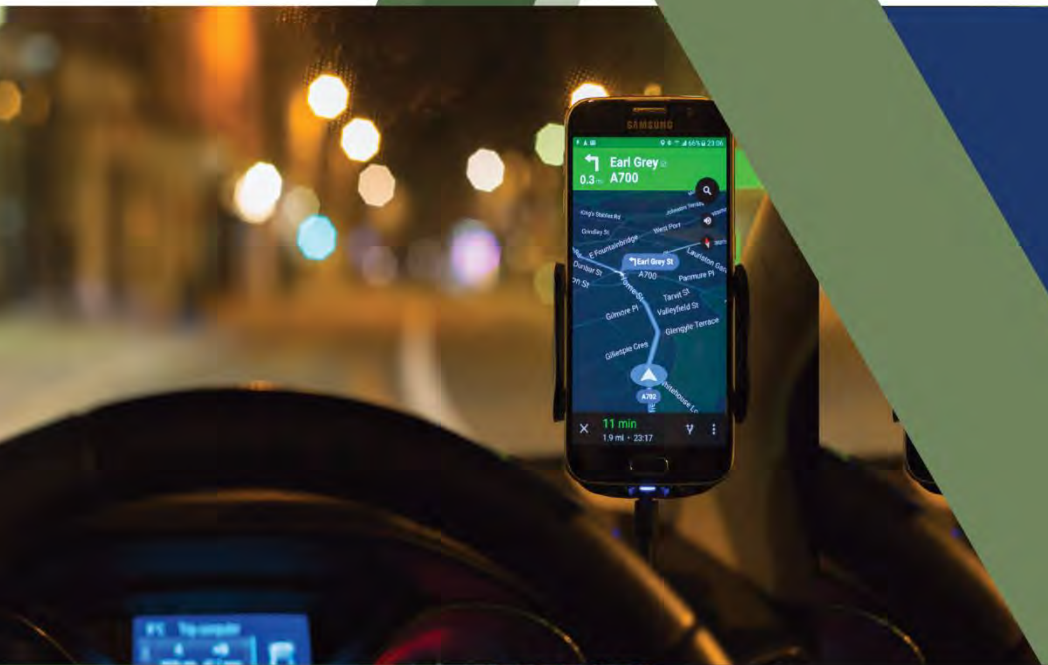

FINAL REPORT

Project A

August 2021

THE IMPACT OF SMARTPHONE APPLICATIONS ON TRIP ROUTING

Trip Routing Choices, Diversion Prediction, and Traffic Management with Decentralized Traveler Information Data

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16. Abstract

The Georgia Institute of Technology-led research evaluated trip re-routing potential of route guidance apps, how drivers utilized the information provided, and the impact of traffic re-routing on roadway facility usage, congestion, and prevailing speeds. Major findings of this study included a variety of characteristics associated with navigation apps and no singular uniform usage of navigation apps for all users or roadway facilities, a difference in stated vs real behavior associated with navigation app usage and travel behavior. Additionally, this study reveals the many challenges associated with collecting personal location history data through face-to-face surveys and online. The Florida International University led research developed a direct method to estimate the diversion for individual incidents based on mainline detector data and incident data. The study found evidence that the diversion was constrained by the capacity of the signals at the off-ramps, indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the main parallel routes. Data analytic models were developed in the study, allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations. Three different models were developed utilizing LR, SVM, and MLP. Among the developed models, the MLP model appeared to produce the best results. The models developed in this study can be used for prediction of diversion rate based on incident characteristics. The Jackson State University led research focused on the application of the traveler information data in congestion management. This part of the study used decentralized traveler information data to locate potential congestions to be applied with the gating control traffic management strategies to reduce traffic congestions in emergency events. Travel time reliability measures were applied to account for delays and identify significant traffic congestions for potential gate locations in evacuation zones. Performance of the gating control traffic management strategies were evaluated using a case study, with DTALite program, a simulation based DTA tool. The traffic simulations in the case study for the evacuation network in Memphis, TN configured with the gating control strategies using the decentralized traveler information data showed the effectiveness of the gating control traffic management strategies in managing evacuation traffic operations.

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ABSTRACT

Most smartphone owners today regularly use navigation applications such as Google Maps and Waze, for route guidance. By accessing real-time information, these apps provide users with updated maps and guidance on the quickest routes to avoid possible delays and congestion. These apps have become so popular that a number of communities have blamed navigation apps for increased local cut-through traffic. Although the use of mobile devices for in-vehicle navigation has become ubiquitous among drivers, there is limited research investigating the true impact of routing apps on trip routing or travel behavior. The goal of this research was to study the impact of such decentralized traveler information on the choice of trip routing by individuals and develop approaches for diversion prediction and traffic management for congestion management. This research used a three-pronged approach.

The Georgia Institute of Technology-led research evaluated trip re-routing potential of route guidance apps, how drivers utilized the information provided, and the impact of traffic re-routing on roadway facility usage, congestion, and prevailing speeds. This research investigated the travel behavior associated with navigation app usage through the collection of a stated preference questionnaire (N=237) and location history data (N=27). Major findings of this study included a variety of characteristics associated with navigation apps and no singular uniform usage of navigation apps for all users or roadway facilities, a difference in stated vs real behavior associated with navigation app usage and travel behavior. Additionally, this study reveals the many challenges associated with collecting personal location history data through face-to-face surveys and online.

The Florida International University led research developed a direct method to estimate the diversion for individual incidents based on mainline detector data and incident data. It was found that the diversion rate can range from about 4% to 22%, depending on the severity (mainly reflecting duration), lane blockage (up to three out of five lanes), and the time of incident occurrence. The study found evidence that the diversion was constrained by the capacity of the signals at the off-ramps, indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the main parallel routes. Data analytic models were developed in the study, allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations. Three different models were developed utilizing LR, SVM, and MLP. Among the developed models, the MLP model appeared to produce the best results. The models developed in this study can be used for prediction of diversion rate based on incident characteristics. The Florida International University study also performed a survey similar to the Georgia Tech survey in Florida and found out the stated diversion rates in the surveys were higher than the observed diversion in the detector data.

The Jackson State University led research focused on the application of the traveler information data in congestion management. This part of the study used decentralized traveler information data to locate potential congestions to be applied with the gating control traffic management strategies to reduce traffic congestions in emergency events. Travel time reliability measures were applied to account for delays and identify significant traffic congestions for potential gate locations in evacuation zones. Performance of the gating control traffic management strategies

were evaluated using a case study, with DTALite program, a simulation based DTA tool. The traffic simulations in the case study for the evacuation network in Memphis, TN configured with the gating control strategies using the decentralized traveler information data showed the effectiveness of the gating control traffic management strategies in managing evacuation traffic operations.

Executive Summary

Proliferation of mobile devices with routing apps such as Google Maps, Waze, INRIX, TomTom, etc., allows any mobile-enabled drivers to avoid congestion through real-time re-routing. However, to date, the real impacts of these routing apps on system and local traffic across the roadway infrastructure are largely unknown. The goal of this research was to study the impact of such decentralized traveler information on the choice of trip routing by individuals and develop approaches for diversion prediction and traffic management for congestion management.

This report is organized as a compendium of three reports from the three participating universities: Georgia Institute of Technology, Florida International University, and Jackson State University. The Georgia Institute of Technology study focuses on trip re-routing potential of route guidance apps. The Florida International University study focuses on quantifying and predicting diversion. The Florida International University study also administered the Georgia Tech developed survey in Florida and used the stated preference results obtained from it to compare with the revealed preference results from the diversion study. The Jackson State University study focused on the application of the traveler information data in congestion management and used decentralized traveler information data to locate potential congestions to be applied with the gating control traffic management strategies to reduce traffic congestions in emergency events. Summaries of these three studies are provided in the following subsections.

Chapter 1: Trip Re-routing Potential of Route Guidance Apps (Georgia Institute of Technology Study)

As more drivers turn to smartphone navigation apps, such as Google Maps and Waze, for up-to-date traffic information and trip routing, it is increasingly important to understand the impact of these devices on the choices of trip routing by individuals and the potential impact on roadway facility selection by drivers, congestion, and congestion management. The goals of this part of the study were to evaluate, based on stated preference by users, (1) the trip re-routing potential of route guidance apps, (2) how drivers utilized the information provided, and (3) the impact of traffic re-routing on roadway facility usage, congestion, and prevailing speeds.

The findings of this project from a user survey and location data include the behavior characteristics of navigation apps users. Navigation apps, most commonly Google Maps, were typically used for first-time and infrequent trips. Across all types of roadways, neighborhood, major, and freeway, the use of apps was less frequent than the actual use of the road. Navigation apps had a strong rerouting potential as smartphone app users followed the suggested route for at least 80 - 99% of trips (47%) and another 25% of users followed the suggested route for 100% of trips. A 3-5 min time savings was required for users to accept a routing change from the app. The survey captured a difference in general and personal perception of driver speed and alertness in neighborhood roads due to navigation apps. Although individuals reported an overall decrease of alertness of drivers in neighborhood roads due to navigation apps, they did not perceive the same decrease in their personal driving alertness. In addition to survey responses, empirical evidence of smartphone app routing usage

was collected through personal Google Location History (GLH) data donated by survey respondents. GLH data has the potential to provide high-resolution location and routing data that can be used to study route choice without a burden on the respondent. In this study, the collection process and nature of the sensitive data limited sample size of responses. Initial GLH data analysis results indicated a month of decreased travel and no change in navigation app usage after the I-85 bridge collapse in Atlanta, but full conclusions could not be drawn from the results of the analysis due to sample size limitations of the GLH dataset.

The results of the study will be useful in providing input to transportation management agencies on the current state of navigation app usage and the associated potential rerouting behavior.

Chapter 2: Diversion Prediction (Florida International University Study)

Existing studies have used stated and revealed preference surveys to estimate route diversion during incidents. This part of the study developed a more direct method to estimate the diversion for individual incidents based on mainline detector data and incident data. It was found that the diversion rate can range from about 4% to 22%, depending on the severity (mainly reflecting duration), lane blockage (up to three out of five lanes), and the time of incident occurrence.

The study found evidence that the diversion was constrained by the capacity of the signals at of the off-ramps, indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the main parallel routes. Capacity analysis of the off-ramp signals indicated that the two off-ramps that provided exits to the main connectors to the alternative routes had a limited amount of access capacity available for vehicles to exit the freeway to alternative routes.

Data analytic models were developed in the study, allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations. Three different models were developed utilizing LR, SVM, and MLP. Among the developed models, the MLP model appeared to produce the best results. The models developed in this paper can be used for prediction of diversion rate based on incident characteristics.

A limitation of this study is that the developed method estimates the overall diversion rate and not the diversion at each off-ramp. Most transportation agencies in the United States do not install sensors on the off-ramps. It is recommended that agencies start installing sensors at the off-ramps to allow more detailed examination of the diversion.

Based on the results from this section, it can be concluded that the use of detector data combined with traffic flow and statistical techniques is viable to estimate diversion. This will become even more important, as agencies increase their emphasis on performance-based planning, planning for operations, and operations of their systems. It is expected that the diversion models are site specific and depend on the available capacity and characteristics of the alternative routes. The transferability of the models between locations and similar locations in different regions should be investigated in future studies.

CHAPTER 3: GATING CONTROL TRAFFIC MANAGEMENT USING DECENTRALIZED TRAVELER INFORMATION DATA (JACKSON STATE UNIVERSITY STUDY)

This part of the study used decentralized traveler information data to locate potential congestions to be applied with the gating control traffic management strategies to reduce traffic congestions in emergency events. Travel time reliability measures were applied to account for delays and identify significant traffic congestions for potential gate locations in evacuation zones. Performance of the gating control traffic management strategies were evaluated using a case study, with DTALite program, a simulation based DTA tool. The traffic simulations in the case study for the evacuation network in Memphis, TN configured with the gating control strategies using the decentralized traveler information data showed the effectiveness of the gating control traffic management strategies in managing evacuation traffic operations. From this research, the following findings were observed.

1. The gating control traffic management strategies deployed using the decentralized traveler information data, could well reduce congestion for emergency events under extreme weather. The travel time reliability data analysis based on the probe data could catch the dynamic nature of potential congestions and achieve improved performance of average travel time and traffic conflicts in a realistic large scale evacuation network.
2. According to the average buffer time index results, there was one segment checked during AM peak hours and four segments checked during PM peak hours. Compared to AM peak hours, there was more low travel reliability during PM peak hours. The segments on which the index values were larger than 0.55 during PM peak hours were segment 6 on TN-277 Southbound and segment 10 on Democrat Road Eastbound in Zone I, segment 17 on Getwell Road Southbound in Zone II, and segment 29 on TN-204 Northbound in Zone III. They were identified as the potential traffic congestion locations.

3. Simulation results of the gating traffic management strategies with the realistic large scale evacuation network in fourteen scenarios, showed that all the gating scenarios could achieve better evacuation performance with reduced average travel time than the non-gating strategy could. The smallest average travel time for scenario was from 57.8 minutes with 72.9% improvement at the lowest demand of 286,000 vehicles to 151.2 minutes with 48.0% improvement at the highest demand of 640,000 vehicles. The simulation results also showed that the number of possible traffic conflicts using a gating strategy was always lower than that using the non-gating strategy. The best scenario improved traffic conflicting with 59.9% improvement at 376,000 evacuating vehicles and 63.1% at 64,000 vehicles. The simulation results confirmed that a gating control strategy could improve the evacuation performance by reducing the average travel time and total possible traffic conflicts in evacuation traffic operations in the network.

Study Description

Proliferation of mobile devices with routing apps such as Google Maps, Waze, INRIX, TomTom, etc. has made possible congestion avoidance through real-time re-routing of vehicles for any mobile-enabled driver. However, to date, the real impacts of these routing apps on system and local traffic across the roadway infrastructure are largely unknown. There is a limited amount of research that has broadly investigated issues such as the impact of social media on transportation policy (Gal-Tzur et al., Bregman and Watkins), usage patterns of smartphone apps (Jones et al.), and use of gaming concepts to influence driver behavior (McCall and Koenig). However, there is a dearth of research investigating the impact of routing apps on trip routing or travel behavior. This study attempts to fill this gap and gather evidence and quantify the relationship between routing app usage and propensity of alternative route choices by routing app users.

The goal of this research was to study the impact of such decentralized traveler information on the choice of trip routing by individuals and develop approaches for diversion prediction and traffic management for congestion management.

This report is organized as a compendium of three reports from the three participating universities: Georgia Institute of Technology, Florida International University, and Jackson State University. The Georgia Institute of Technology study (Chapter 1) focused on trip re-routing potential of route guidance apps. The Florida International University study (Chapter 2) focused on quantifying and predicting diversion. The Florida International University study also administered the Georgia Tech developed survey in Florida and used the stated preference results obtained from it to compare with the revealed preference results from the diversion study. The Jackson State University study (Chapter 3) focused on the application of the traveler information data in congestion management and used decentralized traveler information data to locate potential congestions to be applied with the gating control traffic management strategies to reduce traffic congestions in emergency events.

Chapter 1: Trip Re-routing Potential of Route Guidance Apps (Georgia Institute of Technology Study)

1.1 Introduction

With the introduction of smartphone navigation apps, drivers have an increasing number of options to make informed route choice decisions using information from all available routes and current traffic conditions. It is important to understand how information from these apps affect route choice behavior as governments invest in variable message signs (VMS) and other Active Transportation and Demand Management (ATDM) strategies. In addition to potentially disrupting the effectiveness of traditional traffic information management strategies, several communities have pointed to navigation apps for disrupting typical traffic patterns and increasing local cut-through traffic. Although most smartphone owners today regularly use navigation applications such as Google Maps and Waze for guidance of the quickest routes, there is limited research investigating the true impact of routing apps on trip routing or travel behavior. This research aims to fill the gap of knowledge surrounding navigation apps by analyzing the impact of traffic routing smartphone applications on roadway facility selection.

1.1.1 Objective

The goal of this study was to understand the usage of smartphone navigation apps and their potential impact on trip routing. Objectives of this project include evaluating (1) trip re-routing potential of route guidance apps, (2) how drivers utilize the information provided, and (3) the impact of traffic re-routing on roadway facility usage, congestion, and prevailing speeds.

1.1.2 Scope

The tasks for this project were as follows:

1. Conduct a literature review of trip diversion potential of smartphone apps and trip routing studies using location history data.
2. Implement and analyze a survey questionnaire in Atlanta, GA to study the trip re-routing potential of navigation apps by asking users about their preferences and behavior related to their usage.
3. Obtain and analyze Android location data to uncover empirical evidence of smartphone routing app usage and roadway function class frequency in trips.

1.2 Literature Review

Over the past ten years, the ownership of mobile devices has dramatically risen to over 80% of the US adult population (Pew Research Center 2019). The increasing penetration of smartphones has allowed access to real-time crowdsourced traffic data with routing apps such as Google Maps, Waze, INRIX, and TomTom. Today, navigation apps are ubiquitous as almost all smartphone users utilize mobile driving directions at least some of the time (Anderson 2016). These routing apps access network-wide traffic information to relate the overall traffic conditions and users' shortest origin-destination path. Real-time information allows users to make both pre-trip and en-route navigation decisions. Although these apps provide users with the possibility of congestion avoidance, they have also resulted in a number of traffic incidents and a growing concern of new congestion patterns (Cabannes et al. 2018).

Incidents involving navigation app users following routes into dangerous environments have become frequent headlines in the news; vehicles have incorrectly routed through insufficient roads, off cliffs, and through fire and floods (Kennedy 2019, Graham 2017). Drivers' willingness to diverge and rely on real-time smartphone navigation apps has become an increasing safety concern. However, there is a limited understanding of how these apps are truly used and impact traffic behavior. Previous research on the impact of real-time information on traffic diversion and the human factors of route diversion has typically involved in-vehicle navigation systems, not smartphone apps (Mahmassani et al. 1991, Allen et al. 1991,). These studies suggest navigation system characteristics such as the clarity of directions and visibility of real time traffic information have significant effects on driver diversion yet only a limited amount of research investigates the usage patterns and consumer preferences of today's crowdsourced traffic apps (Khoo et al. 2016, Paniko 2018). Additionally, it has been found that as the familiarity of drivers with the route increases, they are more reluctant to follow advice unless they find it convincing (Bonsall 1992). This dearth of research investigating the impact of routing apps on trip routing and travel behavior is concerning because of the current reliance of many users on these apps.

A number of anecdotal claims from communities across the US blame navigation apps for induced, cut-through traffic and increased congestion (Cabannes et al. 2018). Several public policy concerns are associated with potential cut-through traffic due to higher demands on local infrastructure, disruptions to residential travel times, and pedestrian safety concerns. Local roads and residential streets were not built for a large volume of vehicles associated with rerouting via cut-throughs. In response, cities and residents have taken unsuccessful measures to prevent rerouting, including adding fake detours and prohibiting travel of non-residents on neighborhood streets (Britschgi 2018). Although an increase in cut-through traffic has been observed at specific sites through field data (Cabannes et al. 2018, Streetlight 2019), there has not been an explicit correlation with navigation apps because of limited data related to driver utilization of the information provided. Real-time shortest path routes are available to anyone using a navigation app but driver behavior may not match the recommended routing. Although these apps allow access to the "quickest" route, drivers may not choose to use the app or follow the suggested route. Therefore, understanding users' stated preferences and revealed behavior in the use of navigation apps is especially important. Theoretical models have attempted to simulate the usage of local rerouting potential of navigation apps by considering the behavioral differences between app users and non-app users (Cabannes et al. 2018, Thai et al. 2016). Yet, there has not been a multi-scale analysis to determine if the apps are better or worse for traffic networks as a whole.

The true impacts of the navigation app trend on the roadway infrastructure and system remain largely unknown. The aim of this work is to study the impact of smartphone route guidance apps on the choice of trip routing by individuals and the potential impact on roadway facility selection by drivers.

1.3 Methodology

To capture route guidance app user's preferences and behavior, a navigation app behavior questionnaire accompanied by quantitative spatial historical location data was implemented. The questionnaire was developed to evaluate rerouting potential of navigation apps and the trips types and lengths associated with navigation app usage. In addition, travel time and location information were obtained from a subset of participants through voluntary download of Google Location History (GLH) data. GLH data can be passively collected from smartphone users with varying accuracy and frequency depending on the mobile phone configuration and environment. GLH Timeline, a smartphone feature that tracks mobile devices and saves locations over a large temporal and spatial span and granularity, allows device users to download their historical location data. This active nature of data retrieval, in addition to user privacy concerns, make it an underutilized dataset (Ruktanonchai et al. 2018).

While the survey provides a method to evaluate the proclivity of drivers to use cut-throughs suggested by navigation apps, it is challenging to quantify the likelihood of doing so. The GLH data was collected to provide the ability to better quantify the percentage of re-routing and the conditions under which re-routing occurred by observing the differences in behavior of drivers over time as well as with and without smartphone-based navigation use.

A specific experiment was designed to study the effect of smartphone-navigation related diversions. There was a major incident in Atlanta on March 30 of 2017 in which there was a failure of a section of a bridge on I-85 which caused a complete shutdown of a significant section of the interstate road. This forced rerouting to alternate routes and potentially increased use of navigation application to get around this blockage. GLH data was therefore requested from the survey participants for the months immediately before and after the incident (March and April 2017) and the corresponding control period of March and April of the following year (2018).

In addition to the use case of the I-85 bridge collapse experiment, the GLH data was also expected to serve to verify the reliability of the revealed preference information provided by the participants in the survey. For the participants who answered the questionnaire as well as provided GLH data, the GLH data was analyzed to find evidence to support the cut-through and diversion behavior that the participants indicated in their responses.

1.3.1 User Survey

To evaluate the relationship between routing app usage and propensity of alternative route choices by users, attitudinal survey data and empirical location history data were collected through an interview-administered questionnaire. In June, August, and November of 2018, the survey was deployed at four community events in the Atlanta, Georgia area (Figures 1-1 to 1-3):

- June 10, 2018, Atlanta Streets Alive, Marietta St., Atlanta, GA 30318
- August 18, 2018, Piedmont Arts Festival, Charles Allen Dr. and 10th St., Atlanta, GA 30309
- August 19, 2018, Piedmont Arts Festival, Charles Allen Dr. and 10th St., Atlanta, GA 30309
- November 11, 2018, Georgia Tech Football Tailgate, Bobby Dodd Way, Atlanta, GA 30313*

Figure 1-1: Survey 1, June 10, 2018, Atlanta Streets Alive

The fourth event, indicated with *, deployed a modified and shortened survey to target Android users in an attempt to increase the GLH data downloads. The attitudinal survey instrument was a four-page paper script with 24 questions to be completed by a personal interview, with a shortened version for the fourth event. The average questionnaire interview completion time was six minutes (a maximum of 13 minutes). By conducting interviews face-to-face, there was a higher response rate and interviewers built a sense of trust during the questionnaire portion of the survey, in hopes that the respondents would feel comfortable sharing sensitive GLH during the data download process. Interviewers followed the questionnaire script to ask participants a series of questions about their navigation app usage. A small novelty pen was used as an incentive to those participants willing to complete the questionnaire and a $10 Amazon gift card was offered to those participants willing to donate GLH data.

1.3.2 Location History Data Collection

Although a survey can capture stated travel behavior and preferences, spatiotemporal location history can reveal actual travel behavior. Through the face-to-face survey, participants who responded to the survey about navigation use had the option of providing four months of smartphone location data for the months of March 2017, April 2017, March 2018, and April 2018. These months were chosen because of their relationship with the I-85 bridge collapse in Atlanta, Georgia and associated increase in navigation app usage. After I-85 was closed on March 20, 2017, the public turned to real-time commute data to adapt to the new traffic patterns (Douglas 2017). Only Android phone users were eligible to participate in the data download process because android phones passively share more location data than iOS users (Schmidt 2018). Interviewers explained the GLH data collection procedure, consent and confidentiality agreement, and participant rights, before the participants started the automated GLH data collection process. Participants were asked to log into their Google account on a secure research laptop, click a link on the survey webpage that would automatically download specified smartphone location data stored in their Google account, and then logout of their account to ensure no further access for the researchers to their account. Data was downloaded in a Keyhole Markup Language (KML) format with attributes including a timestamp, latitude, longitude, calculated activity, and distance traveled.

1.3.3 Survey Methodology

Survey participants were sampled using a convenient intercept method. Interviewers at a central hub approached individuals walking by and asked to interview them about how they use navigation in their vehicle. Participants were further screened as only adults who regularly drive a vehicle and mainly use a smartphone were eligible for participation in the survey. For the Georgia Tech football tailgate data collection this was further constrained to only Android users to increase the sample of respondents who could potentially provide GLH data as well. If respondents did not meet the eligibility criteria, they were not able to participate in the survey and were recorded as an uncaptured response. Although this is a population selection bias, this technique eased the difficult nature of sensitive data collection and the results can still be used for detecting relationships among different phenomena.

Figure 1-2: Survey 2 & 3, August 18 & 19, 2018, Piedmont Arts Festival

Participants answered a variety of questions including frequency experience questions associated with their usage of roadways and navigation apps, multiple choice questions about their typical behavior with navigation apps, and Likert-scale questions to quantify relative changes in driving behavior associated with navigation app usage. The end of the questionnaire included sociodemographic questions and an open-ended section where the respondent could relay any additional comments related to the use of navigation apps. After completing the questionnaire, respondents had the option of continuing to the GLH data collection procedure. The full-length interviewer script is available in Appendix B with * indicating the questions slightly modified and ** indicating the questions removed in the shortened survey used on 11/10/18.

Figure 1-3: Survey 4, November 11, 2018, Georgia Tech Football Tailgate

1.3.4 Location History Data Collection and Processing

Eligible participants that were willing to provide their GLH data for this study were challenging to recruit. Only 11% of questionnaires resulted in GLH data collection. A limiting factor for the number of data downloads was the eligibility process, in which participants were restricted to Android users with location services enabled on their smartphone; only 25% of questionnaire respondents were eligible to participate in the data collection after the first three survey implementations. The data collection time commitment and data privacy concerns were two of the most cited refusals when asked to continue with the location data process. With half of eligible participants willing to share GLH data and 8 participant dropouts during the data collection process, a total of 22 GLH data downloads were completed during the first three survey implementations.

Table 1-1: Initial GLH Data Collection Responses

		Possible GLH Data Collection Participants		*Willing Data Collection Participants*		
Date	**Completed Questionnaire**	**Android Users with Location Services**	**% of Completed Questionnaires**	**Started Data Collection Process**	**Data Collected**	**% of Completed Questionnaires**
6/10/2018	30	10	33%	8	8	27%
8/18/2018	117	28	24%	8	6	5%
8/19/2018	61	22	36%	11	8	13%
Initial Total	**208**	**60**	**29%**	**27**	**22**	**11%**
11/10/2018 *	29*	11*	38%	8*	5*	17%
Total	**237**	**71**	**30%**	**35**	**27**	**11%**

Limited participants in the GLH data collection during the first three face-to-face survey implementations resulted in the development of a shorter survey attempting to target participants that could provide GLH data. The shorter navigation use survey included 17 questions to gather how respondents use navigation in their vehicle. Initial screening limited survey participants to respondents older than 18 years of age, who are regularly driving, and use an Android smartphone for vehicle navigation. Questions involved the frequency of app usage on different road facilities, the trip durations of app usage on different road facilities, percent of trips that respondents follow the suggested route, and the primary reason they do not follow the suggested route. In addition to the data collected during the survey process, additional data was collected through an online portal described in Appendix C. However, most of the data collected through the online portal was screened out of the analysis because the datasets did not contain at least 85% of collected days with trips in the Atlanta area.

Specific criteria attempted to limit the study to only participants meeting the criteria: participants must be above 18, regularly drive a car, primarily use an Android phone for vehicle navigation, have "Google location services" turned on, and have a primary residence in Metro Atlanta, GA. The survey collected 27 responses with a variety of quality in data downloads as seen in Table 1-2. 23 of the 27 responses contained data for over half of the days requested. Days without data may be due to study participants not using an Android smartphone for the entire period or study participants turning off location history collection. Location services are turned off when an Android phone is not on but not when the phone is in Flight Mode. The average number of trips downloaded per respondent was 542 trips with a minimum and maximum of 1 and 982 trips, respectively. A full table for frequency for each of the 27 downloads can be found in Appendix E.

Table 1-2: GLH Data Quality Frequency Table

Type	Count	Percent of Data Survey Respondents
Count of Days with available data (N=27)		
1 - 30 Days	2	7%
31 - 60 Days	2	7%
61 - 90 Days	6	22%
91 - 120	15	56%
121 +	2	7%
Count of Trips (N=27)		
1- 150	2	7%
151 - 300	3	11%
301 - 450	3	11%
451 - 600	6	22%
601 - 750	7	26%
751 +	6	22%
Percent of Active User Driving Trips in Atlanta (N=27)		
0 - 20 %	2	7%
21 - 40 %	2	7%
41 - 60 %	2	7%
61 - 80 %	3	11%
81 - 90 %	7	25%
91 - 100 %	11	39%

Each complete data download resulted in a KML file for each day containing trips and stops with attributes including activity type e.g., driving, walking, biking, timestamp, latitude and longitude of location points, and distance. To process the large amount of data for each individual, a python script pulled out the latitude and longitude of location points and activity point for each trip on each day. All trip files were merged into a csv for each respondent. Although GLH Timeline provides routes for each trip, extracting the location data points instead of the trip line allowed for finer analysis of the data. Data was refined to points in the area of interest by clipping points to the Atlanta Metro area (boundary of Atlanta Metro area determined as per the Atlanta Regional Commission definition). Points were further refined to only include points associated with a driving type trip. The nearest roadway facility classification, as defined by the Georgia Department of Transportation (GDOT) road inventory, was associated with each data point (GDOT 2019). Each trip can be associated with multiple roadway classifications. Using ARCGIS data management tools, line features were created from temporally consecutive points of the same trip. By using the location data points to build trips instead of evaluating the provided trip line, the distance between points was calculated and used to estimate trips as active or passive phone engagement. Navigation app usage associated with GPS signal contains a higher accuracy and additional frequent location points (Rodriguez et al. 2018).

1.3.5 Survey Results

From the sample of 694 interactions, there were roughly 237 usable survey responses and 27 usable GLH data collections, after removing severely incomplete cases. Table 1-3 presents the socio demographics of the pooled sample of survey respondents and matching GLH respondents compared with the 2017 Atlanta American Community Survey (ACS) data (United States Census Bureau 2017). The small chi-squared goodness of fit test values indicates a difference between the sociodemographic characteristics of survey and GHL data respondents as compared to the population. Survey participants tended to be higher educated and younger than the average study area population. This trend mirrors the characteristics of the sample population of smartphone owners (Pew Research Center 2019).

The detailed survey results can be found in Appendix D. Some of the important results are highlighted in the following sections.

Table 1-3: Sociodemographic for Pooled Sample and ACS Population

	Survey Responses	% Respondents Answering Question*	GLH Responses	% of GLH Reponses's Answering Questions	% Population from ACS
Gender	*(N=232, Chi-squared goodness of fit P<0.95)*		*(N=13, Chi-squared goodness of fit P<0.0001)*		
Male	114	49.10%	9	69%	49.60%
Female	118	50.90%	4	31%	50.40%
Age	*(N=235, Chi-squared goodness of fit P<0.001)*				
18-24	28	11.90%	2	15%	22.20%
25-34	66	28.10%	5	38%	19.50%

	Survey Responses	% Respondents Answering Question*	GLH Responses	% of GLH Reponses's Answering Questions	% Population from ACS
35-44	40	17.00%	3	23%	13.10%
45-54	52	22.10%	2	15%	10.50%
55-64	39	16.60%	1	8%	16.20%
65-74	9	3.80%	0	0%	11.00%
75+	1	0.40%	0	0%	7.60%
Highest Level of Education	*(N=234, Chi-squared goodness of fit P<0.001)*		*(N=13, Chi-squared goodness of fit P<0.0001)*		
From 9th grade to 12th grade	1	0.40%	0	0%	10.10%
High school graduate	7	3.00%	1	8%	19.20%
Some college but no bachelor's degree	32	13.70%	2	15%	26.90%
Bachelor's degree	100	42.70%	6	46%	25.90%
Graduate work or postgraduate degree	94	40.20%	4	31%	17.90%
Persons in Household	*(N=235, Chi-squared goodness of fit P<0.001)*		*(N=13, Chi-squared goodness of fit P<0.0001)*		
1	42	17.90%	3	23%	43.10%
2	97	41.30%	6	46%	31.70%
3	47	20.00%	3	23%	11.70%
4+	49	20.90%	1	8%	13.50%
Persons in Household Under the Age of 18	*(N=235, Chi-squared goodness of fit P<0.1)*		*(N=13, Chi-squared goodness of fit P<0.95)*		
0	165	68.50%	10	77%	77.40%
1 or more	70	29.00%	3	23%	22.60%

1.3.5.1 Usage of Different Navigation Apps

The survey began by asking participants their situational behavior when they enter their car and use a device for vehicle navigation. With over 78% of participants stating their main device for navigation is a smartphone, as seen in Figure 1-4, this predominant result is similar to the national average (Pew Research Center 2016).

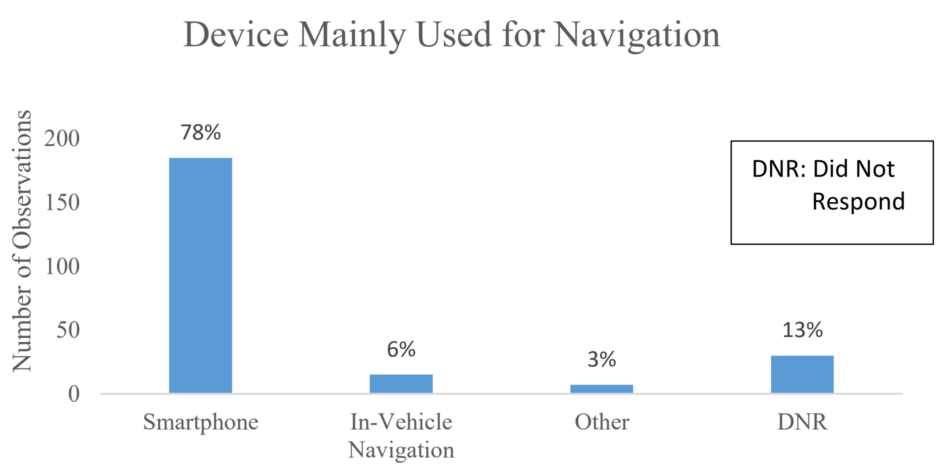


Figure 1-4: Device Mainly Used for Navigation

The type of smartphone used was recorded and used as a qualifier for location data collection. The sample of surveys collected was largely iPhone users, 67% as seen in Figure 1-5, which differs from the national proportion of smartphone operating systems, 45% iPhone (Statista 2019).

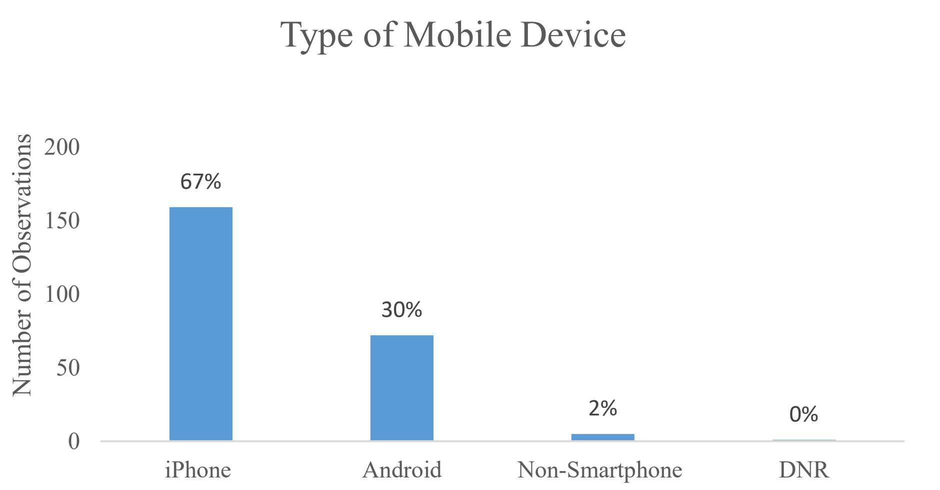


Figure 1-5: Type of Mobile Device of Sample

The distribution of the app used for navigation also differed from the national proportion. The proportion of Waze app users was 36%, which is larger than the proportion captured in a previous study, 11% (Graham 2018). This difference in app used for navigation might be explained by the location of the survey, urban Atlanta, because Waze is used more in large U.S. cities (Drivemode 2018). As seen in Figure 1-6, Google Maps is the most popular app used for directions and almost a third of smartphone users have more than one app for navigation. Although the typical app was recorded in the survey, the following questions were related to general navigation app usage. Comments made by respondents indicate that type of app usage may impact the travel behavior and should be researched further.

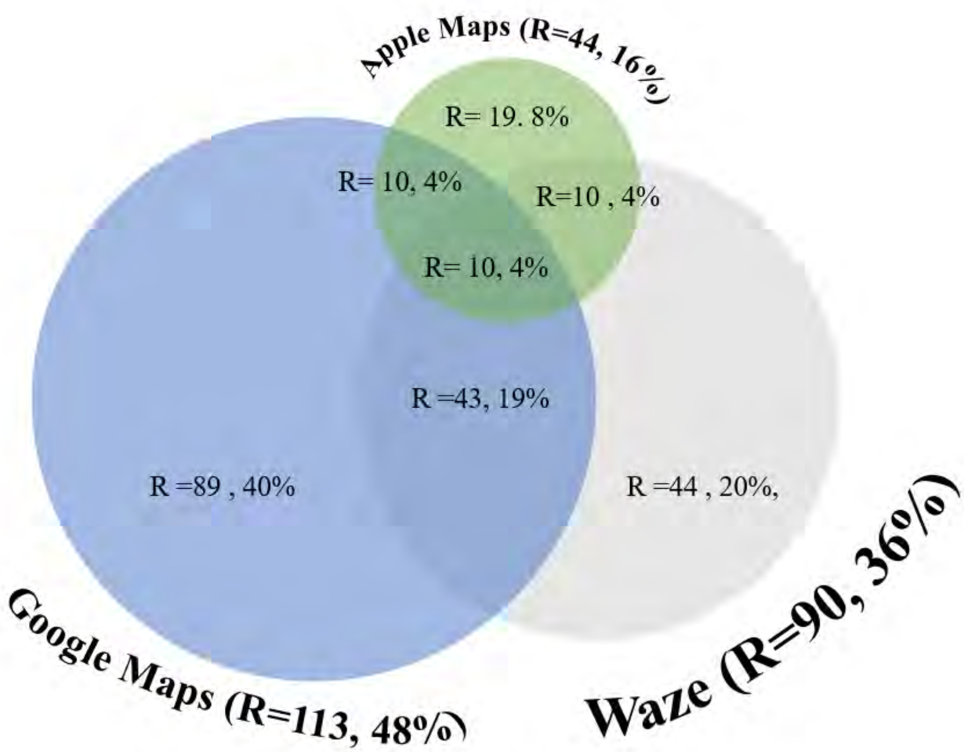


Figure 1-6: App Used for Navigation (N=225)

1.3.5.2 Usage on Various Types of Roadways

The next set of questions were related to the frequency of road usage (i.e., daily, once a week, once a month, and several times a year) and roadway facility type (i.e., freeway, major road, and neighborhood road). Respondents were initially asked for the categorical frequency of usage on each type of road and then asked for the categorical frequency of usage with navigation apps on each type of road. These relative frequencies of road use with or without a navigation app are displayed in Figure 1-7 as the percentage of respondents (n=185). A chi-squared test confirmed the difference between the frequency of typical road usage and frequency of road usage with navigation apps for each facility type; freeway $\chi2< 0.05$, major roads $\chi2< 0.01$, neighborhood roads $\chi2< 0.01$. This result indicates that users do not use navigation apps uniformly. App users have distinct travel patterns and app usage preferences which may lead to the unequal distribution of road and navigation app usage.

Figure 1-7 also indicates that not every trip is made with a navigation app. Across all types of roadways, the use of apps is less frequent than the actual use of the road. The closest daily road use with and without navigation app occurs on a freeway: 56% of respondents (r=103) indicated that they use a freeway daily and 41% of respondents (r=75) indicated that they use a freeway with a navigation app daily. This high app usage on freeways may be explained by the typical nature of freeway trips in combination with the types of trips that involve navigation apps. Freeways with high levels of congestion will see a high usage of routing apps as drivers try to avoid the congestion. The time spent on neighborhood streets saw the largest difference of app usage. Although 83% of respondents indicated a daily usage of neighborhood roads, only 39% of users indicated daily usage of neighborhood roads with a navigation app.

Figure 1-7: Frequency of Road Usage With and Without Navigation apps

Respondents were asked about the type of trips that typically involves navigation apps for directions. First time trips (78%) and infrequent trips (74%) are the two most common types of trips users use apps for directions, as seen in Figure 1-8 (n=143). Almost half of respondents did indicate that they use navigation apps for regular commute trips (46%). This finding has potential re-routing implications because drivers have a higher tendency to divert to alternate routes if they are more familiar with the suggested route (Khoo et al. 2016).

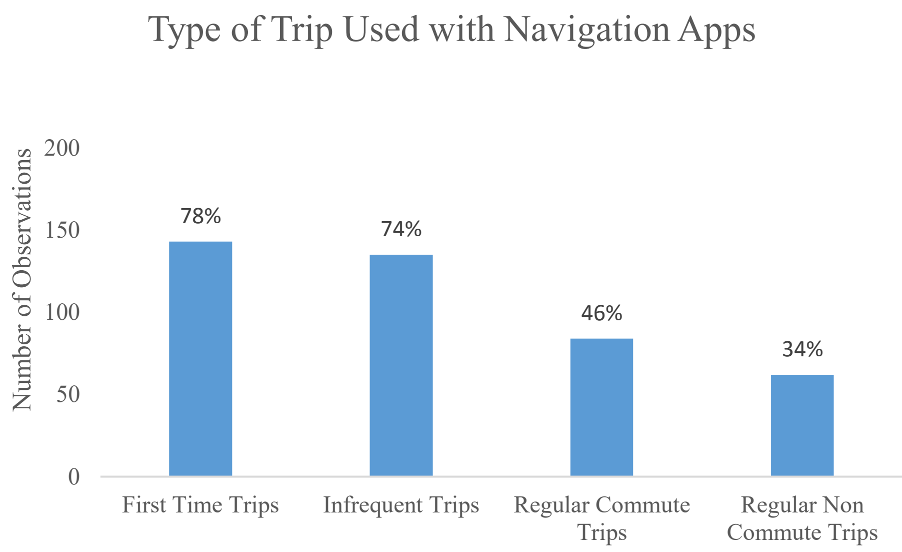


Figure 1-8: Type of Trip Used with Navigation Apps

Respondents were asked to select the trip durations when they typically used navigation apps. Respondents (n=182) had the opportunity to select multiple trip duration ranges. Most trips using navigation apps are typically longer trips with durations of 16-30 minutes (68%), 31- 60 minutes (70%), and 61+ minute (61%) as seen in Figure 1-9.

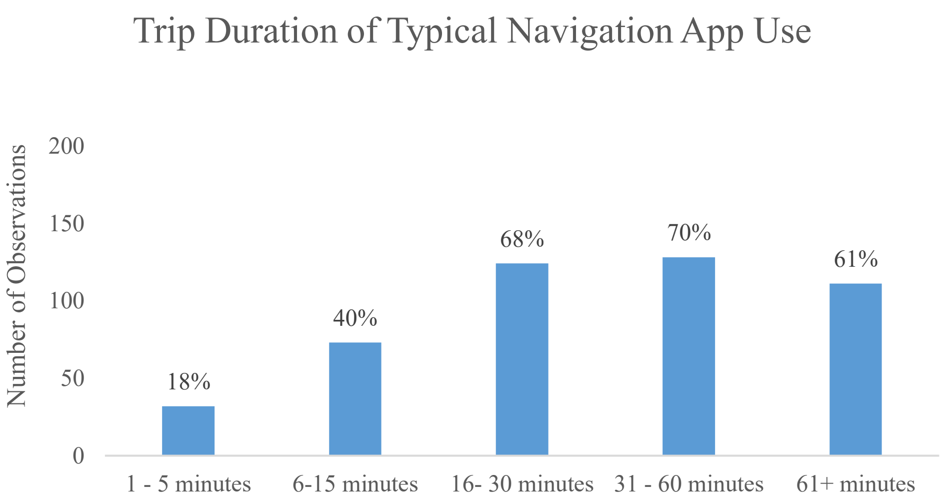


Figure 1-9: Trip Duration of Typical Navigation App Use

1.3.5.3 Navigation App Rerouting Potential

Navigation apps provide up-to-date information to users with updated trip arrival time and best route. Navigation apps provide users information that allows potential rerouting. Although apps like Google Maps and Waze provide the fastest route as an option to users, they do not always select this optimal route at the start of the trip or switch to the most optimal route mid-trip.

The questionnaire contained a series of questions to determine the rerouting potential of navigation apps. Most smartphone app users follow the suggested route for at least 80 - 99% of trips (46%) and another 25% of users follow the suggested route for 100% of trips, as seen in Figure 1-10.

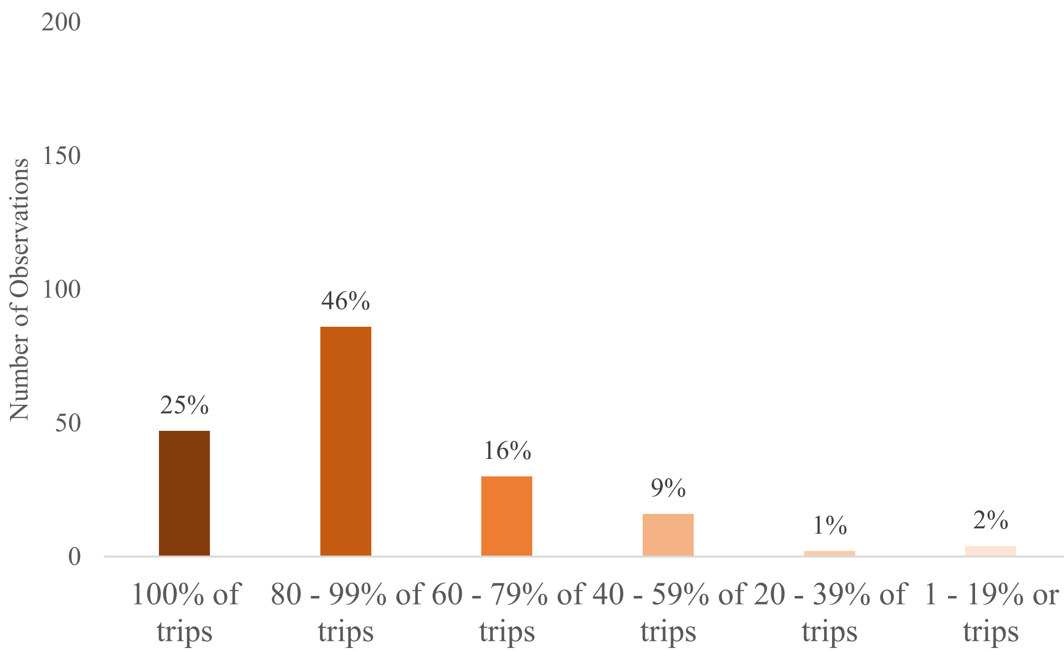


Figure 1-10: Percentage of Trips where Users Follow the Suggested Route

When users do not follow the suggested route, the primary reasons are because they prefer their typical route (42%), or they don't trust the route (33%), as seen in Figure 1-11.

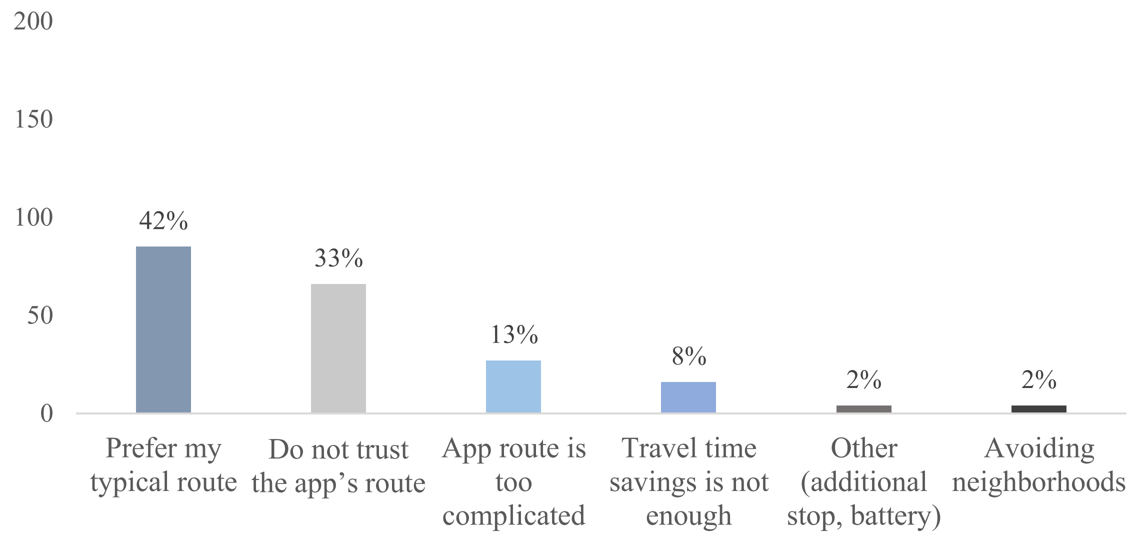


Figure 1-11: Reason for Not Following the Suggested Route

To understand rerouting potential, users were asked about their preference for the times savings required to accept a route change. Over 60% of the respondents expressed that a 3-5-minute time savings would result in taking the recommended route (r=120, n = 194). A 6 to 10-minute time savings threshold would be required for 26% of the respondents to follow the suggest route (r=52, n=194), as seen in Figure 1-12.

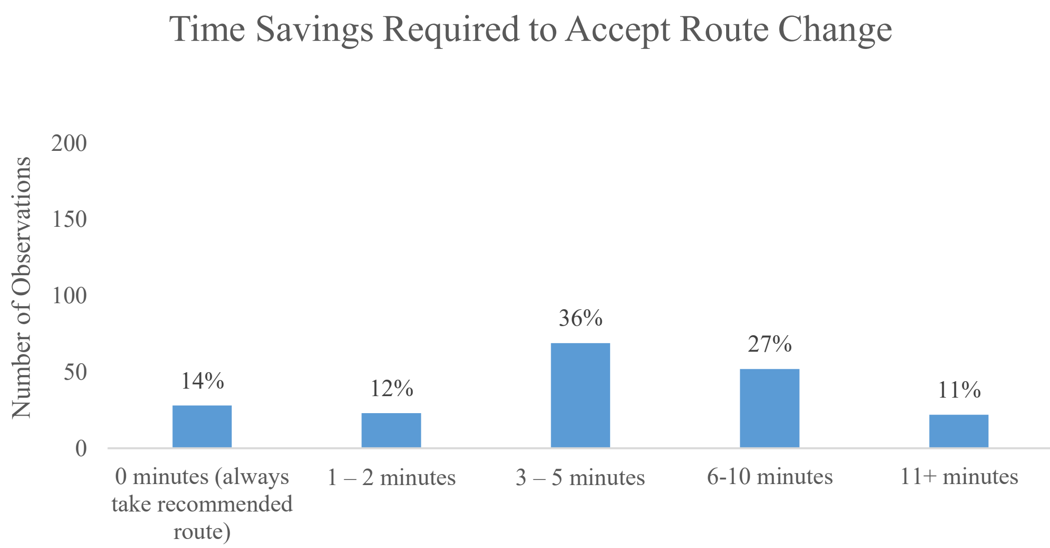


Figure 1-12: Threshold of Timesaving Required for Route Change

1.3.5.4 Perceptions of Behavior Change Due to App Usage

The final section of the questionnaire, before asking sociodemographic related questions, included two multi-part questions regarding their perception of how apps have changed usage on different facility types and how apps have changed user characteristics on neighborhood streets. Each respondent was asked to rate how navigation apps changed the general behavior on a Likert Scale, ranging from large decrease to large increase. They were then asked to rate how navigation apps have changed their personal behavior.

When asked how navigation apps have changed the general road usage (time spent driving on each road type), around a quarter of the respondents perceived no change in general road usage for each facility type. More than a quarter of respondents perceived a small decrease in freeway usage as seen in Figure 1-13. Over half of the respondents perceived either a small increase or large increase in the time spent driving on neighborhood roads. The large variance in change of usage as seen in major roads, may be a result of an error in mode of data collection. During face-to-face interviews, respondents may provide inaccurate answers due to the on-the-spot nature of the question (Lavrakas 2018). The general and personal perception of change in road usage due to navigation apps was not significant across road types: p=0.43 for freeways, p=0.43 for major roads, and p =0.67 for neighborhood roads.

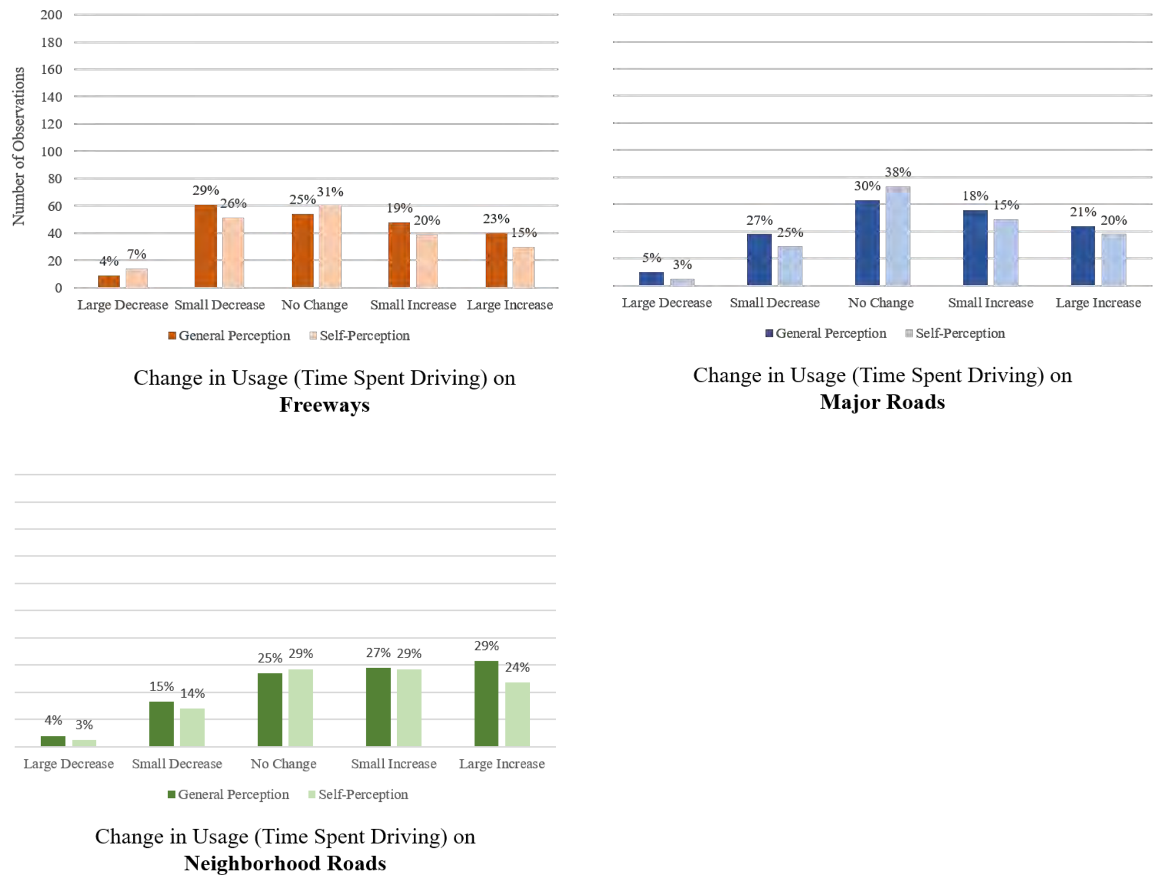


Figure 1-13: Change in Usage of Roadway Types from Navigation Apps

There was a difference in general and personal perception for the changes observed in driver speed and alertness in neighborhood roads due to navigation apps. As seen in Figure 1-14, although individuals reported that navigation apps overall decreased the alertness of other drivers in neighborhood roads, they did not perceive the same decrease in their personal alertness. Similarly, individuals reported that navigation apps increase the driver speed of other drivers in neighborhood roads, they did not perceive an increase in their personal speed. This difference in general and personal perception may be due to the social desirability bias, which is the tendency of survey respondents to reply in a more favorable manner. Respondents may know they are less alert and drive fast in neighborhood streets due to navigation apps but do not want to reveal this undesirable behavior to the interviewer or they may believe they are better than the general population. Biases throughout the stated preference survey may result in an incorrect understanding on how navigation apps impact road usage. Revealed preferences based in quantitative data paired with stated preferences is critical for understanding how navigation apps are used.

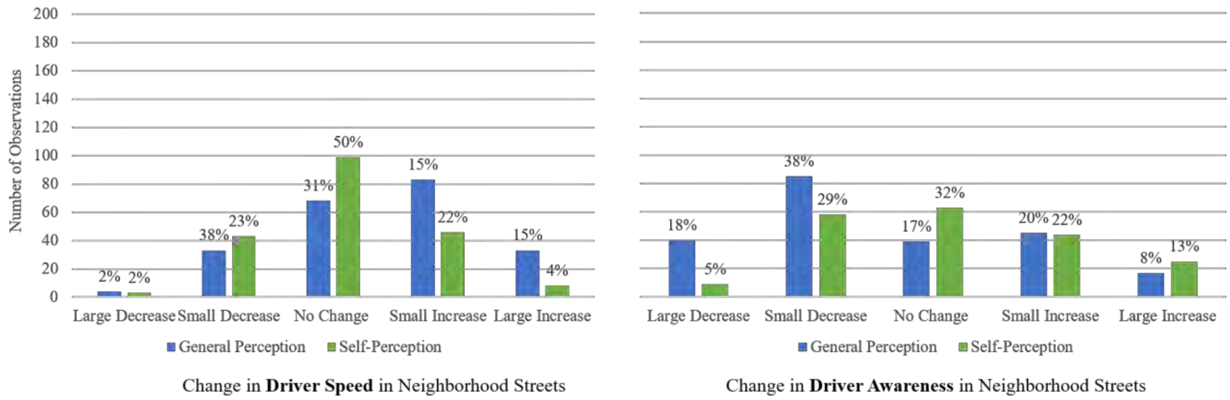


Figure 1-14: Change in Neighborhood Streets Characteristics from Navigation Apps

1.3.6 Location History Data Analysis Results

Of the 27 acceptable quality GLH datasets collected, only 10 downloads contained at least 85% of days with data from trips in the Atlanta area. Of these 10 downloads, there were less days with collected data for all road types in April 2017 than in March 2017, March 2018, and April 2018, as seen in Figure 1-15. This decrease of commuters on the road may be explained by working from home to avoid the heavy congestion following the I-85 bridge collapse.

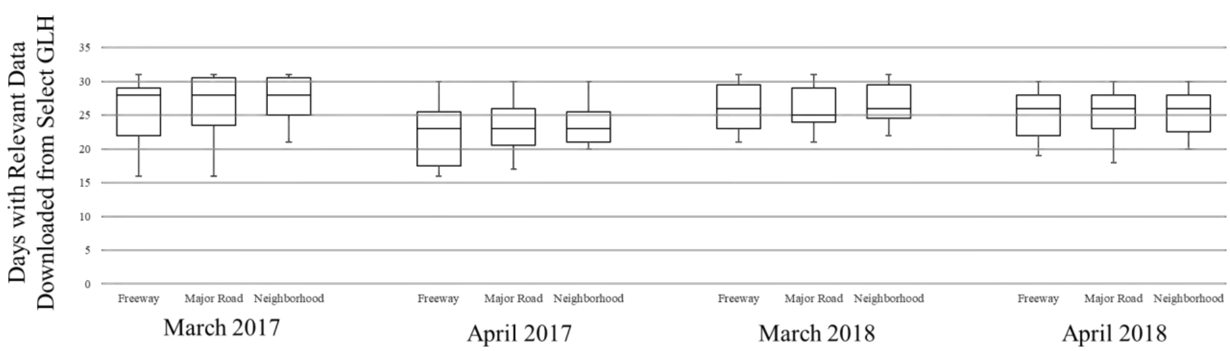


Figure 1-15: Number of Days with relevant GLH Downloads from select surveys

Although the number of driving trips in Atlanta decreased directly after the I-85 bridge collapse in April 2017, there was no change in proportion of the trips associated with the use of a navigation app, as seen in Figure 1-16. The fraction of driving trips with navigation apps over the number of driving trips in Atlanta for each period stayed constant between March 2017 and April 2017. The trend of navigation app usage also did not appear to increase or decrease a year after the I-85 bridge collapse incident.

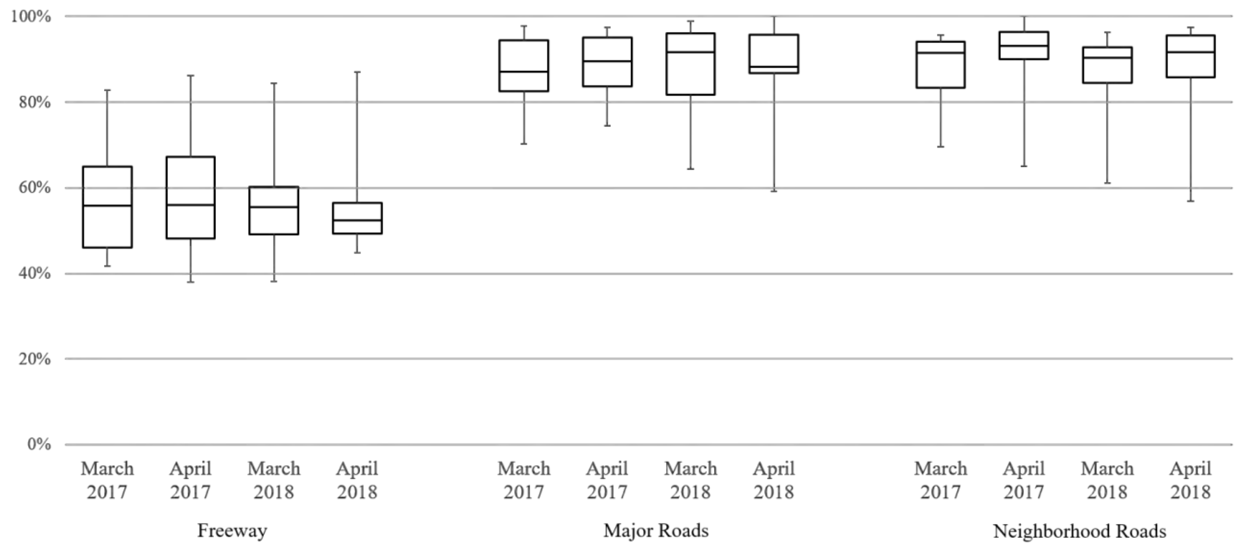


Figure 1-16: Percentage of Trips with Navigation Apps in Metro Atlanta

In addition to an aggregate analysis, a spatial analysis at the individual respondent level can reveal the cut-through behavior of individuals. Due to the limited number of usable responses, further research is necessary to reach a definitive conclusion. Using only the 17 responses with more than 90 days of data available, 15,424 trips can be visually displayed over the four-month period to observe trends in routes over time. Figure 1-17 presents the location history of these 17 respondents within a 5-mile radius around the I-85 bridge collapse. Road facility types are given distinct colors to visually see the change in facility usage across the four months. The difference in routing caused by the bridge collapse and I-85 closure, identified in the red circle, shows less freeway usage, blue colored, and a different pattern of major and neighborhood road usage in the April 2017 panel when compared with other monthly panels. The temporary re-route on major roads and neighborhood streets because of the I-85 bridge collapse can be seen in the increase of red and orange routes the upper right panel.

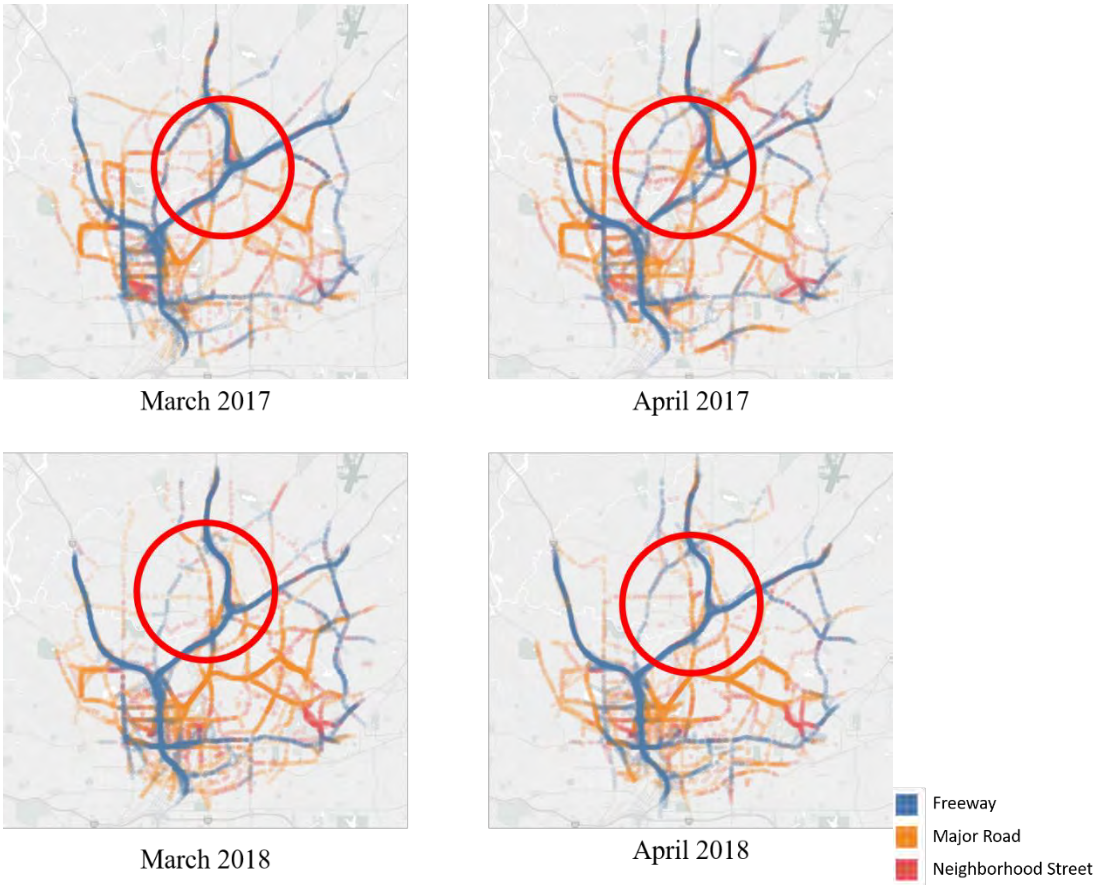


Figure 1-17: Location Data by Facility Classification of 5-Mile Radius Around I-85 Closure

At a more disaggregate level, the GLH data provides a fine level of daily trips and location points. This high-quality data can be used to verify stated travel behavior and identify potential re-routing cut-throughs. Actual roadway usage and routing behavior compared to the travel behavior expressed by an individual provides insight into biases found in stated preference surveys. Thorough analysis of the typical use patterns between frequented origins and destinations found in GLH data reveals deviations of typical routes. This analysis must be completed on an individual basis because each individual's daily route choices are unique depending on location of frequented origins and destinations.

By comparing the actual travel behavior revealed in the location data and the stated travel behavior from the paired questionnaire, location history can confirm the described usage pattern. In this case, data downloads collected during the face-to-face portion of the survey were each paired with an associated questionnaire describing the stated travel behavior. As an example, one respondent stated that they use navigation apps for most trips; they reported use of navigation apps almost daily on all facility types in their regular commute, regular non-commute trips, infrequent trips, and first-time trips. This behavior was verified by comparing the stated relative frequency and the number of days with roadway usage.

The respondent indicated that they follow the suggested directions during 100% of trips and always accept rerouting suggestions. This behavior paired with typical route patterns identified a navigational app cut-through highlighted blue in Figure 1-18. GLH data provides a format that is easily visual and qualitative in analysis for possible deeper insights.

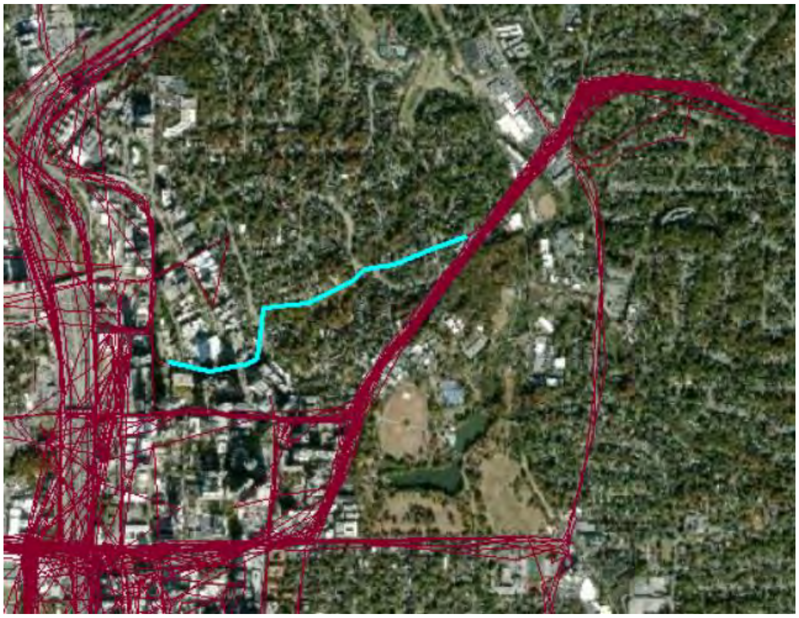


Figure 1-18: Example of potential cut-through from individual GLH data

GLH data has enormous potential to provide a powerful data source if a sufficiently large sample can be obtained. Recent environmental and health studies have started to use GLH because of the potential large sample and extended time periods of the detailed location (Ruktanonchai et al 2018, Yu et al. 2019). In the transportation field, there has only been limited investigation on the possibility of crowdsourcing users' GLH data (Lawson 2017). Possible means for obtaining larger GLH datasets should be further explored to enable deeper and statistically robust analysis and reduce non-response/respondent bias. As the number of Android users, potential survey participants, rises, GLH may serve as a user-friendly and low-cost alternative to study-specific deployment of GPS devices and specialized smartphone-based location tracking applications used in mobility studies today and allow for obtaining data over longer periods of time in a less intrusive fashion than actively instrumenting vehicles with dedicated GPS devices over short study periods.

1.3.7 Conclusion

This study investigated the stated and revealed influence of navigation apps on drivers' route choice behavior. A stated behavior questionnaire based data and location history data were collected to understand the different types of routing apps used and distinct travel behavior of users. Analyzing the impact of smartphone navigation apps was challenging because location history data is currently time-consuming to collect and inconvenient to aggregate at more than an individual level. The data collection process proved to be difficult because of a limited availability of willing and eligible people to provide the location data. Results from navigation app user surveys suffer from a small sample sizes and discrepancies of stated preference.

Results from this study identified that a user's perception of personal and general usage navigation apps isn't the same, e.g. users perceived that navigation apps cause other drivers to travel with faster speeds on neighborhood streets but they did not perceive this increase in themselves. The use of navigation apps on each facility type is not uniform because of the many different types of apps users, ranging from those who use an app the moment they step foot in a car to those who only turn to navigation apps during extreme congestion or when they actively need navigation direction to travel to unfamiliar destinations.

Although stated and revealed travel behavior can be used to gain a deeper insight, the exact impact of navigation apps on roadway facility types must be further studied to understand the impact of navigation apps on trip routing. GLH data has the potential to provide high-resolution data that can be used to study route choice without a burden on the respondent. Although initial GLH results indicated a month of decreased travel and no change in navigation app usage after the I-85 bridge collapse, full conclusions cannot be drawn from the results of the analysis due to sample size limitations from the data collection process. Future studies with a larger sample size can harness the full potential of GLH data to help identify and understand cut-through and detour behavior at an individual level. Given the high rate of penetration of smartphones and the low respondent burden, anonymized data shared directly from Google and Waze could assist agencies to further evaluate the potential impact of navigation apps on roadway facility selection by drivers, congestion, and congestion management.

1.4 Recommendations

Future studies with a larger sample size must be conducted to reach conclusive results about route choice and navigation apps. If data is collected through an online portal, a robust screening process should be conducted to ensure data collected is spatially relevant to the study purpose. In the original study, it is hypothesized that the limited advertisement of the study and the privacy concerns of potential respondents limited the amount of data available to the study. Partnerships with the app providers need to be explored in the future to facilitate the collection of larger datasets.

Although time intensive, a higher rate of data collection success was achieved through in-person surveys instead of an online portal. The use of a monetary incentive, quick and simple data upload process, explanation of data security procedures, friendly surveyors, support from local community and alumni, and the association with a well-respected research institute likely improved the understanding of the privacy protection protocols by the participants and addressed some of their privacy concerns and thereby increased the rate of participation.

The dynamic and frequent updates to navigation apps may limit the scope and application of location history data to trip routing. As of May 2019, Google has released a new auto-delete control for location history and activity data in response to the public outcry regarding privacy rights (Monsees 2019). The impact of these new controls is unknown but may limit data collection for future research with GLH.

Despite the limitations of the GLH data, this study is one of the first attempts at an objective quantification of the routing behavioral response of drivers to navigation apps and rerouting information. This study provides a deeper understanding the nature of the impact of the dynamic congestion related information and routing information derived based on the congestion status on the routing behavior of drivers. Such information has a potential for use in the determination of strategies for active travel demand management and operations as information becomes more ubiquitous with increasing uses of navigation apps and as we usher in the era of connected and autonomous vehicles.

1.5 References

1. Ayelet Gal-Tzur, Susan M. Grant-Muller, Einat Minkov, Silvio Nocera, The Impact of Social Media Usage on Transport Policy: Issues, Challenges and Recommendations, Procedia - Social and Behavioral Sciences, Volume 111, 2014, Pages 937-946, ISSN 1877-0428, https://doi.org/10.1016/j.sbspro.2014.01.128.
2. Bregman, S. (Ed.), Watkins, K. (Ed.). (2014). Best Practices for Transportation Agency Use of Social Media. Boca Raton: CRC Press, https://doi.org/10.1201/b15768.
3. Simon L Jones, Denzil Ferreira, Simo Hosio, Jorge Goncalves, and Vassilis Kostakos. 2015. Revisitation analysis of smartphone app use. In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 1197--1208.
4. McCall R. and V. Koenig. Gaming Concepts and Incentives to Change Driver Behaviour. 2012 Vehicular Communications and Applications Workshop, (2012). 146-151. 10.1109/MedHocNet.2012.6257115.
5. Mobile Fact Sheet, June 12, 2019. Pew Research Center, Washington, D.C. https://www.pewinternet.org/fact-sheet/mobile/. Accessed July 11, 2019.
6. Anderson, M. More Americans using smartphones for getting directions, streaming TV. Pew Research Center, January 2016. https://www.pewresearch.org/fact-tank/2016/01/29/us-smartphone-use/. Accessed July 11, 2019.
7. Cabannes, T., Vincentelli, M.A., Sundt, A., Signargout, H., Porter, E.K., Fighiera, V., Ugirumurera, J., and Bayen, A.M. The Impact of GPS-Enabled Shortest Path Routing on Mobility: A Game Theoretic Approach. Presented at 97th Annual Meeting of the Transportation Research Board, Washington, D.C., 2018.
8. Kennedy, M. Google Maps Leads About 100 Drivers into a Muddy Mess in Colorado. National Public Radio, June 2019. https://www.npr.org/2019/06/27/736572732/google-maps-leads-about-100-drivers-into-a-muddy-mess-in-colorado. Accessed July 11, 2019.
9. Graham, J. Waze sent commuters toward California wildfires, drivers say. USA Today, December 2017. https://www.usatoday.com/story/tech/news/2017/12/07/california-fires-navigation-apps-like-waze-sent-commuters-into-flames-drivers/930904001/ Accessed November 19, 2018.
10. Mahmassani, H.S. and Jayakrishnan,R. System performance and User Response under Real-time Information in a Congested Traffic Corridor. Transportation Research Record: Journal of the Transportation Research Board, 1991. 25A: 293 -307.
11. Allen, R. W., Stein,A.C., Rosenthal,T.J., Ziedman,D., Torres,J.F., and Halati, A. A Human Factor Simulation Investigation of Driver Route Diversion and Alternate Route Selection Using In-Vehicle Navigation Systems. Vehicle Navigation and Information Systems Conference, 1991, Troy, MI, USA, 1991, pp. 9-26.
12. Bonsall, P. The Influence of Route Guidance Advice on Route Choice in Urban Networks. Transportation, 1992. 19: 1. https://doi.org/10.1007/BF01130771
13. Khoo, H.L., and Asitha, K.S. User Requirements and Route Choice Response to Smartphone Traffic Applications (Apps). Travel Behaviour and Society, 2016. 3: 59 -70.

14. Paniko, Riley. The Popularity of Google Maps: Trends in Navigation Apps in 2018. The Manifest, July 2018. https://themanifest.com/app-development/popularity-google-maps-trends-navigation-apps-2018. Accessed November 19, 2018.
15. Britschgi, C. The War on Waze. Reason. April 2018. https://reason.com/2018/04/25/the-war-on-waze/. Accessed November 19, 2018.
16. Did Cut-Through Traffic Prevention Measures Help or Hurt? Before – And-After Study. StreetLight Data, 2019. https://3yemud1nnmpw4b6m8m3py1iy-wpengine.netdna-ssl.com/wp-content/uploads/Cut-Through-Traffic-Prevention-Measures.pdf. Accessed July 11, 2019.
17. Thai,J.,Laurent-Brouty, N.,and Bayen, A. Negative Externalities of GPS-Enabled Routing Applications: A Game Theoretical Approach. 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, 2016, pp. 595-601.
18. Ruktanonchai, N.W,Ruktanonchai, C.W., Floyd, J.R., and Tatem, A.J. Using Google Location History Data to Quantify Fine-Scale Human Mobility. International Journal of Health Geographics, 2018. 17:28 https://doi.org/10.1186/s12942-018-0150-z
19. 2013-2017 American Community Survey 5-year estimates. United States Census Bureau. https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2017/. Accessed July 11, 2019.
20. Douglas, T. Atlanta's Internal Platform Turns Public to Provide Real-Time Commuter Data Following Bridge Collapse. Government Technology, April, 2017. https://www.govtech.com/transportation/Atlantas-Internal-Platform-Turns-Public-to-Provide-Real-Time-Commuter-Data.html. Accessed November 19, 2018.
21. Schmidt, D. Google Data Collection. Digital Content Next, August 2018. https://digitalcontentnext.org/wp-content/uploads/2018/08/DCN-Google-Data-Collection-Paper.pdf. Accessed November 19, 2018.
22. Subscriber share held by smartphone operating systems in the United States from 2012 to 2019. Statista, May, 2019. https://www.statista.com/statistics/266572/market-share-held-by-smartphone-platforms-in-the-united-states/ Accessed July 11, 2019.
23. Waze Gains Traction In Major Cities But Struggles Statewide. Drivemode, December 2018. https://drivemode.com/2018/12/data-report-waze-gains-traction-in-major-cities-but-struggles-statewide/
24. Lavrakas, P. J. Encyclopedia of survey research methods. Sage Publications, Inc., 2018. Thousand Oaks, CA. doi: 10.4135/9781412963947
25. Open Data & Mapping Hub. Atlanta Regional Commission, August 2018. http://opendata.atlantaregional.com/datasets/a1b74290acf241bf96f112a29a8f7166_103. Accessed July 11, 2019.
26. Rodriguez, A.M., Tiberius,C., van Bree, R., and Geradts, Z. Google Timeline Accuracy Assessment and Error Prediction. Forensic Sciences Research, 2018. 3:3, 240-255. DOI: 10.1080/20961790.2018.1509187.
27. Road & Traffic Data. Georgia Department of Transportation, July, 2019. http://www.dot.ga.gov/DS/Data#tab-4. Accessed July 11, 2019.
28. Yu, X., Stuart, A., Liu, Yang., and Ivey, C. On the Accuracy and Potential of Google Maps Location History Data to Characterize Individual Mobility for Air Pollution Health Studies. Environmental Pollution, 2019. 252: pp 924-930.

29. Lawson, C. Innovative Travel Data Collection-Planning for the Next Two Decades. New York Metropolitan Transportation Council (NYMTC), March 2017. http://www.utrc2.org/research/projects/innovative-travel-data-collection-planning
30. Monsees, D. and McGriff, M. Introducing auto-delete controls for your Location History and activity data. The Keyword, May 2019. https://www.blog.google/technology/safety-security/automatically-delete-data/

CHAPTER 2: DIVERSION PREDICTION (FLORIDA INTERNATIONAL UNIVERSITY STUDY)

2.1 Introduction

The provision of information to travelers about changing traffic conditions including travel time, incidents, and potentially other information is an important component of active transportation and demand management (ATDM), advanced traveler information systems (ATIS), and integrated corridor management (ICM). There are a number of platforms available for delivering traveler information including dynamic message signs (DMS), highway advisory radio (HAR), traveler information telephone services, web site services, private sector and public sector smartphone applications, social media, broadcast TV/radio, and in-vehicle infotainment systems (built-in and aftermarket). Traveler information systems are experiencing dynamic changes that are expected to accelerate in the future with the increasing use of smartphone and social media applications, expected increase in the market penetrations of connected vehicles, and the applications of the next generation of traveler information systems referred to as EnableATIS [1] [2]. An important aspect among these is the widespread use of smartphone traveler information applications, which have profoundly impacted the transportation system and the drivers' behaviors. In recent years, travelers have mainly utilized private sector applications such as Google Maps, Waze, Apple Map, HERE, and INRIX Apps. State departments have also developed public sector apps for use by the traveling public. Smart phone applications have been effective in allowing the commuters to modify their trip choices before making the trip (pre-trip) and during the trip (en-route).

The performance of various ATDM, ATIS, and ICM applications have been assessed based on real-world data combined in some cases with the use of Analysis, Modelling, and Simulation (AMS) techniques [3]. An important parameter in the assessment is the estimation of the diversion rates of travelers under different traffic and incident conditions, the diversion routes used by the diverted traffic, and the impacts on the diversion routes. Realistic estimates of these parameters are also needed in order to calibrate simulation and dynamic traffic assignment models such that they can be used to predict changes in the diversion with system improvements under different scenarios.

It is expected that the diversion rate depends on factors such as the incident attributes including the incident duration, the number of blocked lanes, and the time and location of the incident, etc. The diversion rate also depends on other factors such as the expected impacts of the incident on system performance, the quality of the provided traveler information, the availability of alternative route capacity, as well as driver behaviors. The diversion rates are expected to be constrained by the capacities of the freeway off-ramps and the signals that are close to these ramps.

Most studies on traveler information systems have used stated preference and revealed preference surveys. Revealed preference surveys are preferred since it has been reported that the results from stated preference surveys overestimate the diversion rates. Another potential option to estimate or at least confirm the diversion rate and routes is to examine infrastructure sensor measurements and probe vehicle measurements. The Southeast Florida study portion of this project described in this chapter focuses on the use of two sources of data to assess performance: 1) On-line and face-to-face revealed preference surveys of travelers residing in Broward county, Florida. Overall, 246 people over 18 years' old participated in this survey, and

2) Freeway mainliner detector data that is used to estimate and predict the diversion utilizing a method developed in this study. The results from the analyses based on the two sources of data are then compared.

2.2 Estimation of Diversion in Previous Studies

Although there has been research on the subject of diversion rate estimation in the past two decades, there is still not a sufficient amount of information about the route diversion under various operating conditions. Several researchers have used the stated preference approach to determine the percentages of travelers changing trip decisions in response to information disseminated by ATIS technologies [4]. Based on this type of surveys, studies concluded that the disseminated information can result in up to 60% to 70% of freeway traffic exiting the freeway ahead of an incident location [5] [6] [7] [8]. Peeta et al. (2000) investigated the impacts of DMS information content and other relevant factors on diversion rates using the stated preference method [9]. The results indicated that 53% of drivers stated that they will divert to an alternative route when the expected delay on the current route exceeds 10 minutes. On the basis of a stated preference survey, Khattak et al. (1993) found that 42.9% of respondents would definitely take alternative routes under jammed conditions [10]. Huchingson and Dudek (1979) used a linear relationship between diversion rate and posted incident delays on the DMS, with zero diversion for zero delay due to incident and 95% diversion for a one-hour delay [11]. Al-Deek et al. (2009) developed a logit model to estimate diversion behavior when traveling on Central Florida toll roads as a function of travel time, delay, information source, network familiarity, and certain trip characteristics [12]. Kattan et al. (2010) developed a model to estimate the diversion based on driver's socio-economic characteristics, trip purpose, trip time and length, access to en-route traveler information and the users' level of satisfaction with the information. The model estimated up to 63.3% of travelers will divert to an alternate route [13].

It has been reported based on revealed preference survey results and traffic measurements that the actual diversions are lower than those estimated based on stated preference surveys. However, information regarding the actual diversions due to traveler information remains limited. Several European field studies have found that diversion rates due to DMS messages range between 27% and 44% [14]. Chatterjee and MacDonald (2004) conducted an extensive survey in six European countries to examine the impact of DMS on traffic diversion and found with the driver questionnaire results that the diversion rates are zero to 7% for incident messages and zero to 35% with route guidance information [15]. An Enterprise Pooled Fund Study [16] found an increase in diversion rate that ranges from 0% to 12% due to DMS. A study in Maryland [17] found that the diversion rate ranges between 5% and 18% based on Bluetooth detector data. Foo and Abdulhai estimated an average diversion rate of 5.55% with the provision of DMS on Highway 401 in Toronto, Ontario, Canada based on traffic detector data [18]. Hadi. et al. [19] found that the diversion rate ranges from about 8% for one out of five lane blockages to about 25% when four out of the five lanes were blocked.

Researchers estimated the diversion rate using the instantaneous inflow and outflow volumes during the incident [21] [22]. Abdel-Aty and Abdalla used the Maximum Likelihood Estimation (MLE) and Generalized Estimating Equations (GEE) framework using travel simulator data to estimate the diversion rate based on pre-trip and en-route decisions with or without advice to divert and found the percentage of diversion to be 60-80%. [23]. Xiong, et al. used stated-preference driving simulator data to investigate diversion behavior based on naïve Bayes rules and estimated a diversion percentage average of 5.2% [24].

It should be mentioned that due to the rapid changes to traveler information systems, including the wider utilization of private sector smartphone apps and the advancement in public agency systems when reviewing past studies on the subject, more weights should be given to more recent studies.

An important consideration that has not been sufficiently investigated, is the capacity of the exits from the freeway ahead of the incident and the capacity of alternative routes on the diversion. The anticipated congestion of the alternative routes discourages drivers from diverting [25]. This needs to be further investigated, particularly as agencies start deploying ICM strategies.

The above review indicates that there is wide variety of studies using different techniques and the estimated diversion rates vary widely from 5% to 80%. This wide variation is in at least in part due to the unavailability of the use of actual real-world observation of diversion during incidents that have varying impact on the travel time on the freeway facilities. This points to the need for the development of such a method, preferably based on limited amount of data, to support the agencies in their development and activation of operation plans in real-time operations.

2.3 Sensor Data-Based Approaches to Predict Diversion

The most direct method to estimate existing traffic diversion is to use traffic detector data combined with incident data to determine the change in volumes on incident days, compared to the average or median volumes for "normal" days with no incidents. This is facilitated by the increasing availability of traffic data on freeways and more recently on urban streets. However, the main challenge to this approach is that traffic detectors are not installed on freeway off-ramps in most current deployments. Thus, the change in volumes on these ramps cannot be detected to estimate the diverted volumes.

This section focuses on the development of a method to estimate the diversion due to incidents based on the freeway mainline detector data combined with incident data using a combination of clustering, cumulative volume analysis, and predictive data analytics. The purpose of clustering analysis is to find days with no incident that are similar to the incident day traffic patterns, in the time interval of the incident occurrence. The contribution of this study is to develop a more accurate diversion rate calculation method when there are no detectors installed on the off ramps. The method utilizes a combination of the cumulative input/output volume approach to estimate the diversion for each incident, unsupervised learning utilizing clustering for off-line categorization of traffic patterns, and supervised learning approaches for the prediction of the diversion rate based on incident attributes. The clustering analyses is used to increase the accuracy of the method by associating the traffic patterns during normal days with the traffic pattern during the incident day (before the incident occurrence). Three supervised learning techniques are used and compared to predict the diversion rates due to the incident.

The three utilized supervised learning techniques for prediction are linear regression (LR), multilayer perceptron (MLP), and support vector machine (SVM). LR is used as a base for the prediction model comparison since it is the most widely used statistical technique for prediction and the resulting model is easy to derive and understand. For many problems, LR can perform well with a relatively small sample size. However, it cannot fit complex nonlinear functions. MLP and SVM as regression techniques, commonly recommended for use, produce accurate prediction results for complex problems. SVM has a high resistance to overfitting and can deal with high data dimensionality (large number of features) even when the sample size is small. The MLP model has powerful adaptive learning ability and is applicable to fitting non-linearly separable data and can also deal with high dimensionality. A disadvantage of both the SVM and MLP is that the results from them are more difficult to interpret than the LR model.

The results from applying the three techniques are compared in terms of the mean absolute errors of the predictions. The developed models are based on data from detectors located on the facility, on which the incidents occur. The increases in volume on the main alternate parallel freeway routes are also examined to further verify the model estimations.

As stated above, the contribution of this study is to develop a method for diversion rate calculation. The method can be used to derive models based on data from other locations when developing the operation plans for the locations. There is no claim that the models developed in this paper are fully transferable to all other locations, although they can be used to provide a general idea of the magnitude of diversion. The actual diversion rate is a function of many local conditions such as the availability of alternative route capacities, traveler's behaviors in the region, and the degree of congestion in the network. Thus, site specific models are recommended to be derived for each freeway facility and the method developed in this paper can be used for this purpose.

2.3.1 Utilized Data

The utilized data in this study are incident data, traffic detector data, and weather data for the I-95 corridor in South Florida from Palmetto Beach Boulevard (Location 1) to I-595 (Location 6) in Broward County, Florida, in Figure 2-1. As shown in Figure 2-1, the area of the case study is an I-95 section in Broward County, Florida. I-95 corridor is a main freeway route in the subject corridor and two parallel freeways, Sawgrass and Turnpike are located alongside of this interstate route. Ramps connected to the arterials from the subjected corridor consists of one or two lanes. I-95 is a congested corridor with annual average daily traffic of 225000, where AADT of Sawgrass and Turnpike route is 72000 and 115000 respectively (source: Florida Traffic Online - FDOT).

The traffic data for the year 2017 was retrieved from the regional data warehouse, which is a part of the Regional Integrated Transportation Information System (RITIS). The data was collected for the period between 5:30 AM and 11:30 AM. The traffic data was matched and fused with weather and incident data for the southbound direction of the I-95 corridor in order to separate normal days and incident days. Rainy day data was excluded from the analysis as the estimation was done for normal day conditions. Weather data was collected from the National Center for Environmental Information– National Oceanic and Atmospheric Administration (NOAA) website. The data was collected for the Pompano Beach Airpark weather station, which is within a 10-mile radius of the study corridor. The data set includes the hourly precipitation (in inches) for each 15 min observations. Incident data for the analysis horizon along the corridor was retrieved from the incident management database managed by Florida Department of Transportation (FDOT) District 4. The collected incident data is very detailed and includes several useful attributes for the analyses of this study including the start and end times, lane blockage duration, total incident clearance time, number of blocked lanes, severity, time stamps of emergency vehicle arrivals, number of vehicles involved in the incident, and so on. Overall, 139 incidents were analyzed to determine the diversion rates during the period of the analysis.

All three types of data (traffic, incident, and weather) were converted to the 15-minute resolution and assembled together for cluster analyses. Rainy days were filtered out and not considered in this study. Incident duration was converted into a categorical variable, utilizing a 15-minute increment in the categorization. For example, 0-minute to 15-minute incident durations were assigned to Category 1, 16-minute to 30-minute incident durations were assigned to Category 2 and so on. Also, the incident start time was converted into a categorical variable for every 15-minute time slice from 5:30 AM to 11:30 AM (from 1 to 25, Category 1 for 5:30 AM and Category 25 for 11:30 AM). The incident locations were also categorized into six locations, each associated with one of the six detectors in Figure 2-1. The R package ‘Geosphere’ feature was used in this association.

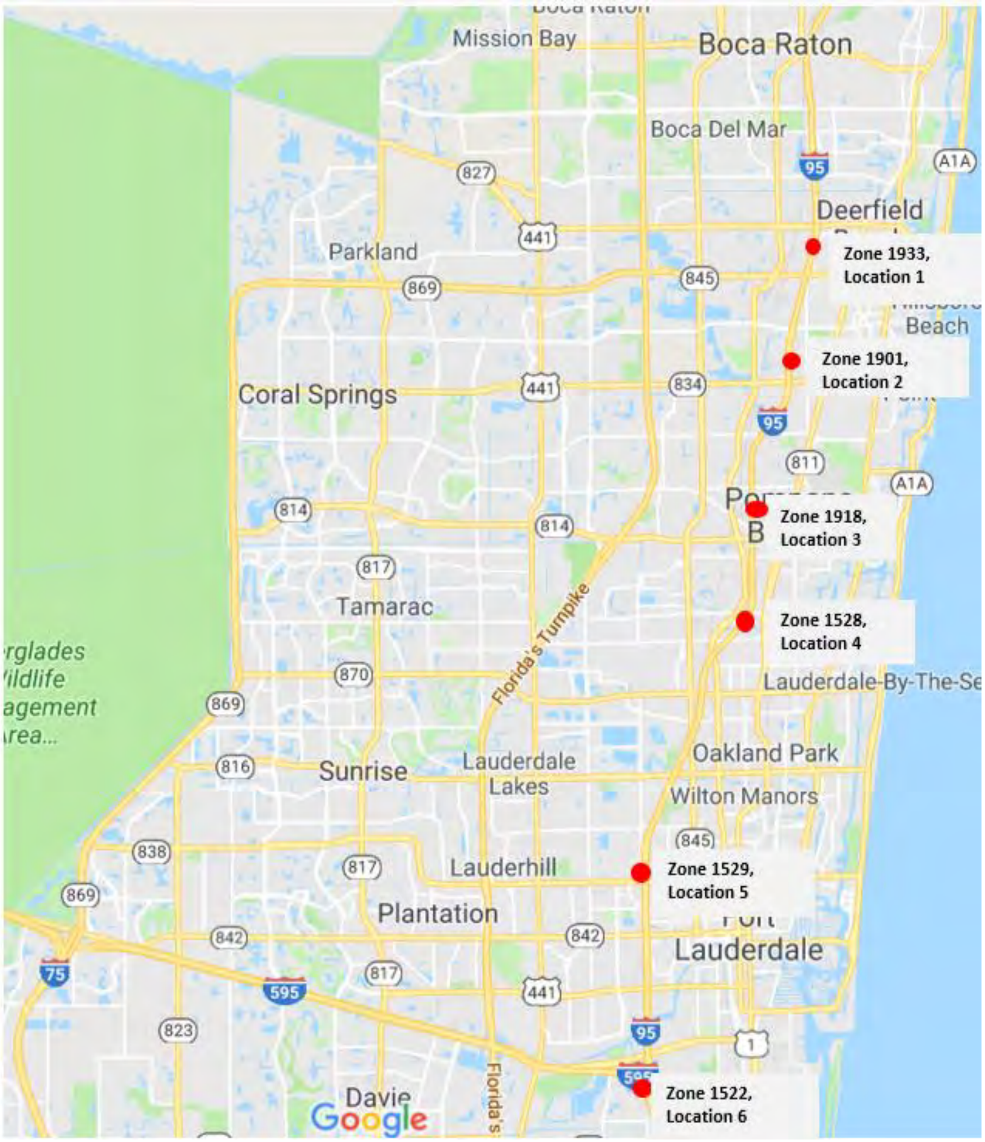


Figure 2-1: Study Area

2.3.2 Association of Incident Day with Normal Day Patterns

The estimation of diversion requires the association of each incident day with normal (no-incident) days that have traffic patterns that are as close as possible to the traffic pattern of the incident day before the occurrence of the incident. This will allow the estimation of the expected demands without the incident to be used as a base in the analysis. The diversion is estimated by subtracting the volume during each incident day from the average of the traffic volumes in the normal days that have similar traffic patterns. The association of patterns was accomplished by first classifying the days into four seasons; winter (December-February), spring (March-May), summer (June-August) and fall (September-November). The separation of the data into seasons is location specific. Studies have clearly shown that the traffic patterns in Florida, at which the case study is located, are greatly influenced by the season with the traffic flow rates in the winter and spring are higher than those in the summer season, with a large proportion of travelers in the winter and spring being older people escaping the cold weather in the North [26]. The days within each season were then clustered further into patterns using clustering analysis and an association was made between the traffic pattern of each incident day with the cluster that has the most similarity to the incident day traffic pattern before the incident happens.

For the clustering analysis mentioned above, the normal days (days with no incident and no rain) were clustered based on traffic detector data (volume and speed) using the K-means clustering. One important aspect of clustering is to determine the number of clusters to use in the clustering. This study utilizes a method referred as the Elbow method [27]. The Elbow method is an empirical method that provides an objective approach to determine the optimal number of clusters. The method requires minimal prior knowledge about the data set and the attributes of the data set. The "Elbow Method" allows clustering based on the optimal number of clusters that is determined based on the total within-cluster sum of square (WSS) for each number of clusters [26]. A graph is drawn between the total WSS and the number of clusters and the location of the bend in the plot is generally considered as an indicator of the appropriate number of clusters, as shown in Figure 2-2. From Figure 2-2, four clusters were selected for use in the analysis. The K-means clustering analysis with a total number of four clusters was then performed on each season traffic data for the normal days with no incidents and no rain for every half an hour. An example of the resulting clusters is shown in Figure 2-3. For each incident day, the traffic pattern 30 minutes before the incident clusters were matched with the traffic patterns of the days within a cluster that is in the same season and weekday as the incident day. This matching allows the estimation of the traffic demands with no diversion to use as a base in the estimation of the diversion.

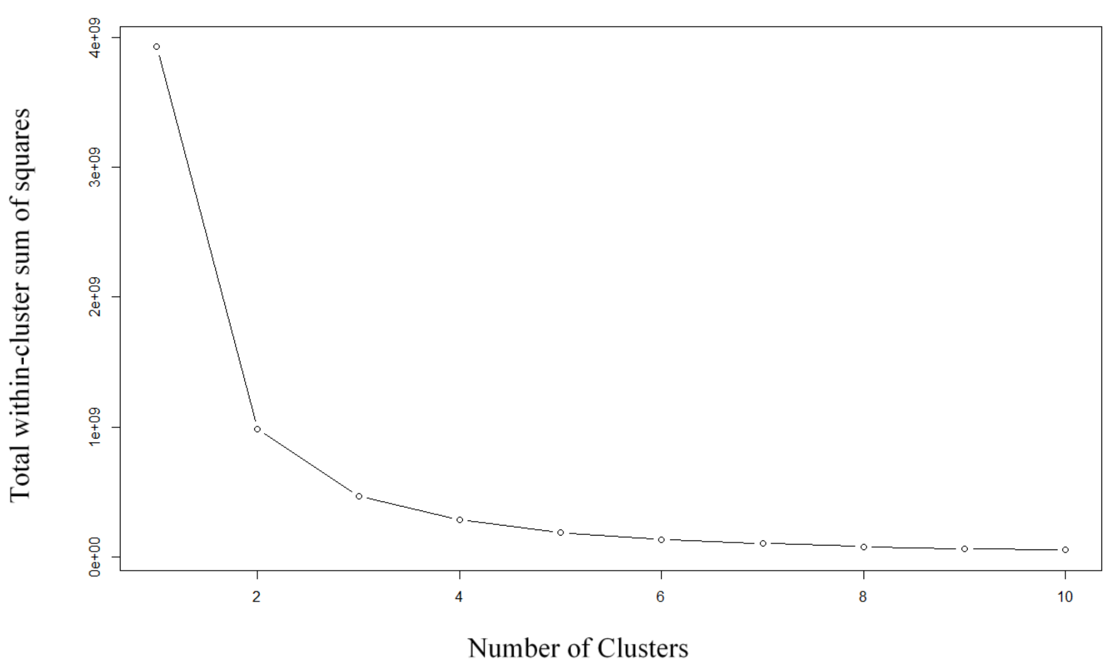


Figure 2-2: Plot of Total Within-Cluster Sum of Square (WSS) Vs. Number of Clusters

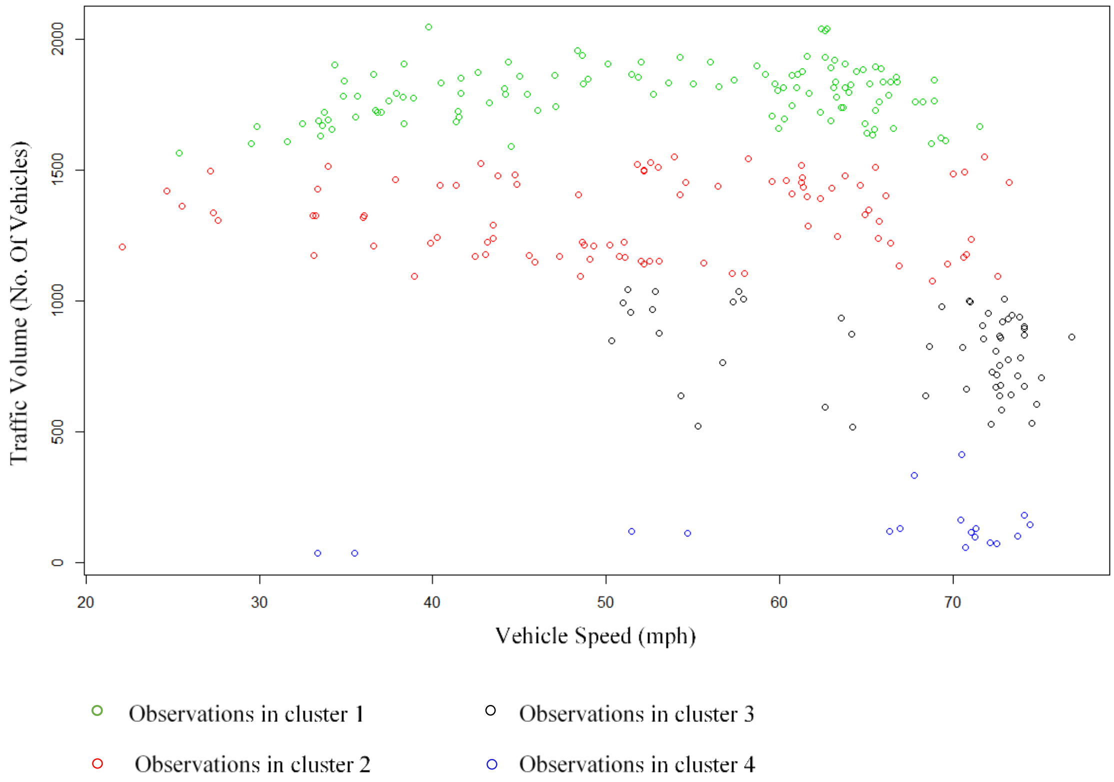


Figure 2-3: Plot of the Volume vs. Speed from 7:00 AM to 7:30 AM Period in the Fall Season

2.3.3 Estimation of Diversion Rate

The diversion rates were then estimated utilizing the difference between the cumulative volume at the end of the queuing period between the incident day and the average cumulative volume of the normal days associated with the incident day, as explained in the previous section. As assumed when utilizing queuing theory to analyze incident mobility impacts, the cumulative demand in the incident day first drops due to the capacity constraint due to the incident (see the incident day plot in Figure 2-4). Once the incident is cleared, the traffic will start leaving at the maximum possible queue discharge rate until the queue is completely dissipated. At that point, the cumulative volume with and without the incident should be equal if there is no diversion. This means that if the patterns of the no-incident days associated with the incident day can be assumed to represent the incident day pattern with no diversion, the plots of the cumulative volumes of the incident and no-incident days should meet at this point, as shown in Figure 2-4 (a). On the other hand, if diversion of traffic occurs the two plots will not meet since some of the vehicles diverted during the incident impact period. In this case, there will be a gap between the normal day cumulative volume and incident day cumulative volume plots after the dissipation of queue, as shown in Figure 2-4 (b). This gap or difference of volume is used in this study as an estimation of the diverted traffic volume. The utilized equation for this estimation is as follows:

$$\text{Diversion Rate} = \frac{\text{Cumulative Vol.of No incident day} - \text{Cumulative Vol. of incident day}}{\text{Cumulative volume of No incident day}} \qquad (1)$$

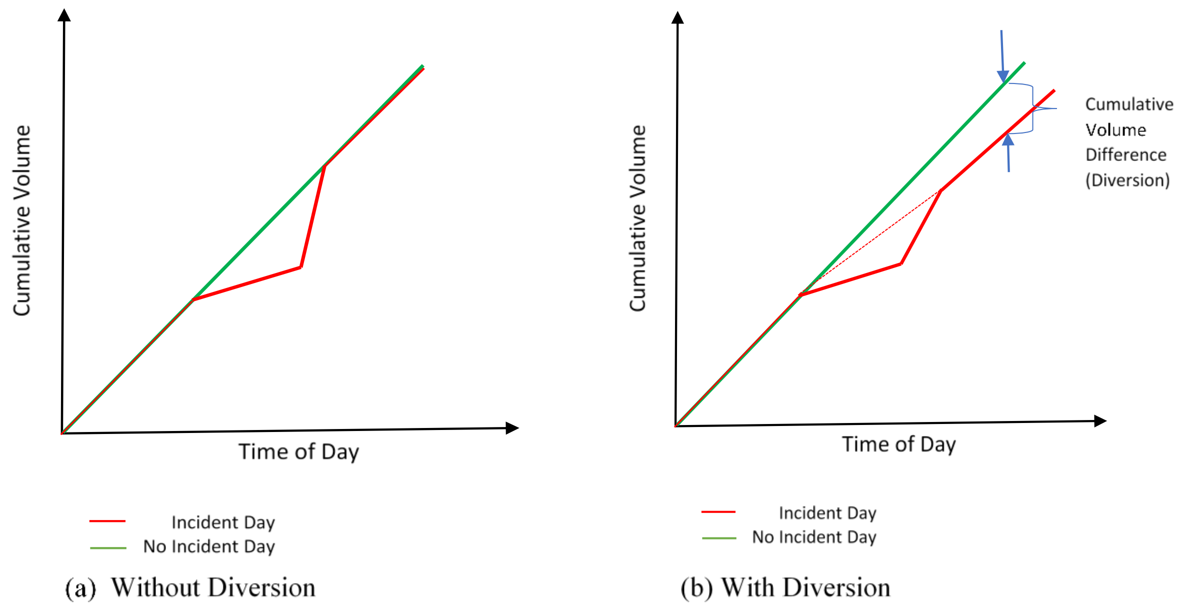


Figure 2-4: Cumulative Volume Diagrams of Incident and No-incident Days (a) Without Diversion, (b) With Diversion

2.3.3.1 Diversion Estimation Results:

The diversion rates were estimated for the study corridor using the methodology discussed above. Table 2-1 shows the mean, median, and 95th percentile diversion rate and the diverted volumes for incidents first detected in the periods between 5:30 AM and 7:00 AM , 7:00 AM to 9:30 AM , and 9:30 and 11:30 AM . Table 2-1 shows that there is a general trend of increase in the diversion rate with the increase in the number of blocked lanes due to the incidents, except for the incidents with the two-lane blockage before 7:00 AM , for which only 4 incidents are available for the analysis, which is insufficient sample size. The estimated 95% diversion rate for the three lane blockage incidents for the period before 7:00 AM is 22%. This indicates that 20% to 25% can be used as an upper limit on the diversion (drivers willing to divert) when up to three lanes out of five lane incidents are blocked. If modelling is to be used in conjunction with real-world data, the DTA model can then be used determine what proportion of this group of drivers will actually divert depending on traffic conditions on the alternative routes and the subject freeway under different conditions. For the existing conditions, the diversion estimated by the DTA can be calibrated using the results of the diversion estimation, as the results presented in Table 2-1 and the models later developed in this paper show.

An interesting observation from Table 2-1 is that the average diversion percentages are higher for the period before 7:00 AM than the period after 7:00 AM. Further examination of Table 2-1 indicates that the actual diverted volumes are about the same in these two periods but by dividing by higher volumes in the peak period after 7:00 AM, the resulting diversion percentage is lower. This indicates a possible upper limit on the number of vehicles that can divert due to capacity constraints. The alternative routes, Florida Turnpike and Sawgrass Expressway, both of which are tolled facilities, have sufficient access capacity. However, there are limited capacities on the off-ramps upstream of the incident location and possibly the arterials leading to the two tolled facilities, particularly during the peak hour. This finding indicates that applying special signal timing plans that flush the traffic at the off-ramps and adjacent arterials have the potential to increase the diversion rate and thus improving the performance of the system. Capacity analysis of the off-ramp signals indicates that the two off-ramps that provide exits to the main connectors to the alternative routes are already operating at 0.8 to 0.9 volume to capacity ratios (v/c) in the peak period, indicating the limited amount of access capacity available for vehicles to exit the freeway to alternative routes.

Table 2-1: Average Diversion Rate for Different Number of Lane Blockage

Time of Day	Incident Condition	No. of Incident Examined	Average Diversion Rate & Volume	95th percentile Diversion Rate	50th Percentile Diversion Rate
Before 7:00 AM	One Lane blocked	20	5.92% (900)	15.46%	4.34%
	Two Lane blocked	4	4.24% (975)	8.23%	3.95%
	Three Lane blocked	15	9.93% (1258)	22.01%	8.77%
After 7:00 AM	One Lane blocked	56	3.90% (822)	9.65%	2.65%
	Two Lane blocked	31	4.19% (1133)	10.12%	3.40%
	Three Lane blocked	8	5.47% (1368)	10.32%	4.62%

2.3.4 Predictive Model Development

As mentioned earlier, three data analytics techniques were used to develop models for predicting diversion rates utilizing a data set of the rates estimated, as described in the previous sections, and the associated incident attributes. The three techniques are linear regression (LR), multilayer perceptron (MLP), and support vector machine (SVM). The results from applying the three techniques are then assessed, as described in the following subsections. Parameters used to predict diversion rate are number of lane blockage, incident severity, incident location, time slice of incident occurrence. Incident severity is directly imported from incident data base, which is representation of lane blockage and incident duration conditions rated from 1 to 3. Severity is 1 if any lane blocked for less than 30 minutes; severity is 2 when any lane blocked between 30 to 120 minutes and severity is 3 if all lanes blocked for any period of time, or individual lanes blocked more than 120 minutes [28]. Incident start time was converted into a categorical variable for every 15-minute time slice from 5:30 AM to 11:30 AM (from 1 to 25, Category 1 for 5:30 AM and

Category 25 for 11.30 AM). In linear regression model, independent variables can be continuous or discrete. If any independent variable is categorical, which may be coded in discrete numbers yet mean categories rather than numerical values. Thus, the time slices of incident occurrence are converted into discrete dummy variables, in this case 1 to 25. Incident locations are coded based on the distance of incident from the diversion location. Latitudes and longitudes of the incident location and freeway detector zone are used to estimate the distance thus the incident location parameter. Descriptive statistics of the parameters used to develop the prediction model is shown in Table 2-2.

Table 2-2 Descriptive Statistics of Input Variables

Independent Variables	Variable Characteristics	Frequency
Lane Blockage	1 Lane Blockage	76
	2 Lane Blockage	35
	3 Lane Blockage	28
Severity	Level 1	107
	Level 2	27
	Level 3	5
Incident Location	Within 1.5 Miles of Detector Zone	26
	1.5 to 3 Miles from Detector Zone	4
	3 to 4.5 Miles from Detector Zone	45
	4.5 to 6 Miles of Detector Zone	42
	6 Miles to 7.5 Miles of Detector Zone	22
Time Slice of Incident Occurrence	Before 7.00 Am	32
	After 9.00 Am	107

2.3.4.1 Linear Regression (LR) Analysis

Multiple Linear Regression analysis was conducted utilizing the R software package to determine the relationship between the diversion rate (Y) as the dependent variable and Xi as explanatory variables that are expected to impact the diversion. The multiple linear regression can be expressed as:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots\ldots\ldots + \beta_n X_n. \qquad (2)$$

where, Y is the Response or dependent variable, X_1, X_2, X_3……………. X_n are the Predictor or independent variables, and β_1, β_2, β_3……. β_n are the Regression coefficients for the predictor variables.

The set of variables considered for possible inclusion in the regression model are the number of blocked lanes, incident severity (mainly related to the expected incident duration), incident location, and time slice of incident occurrence. Table 2-3 shows the relationship derived using regression. The adjusted coefficient of determination for multiple regression (Adjusted R squared) of the developed model is 0.6025. The Mean Absolute Error (MAE) of the predicted diversion (Y) compared to the actual Y is 3.20%. All four variables considered for inclusion are significant at the 5% level, as shown in Table 2-3. Additional tests of the model were conducted including the residual vs fitted plot and Normal QQ Plot. For the model shown in Table 2-3, the plot of the residual vs fitted values shows that the residuals spread horizontally without distinct non-linear patterns. The Q-Q plot shows that the residuals are normally distributed. It is interesting to see that the regression coefficient of the log of the time slice of incident occurrence is negative, which indicates the reduction in the percentage diversion as the operations enter the peak congested period.

Table 2-3: Regression Analysis Results

Variables	Coefficient	Pr(>|t|)
Lane Blockage	1.7089****	0.000392
Incident Severity	2.2655***	0.006277
Incident Location	0.4242**	0.033404
Log_e (Time slice of Incident Occurrence)	-2.6621**	0.010086
Multiple R-squared: 0.614		
Adjusted R-squared: 0.6025		
p-value: 2.2e-16		
Mean Absolute Error: 3.20%		
Significant codes: 0= '****' 0.001= '***' 0.01= '**' 0.05= '*'		

To check how the model fitted the data the Residual vs fitted plot, Normal QQ Plot and Standardized residuals vs fitted value can be useful tools. Plot of Residual vs fitted shows if the residuals have non-linear patterns. Figure 2-5 shows residuals are spread around the horizontal line without distinct patterns of non-linear relationships.

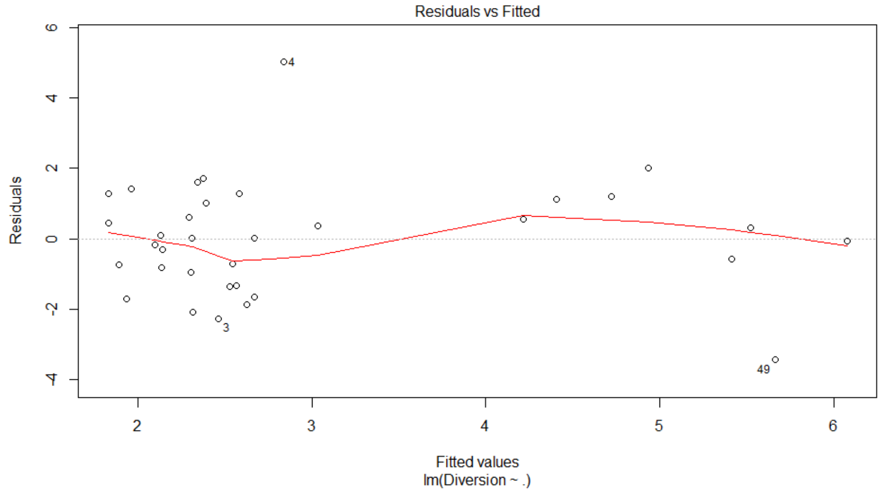


Figure 2-5: Residual vs Fitted Plot

The Q-Q plot, or quantile-quantile plot, is a graphical tool to assess if residuals are normally distributed. From the figure 2-6, it can be stated that standardized residuals follow the straight line, which indicates the normal distribution of standardized residuals and the full model is good fit with the variables as residuals are lined well on the straight dashed line.

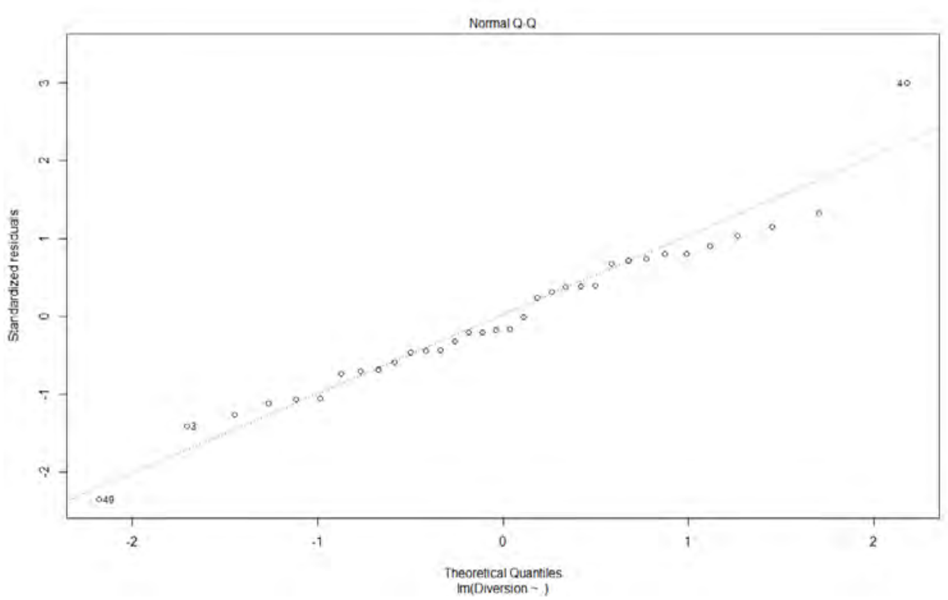


Figure 2-6: Normal Q-Q Plot

2.3.4.2 Multilayer Perceptron (MLP)

MLP is a feed forward deep neural network representing a nonlinear mapping between an input vector and an output vector [29]. MLP consists of an input layer to receive the signal, an output layer that provides the model prediction, and a number of hidden layers between the input and output layers [30]. It has more than one hidden layer with adaptive weights. The intermediate hidden layers enable the perceptron ability to solve nonlinear problems by processing information received from the input nodes and pass the results of the processing to the output layer [31] [32] [33].

The Python programming language with 'Keras' library was used to train and validate the MLP model. The input variables: lane blockage, incident severity, incident location, and time slice of incident occurrence were used to estimate the diversion rate. Three hidden layers were used in the model. The number of hidden layers and the number of neurons in each layer were determined through a trial-and-error process. The optimum number was selected for the lowest mean square error. Before feeding into the model, the input variables were converted using one-hot encoding. The dataset was randomly divided into train and test sets, where 80% of data was used for training the model, and the remaining 20% was utilized to test the model. Best on the test set, the model produced a mean absolute error in the diversion rate of 1.80%, compared with 3.20% with the linear regression model, a 43% improvement. For the entire dataset, the root mean square error (RMSE) value was estimated as 2.976.

2.3.4.3 Support Vector Machine (SVM)

SVM is a learning algorithm that uses a set of mathematical functions referred to as the kernel functions. The kernel functions are applied to solve a nonlinear problem by taking data as input and mapping the data to a high-dimension feature space by transforming it into the required form. Different SVM algorithms use different types of kernel functions. Examples include linear, nonlinear, polynomial, radial basis function (RBF), and sigmoid functions. [34] [35] [36] [37].

In this paper, a SVM model was developed using the same input and output variables used in MLP by applying the RBF as the kernel function. The MAE was found to be 1.95% diversion rate compared with 3.2% with linear regression model, which is a 39% improvement. Other types of Kernel functions were also tested but the RBF was found to produce the least MAE.

2.3.5 Comparison of Model Results

As described above, linear regression, MLP and SVM were used to develop models for the prediction of the diversion rates based on the incident attributes. As stated earlier, the LR model produced MAE of 3.20%. The MLP model produced the lowest MAE at 1.80%. The MAE of the SVM model is very close to that of the MLP model at 1.95%.

Figures 2-7 (a), (b) and (c) show how well these three models predicted the diversion rates based on the freeway incident characteristics. To generate these figures, the estimated diversion rates based on traffic detector data were arranged in ascending order and plotted as the smooth solid lines. The solid lines in the figures show that the lowest estimated diversion rate was 0.14% and the highest diversion rate was 27.66% based on detector data. In the same figures, the corresponding model predicted diversion rates are plotted as scatter dots with Figure 2-7 (a), (b) and (c) showing the predicted diversion rates compared to the measured diversion rates from the LR, MLP and SVM models respectively. It is clear from these figures that the SVM and MLP have better prediction capability than LR. An interesting observation is that the estimates based on the MLP model followed the pattern of the measured diversion rate better than those based on the SVM model. On the other hand, the SVM model produced better fit at higher diversion rates.

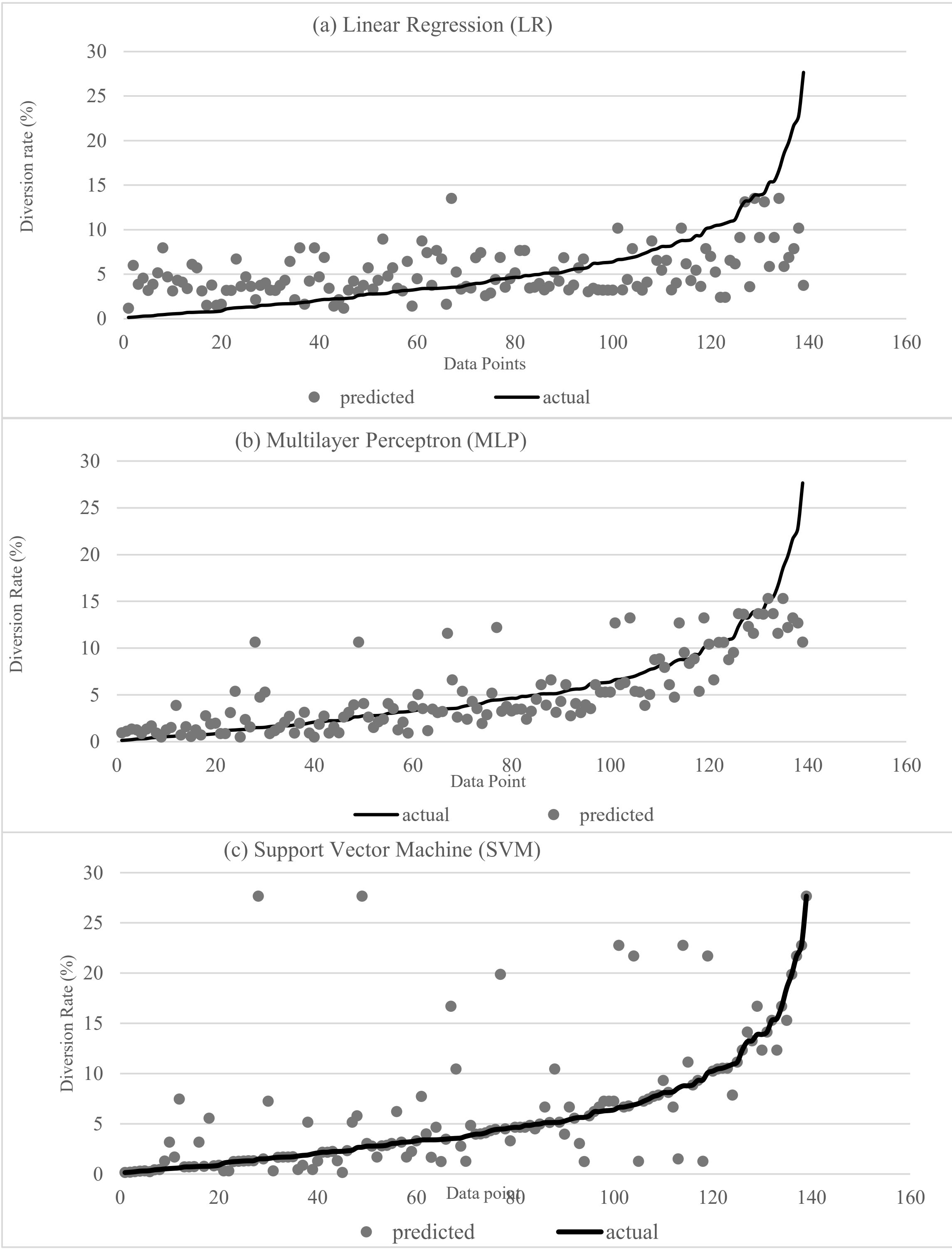


Figure 2-7: Plot of Actual and Predicted Diversion Rates Using (a) Linear Regression (LR) Model, (b) Multilayer Perceptron (MLP) Model, (c) Support Vector Machine (SVM) Model

2.3.6 Model Verification

Further verification of the performance of the models developed in this study was conducted by examining the predicted diversion rate for selected incidents and comparing these rates with those estimated based on detector data. Table 2-4 shows a comparison between the estimated rate of diversion from I-95 for eight individual incidents selected at random with different lane blockage numbers and incident severity levels based on the data, and the diversion rates predicted by the supervised learning models developed in this study. The model that produces the closest estimation to the diversion rate for each incident is highlighted in bold. As can be seen from Table 2-4, the SVM and MLP clearly performs better than the LR. For example, for one of the incidents, the LR predicted 2.42% diversion for an incident with estimated 10.54% diversion based on data. The SVM and MLP models predicted 10.54% and 10.62% diversion, respectively, for this incident. Table 2-4 also illustrates the higher diversion for the incident that occurs before 7:00 AM. As stated earlier, this was attributed to the limited capacity of the off-ramps that prevent further diversion.

Table 2-4: Verification of the Estimation of the Diversion Rate Using the Develop Models

Incident detection time	Time Slice during Start of the incident	Incident Severity	Incident Location	Number of Lane Blocked	Diverted Volume			Diversion Rate (%) from I-95			
					From I-95	To Saw-grass	To Turn-pike	Actual Rate	Model Prediction		
									LR	SVM	MLP
7:45AM	11	1	1	1	499	413	157	1.85	1.63	0.87	**1.96**
6:45AM	7	1	4	1	1138	980	427	3.06	**3.42**	6.20	3.54
6:45AM	7	1	2.5	2	572	259	182	4.60	**4.49**	3.30	3.77
5:30AM	2	2	5	3	991	453	539	13.89	10.98	12.34	**13.69**
6:30AM	6	1	6	3	578	264	314	7.63	7.87	**7.71**	5.04
6:30AM	6	1	5.5	3	740	601	NA	4.83	7.65	**4.65**	3.46
6:45AM	7	3	5	3	1804	359	NA	13.88	11.79	16.70	**11.58**
7:45AM	11	1	3	2	809	464	NA	2.84	4.18	**2.77**	2.61
7:00AM	8	1	2	1	1871	218	NA	10.54	2.42	**10.54**	10.62
5.30AM	2	1	6	3	649	1059	NA	15.46	9.14	12.34	**13.69**

**NA= Sensor data not available for this specific day*

2.3.7 Model Transferability Assessment

Transferability of the developed models are further assessed for a test dataset generated for incidents in two other freeways in the same region, which are the Florida Turnpike and Sawgrass Expressway. Incident data, weather data, and traffic data were fused in the same manner described earlier in this paper. The test results for five separate incidents (three incidents on the Florida-Turnpike and two incidents on the Sawgrass Expressway) are shown in Table 2-5. The results show that for this test data the SVM model shows the least error compared to the other two models, possibly reflecting its resistance to overfitting. The LR model prediction is the least accurate, possibly indicating its inability to fit the diversion function as good as the other two models.

Table 2-5: Model Transferability Assessment for Two Different Freeway Incidents

Incident No.	Freeways	Actual Diversion Rate	Model Prediction		
			LR	MLP	SVM
1	Florida Turnpike	3.09	2.80	4.77	4.30
2	Florida Turnpike	10.96	7.15	13.62	7.69
3	Florida Turnpike	6.84	2.57	8.94	5.54
4	Sawgrass	9.08	10.13	10.5	10.24
5	Sawgrass	10.26	5.13	8.2	10.22
MAE			***2.91***	***1.98***	***1.39***

2.4 Survey Results and Analysis

The results presented in Section 2.3 indicates that the average diversion rate estimated based on main street sensor data ranges between 3.90% and 9.93% and the corresponding 95th percentile diversion rates range between 8.23% and 22.01% depending on the number of blocked lanes and the time of the analysis. This section presents the analysis of the results obtained from two types of traveler information survey. The conducted traveler information surveys are: 1) an on-line survey conducted utilizing the Qualtrics service, and 2) a face-to-face (in-person) survey conducted by the researchers of this study. The survey questionnaire is shown in Appendix B. Conducting the two types of survey in conjunction with utilizing sensor data to derive the diversion as discussed in the previous section allows an interesting comparison of the three methods of diversion rate estimation under various incident conditions.

The online survey was distributed in coordination with Qualtrics to commuters residing in Broward County in southeast Florida. The in-person survey was conducted at major shopping centers and malls in the Broward county area. The same survey questionnaire was utilized in both surveys. The questionnaire included two screening questions to either qualify or disqualify respondents from taking the survey and 18 survey questions. The screening questions were used to eliminate all responses who were 18 years of age or younger and who do not regularly drive a car. The survey questions were designed not only to determine the likelihood of using traveler information/route guidance apps, but also to capture the traveler's diversion behaviors during incidents. For the online survey, data were received from 315 respondents constituting a balanced sample from all of the Broward County's major cities including Sunrise, Plantation, Coconut Creek, Hillsboro Pines, Lauderdale Lakes, and Davie. For the in-person survey, two interviewers conducted the survey of commuters in Broward County area.

The discussion of the results presented in this section is based on the 315 responses of the online survey and the 41 responses of the in-person survey. The survey questions requested data about the respondent's gender and age. All responses were collected from people who regularly drive within the study area at least twice per week. The majority of the respondents who filled the in-person survey were male (61%) and 82.92% were in the 18 to 44-year age category. Only 14.63% of the respondents were in the 45 to 54-year age category and the remaining 2.45 % were above 55 years of age. Moreover, the majority of the respondents who filled the online survey were female (64%) and 68.78 % fell in the 18 to 44-years age category with the remaining above 45 years of age.

Different questions were designed to test the public's awareness and experience with Traveler Information Systems and other means of vehicle navigation. The survey identified to the participants several navigation techniques that are commonly used by drivers such as smartphone apps, DMS, in-vehicle navigation systems, etc. The results from both surveys were quite similar regarding the methods used by people for vehicle navigation. Both surveys indicated that the use of smartphone apps currently dominate the traveler information system utilization. The use of DMS was much lower than expected, possibly indicating that the respondents did not understand what is meant by DMS in the survey and this should be considered in future surveys. Figure 2-8 shows the percentage use of different traveler information methods. Figure 2-9 shows that the Google Maps application is the most widely used among the smartphone applications.

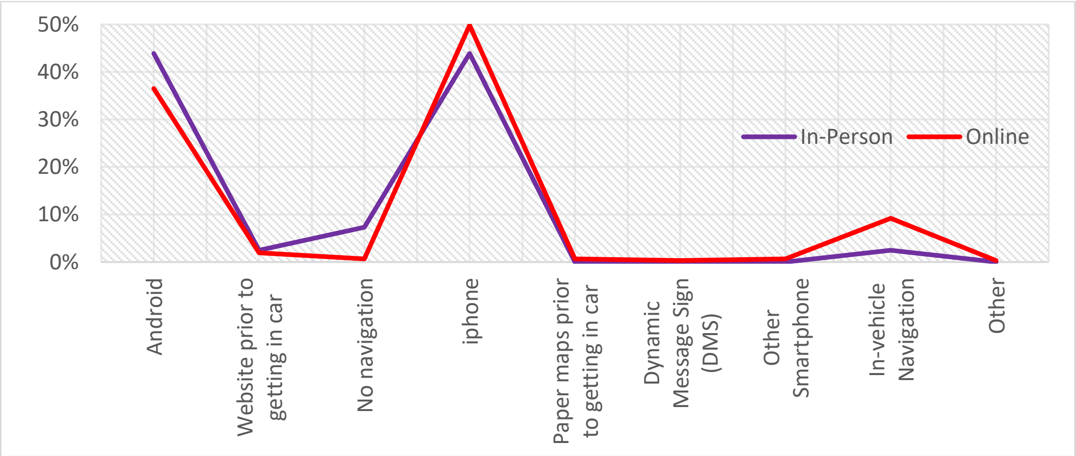


Figure 2-8: Utilization of Traveler Information Methods

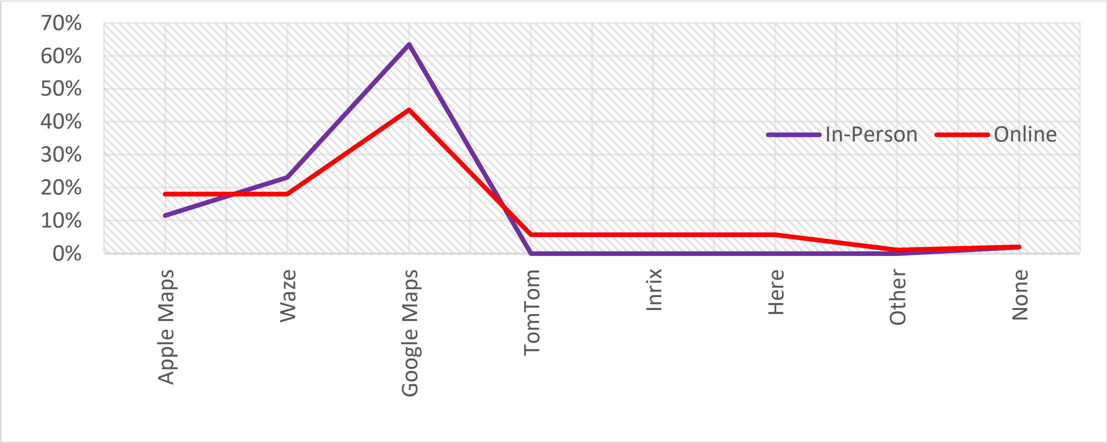


Figure 2-9: Utilization of Smartphone Apps by Type

In order to study the frequency of using the apps by road classification, commuters were asked to estimate their average use of the applications during driving on freeways, arterials, and local roads. Results from the online survey showed that around 40% of drivers use mapping applications almost every day on freeways and local roads, and 38% on major roads. Results from the in-person surveys also show that 32%, 37%, and 25% of drivers use the apps on freeways, major roads, and neighborhood streets, respectively. The details of the responses are shown in Figure 2-10.

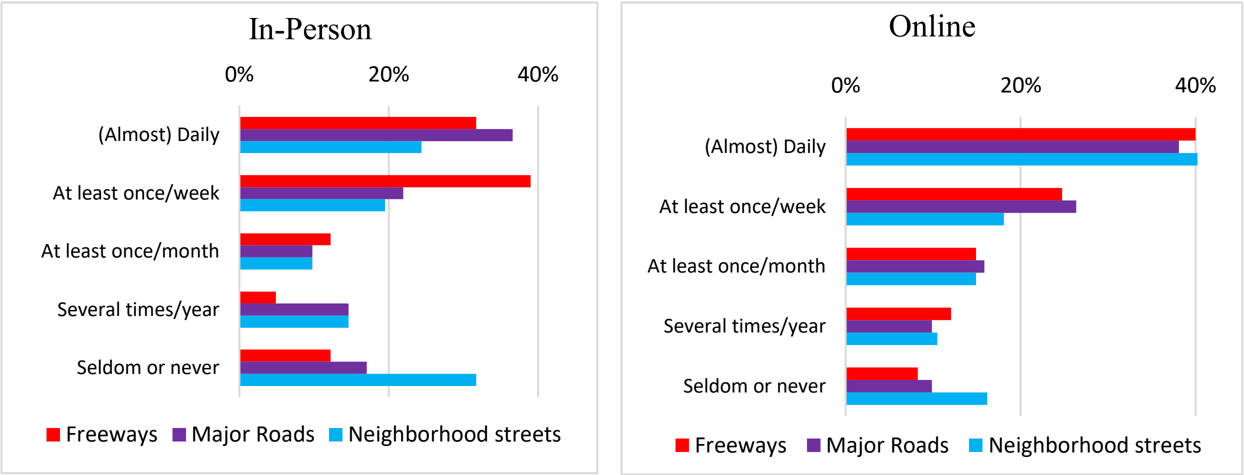


Figure 2-10: Frequency of Using Route Guidance Apps

Trip types and lengths are expected to affect the use of navigation apps. Commuters were asked to estimate their percentage use of navigation applications by trip type (Regular commute, Regular non-commute, Infrequent, and First time trips) and trip duration. The results are shown in Table 2-6 and indicate that the apps are used for all types of trips.

Table 2-6: Percentage of Navigation Applications Use by Trip Type and Duration

	Trip Type/Trip duration	Does not use	1-5 min.	6-15 min.	16-30 min.	31-60 min.	61+ min.	N/A
In-person								
1	Regular commute trips	26%	14%	12%	26%	16%	7%	0%
2	Regular non-commute trips	40%	14%	14%	5%	7%	14%	5%
3	Infrequent trips (doctor, family)	18%	23%	14%	27%	9%	2%	7%
4	First time trips	6%	6%	15%	19%	15%	36%	2%
Online								
1	Regular commute trips	24%	12%	18%	20%	17%	9%	0%
2	Regular non-commute trips	42%	12%	21%	15%	4%	5%	2%
3	Infrequent trips (doctor, family)	16%	13%	21%	28%	13%	8%	2%
4	First time trips	3%	12%	20%	29%	22%	11%	2%

In order to estimate the extent of trip re-routing and diversion rates, the survey participants were asked about the percentage of times they diverted in the last three months when encountering incident conditions. The results, shown in Figure 2-11, indicate that when considering both online survey and the in-person survey, the motorists were equally likely (about 20% of all the respondents) to divert 1-20%, 20-39%, and 40%-59% of the times. The other categories of percentage diversion were less likely. The analysis results show gender and age had no statistically significant correlation with the frequency of diversion.

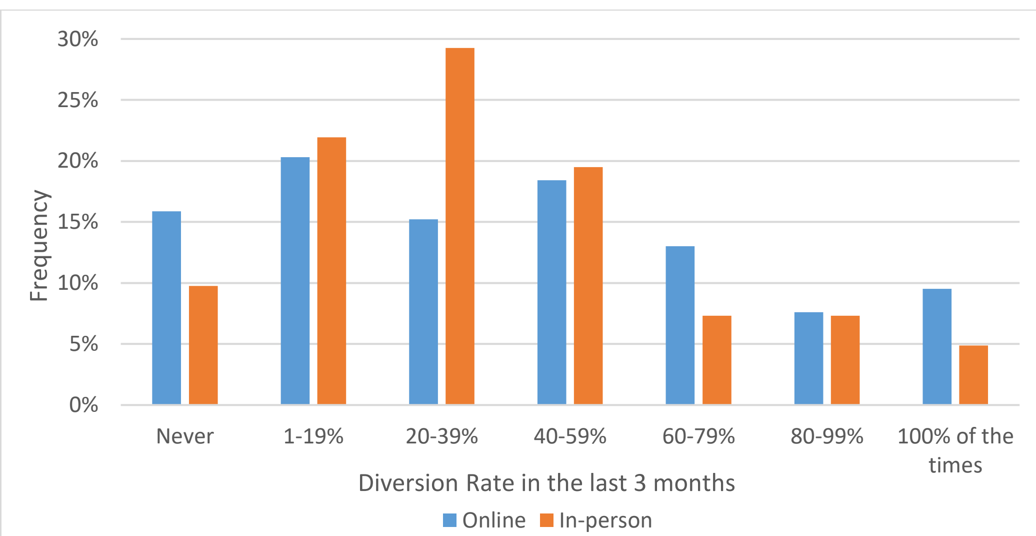


Figure 2-11: Diversion Rate Based on On-Line and In-Person Survey

According to Table 2-7, both the online and the in-person survey results showed that the majority of responses divert when the delay per an hour trip is at least 7 to 24 minutes for an hour trip, with the largest percentage indicating that the diversion threshold is 13 to 18 minute delays.

Table 2-7: Diversion Rates Corresponding to Delay Time Minutes for 1-hour Trip

	Answer	In-person		Online	
		Percentage	Count	Percentage	Count
1	< 7 minutes for an hour trip	7.32%	3	13.65%	43
2	7 to 12 minutes for an hour trip	26.83%	11	23.80%	75
3	13 to 18 minutes for an hour trip	31.71%	13	24.44%	77
4	19 to 24 minutes for an hour trip	24.39%	10	13.65%	43
5	25 to 30 minutes for an hour trip	2.44%	1	7.93%	25
6	More than 30 minutes for an hour trip	4.88%	2	6.66%	21
7	Never divert	2.44%	1	9.52%	30
8	N/A	0.00%	0	0.03%	1
	Total	***100%***	***41***	***100%***	***315***

The compliance rate of using the suggested routes by the apps is expected to be a function of the drivers' familiarity with the alternate route. Researchers reported that drivers were more likely to divert and consider switching decisions when they were familiar with the new routes (Khattak et al. 1995). Accordingly, the surveys asked the users about their preferences and behavior in accepting route guidance. The results from both surveys were similar and showed that the majority of responses followed the suggested route by the applications (60% to 80% of the times). A notable result from this survey was that 19% to 32% of the responses did not follow the suggested route by the applications because the travel time savings was not enough to consider diverting. In addition, 8% to 32% of the app users did not always trust the new suggested routes. Some drivers did not follow the navigation applications when the app's routes were too complicated or required a lot of maneuvering and to avoid neighborhoods.

The surveys asked the users of the application whether the use of the apps changed the people's utilization of different types of roads including freeways, major roads, and neighborhood streets (30 mph or less). The results shown in Table 2-8 show that there was an increase in the utilization of all three types of roads including neighborhood streets when diverting due to navigation app information provision.

Table 2-8: Impact of Roadway Classification Utilization of Navigation Applications

#	Roadway Type	Large increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease
In-person						
1	Freeways	43.90%	31.71%	14.63%	4.88%	4.88%
2	Major Roads	32.50%	30.00%	17.50%	17.50%	2.50%
3	Neighborhood streets (30 mph or less)	34.15%	17.07%	26.83%	12.20%	9.76%
Online						
1	Freeways	41.52%	25.58%	25.58%	5.64%	1.66%
2	Major Roads	37.37%	33.77%	20.98%	6.22%	1.64%
3	Neighborhood streets (30 mph or less)	35.19%	23.35%	31.25%	8.55%	1.64%

2.5 Comparison of Model Results and Survey Results

This section provides a comparison of the diversion rate estimated based on sensor data in Section 2.3 to survey results in Section 2.4.

2.5.1 Diversion Rate Based on Sensor Data

Diversion rate for different delay level was calculated using the model developed in Section 2.3. As discussed in Section 2.3.4, the rate of traffic diversion during freeway incidents is a function of the incident position, incident severity, time of day, and lane blockage. The developed regression model (from Section 2.3.4) is as follows:

Diversion Rate = $(1.7089\times \text{No. of Lane Blockage}) + (2.2655 \times \text{Incident Severity}) + (0.4242 \times \text{Incident Location})$ – $(2.6621\times\text{Log}_e$ (Time slice of Incident Occurrence)

Besides the regression model, two machine learning-based models using MLP and SVM were developed to estimate the diversion rate during incidents. Since the MLP model produced the best result, the model was used to predict the diversion rate and compared the results with the in-person/online survey results. The model predicted the actual diversion rate ranging from 1 to 20%. Figure 2-12 shows the distribution of the predicted diversion rate.

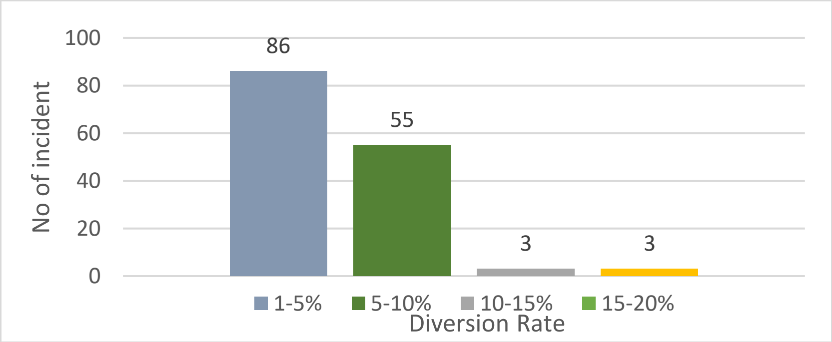


Figure 2-12: Diversion Rate from Regression Model

For those same incidents, the delay for each incident is calculated using queuing theory as follows to estimate the diversion as a function of delay for better comparison with survey data.

$$\text{Individual Vehicle Delay (minutes/vehicle)} = \frac{60t_r(\lambda-\mu_r)}{\lambda}$$

where, t_r is the incident duration (hour), which is calculated from the start and end time of the incident, λ is the traffic demand (vehicle/hour), which is estimated using traffic volume (five-minute resolution) provided by freeway detectors, and μ_r is the reduced capacity due to lane blockage (vehicle/hour) which is calculated using the following equation:

Remaining capacity, μ_r= Capacity adjustment factor*C (pc/hr.)

Where, C is the total capacity of the freeway considering 1900 pc/hr/ln as suggested by the Highway Capacity Manual (HCM), the capacity adjustment factor is the reduction of capacity due to an incident, which is a function of the number of lane blockage. Figure 2-13 shows the predicted model diversion rate as a function of incident delay. Figure 2-13 shows that the average diversion rate increases with the increase of delay.

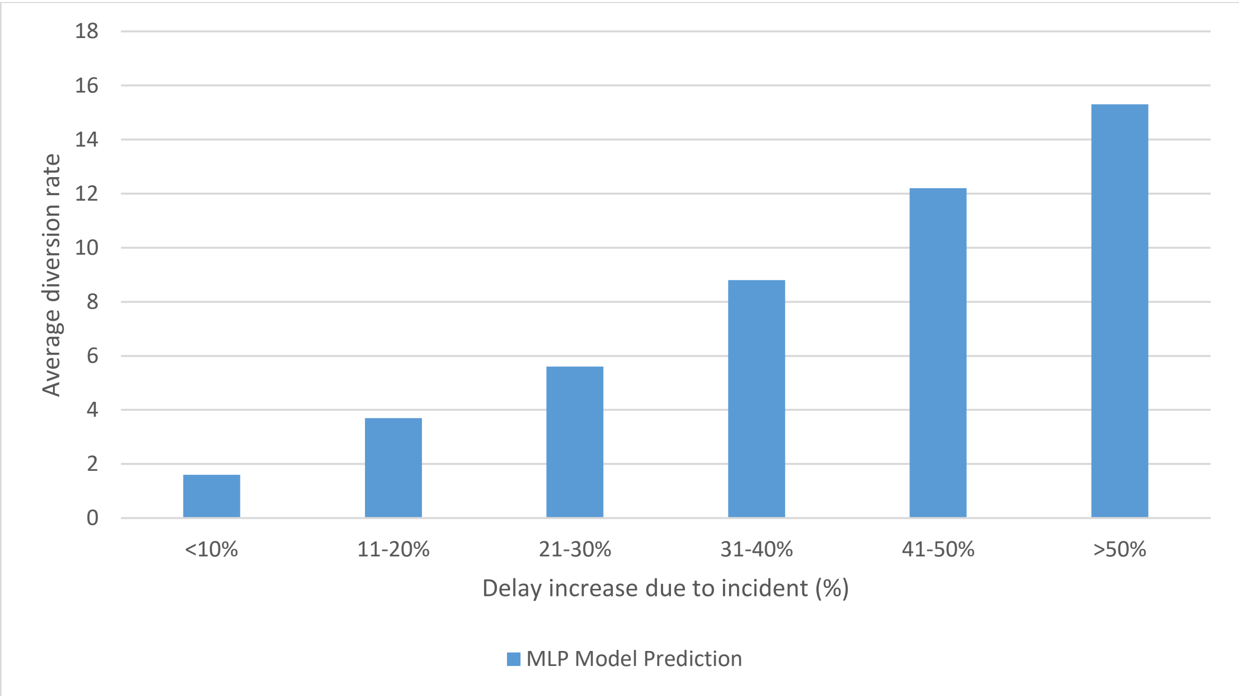


Figure 2-13: Diversion Rate (%) Vs. Individual Vehicle Delay

2.5.2 Diversion Rate Based on Survey Data

The diversion rate at different delay levels is calculated from the responses of Question 6 and Question 7 (See Appendix B). Question 6 provides a statistic of how many times the responders divert during incidents in their recent pasts. Question 7 provides further information of how much increase in delay triggers them to consider diversion. Responses to these two questions were merged together and statistical analyses were performed to get the percentage of diversion at different levels of delay.

For example, consider a survey response that shows someone stated that he/she considers diverting when the delay is more than 20% of their trip and he/she diverts 30% of the time in the last three months. Therefore, the probability of diversion for that person is zero when the delay is less than 20%. If the delay is more than 20%, then he/she considers diversion as an option and diverts 30% of the time based on other factors such as type of trip, time of day, weather etc. In such a case, the probability of diversion is 30% when the delay is more than 20%. Another example is someone stated that he/she diverts 100% of the time, and he/she considers the diversion as an option at 50% increase in delay. This means that this driver always diverts when the delay is more than 50%. Considering this, the responses to Question 6 and Question 7 are combined to get the diversion rate at different delay levels. Figure 2-14 shows the plot of average diversion rate vs delay increase for the in-person survey, online survey and model prediction. The result shows that the in-person survey estimates the lowest diversion among the methods.

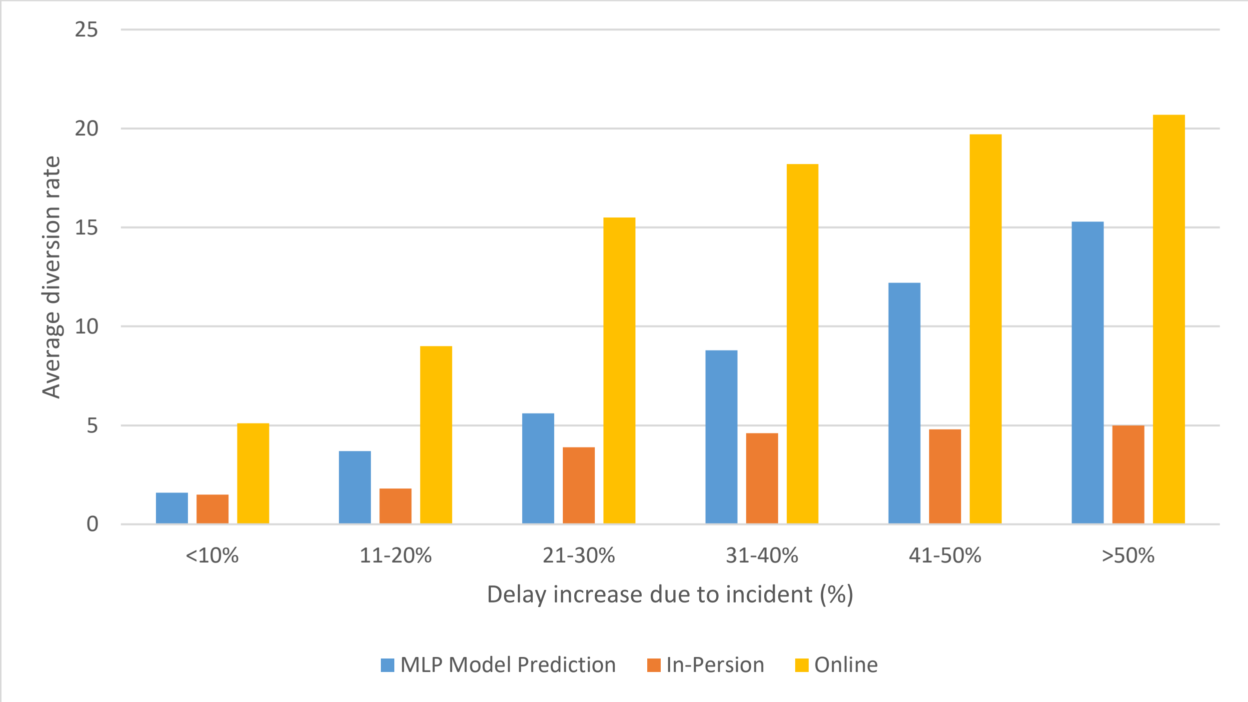


Figure 2-14: Delay Increase vs. Average Diversion Rate

2.6 CONCLUSION

Existing studies have used stated and revealed preference surveys to estimate route diversion during incidents. This study developed a more direct method to estimate the diversion for individual incidents based on mainline detector data and incident data. It was found that the diversion rate can range from about 4% to 22%, depending on the severity (mainly reflecting duration), lane blockage (up to three out of five lanes), and the time of incident occurrence. As part of the study, two travelers revealed preference surveys (i.e., in-person and online) were performed to compare the results with the sensor-based model. Both the surveys' results suggest a diversion rate close to 40% with regularly occurring incidents. This diversion rate seems to be not unrealistic; in that area, it is significantly higher than what the field observations suggest. The study also developed a correlation between the increase in the delay to the diversion rate for all the methods. The in-person survey suggests that the diversion rate doesn't vary with the increase of delay, while the opposite scenario is observed for the online survey and shows a similar trend to the findings of the sensor-based model.

The study found evidence that the diversion is constrained by the capacity of the signals at of the off-ramps, indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the main parallel routes. Capacity analysis of the off-ramp signals indicates that the two off-ramps that provide exits to the main connectors to the alternative routes have a limited amount of access capacity available for vehicles to exit the freeway to alternative routes.

Data analytic models were developed in the study, allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations. Three different models were developed utilizing LR, SVM, and MLP. Among the developed models, the MLP model appears to produce the best results. The models developed in this paper can be used for the prediction of diversion rate based on incident characteristics.

A limitation of this study is that the developed method estimates the overall diversion rate and not the diversion at each off-ramp. Most transportation agencies in the United States do not install sensors on the off-ramps. It is recommended that agencies start installing sensors at the off-ramps to allow a more detailed examination of the diversion.

Based on the results from this section, it can be concluded that the use of detector data combined with traffic flow and statistical techniques is viable to estimate diversion. This will become even more important, as agencies increase their emphasis on performance-based planning, planning for operations, and operations of their systems. It is expected that the diversion models are site specific and depends on the available capacity and characteristics of the alternative routes. The transferability of the models between locations and similar locations in different regions should be investigated in future studies.

2.6 References

1. Adler, J., J. Bottom, C. Nelson, and K. Wunderlich. EnableATIS Strategy Assessment. Final Report. Publication FHWA-JPO-14-113, Washington, D.C., 2014.
2. Burgess, L., A. Toppen, M. Harris. Vision and Operational Concept for Enabling Advanced Traveler Information Systems (EnableATIS). Final Report. Publication FHWA-JPO-12-052, Washington, D.C., 2012.
3. Yelchuru, B., R. Kamalanathsharma, K. Abdelghany, et al. Analysis, Modeling, and Simulation (AMS) Testbed Development and Evaluation to Support Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs — Evaluation Report for ATDM Program. FHWA-JPO-16-385., 2017.
4. Lai, C.-J. Drivers' comprehension of traffic information on graphical route information panels. Accident Analysis and Prevention, 2012. 45 pp. 565–571.
5. Barfield, W., L. Conquest, J. Spyridakis, and M. Haselkorn. Information Requirements for Real-Time Motorist Information Systems. Proc. Vehicle Navigation and Information Systems Conference (VNIS), New York, IEEE, 1989. pp. 101–104.
6. Madanat, S. M., C. Y. D. Yang, and Y.-M. Yen. Analysis of Stated Route Diversion Intentions under Advanced Traveler Information Systems Using Latent Variable Modeling. Transportation Research Record: Journal of the Transportation Research Board, 1995. 1485: 10–17.
7. Benson, B. G. Motorist Attitudes about Content of Variable-Message Signs. Transportation Research Record: Journal of the Transportation Research Board, 1996. 1550: 48–57.
8. Chatterjee, K., N. B. Hounsell, P. E. Firmin, and P. W. Bonsall. Driver Response to Variable Message Sign Information in London. Transportation Research C, 2002.10(2): 149–169.
9. Peeta, S., J. Ramos, & R. Pasupathy. Content of variable message signs and on-line driver behavior. Transportation Research Record: Journal of the Transportation Research Board, 2000. 1725: 102-108.
10. Khattak, A. J., F. S. Koppelman, & J. L. Schofer. Stated preferences for investigating commuters' diversion propensity. Transportation, 1993. 20(2): 107-127. https://doi.org/10.1007/BF01307055
11. Huchingson, R. D., and C. L. Dudek. Delay, Time Saved, and Travel Time Information for Freeway Traffic Management. Transportation Research Record: Journal of the Transportation Research Board, 1979. 722: 36–40.
12. Al-Deek, H., S. Venkata, J. Flick, & A. Khattak. Dynamic message sign deployment and diversion behavior of travelers on Central Florida toll roads. Transportation Research Record: Journal of the Transportation Research Board, 2009. 2129: 24-34.
13. Kattan, L., K. Habib, S. Nadeem & T. Islam. Modeling Travelers' Responses to Incident Information Provided by Variable Message Signs in Calgary, Canada. Transportation Research Record: Journal of the Transportation Research Board, 2010. 2185: 71-80.
14. Wang, J., & Niu, H. A distributed dynamic route guidance approach based on short-term forecasts in cooperative infrastructure-vehicle systems. Transportation Research Part D: Transport and Environment, 2018.

15. Tarry, S., and A. Graham. The Role of Evaluation in ATT Development. Traffic Engineering and Control,1995. 36(12): 688–693.
16. Chatterjee, K., and M. Mcdonald. Effectiveness of using variable message signs to disseminate dynamic traffic information: Evidence from field trails in European cities. Transport Reviews, 2004. 24(5): 559-585.
17. Deeter, D. Impacts of Traveler Information on the Overall Network. ENTERPRISE Pooled Fund Study TPF-5(231), Report No. ENT-2012-2, Lansing, MI., 2012.
18. Haghani, Ali, M. Hamedi, R. L. Fish, and A. Nouruzi. Evaluation of dynamic message signs and their potential impact on traffic flow. No. MD-13-SP109B4C. 2013.
19. Foo, S., & B. Abdulhai. Evaluating the impacts of changeable message signs on traffic diversion. Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE pp. 891-896.
20. Hadi, M., Y. Xiao, & M. Rojas, Estimation of Diversion Rate During Incidents on Basis of Main-Line Detector Data. Transportation Research Record: Journal of the Transportation Research Board, 2013. 2396: 54-60.
21. He, Z., Guan, W., & Ma, S. A traffic-condition-based route guidance strategy for a single destination road network. Transportation Research Part C: Emerging Technologies, 2013, 32(4), 89–102.
22. He, Z., Zheng, L., Guan, W., & Mao, B. A self-regulation traffic-condition-based route guidance strategy with realistic considerations: overlapping routes, stochastic traffic and signalized intersections. Journal of Intelligent Transportation Systems, 2016. 20(6), 545–558.
23. Abdel-Aty, M., & Addalla, M. F. Modeling drivers' diversion from normal routes under ATIS using generalized estimating equations and binomial probit link function. Transportation, 2004. 31(3), 327-348.
24. Xiong, C., Chen, X., He, X., Lin, X. and Zhang, L. Agent-based en-route diversion: Dynamic behavioral responses and network performance represented by macroscopic fundamental diagrams. Transportation Research Part C: Emerging Technologies, 2016. 64, pp.148-163.
25. Khattak, A., H. Al-deek, Y. Yim, & R. Hall. Bay Area ATIS testbed plan. Research Report UCB-ITS-PRR92-1, Partners for Advanced Transit and Highways (PATH). Institute of Transportation Studies, University of California at Berkeley, California, 1992.
26. Zhao, Fang, Min-Tang Li, and Lee-Fang Chow. Alternatives for estimating seasonal factors on rural and urban roads in Florida. No. Final Report. 2004.
27. Ketchen, D. J., & C. L. Shook. The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique. Strategic Management Journal, 1996. 17(6):441-458.
28. Florida, D. O. T. Refinement of Florida statewide op-erations performance measures and data collection methodology. Florida Department of Transportation Statistics Office, USA, 2006.
29. Hecht-Nielsen, R. Neurocomputing. Addison-Wesley. Reading, MA. 1990.
30. Haykin, S. S. Neural networks and learning machines. Simon Haykin. New York: Prentice Hall, 2009.

31. Basheer, Imad A., and Maha Hajmeer. Artificial neural networks: fundamentals, computing, design, and application. Journal of microbiological methods, 2000. 43.1: 3-31.
32. Baum, Eric B. On the capabilities of multilayer perceptrons. Journal of complexity, 1988. 4.3: 193-215.
33. Pasini, A. Artificial neural networks for small dataset analysis. Journal of thoracic disease, 2015. 7(5), 953.
34. Cristianini, N., & Shawe-Taylor, J. An introduction to support vector machines. New York: Cambridge Univ. Press, 2000.
35. Cristianini, N., & Scholkopf, B. Support vector machines and kernel methods: the new generation of learning machines. AI Magazine, 2002. 23(3), 31-31.
36. Vapnik, Vladimir, Steven E. Golowich, and Alex J. Smola. Support vector method for function approximation, regression estimation and signal processing. In Advances in neural information processing systems, pp. 281-287. 1997.
37. Kavaklioglu, K. Modeling and prediction of Turkey's electricity consumption using Support Vector Regression. Applied Energy, 2011. 88(1), 368-375.

CHAPTER 3: GATING CONTROL TRAFFIC MANAGEMENT USING DECENTRALIZED TRAVELER INFORMATION DATA (JACKSON STATE UNIVERSITY STUDY)

3.1 Introduction

Over the past decades, traffic congestion has resulted in greater amounts of required travel time than before. It is a sign of deteriorating quality-of-life in a community. As an inexpensive, cost-efficient, and energy and environment friendly transportation service, traffic management through an Intelligent Transportation System (ITS) is naturally gaining more popularity in reducing traffic congestion. Emergency evacuation, in response to both natural and man-made disasters, aims to move a large disaster affected population through a transportation network towards safer areas both quickly and efficiently. Evacuations that are caused by disastrous incidents generally involve a large number of evacuees that increase traffic congestion, and there are necessities of accurately collecting traveler information and developing effective traffic management strategies in reducing traffic congestion.

3.1.1 Traffic Congestion and Decentralized Traveler Information

According to the 2015 Urban Mobility Scorecard (Schrank et al. 2015), every auto commuter spent an average of extra 42 hours traveling in 471 urban areas in 2014, which is up from 18 hours in 1982. From 2013 to 2014, 95 of America's 100 largest metro areas saw increased traffic congestion, while from 2012 to 2013 only 61 cities experienced increases. In order to ensure timely arrivals for important trips, travelers had to allow 48 minutes to make a trip that takes 20 minutes in light traffic. The 2016 Urban Congestion Trends Report (FHWA 2017) provides the current status of congestion and reliability in 52 of the largest metropolitan areas in the United States and highlights successful relevant operation strategies and performance management approaches implemented by State and local transportation agencies. It indicates that congestion has overall remained relatively flat, increasing by 3 minutes from 2015 to 2016.

For two widely accepted types of traffic congestion of non-recurrent congestion and recurrent congestion, the Federal Highway Administration (FHWA) (2017) states that non-recurrent congestion makes up 55%, including 25% due to traffic incidents, 15% due to bad weather, 10% due to work zones, and 5% due to special events. Recurrent congestion makes up 45%, including 40% due to bottlenecks, and 5% due to poor signal timing. Unlike non-recurring congestion, the sources of recurring congestion are more easily identified and can be addressed by working to develop proper signal timing and focusing on reducing bottlenecks during peak commuting hours. Reducing non-recurring congestion, especially under extreme weather, is more difficult. In order to successfully develop and deploy the traffic management strategy to reduce traffic congestion, two basic studies are necessary to be conducted: one is the traveler information collection and analysis, and the other is the trip route optimization modeling. Traveler information, as the basic information used for developing and deploying the traffic management strategy, is crucial to be collected accurately. There are two types of traveler information: the centralized traveler information and the decentralized traveler information. The typical deployment of centralized collection of traveler information for an ITS is to install vehicle sensors and loop detectors buried under pavement surfaces and connected through wired or wireless communications hardware/software to the Traffic Management Center (TMC). The disadvantage of this information collection method is that there are potential single point failures on the roadway without embedded loop detectors. With the advancements in communications and computer technologies, traveler information such as travel time and travel speed can also be collected as decentralized data using on-board devices, such as smartphones, or probe vehicles. Collecting decentralized traveler information (Xu 2006) using smart devices, compared to collecting traditional centralized traveler information by sensors, could avoid potential single point failures that a TMC-based system might have. The decentralized traveler information is capable to cover roadways that do not have embedded loop detectors. Hence, this kind of information could well reflect the traveler trip and trajectory information, especially the recurrent traffic congestion on a road network. Decentralized traveler information can effective help determine the potential congestion locations where traffic management strategies are considered.

3.1.2 Emergency Evacuation

Evacuations caused by disastrous incidents generally involve a large number of evacuees, possibly from more than one community or even jurisdiction, who need to move away from the at-risk area as soon as possible. This requires intensive efforts by emergency managers, first responders, law enforcement officers, and transportation professionals to coordinate, guide, transport, and shelter the affected population (Zimmerman et al. 2007).

In contrast to a widespread disaster that may result in a large-scale regional emergency evacuation, a smaller incident such as a hazardous material spill due to a derailed train usually affects a localized area, and only the population within the affected area needs to be evacuated (Murray-Tuite and Wolshon 2013; Li et al. 2015). A localized evacuation may also be needed for a large-scale emergency evacuation when evacuation priorities are placed on a population in a subarea due to more imminent vulnerability of the subarea than the rest of the region. In studying a localized evacuation using traffic assignment simulations, a traffic assignment program tends to model the trip of an evacuee (in a vehicle) who seeks to leave the origin point within the subarea for a safe destination point outside the subarea as a “shortest path”. The seeking of the “shortest path” in a trip route corresponds well to a driver’s behavior under a normal traffic operation condition (Yang and Zhou 2014; Zheng et al. 2015; Bu et al. 2016; Wang et al. 2016). However, a reconsideration of the evacuation problem would reveal that the most effective strategy of evacuating a large number of people (in the format of vehicles hereafter) under a subarea emergency evacuation situation would be a 2-stage process: 1) first move all the evacuees out of the subarea (frequently to a point on the boundary of the subarea) in the least amount of total time, and 2) then, starting from the boundary of the subarea, the evacuees continue their trips to their destinations via their respective shortest paths. Intuitively, if every evacuee individually seeks the shortest path to leave the subarea for a safe destination, the possibility of having conflicts between traffic movements of these “shortest” trip paths would be high considering the tremendous number of evacuation trips generated after an evacuation order (assuming individual response time toward the evacuation is different). These increased conflicts of traffic movements and trip paths can cause widespread cascading traffic congestion within the subarea and impair the evacuation effort. Therefore, instead of seeking the individual shortest paths for the trip segments within the subarea, evacuation traffic could be encouraged or guided to go through selected “gate” nodes/links in the subarea, on or near the subarea boundary with large access and throughput capacities to reduce the otherwise conflicts of traffic movements.

This research will address how to use decentralized traveler information to determine potential congestion locations with highly unreliable travel times and identify weak points in urban network to be deployed with gating traffic control strategies to achieve the minimum travel cost in emergency evacuation. The research will contribute to using probe data in design of a traffic control or management strategy and reducing traffic congestion in emergency evacuation.

3.2. Literature Review

Several studies investigated measures of travel time reliability (Carrion and Levinson 2012; Beaud et al. 2016; Xiao et al. 2017) on traffic congestion and effects of traffic management strategies on the performance of emergency evacuation. Congestion during emergency evacuation is the major concern because of the resulting traffic breakdown it may cause. In order to effectively extract previous research achievements, the literature review presented herein will focus on three major aspects: 1) travel time reliability analysis; 2) route choice behaviors in evacuation; and 3) optimization approach and traffic simulation. A review of the collected studies, classified by the major aspects considered, is presented in the following subsections.

3.2.1 Travel Time Reliability Analysis

In the past years, investigation of traffic congestion on roadways has received a lot of attention from researchers. Congestion measure can describe how well the system meets stated goals and targets, which can also explain the variations in user experiences with the system. Among the measures, some, including delay, risk of delay, mean speed, travel time and vehicle hours traveled (VHT), explain the duration of congestion experienced by users. Some measures, including the volume-to-capacity (V/C) ratio, usually expressed as a level-of-service (LOS), describe how well the system is functioning at a given location. Some are spatial measures, such as queue length, queue density, and vehicle miles traveled (VMT). Some others are measures for travel time reliability and the number of stops (Lyman and Bertini 2008; Bertini 2005).

Travel time reliability, as a measure of consistency or dependability in travel times at a given time, has been studied in the following categories: 1) statistical range measures, e.g., variance, standard deviation, and coefficient of variation (Lint et al. 2008; Sumalee and Zhong 2013; Zhang et al. 2016); k-th percentile, skewness and width statistic (Lint and Zuylen 2005; Guo et al. 2012; Sumalee et al. 2013; Jong and Bliemer 2015; Woodard et al. 2017); and travel time index; 2) buffer time measures, e.g., planning time, planning time index, buffer index, failure/on-time performance, and frequency of congestion; 3) tardy trip, e.g., misery index; and 4) probabilistic measure (Lint et al. 2008). Some standard measures of travel time reliability are used by the FHWA based on travel time estimates directly calculated from continuous probe vehicle data, estimates from continuous point-based, detector data, data collected in periodic special studies, or estimation created through simulation (FHWA 2017). The measures include 95th percentile travel time, travel time index, buffer index, and planning time index (Lint et al 2005; Lyman and Bertini 2008). These indicators are mostly related to properties of the day-to-day travel time distribution on a corridor or segment, which is a result of day-to-day fluctuations in both traffic demand and supply characteristics.

Lyman and Bertini (2008) studied 10 Portland freeway corridor buffer indices by segment level and corridor level, in which all freeway segments included in this analysis showed higher buffer indices in the PM peak than in the AM peak. It was because traffic volumes were generally higher in the PM peak or because the PM peak had experienced peak spreading to a greater degree than the AM peak. According to the study results, several corridors had lower buffer indices in the range of 50%, while several corridors had higher buffer indices. It was suggested that priority should be given to the freeway with higher buffer indices in one direction in the AM peak or in the PM peak to improve reliability ratings. Lint et al. (2008) also conducted a study, aiming to investigate the actual and acceptable travel time reliability on a typical long route for three days of the week over one year. The buffer time indices during weekdays indicated that travel time reliability dropped well below 70% during both morning and afternoon peak-hour periods. Buffer time index was also advanced using multi-state models by proposing skewed component distributions (Guo et al. 2012), providing superior model fitting for travel time during peak conditions, especially for the congested environment.

Several studies investigated different travel time reliability indices to analyze travel time reliability. Higatani et al. (2009) studied planning time, planning time index, buffer time, and buffer time index for multi routes. They showed the average travel time profile for each hour of a day over one year, during morning and evening peaks. Peak hours of planning time and average travel time showed the busiest route, and the buffer index was used to prioritize corridors and roadway segments according to travel time reliability. Chen et al. (2018) used coefficient of variation and buffer time index to explore the day-of-week travel time variability patterns. The study showed that urban expressways, auxiliary roads of urban expressways, and major roads have regular and distinct morning and afternoon peaks on weekdays. They revealed the volatile travel time characteristics of each road type in urban network.

3.2.2 Route Choice Behaviors in Evacuation

The modeling and design of a more effective traffic operation plan for emergency evacuation has been rigorously investigated using traffic simulation programs (Urbina and Wolshon 2003; Qiao et al. 2009; Hardy 2010; Sadri et al. 2014; Yang and Zhou 2014) since early studies dealing with traffic management under emergency conditions. These studies shared some similarities in route choice behavior and traffic assignment procedures. Evacuation demand in terms of origin-destination (O-D) matrix was determined for each evacuation scenario and a Geographic Information System (GIS) based roadway network was available for a simulation program to assign traffic for each trip O-D pair. Generally, the result of the traffic assignment was a trip trajectory, which is a “shortest path” with a sequence of nodes and links connecting the origin to the destination. These studies considered shortest-path traffic assignments for the whole routes of all evacuation trips even under a localized evacuation situation, in which a Protective Action Zone (PAZ) is normally determined for the incident affected area, and the evacuation of people out of the PAZ would take a higher priority than the trip segment in the area outside the PAZ. The priority in the evacuation trip assignments inside the subarea with an emergency could be achieved by using an optimized evacuation strategy in which evacuees would follow optimal routes to safe locations outside the affected zone and then select behaviorally realistic routes to their final destinations (Zheng et al. 2010). The destinations could initially be assigned to the exits of the affected area by assuming a super-node and ignoring the travel to the real destinations outside the affected area (Lu et al. 2014).

Based on OD-demand pairs in the PAZ, route choice models such as traffic assignment and route guidance are commonly used as components in large network modeling, and these choice models generally consist of finding the least-cost paths (Bekhor et al. 2008; He and Peeta 2014). Household behavior is also the most important aspect of hurricane evacuation by which a number of vehicles are generated and entered in the evacuation transportation network, following the routing strategy based on the user equilibrium (Ho et al. 2007; Bekhor et al. 2008; Lim and Kim 2016; Ukkusuri et al. 2017).

According to a panel survey (Yin et al. 2014) that focused on Hurricanes Ivan and Katrina, most evacuees selected the same type of accommodations in the consecutive evacuations, and the number of household vehicles used in the evacuations did not change. Also, in an emergency evacuation, evacuees often seek familiar routes instead of selecting the routes contributing to relief of the traffic congestion and decrease of travel cost (Lindell and Prater 2007; Murray-Tuite et al. 2012). Meanwhile, as individual drivers all attempt to use shortest routes of their own, some or all of the road network links and intersections on the evacuation routes would become over utilized due to unresolved conflicts of traffic movements, which may cause traffic congestion and potential blocking along the routes in the evacuation zone (Pel et al. 2010).

3.2.3 Optimization Approaches and Traffic Simulation

Optimization modeling over highway networks using static traffic assignment (STA) or dynamic traffic assignment (DTA) was conducted in numerous studies in the past years. In an optimization model for evacuation network, the concept of one-destination evacuation (ODE) was introduced by Yuan et al. (2006) to achieve the optimal traffic flow destination assignment by using minimum travel cost. In the study, a linear programming model was constructed with constraints of link flow and OD demand. Based on static traffic assignment, a link-path incidence variable was used to determine if a link was part of a path. Traffic operations in networks were studied using optimization modeling for different evacuation performance parameters or measurements of effectiveness (MOEs) (such as total trip cost, total conflicting risk, evacuation time, evacuation exposure, and average v/c ratios along with static traffic assignments) and various traffic management strategies including contraflow and crossing elimination for evacuation planning (Yusoff et al. 2008; Yuan and Han 2010; Xie et al. 2010; Qian and Zhang 2012; Bu et al. 2016). Meng et al. (2008) formulated the optimal contraflow lane configuration problem as a bi-level programming mode. In the model, the upper-level problem was a binary integer programming formulation aimed to minimize the total travel time of a study area, while the lower level problem was a microscopic traffic simulation model that simulated the dynamic reaction of the drivers resulting from a contraflow lane configuration scheme. Constraints of the sequence and direction of reversal were considered in the model.

Optimization methods have been widely used in network modeling for recurring congestion problems as well. In a recent study, Yang and Zhou (2014) constructed an integer programming model to find priori least expected time paths. The non-anticipativity constraint associated with the priori path in a time-dependent and stochastic network was considered in the model, and a number of reformulations were proposed to establish linear inequalities that can be easily dualized by a Lagrangian relaxation solution approach. Later, a time-dependent network flow programming model was proposed to maximize the accessibility of travelers. In the model, constrains of space-time flow balance, construction budget and coupling constraints between space-time arcs and physical links were introduced (Tong et al. 2015). A nonlinear programming model was formulated to describe the route choice behavior of the perfect information (PI) and expected travel time (ETT) user classes under stochastic day-dependent travel time (Li et al. 2017). In the model, constraints of path-link flow balance, path-link cost connection, expected path disutility, and least disutility were considered to minimize the gap between the current iteration solution and the ideal solution. In these studies, traffic simulations were frequently used for verification of optimization modeling on small road networks. In addition, traffic simulations were specifically introduced by the researchers to seek traffic detail and resolution in different levels using macroscopic, mesoscopic, or microscopic approaches.

In order to develop traffic simulation-based models, a platform was developed by Zhou et al. to provide a robust framework for demand modeling and network analysis, which addressed emerging Intelligent Transportation System (ITS) and demand management technologies. The platform was latter developed as a theoretically rigorous and computationally efficient traffic network modeling tool, DTALite (Zhou and Taylor 2014; Zhou 2016), based on mesoscopic DTA procedure and queue-based traffic flow simulation models. The optimization modeling of traffic flows was introduced in this study, which was on a theoretically small-scale evacuation network, under a proposed gating control strategy along with a static traffic assignment algorithm and the verification of the optimization model using traffic simulations for a realistic highway network.

The aforementioned study results have well suggested the advantage of aggregate optimization of traffic assignments and route selections over individual “shortest paths” for a localized emergency evacuation and the importance of traffic guidance (Xu et al. 2014; Kaviani et al. 2017) in such an evacuation operation. A subject that the researchers have not explored is the identification of traffic congestion at extreme events based on recurrent congestion, and the effectiveness of large-scale emergency evacuation using route choice and optimization modeling approaches. This study has been done to fill this gap.

3.3. Data Description

3.3.1 Probe Data

Historical probe data with travel time on segment by one minute of highways and arterial roads at Memphis Metropolitan area from October 1, 2016 to October 1, 2017, and corresponding road network data were acquired from INRIX. Table 3-1 describes the raw data information, and Table 3-2 is the list of variables and attributes used in this study.

Table 3-1: Raw Data Information

Number	Data	Description
1	Vehicle probe data	Date: Oct 1, 2016-Oct 1, 2017 Time interval: 1 minute Number of data file: 85 Number of metadata file: 85 File format: CSV Data size: 334 GB
2	Road network data	BEST12

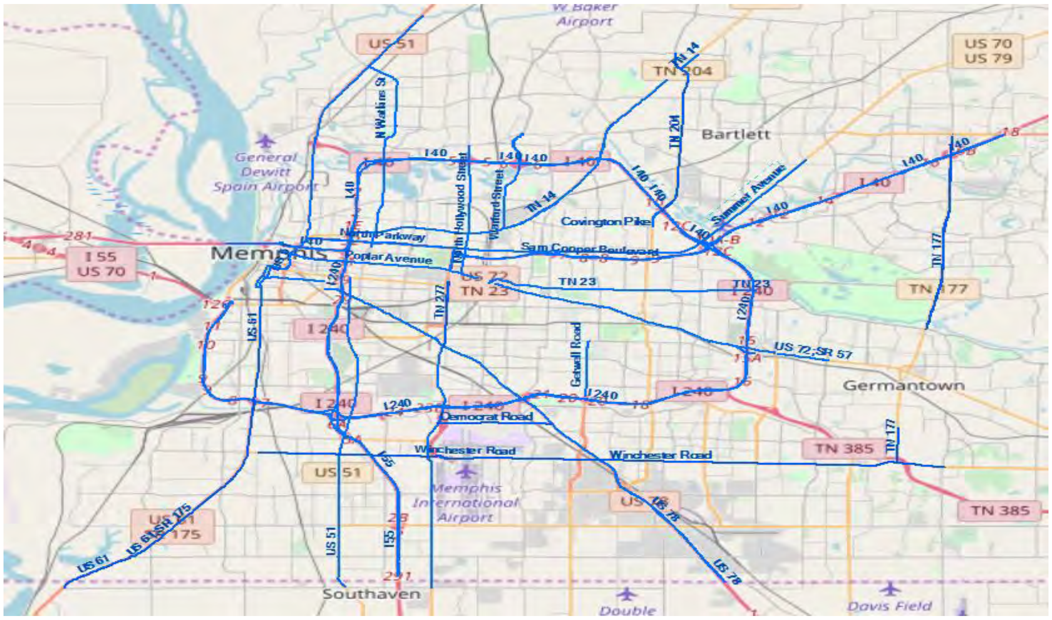
Table 3-2: List of Variables and Attributes

Number	Variable	Type	Length	Format	Informat
1	Date Time	Numeric	8	YYMMDD10	YYMMDD10
2	Segment ID	Numeric	8	BEST12	BEST32
3	Travel Time (minutes)	Numeric	8	BEST12	BEST32
4	Speed (miles/hour)	Numeric	8	BEST12	BEST32

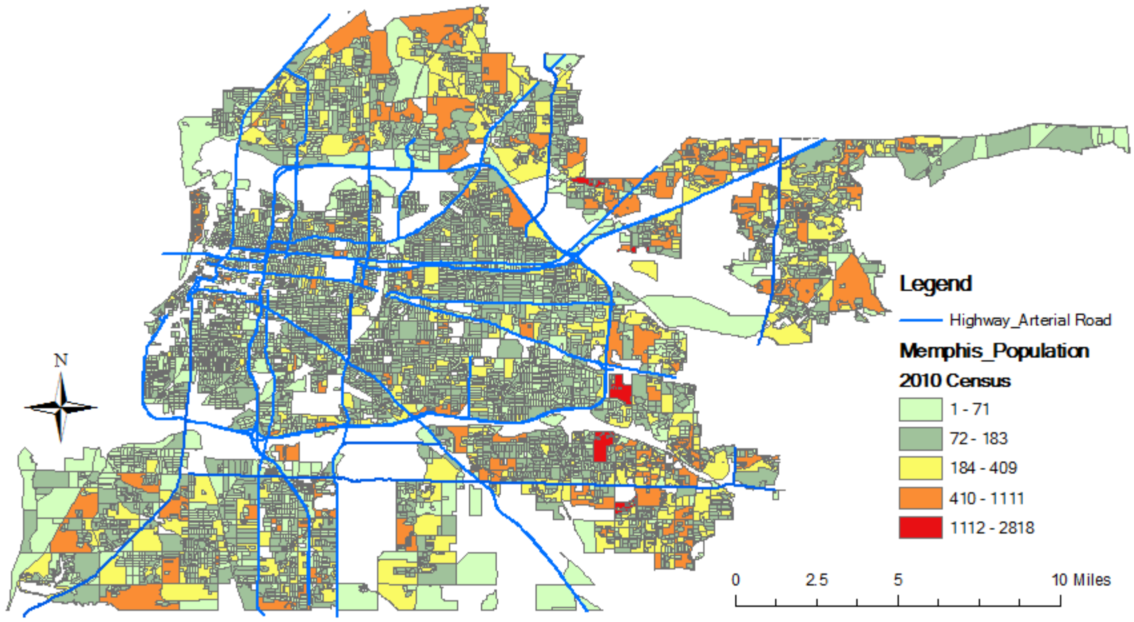
For the raw data, there are two major types, vehicle probe data and road network data. For the vehicle probe data, there are a total of 170 files including 85 data files and 85 metadata files. Each file is stored as .csv format. The data size is 334 GB. For the road network data, there are 5830 segments. The data are stored as .shp format and data size is 33.5 MB. The variables used for the analysis are Date Time, Segment ID, Travel Time, and Speed.

3.3.2 Network in Memphis City

The road network in Memphis studied in this project includes interstate highways, US highways, state highways, and arterial roads, as shown in Table 3-3 and Figure 3-1(a). As shown in Figure 3-1(b), US highways, interstate highways, state highways, and arterial roads form the road network serving daily traffic in the city of Memphis and are accessed by residents and the driving public.



(a) Road network in city of Memphis, TN



(b) Highway and arterial roads accessed by residents

Figure 3-1: Description of road network in Memphis, TN.

Table 3-3: Major Highways and Arterial Roads in Memphis, TN

Category	Name
US highway	US-61, US-51, US-78, US-72
Interstate highway	I-55, I-40, I-240
State highway	TN-23, TN-177, TN-14, TN-204, TN-277
Arterial road	Democrat Road, Winchester Road, Airway Blvd, Poplar Avenue, North Parkway, Sam Cooper Blvd, Summer Avenue, Getwell Road, North Watkins Street, North Hollywood Street, Warford Street, Covington Pike

3.4. Travel Time Analysis Method

Travel time reliability measures, network representations in traffic assignment problem, simulation-based DTALite modeling, and mathematics-statistical models are adopted to identify potential gate locations in each subarea zone, to design and deploy gating control traffic management strategies, and to evaluate performance of the traffic management strategies.

3.4.1 Travel Time Reliability Measures

Travel time reliability measures used in this research include statistical range index and buffer time index (Lint et al. 2008), which are both for a given time-of-day (TOD) period.

3.4.1.1 Statistical range measures

Statistical range measures include standard deviation, coefficient of variation, and planning time. The standard deviation (STD) is a measure that is used to quantify the amount of variation or dispersion of a set of travel time data values. A low standard deviation indicates that the data points tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. The population travel time variance is found by

$$\sigma^2 = \frac{\sum_{i=1}^{N} (TT_i - \mu)^2}{N} \tag{1}$$

where:

σ^2 is the population variance.

TT_i is the value of a travel time observation in the population.

μ is the population mean of travel time.

$\overline{TT}$ is the arithmetic mean of travel time of the data sample

m is the number of travel time observations or sample size of a sample of the population

The travel time sample standard deviation is found by the formula

$$STD = \sqrt{\frac{\sum_{i=1}^{m}(TT_i - \overline{TT})^2}{m-1}} \qquad (2)$$

Coefficient of variation (COV), is a standardized measure of dispersion of a probability distribution or frequency distribution. It is often expressed as a percentage and defined as the ratio of the standard deviation to the mean. The coefficient of variation for a data sample is calculated by the formula:

$$COV = \frac{STD}{\mu} \times 100\% \qquad (3)$$

3.4.1.2 Buffer time measures

Buffer time indicates the extra travel time a traveler should leave earlier than average time, to still arrive on time (in 95% percentile in this research) on a given TOD period. Buffer time measures used in this research are planning time (PT) and buffer index (BI).

The planning time represents the total travel time expected or planned before trip starts with a given probability p , which is presented by

$$PT = \Phi_s^{-1}(p)$$

The 95% percentile value indicates the travel time on the worst day of the month, namely, TT_{95th} , which is presented by

$$PT = TT_{95th} \qquad (4)$$

Buffer time is the extra time to ensure on-time arrival to the destination, which is presented by

$$BT = TT_{95th} - \overline{TT} \qquad (5)$$

Buffer time index is the ratio of buffer time to the average travel time. It is a measure of the reliability of travel service, which can be viewed as the extra time ratio that travelers must add to their average commute to ensure an on-time arrival most of the time. It is calculated as follows:

$$BI_{mean} = \frac{TT_{95th} - \overline{\overline{TT}}}{\overline{\overline{TT}}} \qquad (6)$$

Where, TT_{95th} is the 95th percentile travel time and $\overline{\overline{TT}}$ is mean travel time.

Travel time reliability measures are listed in Table 3-4.

Table 3-4: Summary of Travel time Reliability Measures for Given TOD Period

Category	Name	Formula
Statistical parameter	Standard Deviation	$STD = \sqrt{\frac{\sum_{i=1}^{m}(TT_i - \overline{TT})^2}{m-1}}$
	Coefficient of Variation	$COV = \frac{STD}{\mu} \times 100\%$
Buffer time	Planning Time	$PT = TT_{95th}$
	Buffer Time	$BT = TT_{95th} - \overline{TT}$
	Buffer Time Index	$BI_{mean} = \frac{TT_{95th} - \overline{TT}}{\overline{TT}}$

3.4.2 Network Representations in Traffic Assignment Modeling

Network representations in traffic assignment problem were introduced by Patriksson (2015). Let *N* be a set of nodes, corresponding to intersections and origin-destination zones, and A be directed links, corresponding to roads joining the intersections. We define the link flow variable as f_{ij}, denoting the flow on the directed link (i, j), from node *i* to *j*. Further, let $\mathrm{f}_k = (f_{ijk})$ denote the vector of flows for commodity. Assuming that demands are fixed, a feasible flow for commodity *k* is a vector f_k satisfying

$$\sum_{j \in W_i} f_{ijk} - \sum_{j \in V_i} f_{jik} = d_{ik}, \quad \forall i \in N, \tag{7}$$

$$f_{ijk} \geq 0, \quad \forall (i, j) \in A, \tag{8}$$

where

$$d_{ik} \stackrel{def}{=} \begin{cases} d_k, & \text{if node } i \text{ is the origin of commodity } k, \\ -d_k, & \text{if node } i \text{ is the destination of commodity } k, \quad \forall i \in N \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

defines the demand vector d_k for commodity *k*, and

$$W_i \overset{def}{=} \{j \mid (i, j) \in A\}, \tag{10}$$

$$V_i \overset{def}{=} \{j \mid (j, i) \in A\} \tag{11}$$

denotes, respectively, the set of links initiated and terminating at node *i*.

With the node-link incidence matrix, for all O-D pairs, this could be compactly summarized as

$$\mathrm{Af}_k = \mathrm{d}_k, \qquad \forall k \in C, \tag{12}$$

$$\mathrm{f}_k \geq 0, \qquad \forall k \in C, \tag{13}$$

and the total link flows are given by

$$f_a \overset{def}{=} \sum_{k \in C} f_{ak}, \qquad \forall a \in A \tag{14}$$

3.4.3 Simulation-Based DTALite Modeling

There are capacity and traffic flow models and queue-based traffic simulation models constructed for simulation-based DTALite modeling.

3.4.3.1 Capacity and traffic flow models

To capture queue formation, spillback, and dissipation through simplified traffic flow models, DTALite uses a number of traffic queuing models (e.g. point queue model, spatial queue, and Newell's kinematic wave model) to track forward and backward wave propagations in its light-weight mesoscopic simulation engine. By doing so, traffic simulation in DTALite only requires a minimal set of traffic flow model parameters, such as outflow, inflow capacity, and storage capacity constraints, which are illustrated in Figure 3-2.

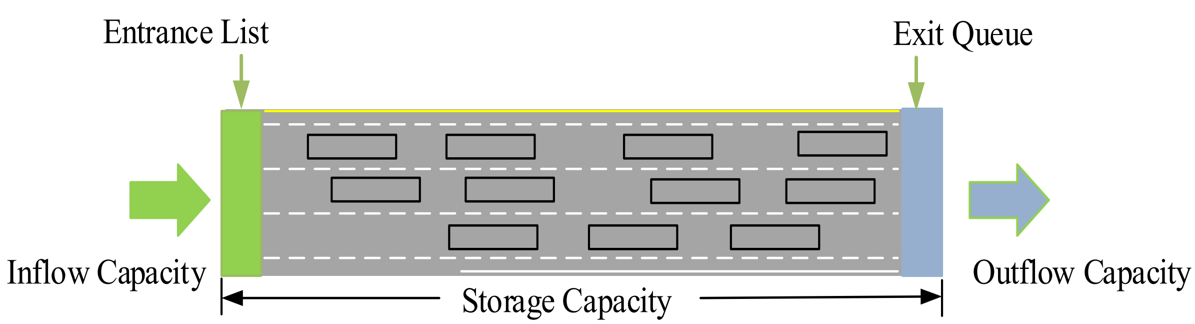


Figure 3-2: Modeling traffic dynamics through essential constraints.

To capture the queue dynamics at typical bottlenecks (e.g. lane drop, merge, and weaving segments), the classical kinematic wave theory needs to be integrated with (1) flow conservation constraints, (2) traffic flow models that represent speed (or flow) of traffic as a function of density, and (3) partial differential equations. The flow conservation constraints typically follow a hyperbolic system of conservation laws,

$$\frac{\partial q}{\partial x} + \frac{\partial k}{\partial t} = g(x,t) \tag{15}$$

where *q* and *k* are flow and density, respectively, and g(x, t) is the net vehicle generation rate.

3.4.3.2 Queue-based traffic flow simulation model

The simplest queue model implemented in DTALite is the point queue model. By imposing a single outflow capacity constraint on each link, a point queue model aims to capture the effect of traffic congestion at major bottlenecks. Using a point queue model in the first few iterations and then applying a simplified kinematic wave model in the later assignment process, one can avoid unrealistic and unnecessary gridlock in the initial assignment process, and further allow agents to learn travel times from previous iterations and switch routes to achieve a smooth and close-to-reality traffic pattern. Table 3-5 lists the notations in the simple queue-based dynamic network loading (DNL) model.

Table 3-5: Notations in Simple Queue-Based DNL Model

Notation	Description
N	Number of nodes in a corridor
n	Index of nodes, $n = 1,2,...,N$
L	Number of links in a corridor
l	Index of links, $l = 1,2,...,L$
Δt	Length of simulation interval
Δx	Length of link
$k_{l,t}$	Prevailing density during the *t*-th time step on link *l*
$q_{l,t}$	Transfer flow rate from link *l* to link *l+1*during the *t*-th time interval $[t, t+\Delta t]$
$cap_{l,t}^{out}$	Outflow capacity on link *l* during the *t*-th time interval $[t, t+\Delta t]$
v_{free}	Free-flow speed
k_{jam}	Jam density

The main steps in the computational procedure are 1) to calculate traffic flow ready to move from current link; 2) to calculate traffic flow from current link to its adjacent link; and 3) to update prevailing density at current link, which are described as follows:

For time t = 0 to T

For link l = 0 to L

Step 1: Calculate flow ready to move from link l: $v_{free} \times k_{l,t}$

Step 2: Calculate transfer flow $q_{l,t}$ from link l to link l + 1

$$q_{l,t} = \min\{v_{free} \times k_{l,t}, cap_{l,t}^{out}\}$$

Step 3: Update prevailing density at link l

$$k_{l,t+1} = k_{l,t} + q_{l-1,t} - q_{l,t} \times \Delta t / \Delta x$$

End for //link

End for //time

3.5. Travel Time Analysis Results

3.5.1 Zone Categorization

The study area is divided into three analysis zones, Zone I, Zone II, and Zone III by subarea zone method, as shown in Figure 3-3.

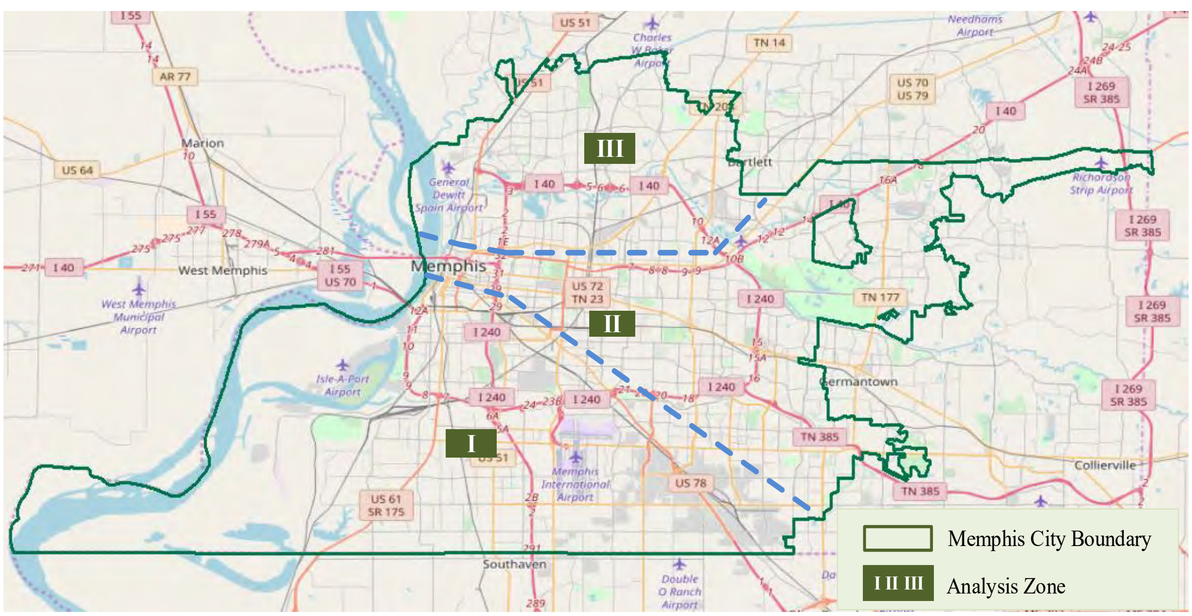


Figure 3-3: Analysis zones for travel time reliability analysis.
(Basemap source: OpenStreetMap in ArcMap)

Table 3-6 lists the road information in each zone. There are nine major roads in Zone I, two interstate highways (I-55 and I-240), three US highways (US-61, US-51, and US-78), one state highway (TN-277), and three arterial roads (Airways Blvd, Democrat Road, and Winchester Road). Five major roads are studied in Zone II, one US highway (US-72), one state highway (TN-23), and three arterial roads (Sam Cooper Blvd, Summer Ave, and Getwell Road). As for Zone III, there are eight major roads, one US highway (US-51), one interstate highway (I-40), two state highways (TN-14 and TN-204), and four arterial roads (North Watkins St, North Hollywood St, Warford Street, and Covington Pike).

Table 3-6: Zone and Segment Information

Zone Number	Segment Number	Road Name
I	1	I-55 Southbound
	2	I-55 Southbound
	3	US-61 Southbound
	4	US-51 Southbound
	5	I-240 Southbound
	6	TN-277 Southbound
	7	US-78 Southbound
	8	US-78 Southbound
	9	Airways Blvd Southbound
	10	Democrat Road Eastbound
	11	Winchester Road Eastbound
II	12	US-72 Eastbound
	13	TN-23 Eastbound
	14	Sam Cooper Blvd Eastbound
	15	Summer Ave Eastbound
	16	Summer Ave Northbound
	17	Getwell Road Southbound
III	18	US-51 Northbound
	19	US-51 Northbound
	20	I-40 Eastbound
	21	I-40 Eastbound
	22	North Watkins St Northbound
	23	North Watkins St Northbound
	24	North Hollywood St Northbound
	25	Warford Street Northbound
	26	TN-14 Eastbound
	27	TN-14 Northbound
	28	Covington Pike Northbound
	29	TN-204 Northbound

3.5.2 Segment Selection

On each highway or arterial road, the outbound segment close to ring roads (I-40 and I-240) or city boundary is selected for the analysis. The geographical information of segment is shown in Table 3-6 and Figure 3-4. There are twenty-nine segments selected in the study area, eleven segments in Zone I, six segments in Zone II, and twelve segments in Zone III. The travel time analysis results are shown in the next subsection.

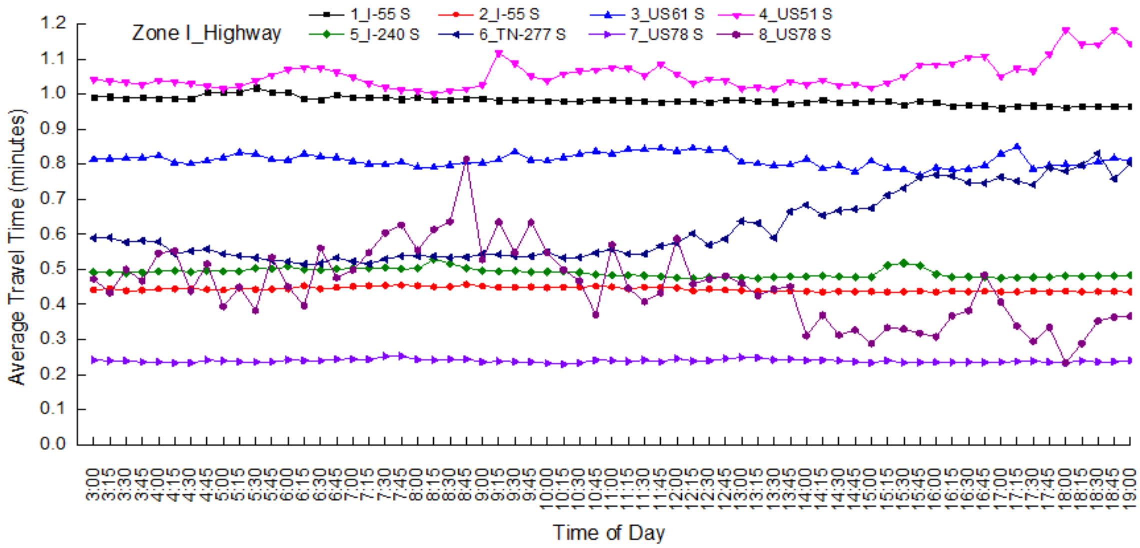
Figure 3-4: Segments for travel time reliability analysis.
(Base map source: OpenStreetMap in ArcMap)

3.5.3 Travel Time Reliability Analysis Results

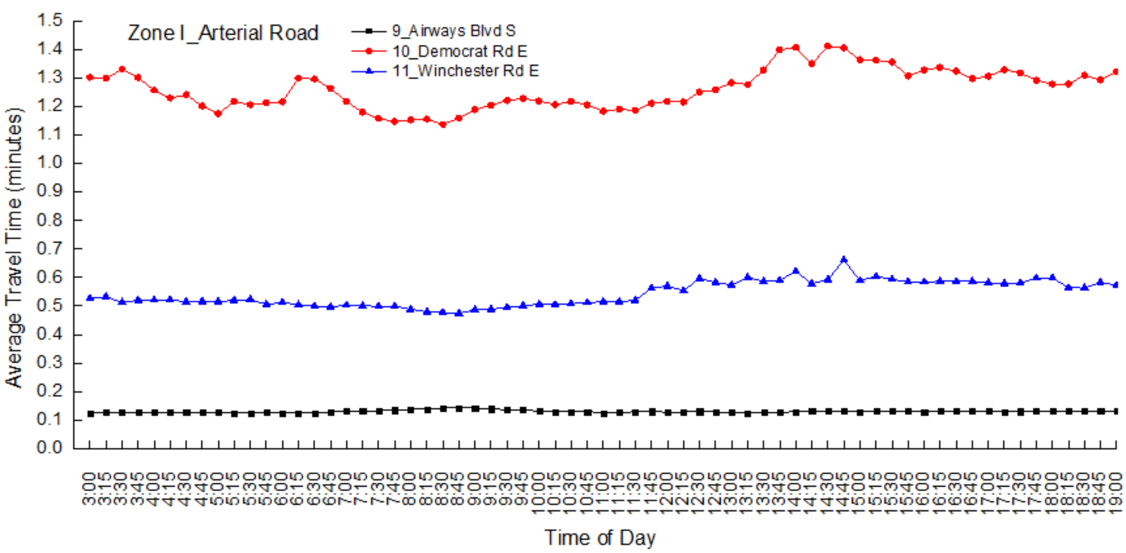
Travel times on the highways were analyzed for each zone, including average travel time, coefficient of variation, planning time, and buffer time index.

3.5.3.1 Average travel time for time of day

Figures 3-5 to 3-7 show the average travel time for time-of-day for the highways and arterial roads in each zone. The figures show higher values between 6:00 AM and 9:00 AM or 12:00 PM and 19:00 PM for the highways and arterial roads in each zone. Obviously, there are average travel time fluctuations in all day-time period on segments 4_US51 S, 6_TN-277 S, 8_US78 S, and 10_Democrat Rd E in zone I, 12_US 72 E, segments 14_ Sam Cooper Blvd E, 15_ Summer Ave E, and 16_ Summer Ave N in zone II, segments 19_US51 N, 23_ North Watkins St N, 26_ TN14 E, 28_Covington Pike N, and 29_ TN204 N in zone III.

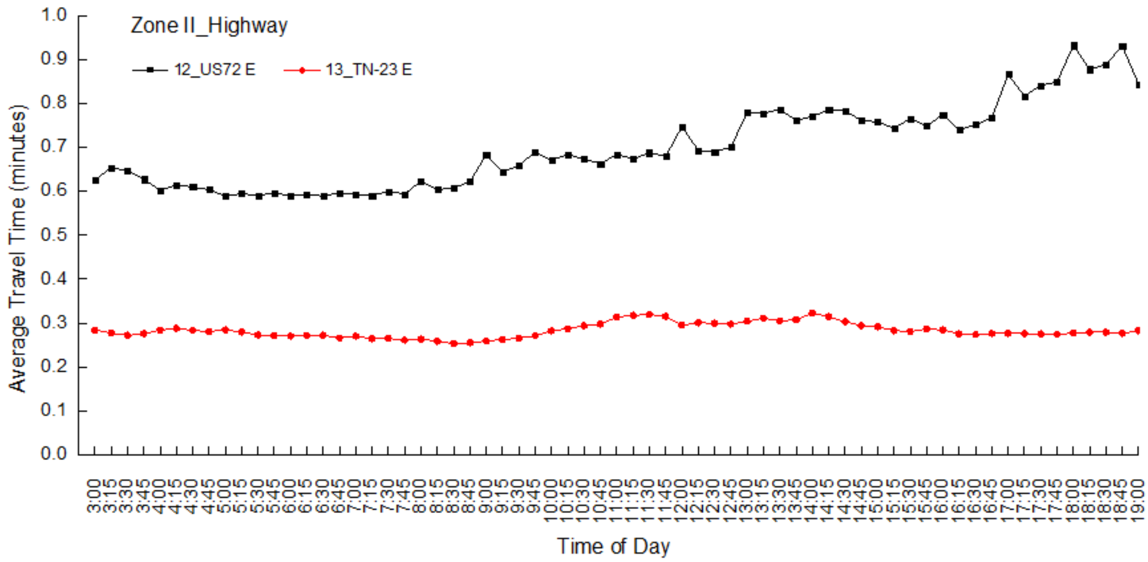


(a) Highways

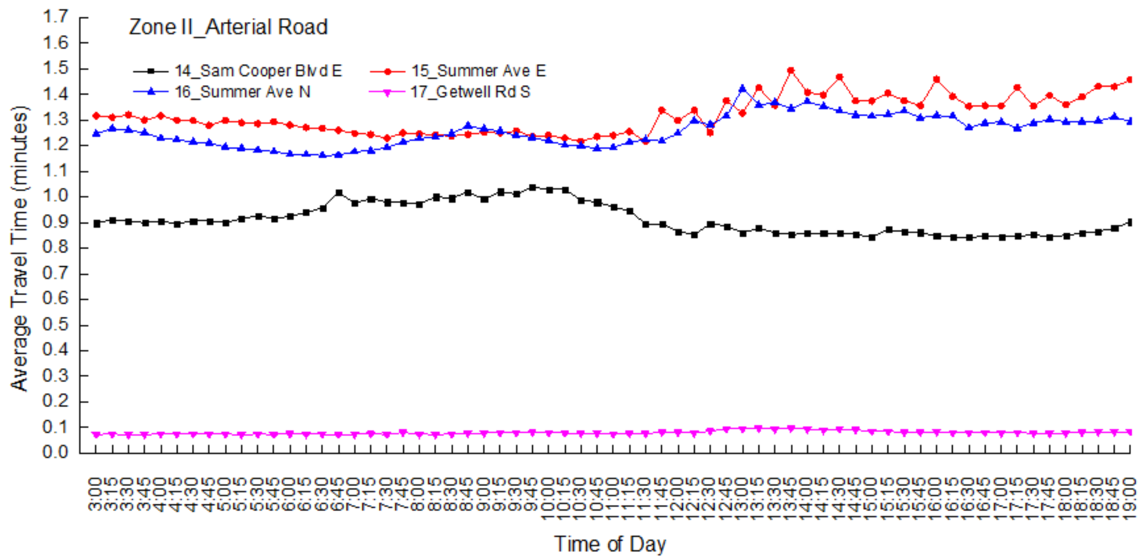


(b) Arterial roads

Figure 3-5: Average travel time analysis results for Zone I.

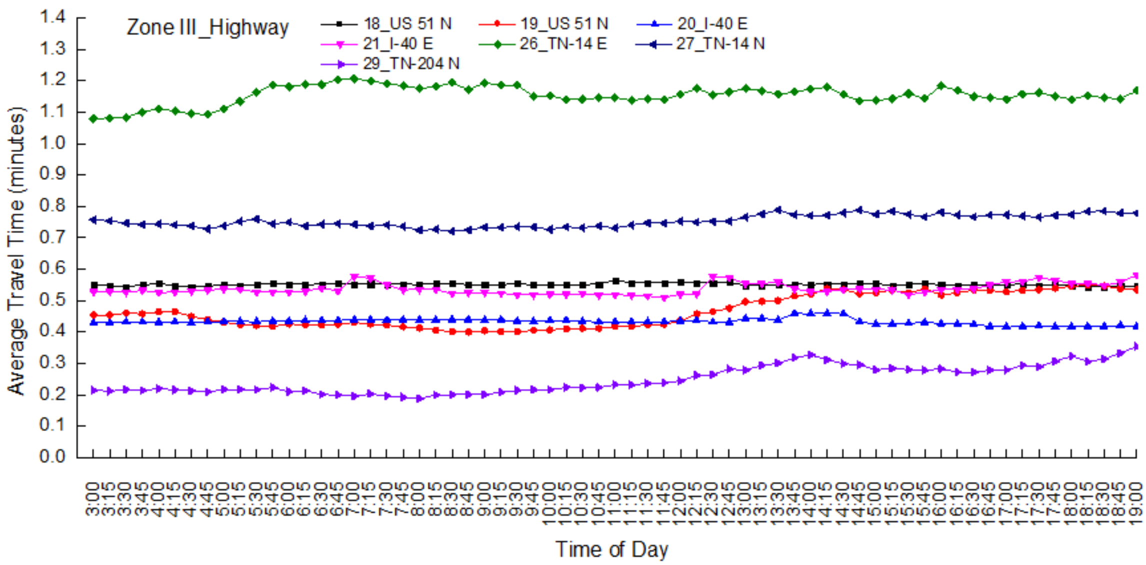


(a) Highways

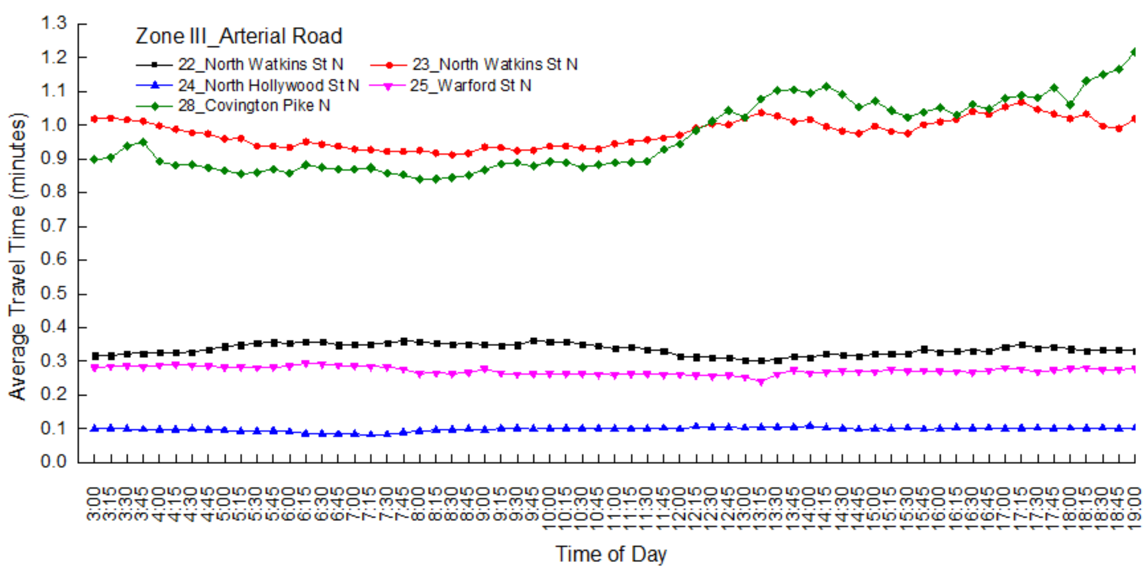


(b) Arterial roads

Figure 3-6: Average travel time analysis results for Zone II.



(a) Highways



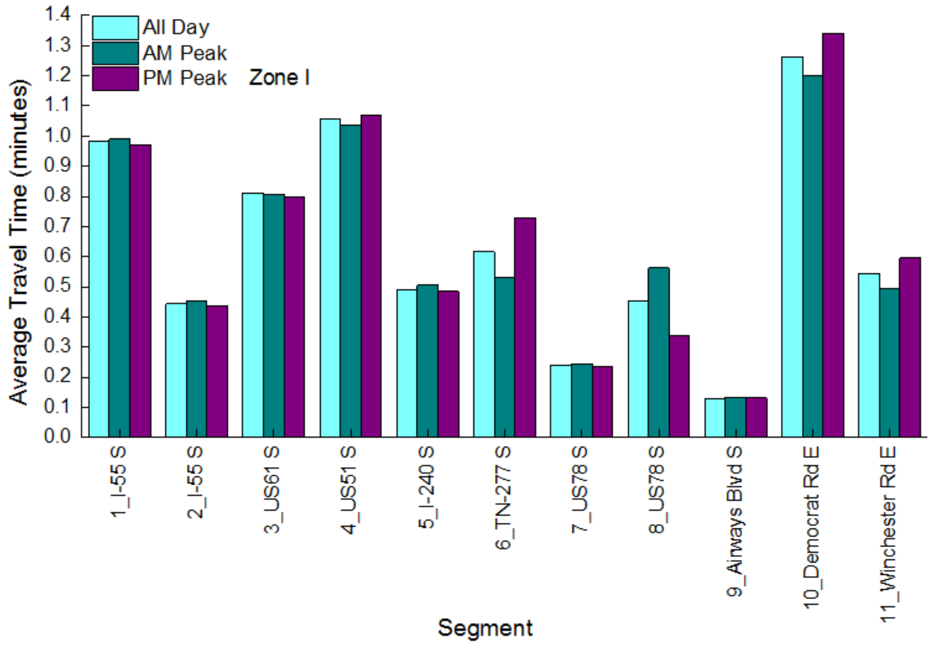
(b) Arterial roads

Figure 3-7: Average travel time analysis results for Zone III.

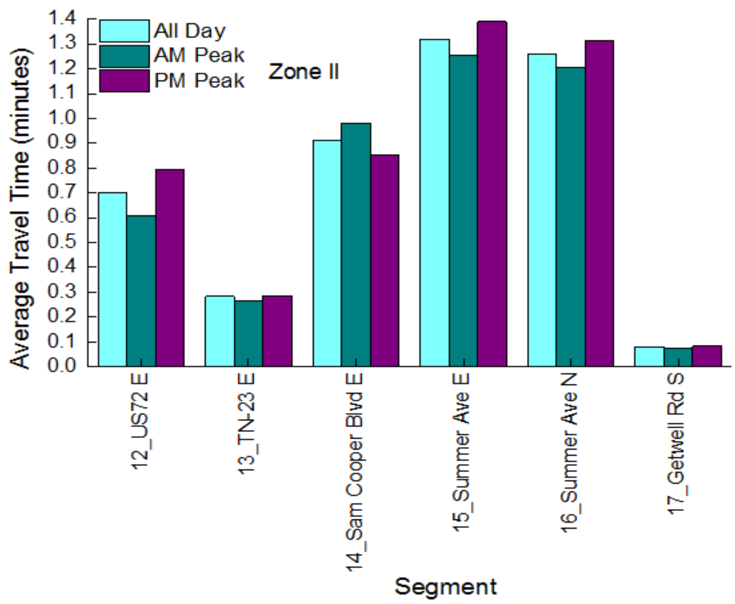
3.5.3.2 Average travel time for time periods

Figure 3-8 displays the average travel time analysis results during all day, AM and PM peak hours for all the roads in each of the three zones, respectively. Compared to the average travel time during all day, Figure 3-8(a) shows that the average travel time among segments 1_I-55 S, 2_I-55 S, 5_I-240 S, 7_US78 S, 8_US78 S, and 9_Airways Blvd S in zone I, during AM peak hours, increases from 0.77% to 24.1%. The average travel time among segments 4_US51 S, 6_TN 277 S, 9_Airways Blvd S, 10_Democrat Rd E, and 11_Winchester

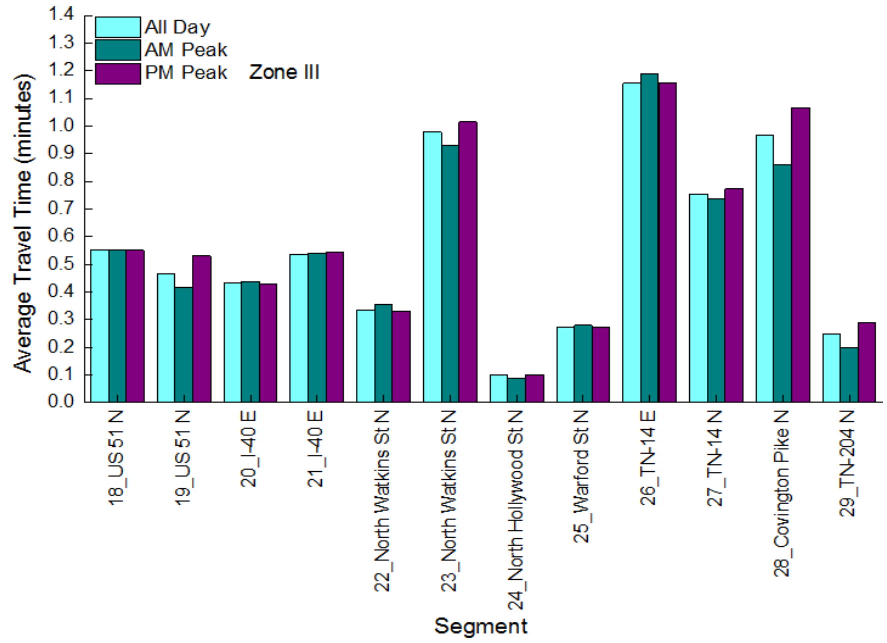
Rd E, during PM peak hours, increases from 0.35% to 18.5%. It can be observed from Figure 3-8(b) that in Zone II, during AM peak hours, the average travel time increases by 7.35% on segment 14_Sam Cooper Blvd E; during PM peak hours, it increases from 1.04% to 12.89% among segments 12_US72 E, 13_TN-23 E, 15_Summer Ave E, 16_Summer Ave N, and 17_Getwell Rd S. Figure 3-8(c) displays that in Zone III, during AM peak hours, the average travel time increases from 0.19% to 5.3% among segments 18_US 51 N, 20_I-40 E, 21_I-40 E, 22_North Watkins St N, 25_Warford St N, and 26_TN-14 E; during PM peak hours, it increases from 0.04% to 17.24% among segments 19_US 51 N, 21_I-40 E, 23_North Watkins St N, 24_North Hollywood St N, 26_TN-14 E, 27_TN-14 N, 28_Covington Pike N, and 29_TN-204 N.



(a) Zone I



(b) Zone II



(c) Zone III

Figure 3-8: Average travel time analysis results for different time periods.

Table 3-7 checks the segments which have aforementioned positive increase value. As shown in the table, 45% of segments have higher average travel time during AM peak hours, while 55% of segments have higher average travel time during PM peak hours.

Table 3-7: Segment Check with Positive ATT Increase Values

Zone Number	Segment Number	Average Travel Time	
		AM peak	PM peak
I	1	√	
	2	√	
	3		
	4		√
	5	√	
	6		√
	7	√	
	8	√	
	9	√	√
	10		√
	11		√
II	12		√
	13		√
	14	√	
	15		√
	16		√
	17		√
III	18	√	
	19		√
	20	√	
	21	√	√
	22	√	
	23		√
	24		√
	25	√	
	26	√	√
	27		√
	28		√
	29		√

3.5.3.3 Coefficient of variation for time periods

Table 3-8 checks the segments with COV values larger than 0.3. 34% of segments have high values during AM peak hours, while 45% of segments have higher values during PM peak hours.

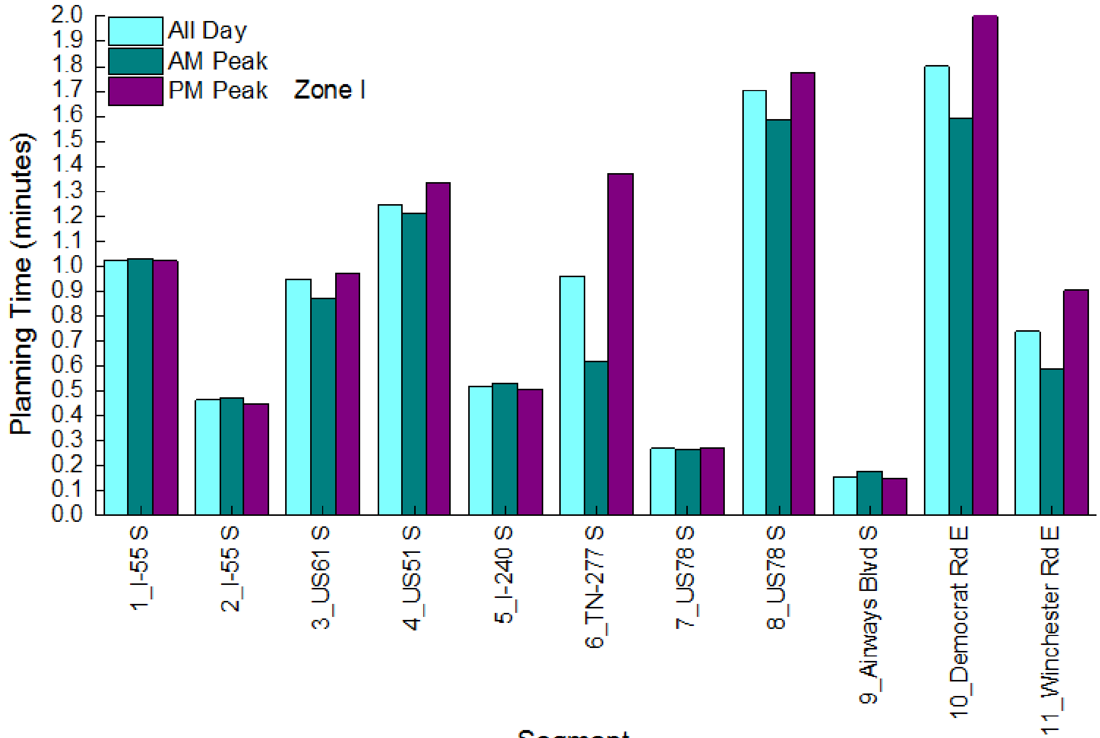
3.5.3.4 Planning time for time periods

Figure 3-9 displays the planning time analysis results during all day, AM and PM peak hours for all the roads in each zone. Compared to the planning time during all day, Figure 3-9(a) shows that in Zone I, the planning time among segments 1_I-55 S, 2_I-55 S, 5_I-240 S, and 9_Airways Blvd S, during AM peak hours, increases from 0.68% to 15.58%; the planning time among segments 3_US61 S, 4_US51 S, 6_TN-277 S, 8_US78 S, 10_Democrat Rd E, and 11_Winchester Rd E, during PM peak hours, increases from 2.33% to 42.8%. In Zone II, Figure 3-9(b) shows that during AM peak hours, the planning time increases by 1.68% on segment 14_Sam Cooper Blvd E; during PM peak hours, it increases from 16.69% to 25.62% among segments 12_US72 E, 15_Summer Ave E, 16_Summer Ave N, and 17_Getwell Rd S.

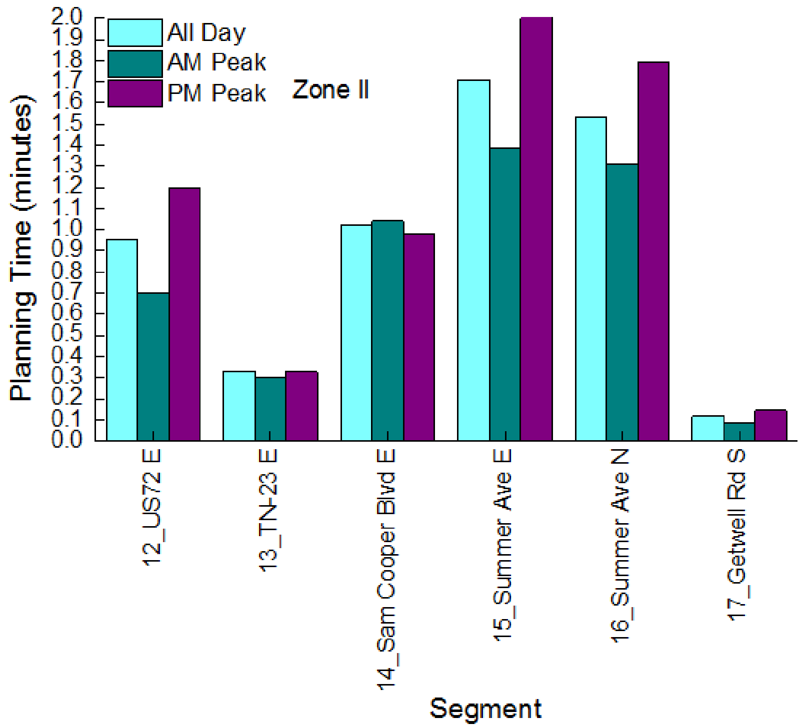
In Zone III, Figure 3-9(c) shows that during AM peak hours, the average travel time increases from 0.45% to 3.62% among segments 20_I-40 E, 22_North Watkins St N, and 26_TN-14 E; during PM peak hours, it increases from 0.2% to 34.58% among segments 18_US 51 N, 19_US 51 N, 21_I-40 E, 22_North Watkins St N, 23_North Watkins St N, 24_North Hollywood St N, 25_Warford St N, 26_TN-14 E, 27_TN-14 N, 28_Covington Pike N, and 29_TN-204 N.

Table 3-8: Segment Check with Higher COV Values

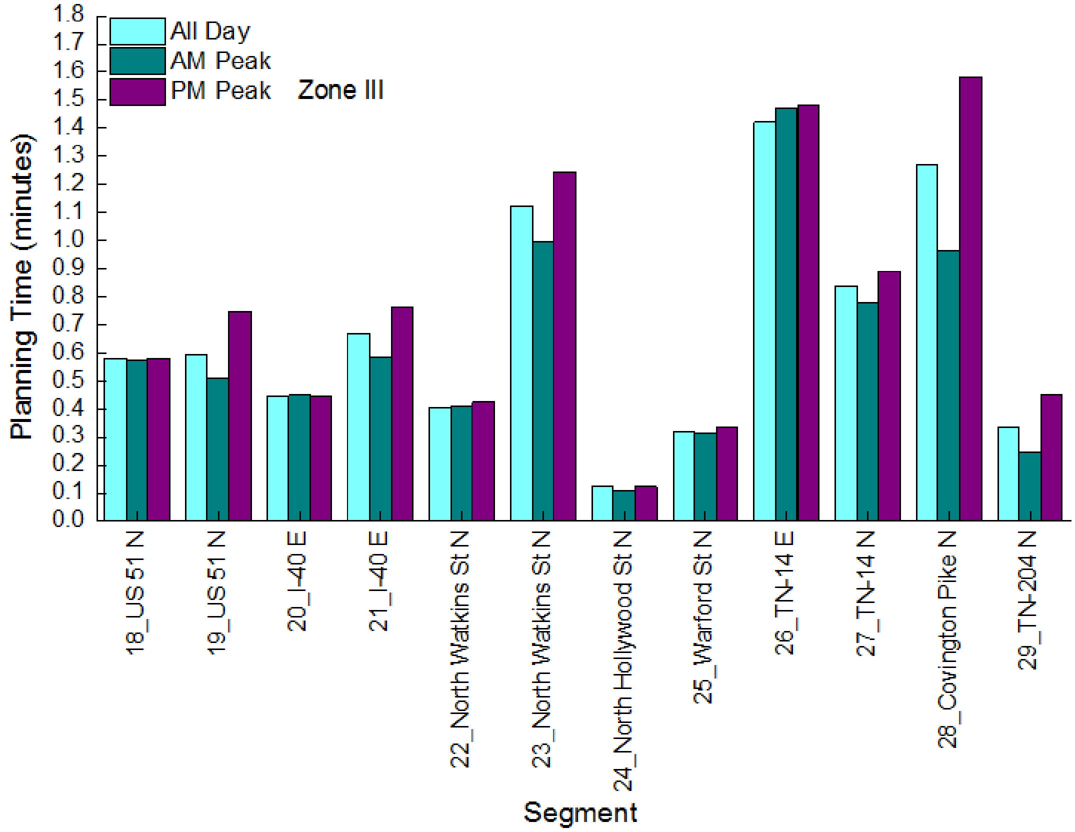
Zone Number	Segment Number	Coefficient of Variation	
		AM peak	PM peak
I	1	√	
	2		
	3	√	
	4		√
	5	√	√
	6	√	√
	7		
	8	√	
	9		
	10		√
	11	√	√
II	12		√
	13		
	14	√	
	15		√
	16		
	17	√	√
III	18		
	19		
	20		
	21	√	√
	22		
	23		√
	24		√
	25		
	26		
	27		
	28		√
	29	√	√



(a) Zone I



(b) Zone II



(c) Zone III

Figure 3-9: Planning time analysis results for different time periods.

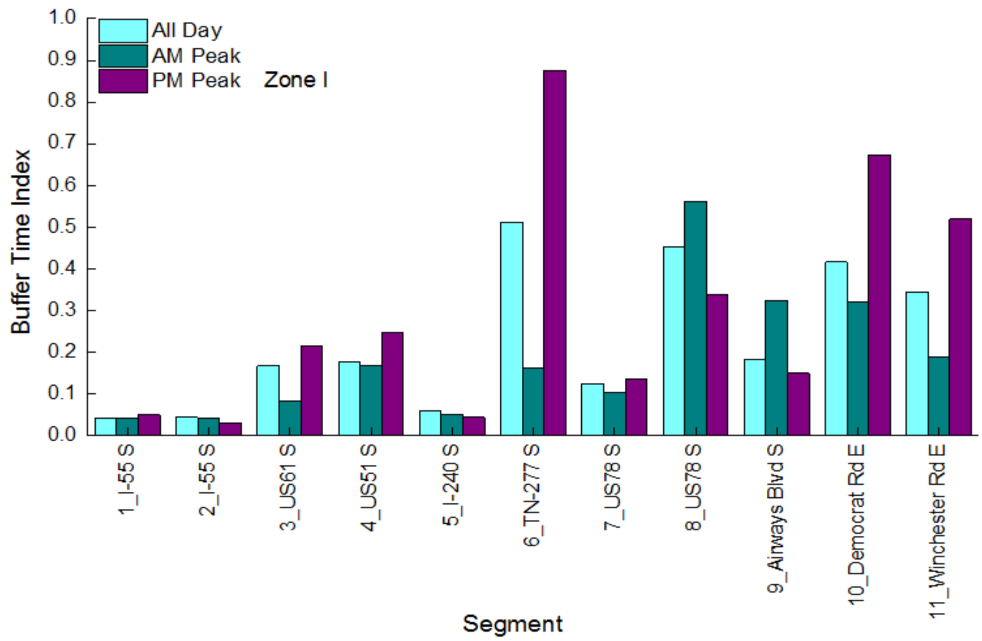
Table 3-9 checks the segments which have aforementioned positive increase values in planning time. As shown in the table, 28% of the segments have higher planning time during AM peak hours, and 72% of the segments have higher average travel time during PM peak hours.

Table 3-9: Segment Check with Positive PT Increase Values

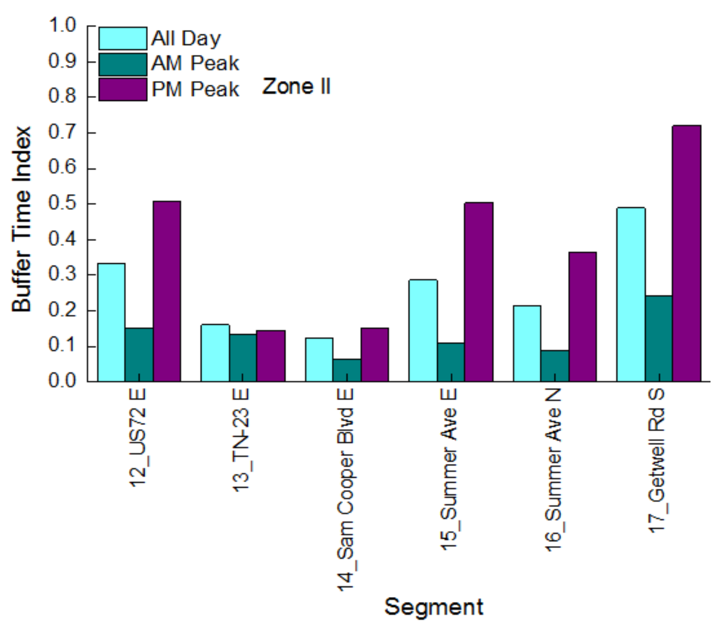
Zone Number	Segment Number	Planning Time	
		AM peak	PM peak
I	1	√	
	2	√	
	3		√
	4		√
	5	√	
	6		√
	7		
	8		√
	9	√	
	10		√
	11		√
II	12		√
	13		
	14	√	
	15		√
	16		√
	17		√
III	18		√
	19		√
	20	√	
	21		√
	22	√	√
	23		√
	24		√
	25		√
	26	√	√
	27		√
	28		√
	29		√

3.5.3.5 Buffer time index for time periods

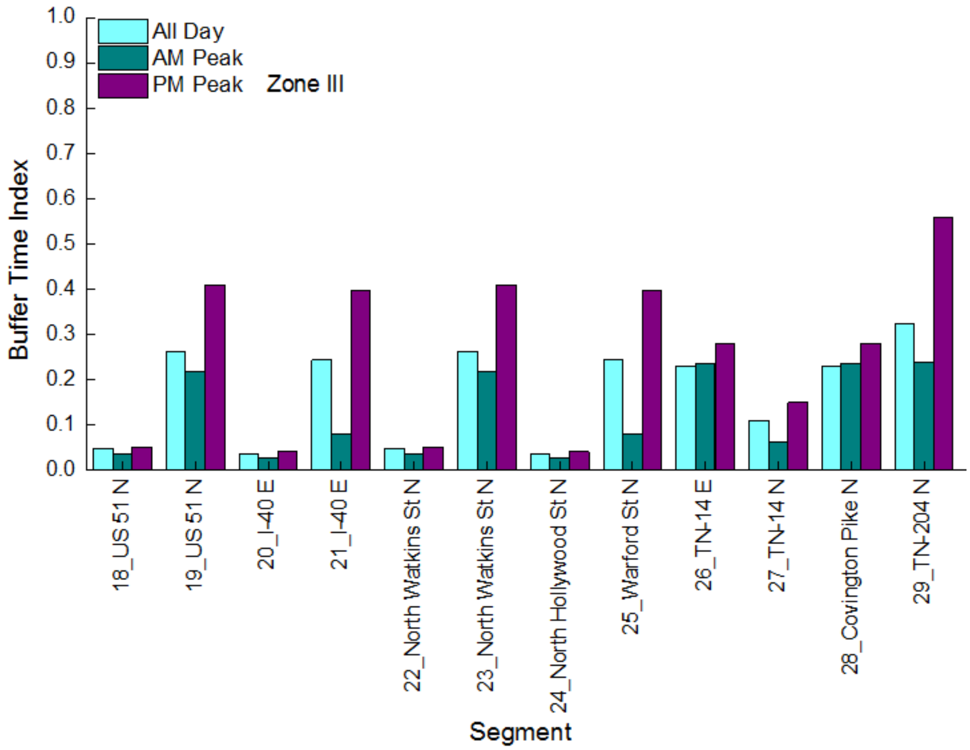
Figure 3-10 displays the buffer time index analysis results during all day, AM and PM peak hours, respectively, for all the roads in each zone.



(a) Zone I



(b) Zone II



(c) Zone III

Figure 3-10: Buffer time index analysis results for different time periods.

Among the measures in the analysis, buffer time index is the most effective travel time reliability measure that can be used to identify the congestion situation with low reliability, because it indicates the traffic situation by ratio value to mean, regardless of segment length. Therefore, the buffer time index analysis results for different time periods are used to identify traffic congestion locations, which are described in the next subsection.

3.5.4 Traffic Congestion Identification

In this study, we define that the threshold of average buffer time index is 0.55. If the average travel time index is larger than 0.55, the segment is checked as low travel reliability. Hence, the road segment on which average buffer time index is larger than 0.55 will be checked in order to identify the congestion locations. Based on the peak hour clearance definition in a congestion management process report by the Memphis urban area Metropolitan Planning Organization (2015), the average buffer time index analysis results, during AM peak hours (6:00 AM-9:00 AM) and PM peak hours (2:00 PM-6:00 PM), are calculated, checked, and listed in Table 3-10. According to the average buffer time index results in Table 3-10, there is one segment checked for AM peak hours and four segments checked for PM peak hours. Compared to AM peak hours, travel reliability is lower during PM peak hours.

Table 3-10: Average Buffer Time Index Calculation Results

Zone Number	Segment Number	Average Buffer Time Index			
		AM peak		PM peak	
		> 0 and < 0.55	≥ 0.55	> 0 and < 0.55	≥ 0.55
I	1	√		√	
	2	√		√	
	3	√		√	
	4	√		√	
	5	√		√	
	6	√			√
	7	√		√	
	8		√	√	
	9	√		√	
	10	√			√
	11	√		√	
II	12	√		√	
	13	√		√	
	14	√		√	
	15	√		√	
	16	√		√	
	17	√			√
III	18	√		√	
	19	√		√	
	20	√		√	
	21	√		√	
	22	√		√	
	23	√		√	
	24	√		√	
	25	√		√	
	26	√		√	
	27	√		√	
	28	√		√	
	29	√			√

The segments on which the index values are larger than 0.55 during PM peak hours in each zone are described in Table 3-11. Segment 6 on TN-277 Southbound, segment 8 on US-78 Southbound, and segment 10 on Democrat Road Eastbound in Zone I, segment 17 on Getwell Road Southbound in Zone II, and segment 29 on TN-204 Northbound in Zone III are identified as the potential traffic congestion locations.

Table 3-11: Segment Information with Low Travel Reliability

Zone Number	Segment Number	Road Name
I	6	TN-277 Southbound
	8	US-78 Southbound
	10	Democrat Road Eastbound
II	17	Getwell Road Southbound
III	29	TN-204 Northbound

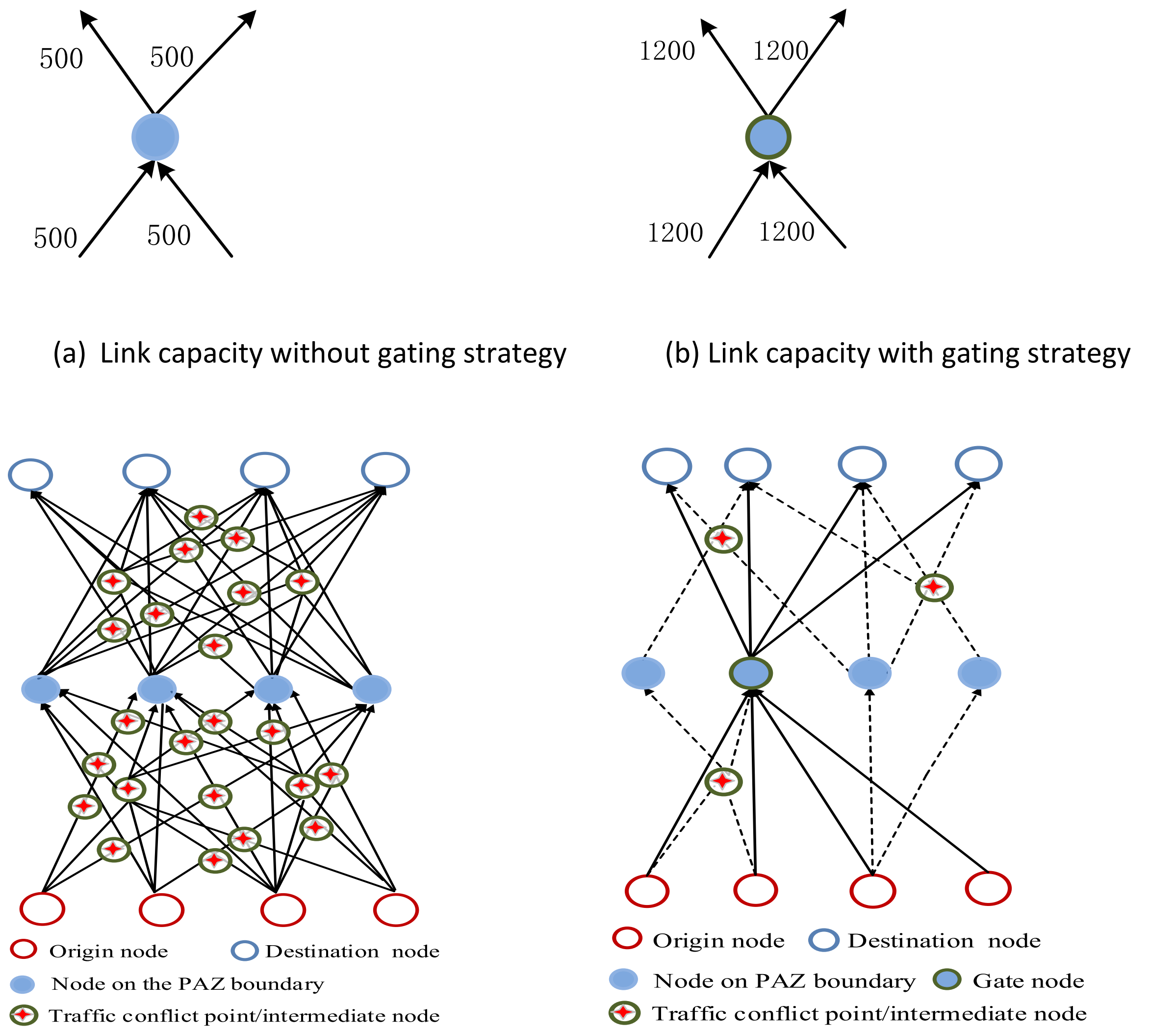
3.6 Traffic Simulation Case Study

3.6.1 Gating Control Strategy

Assuming that the contra-flow strategy could be deployed for a node, in the proposed gating control strategy, a node on or near the boundary of the emergency affected subarea with multiple links having large link volume capacities may be selected and set as an evacuation egress gate. The node achieving the ‘gating’ strategy could be an arterial road intersection to a multi-lane national or state highway or an entrance ramp to an interstate highway. The ‘gating’ strategy is configured at selected gate nodes to use increased egress link capacities on the subarea boundary to improve evacuation performance. Since the trip demands entering the emergency affected subarea are much lower than the demands leaving the subarea, the egress link capacities at the gate nodes could be possibly increased through a contra-flow deployment. To avoid traffic congestion at the gate node, traffic guidance (sometimes with law enforcement) and information dissemination such as portable variable message signs (VMS) are needed upstream as a part of the gating control strategy.

In modeling the network, the capacities of the incoming and outgoing links would be increased for a gate node, which is schematically described in Figures 3-11(a) and 3-11(b). The motivation lies in that the evacuation traffic would tend to use the links through the gate nodes to save travel cost because the traffic encounters less impedance using a link with a larger capacity.

The crossing of different trip trajectories or trip movements at a node is counted as traffic conflicts. Traffic conflicts have the potential threat of causing trip delays and even crashes. To quantify the total number of traffic conflicts, the conflicting of traffic at an intermediate node is defined as the total product of vehicle trips that cross the node during the evacuation period. Figures 3-11(c) and 3-11(d) show the traffic conflict situations without and with a gate node setting, respectively. During an emergency evacuation trip operation, the responsive evacuees would tend to respond to the incident by “escaping” (equivalently taking the shortest paths) from the origins in the affected area and “heading” to their destinations, which are out of the subarea. The evacuees can freely choose any route they believe to be the shortest path without knowing whether the route in the subarea is congested or not, and most likely the decision on the route is made in a hurry and/or based on previous experience. As a result, there are tremendous numbers of movement conflicts due to the many route crossings and, therefore, heavy congestion would be soon produced in multiple places in the subarea. These points of congestion will decrease the evacuation traffic mobility and eventually the performance of the emergency evacuation.



(a) Link capacity without gating strategy

(b) Link capacity with gating strategy

(c) Conflicts before using gating control

(d) Conflicts after using gating control

Figure 3-11: Schematic gating strategy in evacuation network.

Figure 3-11(d) shows that gates with large or increased link volume capacities are selected and set among nodes on or near the boundary to help relieve the heavy congestion points in the subarea. Under the gating control strategy, evacuation trips are suggestively guided through designated gates to leave the subarea and then continue to their destinations through the rest of the network outside the subarea. Since the evacuation trips are guided to the designated gates based on traffic assignment method to minimize path crossings, unnecessary conflicts of traffic movements may be reduced.

It is noticeable that the gate nodes must have increased link capacities to sustain the processing of the evacuation traffic, which means the gate nodes and the involved links must be well “managed” by transportation professionals. Meanwhile, the non-gate nodes are still passable but may only allow limited traffic movements (with dashed lines in Figure 3-11(d)). Since the gating control strategy aims to minimize travel cost inside the subarea and path crossings and conflicts of traffic movements, the cascading effect of congestion could be controlled and the evacuation performance could be improved. In order to demonstrate how a gating control strategy could possibly reduce the travel cost and traffic conflicting in evacuation traffic operations, optimization models were developed in a previous study and in Bu's dissertation research to seek the modified shortest paths for trips inside the emergency affected subarea with the gating control strategy and through experimental tests to show the strategy's effectiveness of reducing travel cost/time and traffic conflicting in the evacuation networks (Bu et al. 2016; Bu 2018).

Capacity of a link/node, travel time of a link, congestion related travel cost of using a link, weights of links inside and outside the subarea, and conflicting status between links are considered in the modeling, and the objective function is to minimize the total travel cost and the total traffic conflicting for different trip demands in the evacuation network. In the model, the gating control strategy proposed in an evacuation network is described as follows: a node/link on the subarea boundary having a large volume capacity can be set as an evacuation egress gate, for example an arterial intersection, or an entrance to a freeway ramp.

The capacity of a link could be increased by using traffic management strategies such as contra-flow control. In situations where inbound traffic demand is far less than outbound traffic demand (as in an evacuation operation), a reversal use of part or all of inbound traffic lanes would help increase the capacity of the outbound link. A contraflow is frequently deployed with variable message signs to disseminate information providing effective traffic guidance to users. These traffic management strategies could be deployed to achieve the gating strategy and improve evacuation performance. As well-designed contra-flow deployments, reversible lanes have been implemented in the US in which traffic may travel in either direction under certain conditions (Wolshon 2001; Wolshon and Lambert 2006), such as the reversible single lane tunnel shared between vehicular traffic and trains in Alaska, the center lanes opened for different bound traffic between different time periods considering daily rush hours in Arizona, California, Kentucky, Maryland, Nebraska, New York, Pennsylvania, and Texas, the center lanes reversed using overhead lane-use control signals in Georgia and Virginia, the reversible lanes allowing quick departure of special evacuees in Ohio, and the reversible lanes including a center turning lane at all times in Utah. In this study, we assumed that contra-flow operations could be deployed on the arterial corridors with a short notice of evacuation.

3.6.2 Network Description

Figure 3-12 shows the nodes and links of the road network to which the evacuation trips were assigned in the traffic simulations of the study. It includes Memphis city and Shelby County map of Tennessee. The road network of area with 24, 082 nodes, 67, 385 links, and 1, 014 traffic analysis zones (TAZ) in Shelby County (788 TAZs in Memphis metropolitan area) was included in the traffic simulation of the gating control strategy for an evacuation operation study.

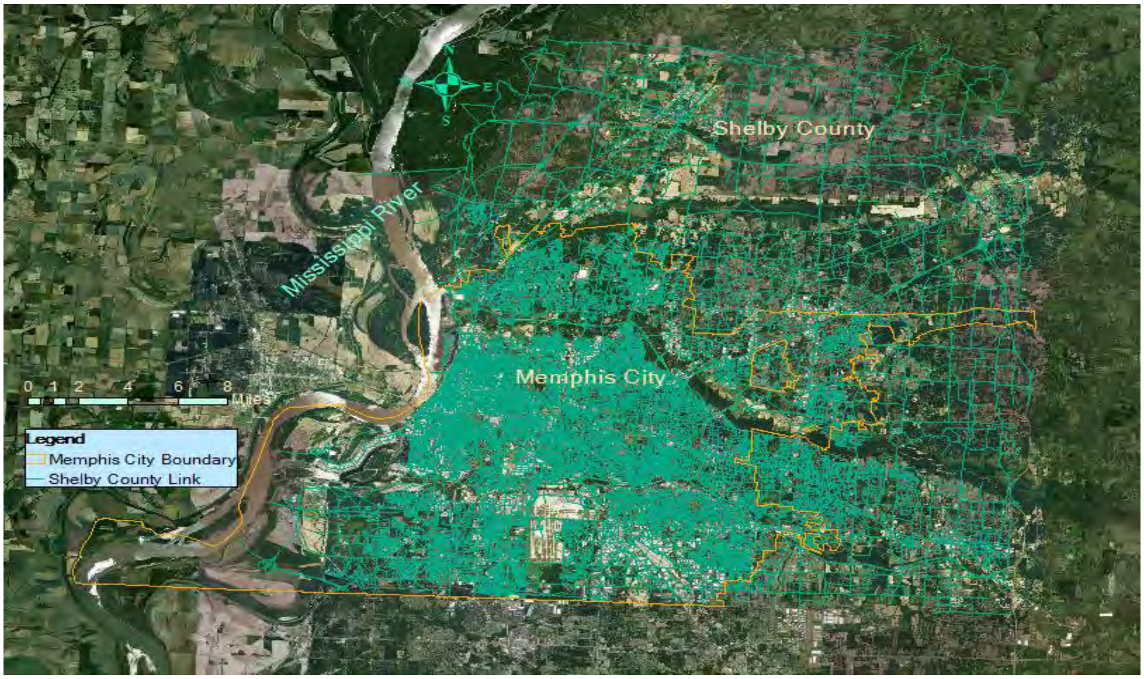


Figure 3-12: Road network in evacuation in Memphis, Shelby County.

3.6.3 Scenario Design

3.6.3.1 Potential gate nodes

Considering the direction of an invading flood and potential traffic congestion, potential gate nodes were selected at the locations where the travel reliability is relatively low. The locations with low travel time reliability are analyzed and listed in Table 3-11 of Section 3-5. Figure 3-13 shows the four locations with low travel reliability in each zone. Nodes 2 and 3 are in zone I. Node 4 is in zone II, and node 5 is in zone III.

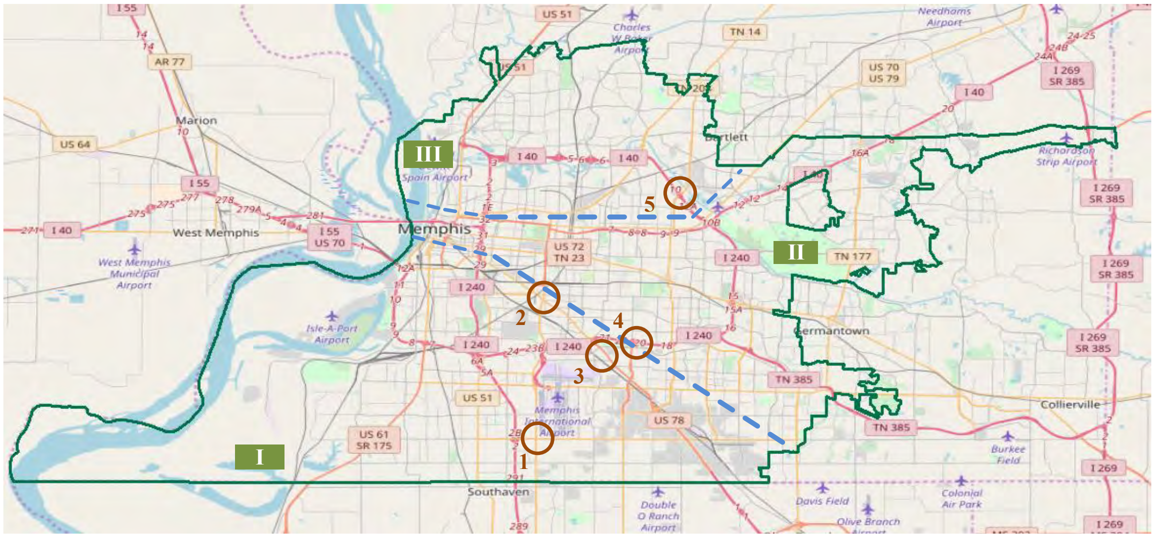


Figure 3-13: Potential gate node locations.

For each potential gate node location, the geographical information, such as zone number, gate node number, road name, number of lanes, number of shoulders, and intersecting roads, is described in Table 3-12. Both gate node 2 and gate node 3 are on highway US-78, whereas gate node 1 is considered as a potential gate location in order to reduce the traffic congestion on highway US-78. Therefore, there are five potential gate node locations in the simulation study.

Table 3-12: Potential Gate Node Locations in Simulation Study

Zone No.	Gate Node No.	Road Class	Direction	Number of Lanes	Number of Shoulders	Intersecting Road(s)
I	1	Airways Blvd	Southbound	6	0	TN-175
	2	TN-277	Southbound	6	0	US-78/TN-4
	3	Democrat Rd	Eastbound	4	0	Tchulahoma Rd/US-78
II	4	Getwell Rd	Southbound	4	0	I-240
III	5	TN-204	Northbound	4	0	I-40

3.6.3.2 OD demands

The evacuation demand was estimated at 490, 000 vehicles for the Memphis metropolitan area. Let all the trips entering the city be canceled, and retain the trips leaving the city. According to the Metropolitan Planning Organization (MPO) data, we assumed the background traffic demand (the trip demand in addition to the evacuation trips, reduced due to evacuation event) during PM peak hours to be 62,700 vehicles. Each traffic analysis zone was an origin node in the study area, and the destination nodes were located at the east boundary of the evacuation area, considering the evacuation routes need to be far away from the Mississippi River. There were 788 origin nodes and 21 destination nodes.

3.6.3.3 Simulation scenarios

As shown in Table 3-13, to evaluate the performance of achieving a gate control strategy, different gating scenarios of traffic management were developed and simulated in the study at the potential gate nodes which are described in subsection 3.6.3.1. Scenarios of non-gate, single gate, double gates, triple gates, quadruple gates, and quintuple gates were tested by selecting the potential gate nodes in simulations.

Table 3-13: Description of Gating Control Scenarios for Simulation Study

Scenario		Description
No gate	-	No node was selected as a gate node in each zone. Each node was a non-gate node in each zone.
Single Gate	Gate 1	Node 1 in zone I was selected as a gate node. Node 2 and node 3 in zone I, node 4 in zone II, and node 5 in zone III were non-gate nodes.
	Gate 2	Node 2 in zone I was selected as a gate node. Node 1and node 3 in zone I, node 4 in zone II, and node 5 in zone III were non-gate nodes.
	Gate 3	Node 3 in zone I was selected as a gate node. Node 1and node 2 in zone I, node 4 in zone II, and node 5 in zone III were non-gate nodes.
	Gate 4	Node 4 in zone II was selected as a gate node. Node 1, node 2, and node 3 in zone I, and node 5 in zone III were non-gate nodes.
	Gate 5	Node 5 in zone III was selected as a gate node. Node 1, node 2, and node 3 in zone I, and node 4 in zone II were non-gate nodes.
Double Gates	Gates 4_5	Node 4 in zone II and node 5 in zone III were selected as gate nodes. Node 1, node 2 and node 3 in zone I were non-gate nodes.
Triple Gates	Gates 1_4_5	Node 1 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 2 and node 3 in zone I were non-gate nodes.

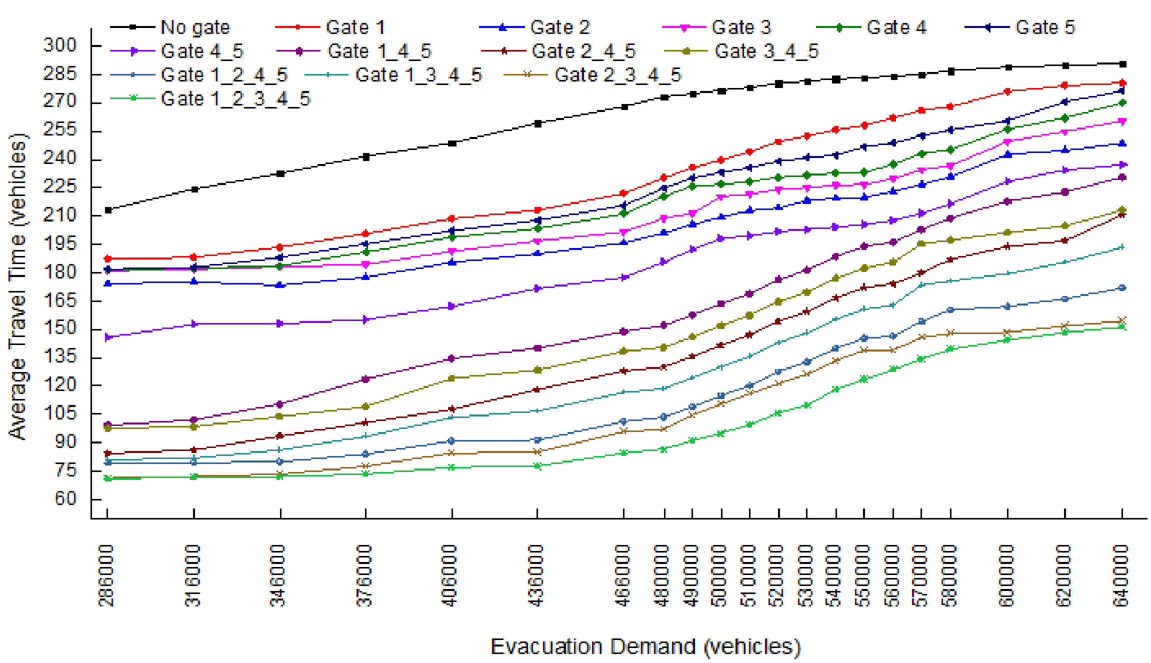
Scenario		Description
	Gates 2_4_5	Node 2 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 1 and node 3 in zone I were non-gate nodes.
	Gates 3_4_5	Node 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 1 and node 2 in zone I were non-gate nodes.
Quadruple Gates	Gates 1_2_4_5	Node 1 and node 2 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 3 in zone I was non-gate node.
	Gates 1_3_4_5	Node 1 and node 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 2 in zone I was non-gate node.
	Gates 2_3_4_5	Node 2 and node 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. Node 1 in zone I was non-gate node.
Quintuple Gates	Gates 1_2_3_4_ 5	Node 1, node 2 and node 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes. No node was selected as a non-gate node in each zone.

In the scenarios of single gate, each node in each zone was selected as the gate node respectively. To test if the road class or the node geographical location impacts the performance, in the scenario of double gates, node 4 in zone I and node 5 in zone II were selected as gate nodes, and nodes 1, 2, and 3 in zone I were non-gate nodes. In the scenarios of triple gates, three scenarios with different node locations were simulated: (1) node 1 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and nodes 2 and 3 in zone I were non-gate nodes; (2) node 2 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and nodes 1 and 3 in zone I were non-gate nodes; (3) node 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and nodes 1 and 2 in zone I were non-gate nodes. In the scenario of quadruple gates, three scenarios with different node locations were simulated: (1) nodes 1 and 2 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and node 3 in zone I was non-gate node; (2) nodes 1 and 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and node 2 in zone I was non-gate node; (3) nodes 2 and 3 in zone I, node 4 in zone II, and node 5 in zone III were selected as gate nodes, and node 1 in zone I was non-gate node. In the scenario of quintuple gates, all the five nodes 1, 2, 3, 4, and 5 were selected. As a bench mark, the scenario with non-gate control was also simulated. In this study, we assumed that contra-flow operations could be deployed on the highway or arterial corridors with a short notice of evacuation.

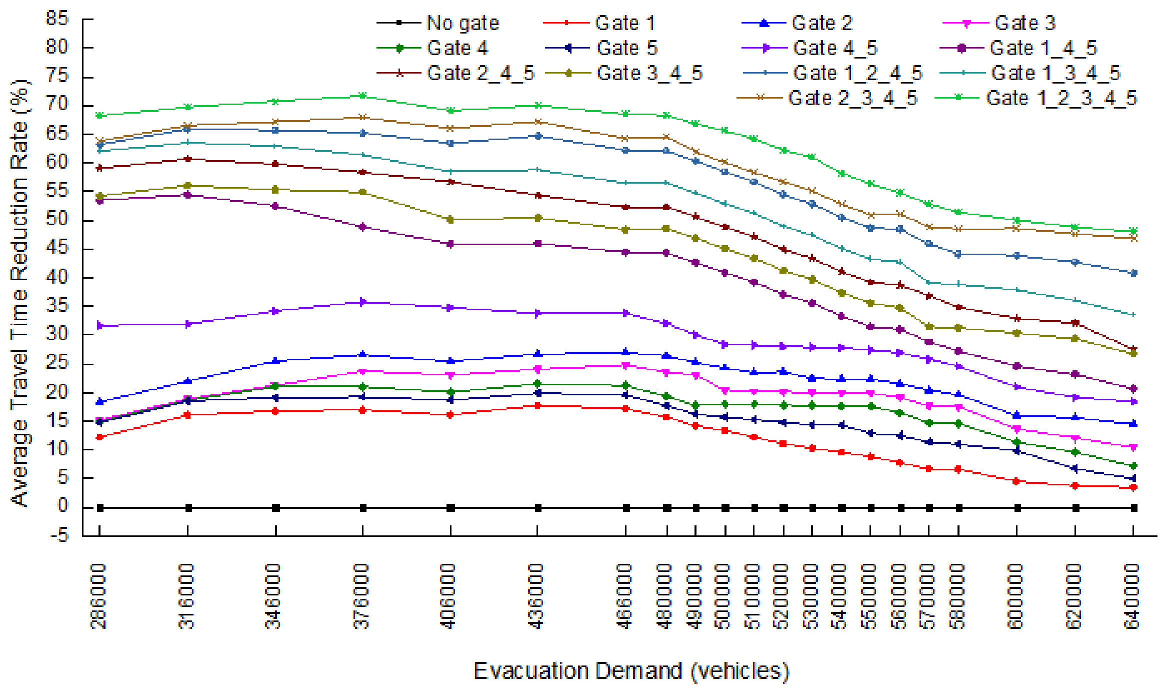
In order to test the performance with different evacuation demand level, the evacuation demand was increased from 286,000 to 640,000 vehicles by three value ranges: (1) the evacuation demand was increased from 286,000 to 466,000 vehicles with an increment of 30,000 vehicles, and then to 480,000 vehicles with an increment of 14,000 vehicles; (2) the evacuation demand was increased from 480,000 to 580,000 vehicles with an increment of 10,000 vehicles; (3) the evacuation demand was increased from 580,000 to 640,000 vehicles with an increment of 20,000 vehicles. Dynamic traffic information on congestion was assumed to be accessible to the evacuees throughout evacuation trip routes and only medium to low detouring response rates of evacuees to congestion situations were considered to follow the behaviors learned from past evacuations. The measures of effectiveness (MOE) including average travel time and traffic conflicting for the evacuation performance are shown in Figures 3-14 and 3-15.

3.6.4 Simulation Results

Average travel time results are shown in Figure 3-14. Figure 3-14(a) shows the average travel time curves along with evacuation demand of the fourteen traffic control scenarios, and Figure 3-14(b) shows the percentages of improvement over the non-gating scenarios in average travel time along with evacuation demand.



(a) Average travel time before and after using gating strategy

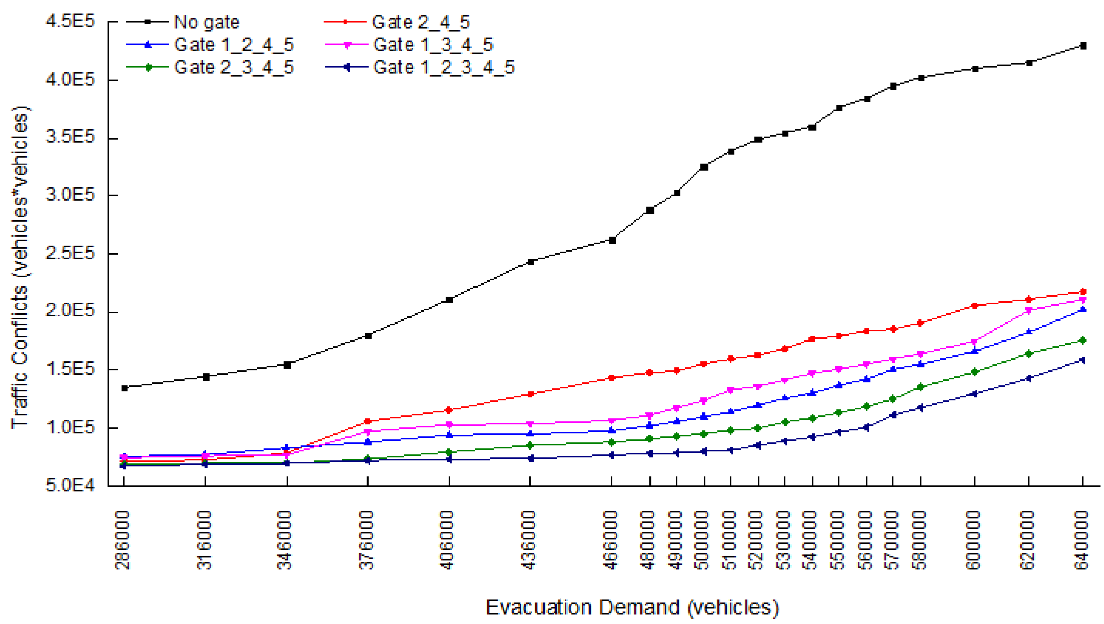


(b) Reduction of average travel time

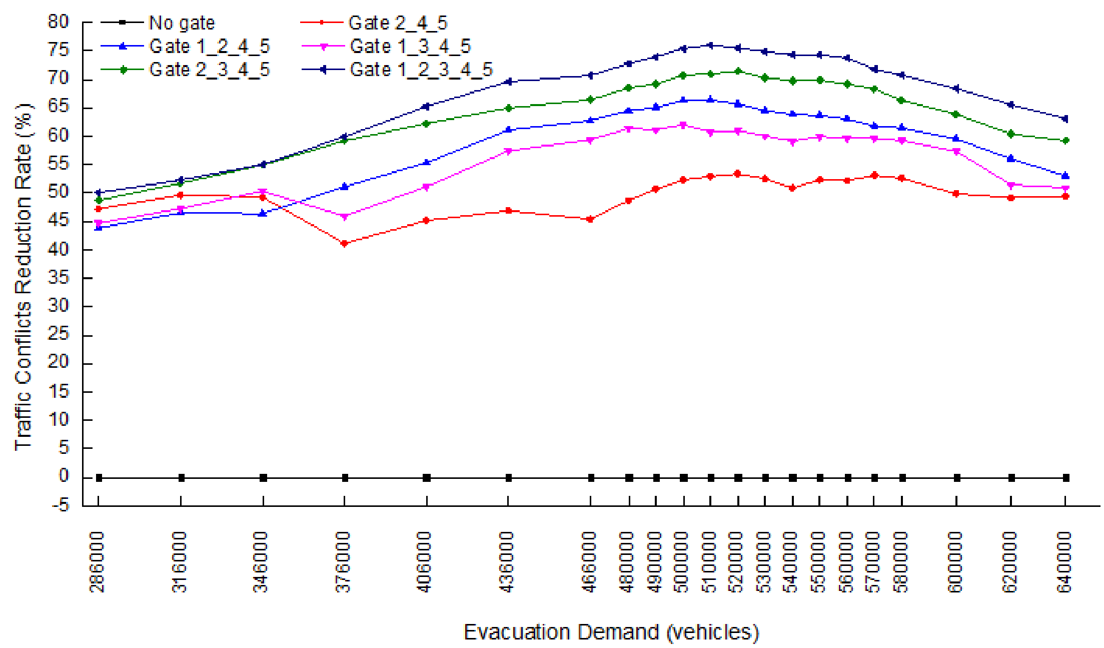
Figure 3-14: Performance of reducing average travel time.

As shown in Figure 3-14(a) and Figure 3-14(b), all the gating scenarios could achieve better evacuation performance with reduced average travel time than the non-gating strategy could. The average travel time for Scenario Gate 1_2_3_4_5 is the smallest of the fourteen scenarios which is from 57.8 minutes with 72.9% improvement at the lowest demand of 286,000 vehicles to 151.2 minutes with 48% improvement at the highest demand of 640,000 vehicles. The ascending order of the 14 scenarios in average travel time are Scenario Gate 1_2_3_4_5, Scenario Gate 2_3_4_5, Scenario Gate 1_2_4_5, Scenario Gate 1_3_4_5, Gate 2_4_5, Gate 3_4_5, Gate 1_4_5, Gate 4_5, Gate 2, Gate 3, Gate 4, Gate 5, Gate 1, and no gate. Among the top five scenarios of Gate 1_2_3_4_5, Scenario Gate 2_3_4_5, Gate 1_2_4_5, Gate 1_3_4_5, and Gate 2_4_5, the results for average travel time are almost the same for the lower evacuation demand from 286,000 to 316,000 vehicles, while the scenarios with more gates generally tend to have better performances at higher evacuation demands from 346,000 to 640,000 vehicles. Noticeably, a gating control strategy deployed with Gate 2 tends to have a better performance in average travel time than any simulation scenario without Gate 2 except for the single gate scenario. The good connectivity of Gate 2 with two multilane highways may have contributed to the superior performance in the scenarios including the gate node. Considering the deployment complexity and the cost involved in setting up for contraflow operations on inbound traffic lanes, Gate 2_4_5 would be considered the best scenario based on the simulations.

Traffic conflicts of the top five scenarios before and after using gating strategy are shown in Figure 3-15. Figure 3-15(a) shows the traffic conflicting curves, and Figure 3-15(b) shows the percentages of reduction.



(a) Traffic conflicts before and after using gating strategy



(b) Reduction of traffic conflicts

Figure 3-15: Performance of reducing traffic conflicting.

In Figure 3-15(a), the number of possible traffic conflicts using a gating strategy is always lower than that using the non-gating strategy. When the evacuation demand is low, the gating strategy improves the traffic conflicts slowly by showing the number of avoided traffic conflicts between 67,500 vehicles and 69,500 vehicles in each scenario. The percentage of improvement over the non-gating scenario is roughly between 43.9% in Gate 1_2_4_5 and 54.9% in Gate 2_3_4_5 at the low evacuation demands. When the evacuation demand is high, a gating strategy could well improve the traffic conflicting by showing the reduced number of possible traffic conflicts in each gating scenario. Figures 3-15(a) and 3-15(b) show that at an evacuation demand larger than 376,000 vehicles, out of the five gating strategies, Gating 1_2_3_4_5 is the best scenario to improve traffic conflicting with 59.9% improvement at 376,000 evacuating vehicles and 63.1% at 64,000 vehicles. Respectively, the other scenarios Gate 2_3_4_5, Gate 1_2_4_5, Gate 1_3_4_5, and Gate 2_4_5 could have 46.8, 53.0, 50.9 and 49.4% improvement rates at the demand of 640,000 vehicles.

The simulation results with the realistic large scale evacuation network confirmed that a gating control strategy could improve the evacuation performance by reducing the average travel time and total possible traffic conflicts in evacuation traffic operations in the network.

3.7. Conclusions

This research uses decentralized traveler information data to locate potential congestions to be applied with the proposed gating control traffic management strategies to reduce traffic congestions in emergency events. Travel time reliability measures are applied to account for delays and identify significant traffic congestions for potential gate locations in evacuation zones. Performance of the gating control traffic management strategies are evaluated using a case study, with DTALite program, a simulation based DTA tool. The traffic simulations in the case study for the evacuation network in Memphis, TN configured with the gating control strategies using the decentralized traveler information data have shown the effectiveness of the gating control traffic management strategies in managing evacuation traffic operations. From this research, the following findings are observed.

1. The gating control traffic management strategies deployed using the decentralized traveler information data, could well reduce congestion for emergency events under extreme weather. The travel time reliability data analysis based on the probe data could catch the dynamic nature of potential congestions and achieve improved performance of average travel time and traffic conflicts in a realistic large scale evacuation network.
2. According to the average buffer time index results, there is one segment checked during AM peak hours and four segments checked during PM peak hours. Compared to AM peak hours, travel reliability is lower during PM peak hours. The segments on which the index values are larger than 0.55 during PM peak hours are segment 6 on TN-277 Southbound and segment 10 on Democrat Road Eastbound in Zone I, segment 17 on Getwell Road Southbound in Zone II, and segment 29 on TN-204 Northbound in Zone III. They are identified as the potential traffic congestion locations.
3. Simulation results of the gating traffic management strategies with the realistic large scale evacuation network in fourteen scenarios, show that all the gating scenarios could achieve better evacuation performance with reduced average travel time than the non-gating strategy could. The smallest average travel time for scenario is from 57.8 minutes with 72.9% improvement at the lowest demand of 286,000 vehicles to 151.2 minutes with 48.0% improvement at the highest demand of 640,000 vehicles. The simulation results also show that the number of possible traffic conflicts using a gating strategy is always lower than that using the non-gating strategy. The best scenario could improve traffic conflicting with 59.9% improvement at 376,000 evacuating vehicles and 63.1% at 64,000 vehicles. The simulation results confirm that a gating control strategy could improve the evacuation performance by reducing the average travel time and total possible traffic conflicts in evacuation traffic operations in the network.

Assessing network vulnerability serves the ultimate goal of achieving resiliency for the flood affected communities that are under constant threats of extreme weather and flooding. Network vulnerability measurement spans many application areas in long-term preparedness planning and is also vitally important for the development of a short-term or even dynamic response plan for an imminent emergency. Many models have been proposed to facilitate the search for vulnerabilities by identifying nodes and arcs vital to network operations. A variety of existing methods are essential given that disruption to network operation can be hypothesized to impact network traffic operations in a number of ways (e.g., low time reliability, loss of capacity, connectivity, efficiency, etc.). However, many researches failed to consider the interacting responses of evacuees and the recovering efforts of traffic engineers and traffic management to the link disruption and link risk. This study tries to approach the problem with an effort in time reliability analysis framework, that can help remind the local authorities not only to identify which weak links could lead to recurring congestion to the network, but also to understand how a gating control strategy associated with appropriate traffic management would possibly be deployed at these weak points and improve evacuation performance. In addition, traffic simulations based on traffic flow theory, traffic assignment, driver rerouting behaviors with dynamic traffic information (considering the recent near ubiquity of mobile devices, often with routing applications such as Google Maps, Waze, etc.), and available traffic control strategies should be conducted for an evacuation network to identify possible critical links of the road network in case of an emergency evacuation.

It should be noted that the study was based on a few assumptions which may not be true for a problem at hand. First, the research assumed the traveler information data reflects a recurring traffic pattern for the study area. Second, the study assumed an evacuation order should allow enough time for the gating control strategy and the associated lane reversal and contra-flow to be set up. How to make the decentralized travel data more useful for ITS based and traveler information data enabled traffic management in emergency evacuation operations and planning would be a direction for our future study.

3.8 References

1. Beaud, M., T. Blayac, and M. Stéphan (2016). The impact of travel time variability and travelers' risk attitudes on the values of time and reliability. Transportation Research Part B: Methodological, Vol. 93, Part A, pp 207-224.
2. Bekhor, S., T. Toledo, and J. Prashker (2008). Effects of choice set size and route choice models on path-based traffic assignment. Transportmetrica A: Transport Science, Vol. 4 (2), pp 117-133.
3. Bertini, R. L. (2005). Congestion and Its Extent. In access to destinations: rethinking the transportation future of our region. University of Minnesota.
4. Bu, L., F. Wang, X. Zhou, and C. Yin (2016). Modeling gate control strategy for traffic management in emergency evacuation. International Journal of Transportation, Vol. 4 (2), pp 31-46.
5. Bu, L. (2018). Development of Traffic Management Strategies Using Decentralized Traveler Information in Reducing Congestion. PhD Dissertation. Jackson State University. Jackson, MS.
6. Carrion, C. and D. Levinson (2012). Value of travel time reliability: A review of current evidence. Transportation Research Part A: Policy and Practice, Vol.46 (4), pp 720-741.
7. Chen, P., R. Tong, G. Lu, and Y. Wang (2018). Exploring travel time distribution and variability patterns using probe vehicle data: case study in Beijing. Journal of Advanced Transportation, Vol. 2018, pp 1-13.
8. Cirrus Weather Solutions. Attention turns from severe weather to river flooding (2011). https://www.memphisweather.blog/2011/04/attention-turns-from-severe-weather-to.html
9. Federal Highway Administration (2016). Urban Congestion Trends – Using Technology to Measure, Manage, and Improve Operations. US Department of Transportation. FHWA-HOP-17-010. 2017.
10. Federal Highway Administration (2017). Traffic Congestion and Reliability: Linking Solutions to Problems. Final report. https://ops.fhwa.dot.gov/congestion_report_04/executive_summary.htm
11. Federal Highway Administration (2017). Travel time reliability: making it there on time, all the time. www.ops.fhwa.dot.gov/publications/tt_reliability/TTR_Report.htm, accessed on July 14, 2017.
12. Guo, F., Q. Li, and H. Rakha (2012). Multi-state travel time reliability models with skewed component distributions. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2315 (1), pp 47-53.
13. Hardy, M. (2010). Structuring, modeling, and simulation analyses for evacuation planning and operations. The 89th TRB Annual Meeting, Washington D.C.
14. He, X., and S. Peeta (2014). Dynamic resource allocation problem for transportation network evacuation. Networks and Spatial Economics, Vol. 14(3-4), pp 505-530.
15. Ho, H.W., S. C. Wong, and T. D. Hau (2007). Existence and uniqueness of a solution for the multi-class user equilibrium problem in a continuum transportation system. Transportmetrica A: Transport Science, Vol.3 (2), pp 107-117.

16. Higatani, A., T. Kitazawa, J. Tanabe, Y. Suga, and Y. Asakura (2009). Empirical analysis of travel time reliability measures in Hanshin expressway network. Journal of Intelligent Transportation Systems Technology, Planning, and Operations, Vol. 13, No.1: Improving Network Reliability through ITS Technologies, pp 28-38.
17. Jong, G.C., M.C.J. Bliemer, and N. Indra-Payoong (2015). On including travel time reliability of road traffic in appraisal. Transportation Research Part A, Vol. 73, pp 80-95.
18. Kaviani, A., R. G. Thompson, and A. Rajabifard (2017). Improving regional road network resilience by optimised traffic guidance. Transportmetrica A: Transport Science, Vol. 13 (9), pp 794-828.
19. Li, D., T. J. Cova, and P. E. Dennison (2015). A household-level approach to staging wildfire evacuation warnings using trigger modeling. Computers, Environment and Urban Systems, Vol. 54, 2015, pp 56–67.
20. Li, M., N. M. Rouphail, M. Mahmoudi, J. Liu, and X. Zhou (2017). Multi-scenario optimization approach for assessing the impacts of advanced traffic information under realistic stochastic capacity distributions. Transportation Research Part C, Vol.77, pp 113-133.
21. Lim, Y. and H. Kim (2016). A combined model of trip distribution and route choice problem. Transportmetrica A: Transport Science, Vol.12 (8), pp 721–735.
22. Lindell, M. K. and C. S. Prater (2007). Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: examples from hurricane research and planning. Journal of Urban Planning and Development, ASCE, Vol. 133 (1), pp 18-29.
23. Lint, J.V., and H. V. Zuylen (2005). Monitoring and predicting freeway travel time reliability: using width and skew of day-to-day travel time distribution. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1917 (1), pp 54-62.
24. Lint, J. V., H. J. V. Zuylen, and H. Tu (2008). Travel time unreliability on freeways: Why 21 measures based on variance tell only half the story. Transportation Research Part A: Policy and Practice, Vol. 42 (1), pp 258-277.
25. Lu, W., L. D. Han, C. Liu, and K. Long (2014). A multiple source nearest destination shortest path problem in evacuation assignments. CICTP 2014: Safe, Smart, and Sustainable Multimodal Transportation Systems -ASCE, pp 3691-3702.
26. Lyman, K. and R. Bertini (2008). Using travel time reliability measures to improve regional transportation planning and operations. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2046, pp 1-10.
27. Memphis Urban Area Metropolitan Planning Organization (MPO) (2015). Congestion Management Process. August 2015.
28. Meng, Q., H. L. Khoo, and R. L. Cheu (2008). Microscopic traffic simulation model-based optimization approach for the contraflow lane configuration problem. Journal of Transportation Engineering, Vol. 134(1), pp 41-49.
29. Murray-Tuite, P., W. Yin, S. Ukkusuri, and H. Gladwin (2012). Changes in evacuation decisions between hurricanes Ivan and Katrina. Transportation Research Record, Vol. 2312, pp 98-107.
30. Murray-Tuite, P. and B. Wolshon (2013). Evacuation transportation modeling: an overview of research, development, and practice. Transportation Research Part C, Vol. 27, pp 25-45.

31. Patriksson, M. (2015). The Traffic Assignment Problem: Models & Methods. Courier Corporation, 2015.
32. Pel, A. J., S. P. Hoogendoorn, and M. C. J. Bliemer (2010). Impact of variations in travel demand and network supply factors for evacuation studies. Transportation Research Record, Vol. 2196, pp 45-55.
33. Qian, Z. Q., and H. M. Zhang (2012). On centroid connectors in static traffic assignment: Their effects on flow patterns and how to optimize their selections. Transportation Research Part B: Methodological, Vol. 46 (10), pp 1489-1503.
34. Qiao, F., R. Ge, and L. Yu (2009). Evacuation modeling in small and dense area. The 88th TRB Annual Meeting, Washington D.C.
35. Sadri, A. M., S. V. Ukkusuri, P. Murray-Tuite, and H. Gladwin (2014). Analysis of hurricane evacuee mode choice behavior. Transportation research Part C, Vol. 48, pp 37–46.
36. Schrank, D., B. Eisele, T. Lomax, J. Bak (2015). Urban Mobility Scorecard. Project report Published jointly by The Texas A&M Transportation Institute and INRIX.
37. Sumalee, A., T. Pan, R. Zhong, N. Uno, and N. Indra-Payoong (2013). Dynamic stochastic journey time estimation and reliability analysis using stochastic cell transmission model: Algorithm and case studies. Transportation Research Part C: Emerging Technologies, Vol. 35, pp 263-285.
38. Tong, L., X. Zhou, and H. J. Miller (2015). Transportation network design for maximizing space–time Accessibility. Transportation Research Part B, Vol. 81, pp 555-576.
39. Ukkusuri, S., S. Hasan, B. Luong, K. Doan, X. Zhan, P. Murray-Tuite, and W. Yin (2017). A-RESCUE: An agent based regional evacuation simulator coupled with user enriched behavior. Networks and Spatial Economics, Vol. 17(1), pp 197-223.
40. Urbina, E. and B. Wolshon (2003). National review of hurricane evacuation plans and policies: a comparison and contrast of state policies. Transportation Research Part A, Vol. 37, pp 257-275.
41. Wang, L., L. Yang, Z. Ga, S. Li, and X. Zhou (2016). Evacuation planning for disaster responses: A stochastic programming framework. Transportation Research Part C: Emerging Technologies, Vol. 69, pp 150-172.
42. Wolshon, B. (2001). One-way-out: Contraflow freeway operation for hurricane evacuation. Natural Hazards Review, Vol. 2(3), pp 105-112.
43. Wolshon, B. and L. Lambert (2006). Planning and operational practices for reversible roadways. ITE Journal, Vol. 76(8), pp 38-43.
44. Woodard, D., G. Nogin, P. Koch, D. Racz, M. Goldszmidt, and E. Horvitz (2017). Predicting travel time reliability using mobile phone GPS data. Transportation Research Part C: Emerging Technologies, Vol. 75, pp 30-44.
45. Xiao, Y., N. Coulombel, and A. D. Palma (2017). The valuation of travel time reliability: does congestion matter? Transportation Research Part B: Methodological, Vol. 97, pp 113-141.
46. Xie, C., D. Y. Lin, and S. T. Waller (2010). A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. Transportation Research Part E, Vol. 46 (3), pp 295-316.

47. Xu, H. (2006). Decentralized Traffic Information System Design Based on Inter-Vehicle Communication. Doctoral dissertation in electrical engineering. University of California Riverside, December 2006.
48. Xu, H., L. William, and J. Zhou (2014). Modelling road users' behavioral change over time in stochastic road networks with guidance information. Transportmetrica B: Transport Dynamics, Vol. 2 (1), pp 20-39.
49. Yang, L. and X. Zhou (2014). Constraint reformulation and a Lagrangian relaxation-based solution algorithm for a least expected time path problem. Transportation Research Part B. Vol. 59, pp 22-44.
50. Yin, W., P. Murray-Tuite, and H. Gladwin (2014). Statistical analysis of the number of household vehicles used for hurricane Ivan evacuation. Journal of Transportation Engineering – ASCE, Vol. 140 (12), 040140601–040140610.
51. Yuan, F., L. Han, S. M., Chin, and H. Hwang (2006). Proposed framework for simultaneous optimization of evacuation traffic destination and route assignment. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1964, Transportation Research Board of the National Academies, Washington, D.C., pp 50-58.
52. Yuan, F. and L. D. Han (2010). A multi-objective optimization approach for evacuation planning. Procedia Engineering-First International Conference on Evacuation Modeling and Management, Vol.3, pp 217-227.
53. Yusoff, M., J. Ariffin, and A. Mohamed (2008). Optimization approaches for macroscopic emergency evacuation planning: a survey. IEEE, 2008 International Symposium on Information Technology, Vol. 4
54. Zhang, Z, Q. He, J. Gou, and X. Li (2016). Performance measure for reliable travel time of emergency vehicles. Transportation Research Part C: Emerging Technologies, Vol. 65, pp 97-110.
55. Zheng, H., Y. C. Chiu, P. B. Mirchandani, and M. Hickman (2010). Modeling of evacuation and background traffic for optimal zone-based vehicle evacuation strategy. Transportation Research Record, Vol. 2196, pp 65-74.
56. Zheng, H., Y. C. Chiu, and P. B. Mirchandani (2015). On the system optimum dynamic traffic assignment and earliest arrival flow problems. Transportation Science, Vol. 49 (1), pp 13-27.
57. Zhou, X. and J. Taylor (2014). DTALite: A queue-based mesoscopic traffic simulator for fast model evaluation and calibration. Cogent Engineering, Vol. 1 (1), pp 1-719.
58. Zhou, X. (2016). DTA Lite. Github Zhou99, accessed in June 2016.
59. Zimmerman, C., R. Brodesky, and J. Karp (2007). Using highways for no-notice evacuations: routes to effective evacuation planning primer series. Project Report FHWA-HOP-08-003, Federal Highway Administration, USDOT, Washington D.C.

APPENDICES

Appendix A – Acronyms, abbreviations, etc.

Abbreviation	Description
ACS	American Community Survey
AMS	Analysis, Modelling, and Simulation
ATDM	Active Transportation and Demand Management
ATIS	Advanced Traveler Information Systems
ATT	Average Travel Time
BI	Buffer Index
COV	Coefficient of Variation
DMS	Dynamic Message Signs
DNL	Dynamic Network Loading
DNR	Did Not Respond
DTA	Dynamic Traffic Assignment
ETT	Expected Travel Time
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GDOT	Georgia Department of Transportation
GEE	Generalized Estimating Equation
GLH	Google Location History
HAR	Highway Advisory Radio
HCM	Highway Capacity Manual
ICM	Integrated Corridor Management
ITS	Intelligent Transportation System
KML	Keyhole Markup Language
LOS	Level-of-Service
LR	Linear Regression
MAE	Mean Absolute Error
MLE	Maximum Likelihood Estimation
MLP	Multilayer Perceptron
MOE	Measurements of Effectiveness
MPO	Metropolitan Planning Organization
NOAA	National Oceanic and Atmospheric Administration
ODE	One-Destination Evacuation
PAZ	Protective Action Zone
PI	Perfect Information
PT	Planning Time
RBF	Radical Basis Function

RITIS	Regional Integrated Transportation Information System
STA	Static Traffic Assignment
STD	Standard Deviation
STRIDE	Southeastern Transportation Research, Innovation, Development, and Education Center
SVM	Support Vector Machine
TMC	Traffic Management Center
TOD	Time-of-Day
V/C	Volume-to-Capacity
VHT	Vehicle Hours Traveled
VMS	Variable Message Signs
VMT	Vehicle Miles Traveled
WSS	Within-cluster Sum of Squares

APPENDIX B – USER SURVEY (FULL) [GT]

* Indicates a question that was merged with another question in the short survey used on 11/10/2018

** Indicates a question that was removed in the short survey used on 11/10/2018

NAVIGATION USE SURVEY

SURVEYOR NAME:	DATE:	Survey ID# [Office use only]
LOCATION:		

A. (READ STATEMENT) **Hello, Georgia Tech is conducting a research project to find out how you use navigation in your vehicle. Do you have a few minutes to answer some questions and are you at least 18 years of age?** 1. Yes – agree and 18 or older (Go to C) 2. No or under 18 (GO TO B AND FILL OUT REFUSAL)

B. Refusals Count:

Type of refusal:	**Tally:**
1. Verbal refusal (not language barrier)	____________________
2. Non-verbal refusal	____________________
3. Language barrier	____________________
4. **Under 18 years of age**	____________________

C. Do you regularly drive a car? 1. Yes (Go to D) 2. No (STOP SURVEY)

(at least twice per week) Tally: _________________________

D. RECORD INTERVIEW START TIME _____: _____ (Military Time)

E. RECORD GENDER BY OBSERVATION (CIRCLE ONLY ONE) 1. Male 2. Female

1. Imagine you are getting in your car, what do you mainly use for vehicle navigation? (CIRCLE ONLY ONE) *

1. Smartphone	3. Online maps prior to getting in car	5. Other(Specify)_______________
2. In-vehicle Navigation	4. Paper maps prior to getting in car	99. DNR

2. What type of mobile phone do you mainly use? (CIRCLE ONLY ONE) *

1. iPhone	3. Other smartphone (Specify) ____________	5. None (STOP SURVEY)
2. Android	4. Non-smartphone (STOP SURVEY)	99. DNR (STOP SURVEY)

3. Which of the following apps do you use for directions? (READ LIST. CIRCLE ALL THAT APPLY)

1. Apple Maps	4. TomTom	7. Other (Specify)_______________
2. Waze	5. Inrix	8. None (GO TO # 12 & # 14)
3. Google Maps	6. Here	99. DNR

4. How often do you use the following types of roads? (READ LISTS AND CIRCLE ONLY ONE FOR EACH ROW) **

	5.	4.	3.	2.	1.	99.
Freeways	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR
	5.	4.	3.	2.	1.	99.
Major Roads	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR
	5.	4.	3.	2.	1.	99.
Neighborhood Streets **(30 mph or less)**	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR

5. How often do you use navigation apps on the following types of roads? (READ LISTS AND CIRCLE ONLY ONE FOR EACH ROW)

	5.	4.	3.	2.	1.	99.
Freeways	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR
	5.	4.	3.	2.	1.	99.
Major Roads	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR
	5.	4.	3.	2.	1.	99.
Neighborhood Streets	(Almost) Daily	At least once / week	At least once / month	Several times / year	Seldom or never	DNR

(30 mph or less)

6. For what types of trips do you use apps for directions? (READ LIST. CIRCLE ALL THAT APPLY) *

5.	4.	3.	2.	1.	99.
Regular commute trips	Regular non-commute trips (grocery store, weekly dinner)	Infrequent trips (yearly doctor visit, visiting family)	First time trips	Other ______________	DNR

7. For which of the following trip durations do you typically use a navigational app? (READ LIST. CIRCLE ALL THAT APPLY) *

5.	4.	3.	2.	1.	99.
1 – 5 minutes	6 – 15 minutes	16 – 30 minutes	31 – 60 minutes	61+ minutes	DNR

8. What percentage of your trips do you use directions in real-time (listening to or watching app route minute-by-minute)? (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED) **

7.	6.	5.	4.	3.	2.	1.	99.
100% of trips	80 – 99%	60 – 79%	40 – 59%	20 – 39%	1 – 19%	Never	DNR

9. What percentage of your trips do you follow the route suggested by the app? (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

7.	6.	5.	4.	3.	2.	1.	99.
100% of trips	80 – 99%	60 – 79%	40 – 59%	20 – 39%	1 – 19%	Never	DNR

10. When you do not follow the suggested route, what is your primary reason? (READ LIST. CIRCLE ONLY ONE.)

1. Travel time savings is not enough
2. Avoiding neighborhoods
3. Prefer my typical route
4. Do not trust the app's route
5. App route is too complicated
6. Other ____________________

99. DNR

11. What time savings is required for you to accept a route change? (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED) **

5.	4.	3.	2.	1.	99.

0 minutes (always take recommended route)	1 – 2 minutes	3 – 5 minutes	6-10 minutes	11+ minutes	DNR

12. Do you think the use of such apps changes PEOPLE'S USAGE (time they drive on) the following types of roads? (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Freeways	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Major Roads	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Neighborhood Streets **(30 mph or less)**	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR

13. Do you think the use of such apps changes YOUR USAGE (time you drive on) the following types of roads? (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Freeways	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Major Roads	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Neighborhood Streets **(30 mph or less)**	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR

(ADDITONAL SPACE IF RESPONDENT MAKES COMMENTS)

14. How do you think the apps change the characteristics of neighborhood streets in the following areas? (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Speed	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
Driver Alertness	5. Large Increase	4. Small Increase	3. Neither Increase nor Decrease	2. Small Decrease	1. Large Decrease	99. DNR

15. How do you think the apps change YOUR BEHAVIOR on neighborhood streets in the following areas? (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Speed	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
Driver Alertness	5. Large Increase	4. Small Increase	3. Neither Increase nor Decrease	2. Small Decrease	1. Large Decrease	99. DNR

16. What is your home zip code? ________________ (ENTER FIVE-DIGIT NUMBER)

17. What best describes the type of residence you currently live in? (READ LIST. CIRCLE ONLY ONE)

5.	4.	3.	2.	1.	99.
Detached (free-standing) home	Attached home / duplex / townhouse	Apartment / condo building	Dormitory	Other ______________	DNR

18. Which of the following categories best represents your age? (CIRCLE ONLY ONE)

1. 18-24	3. 35-44	5. 55-64	7. 75 or Over
2. 25-34	4. 45-54	6. 65-74	99. DNR

19. What is the highest level of education you have completed? (CIRCLE ONLY ONE)

1. Less than 9th grade	4. Some college but no bachelor's degree	99. DNR
2. From 9th grade to 12th grade	5. Bachelor's degree	
3. High school graduate	6. Graduate work or postgraduate degree	

20. How many persons, including children, are in your household? __________ 99. DNR

21. How many of these persons in your household are children under the age of 18? _________ 99. DNR

22. How frequently do you DRIVE FOR Uber, Lyft, or similar services? (DRIVE FOR, NOT USE. CIRCLE ONLY ONE) **

5.	4.	3.	2.	1.	99.
(Almost) Daily	At least once / week	At least once / month	Previously but no longer	Never have driven Uber/Lyft	DNR

23. Do you have other comments related to the use of navigational apps?

____
____
____
____
____

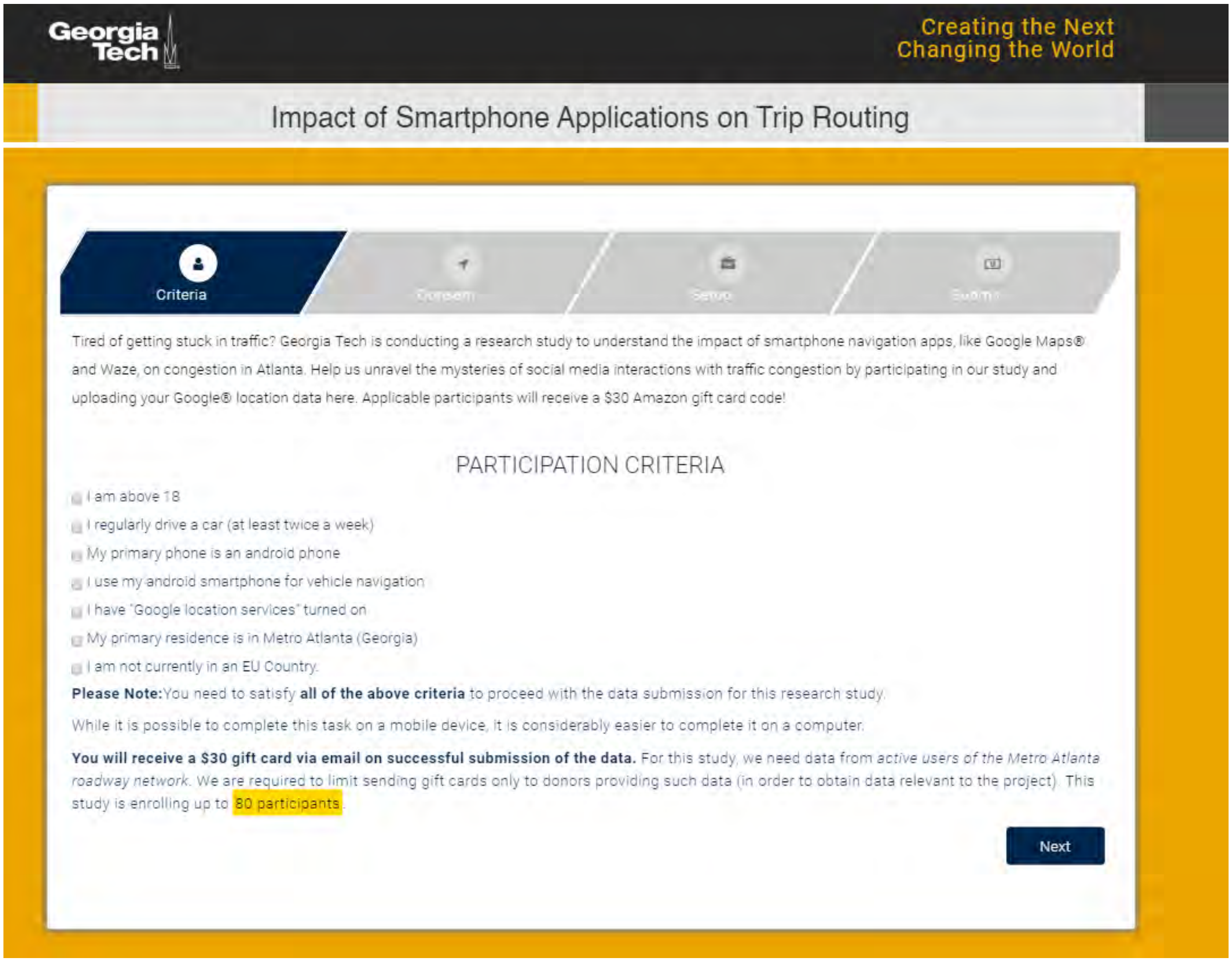
24. Do you have Google Location Services turned on?

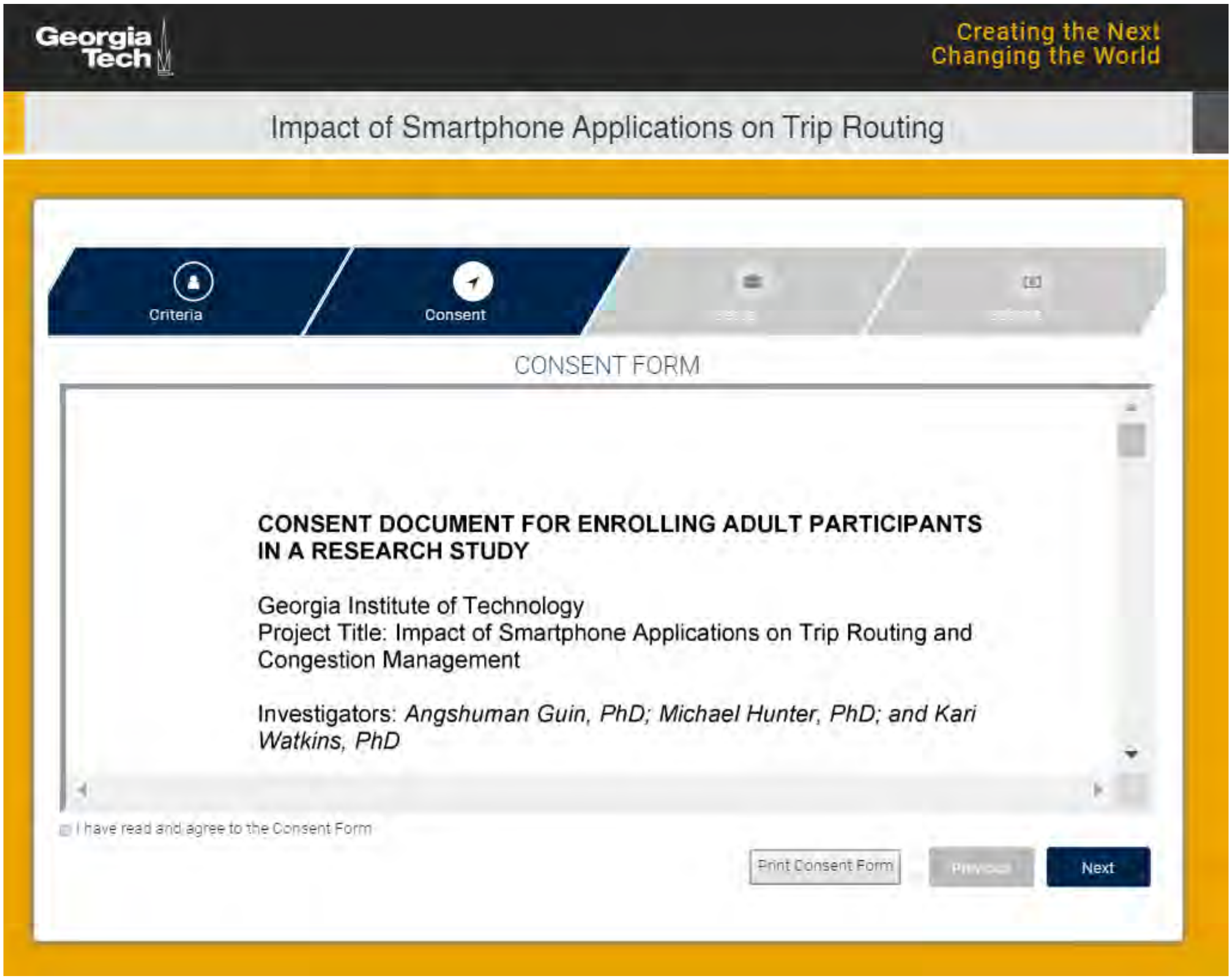
1.	2.	3.
Yes (REFER TO LOCATION DATA SURVEY)	No (THANK THEM AND END SURVEY)	Unsure (REFER TO LOCATION DATA SURVEY)

RECORD INTERVIEW END TIME _____: _____ (Military Time)

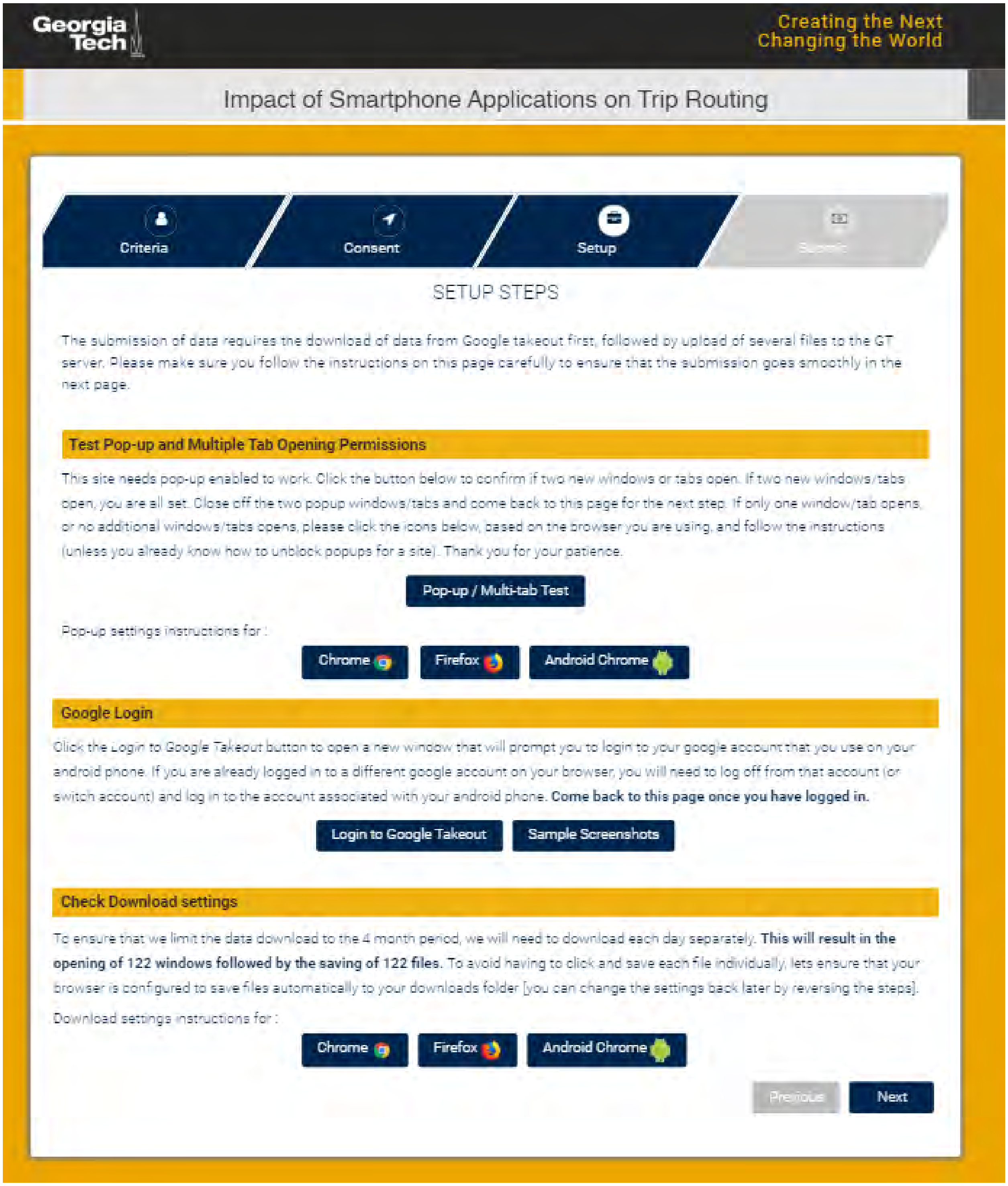
THANK YOU!!

APPENDIX C – WEB DATA COLLECTION





Georgia Tech
Creating the Next
Changing the World
Impact of Smartphone Applications on Trip Routing
Criteria
Consent
CONSENT FORM
CONSENT DOCUMENT FOR ENROLLING ADULT PARTICIPANTS IN A RESEARCH STUDY
Georgia Institute of Technology
Project Title: Impact of Smartphone Applications on Trip Routing and Congestion Management
Investigators: Angshuman Guin, PhD; Michael Hunter, PhD; and Kari Watkins, PhD
I have read and agree to the Consent Form
Print Consent Form
Next


Georgia Tech
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Changing the World
Impact of Smartphone Applications on Trip Routing
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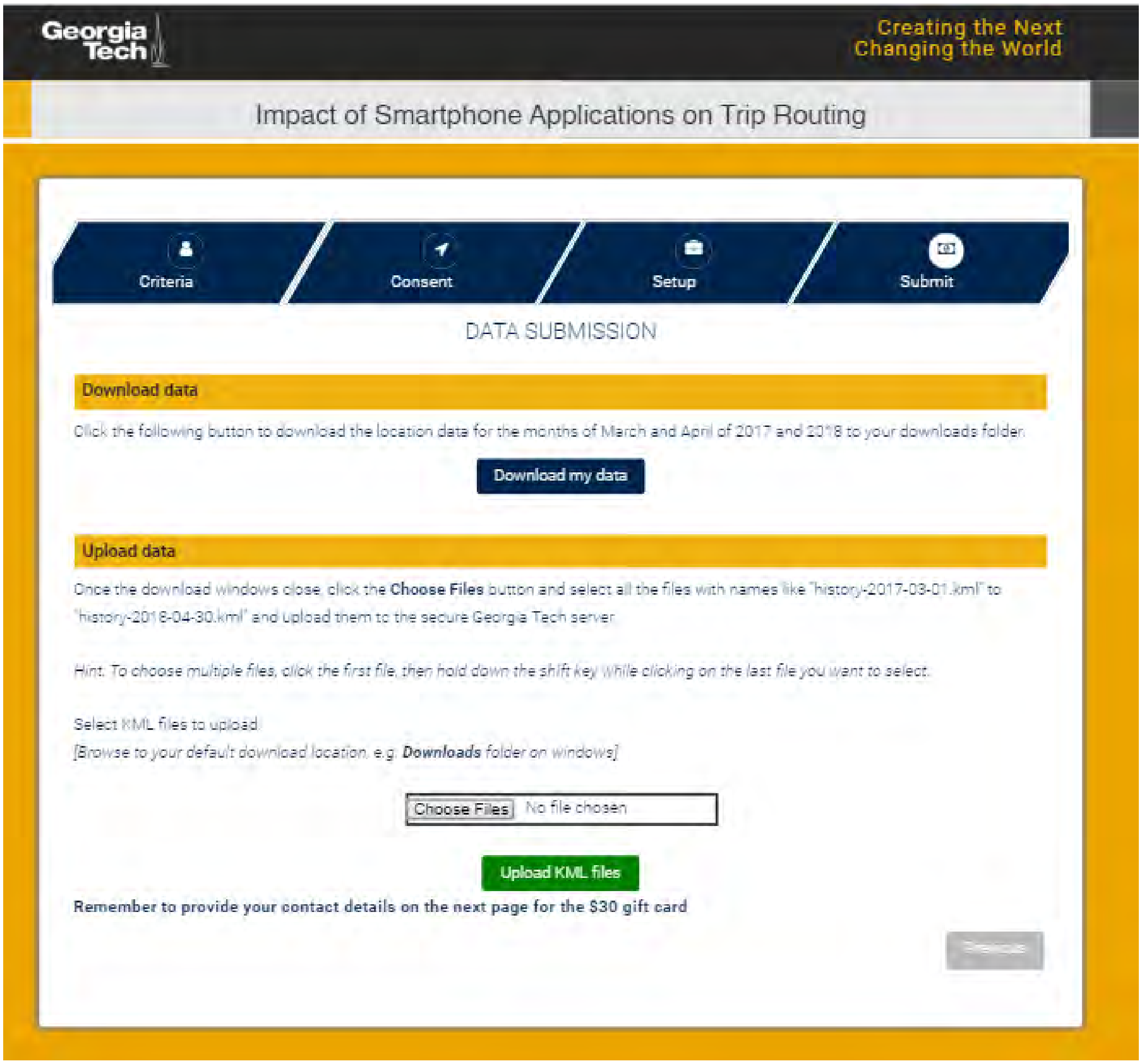
Consent
Setup
SETUP STEPS
The submission of data requires the download of data from Google takeout first, followed by upload of several files to the GT server. Please make sure you follow the instructions on this page carefully to ensure that the submission goes smoothly in the next page.
Test Pop-up and Multiple Tab Opening Permissions
This site needs pop-up enabled to work. Click the button below to confirm if two new windows or tabs open. If two new windows/tabs open, you are all set. Close off the two popup windows/tabs and come back to this page for the next step. If only one window/tab opens, or no additional windows/tabs opens, please click the icons below, based on the browser you are using, and follow the instructions (unless you already know how to unblock popups for a site). Thank you for your patience.
Pop-up / Multi-tab Test
Pop-up settings instructions for :
Chrome
Firefox
Android Chrome
Google Login
Click the Login to Google Takeout button to open a new window that will prompt you to login to your google account that you use on your android phone. If you are already logged in to a different google account on your browser, you will need to log off from that account (or switch account) and log in to the account associated with your android phone. Come back to this page once you have logged in.
Login to Google Takeout
Sample Screenshots
Check Download settings
To ensure that we limit the data download to the 4 month period, we will need to download each day separately. This will result in the opening of 122 windows followed by the saving of 122 files. To avoid having to click and save each file individually, lets ensure that your browser is configured to save files automatically to your downloads folder [you can change the settings back later by reversing the steps].
Download settings instructions for :
Chrome
Firefox
Android Chrome
Previous
Next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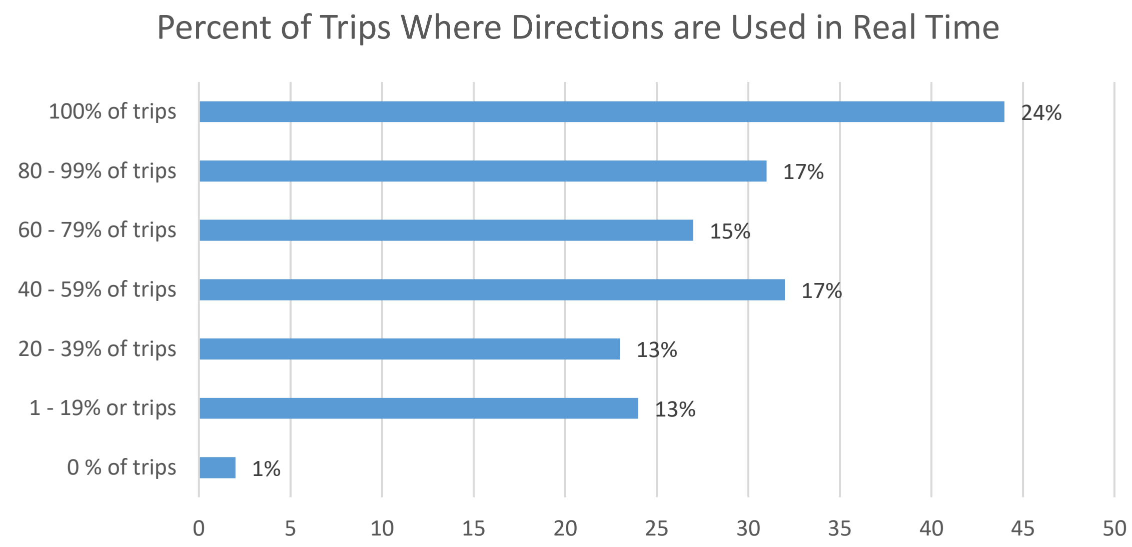
Changing the World
Impact of Smartphone Applications on Trip Routing
Criteria
Consent
Setup
Submit
DATA SUBMISSION
Download data
Click the following button to download the location data for the months of March and April of 2017 and 2018 to your downloads folder.
Download my data
Upload data
Once the download windows close, click the Choose Files button and select all the files with names like "history-2017-03-01.kml" to "history-2018-04-30.kml" and upload them to the secure Georgia Tech server.
Hint: To choose multiple files, click the first file, then hold down the shift key while clicking on the last file you want to select.
Select KML files to upload
[Browse to your default download location, e.g. Downloads folder on windows]
Choose Files
No file chosen
Upload KML files
Remember to provide your contact details on the next page for the $30 gift card

APPENDIX D – ADDITIONAL SURVEY RESULTS



Appendix D – Data by Day

Survey ID	**# of Trips**	Days Collected	**% of Days with Collected Data**	Points in ARC	Trips in ARC	**% Trips in ARC**	Trips Freeway	**% Freeway Trips**	Trips Major Road	**% Major Trips**	Trips Neighborhood	**% Hood Trips**	Freeway Trips per Day	Major Trips per Day	Hood Trips per Day
1	515	64	52%	1948	31	6%	26	84%	28	90%	31	100%	0.4	0.4	0.5
2	601	114	93%	11256	389	65%	202	52%	248	64%	341	88%	1.8	2.2	3.0
3	796	118	97%	11278	796	100%	505	63%	604	76%	655	82%	4.3	5.1	5.6
4	628	122	100%	19696	602	96%	506	84%	507	84%	489	81%	4.1	4.2	4.0
5	544	114	93%	9407	503	92%	254	50%	442	88%	468	93%	2.2	3.9	4.1
6	753	117	96%	19985	685	91%	535	78%	657	96%	548	80%	4.6	5.6	4.7
7	659	118	97%	9207	564	86%	328	58%	512	91%	474	84%	2.8	4.3	4.0
8	191	71	58%	3907	162	85%	96	59%	124	77%	154	95%	1.4	1.7	2.2
9	982	120	98%	1720	954	97%	449	47%	854	90%	903	95%	3.7	7.1	7.5
10	813	120	98%	10859	673	83%	308	46%	634	94%	484	72%	2.6	5.3	4.0
11	485	69	57%	22174	484	100%	312	64%	453	94%	462	95%	4.5	6.6	6.7
12	285	71	58%	6364	287	101%	168	59%	208	72%	271	94%	2.4	2.9	3.8
13	499	115	94%	9550	210	42%	165	79%	187	89%	205	98%	1.4	1.6	1.8
14	749	117	96%	17660	267	36%	196	73%	235	88%	218	82%	1.7	2.0	1.9
15	619	120	98%	15020	508	82%	175	34%	320	63%	488	96%	1.5	2.7	4.1
16	164	51	42%	2899	153	93%	63	41%	129	84%	145	95%	1.2	2.5	2.8

Survey ID	**# of Trips**	Days Collected	**% of Days with Collected Data**	Points in ARC	Trips in ARC	**% Trips in ARC**	Trips Freeway	**% Freeway Trips**	Trips Major Road	**% Major Trips**	Trips Neighborhood	**% Hood Trips**	Freeway Trips per Day	Major Trips per Day	Hood Trips per Day
17	308	52	43%	5838	128	42%	95	74%	123	96%	110	86%	1.8	2.4	2.1
18		108	89%	44014	761		500	66%	659	87%	732	96%	4.6	6.1	6.8
19	126	28	23%	2931	126	100%	41	33%	114	90%	80	63%	1.5	4.1	2.9
20	3	1	1%	17	3	100%	0	0%	2	67%	3	100%	0.0	2.0	3.0
21	898	122	100%	26761	762	85%	395	52%	696	91%	717	94%	3.2	5.7	5.9
22	669	114	93%	10825	599	90%	214	36%	430	72%	586	98%	1.9	3.8	5.1
23	481	61	50%	10279	460	96%	358	78%	385	84%	388	84%	5.9	6.3	6.4
24	432	59	48%	17711	414	96%	266	64%	362	87%	365	88%	4.5	6.1	6.2
25	849	116	95%	7141	199	23%	134	67%	182	91%	178	89%	1.2	1.6	1.5
26	341	69	57%	8662	330	97%	127	38%	310	94%	207	63%	1.8	4.5	3.0

APPENDIX E – SURVEY [FIU]

NAVIGATION USE SURVEY

SURVEYOR NAME:	DATE:	SURVEY ID#:

A. (READ STATEMENT) **Hello, Florida International University is conducting a research project to find out how you use navigation in your vehicle. Do you have a few minutes to answer some questions and are you at least 18 years of age?**

1 Yes – agree and 18 or older

2 No or under 18 (STOP SURVEY)

Tally:_____________________________

B. Do you regularly drive a car? 1. Yes 2. No (STOP SURVEY)

(at least twice per week) Tally: ____________________

....

1. **Imagine you are getting in your car, what do you mainly use for vehicle navigation?** (CIRCLE ONLY ONE)

1. Android	2. Website prior to getting in car	3. No navigation
4. IPhone	5. Paper maps prior to getting in car	6. Dynamic Message Sign (DMS)
7. Other Smartphone	8. In-vehicle Navigation	9. Other
10. Media (Television/Radio)	11. 511 Call/App	10. DNR

2. **Which of the following apps do you use for directions?** (READ LIST. CIRCLE ALL THAT APPLY)

1. Apple Maps	4. TomTom	7. Other (Specify)___
2. Waze	5. Inrix	8. None
3. Google Maps	6. Here	99. DNR

3. **How often do you use navigation apps on the following types of roads?** (READ LISTS AND CIRCLE ONLY ONE FOR EACH ROW)

Freeways	5. (Almost) Daily	4. At least once / week	3. At least once / month	2. Several times / year	1. Seldom or never	99. DNR
Major Roads	5. (Almost) Daily	4. At least once / week	3. At least once / month	2. Several times / year	1. Seldom or never	99. DNR
Neighborhood Streets (30 mph or less)	5. (Almost) Daily	4. At least once / week	3. At least once / month	2. Several times / year	1. Seldom or never	99. DNR

4. **We are trying to figure out for which trip types and lengths you use navigation apps. For each type of trip, which of the following trip durations do you typically use a navigational app?** (READ LIST. CIRCLE ALL THAT APPLY)

Regular commute trips	6. Does not use	5. 1 – 5 minutes	4. 6 – 15 minutes	3. 16 – 30 minutes	2. 31 – 60 minutes	1. 61+ minutes	99. DNR
Regular non-commute trips (grocery store, weekly dinner)	6. 0 minutes	5. 1 – 5 minutes	4. 6 – 15 minutes	3. 16 – 30 minutes	2. 31 – 60 minutes	1. 61+ minutes	99. DNR
Infrequent trips (doctor visit, visiting family)	6. 0 minutes	5. 1 – 5 minutes	4. 6 – 15 minutes	3. 16 – 30 minutes	2. 31 – 60 minutes	1. 61+ minutes	99. DNR

First time trips	6. 0 minutes	5. 1 – 5 minutes	4. 6 – 15 minutes	3. 16 – 30 minutes	2. 31 – 60 minutes	1. 61+ minutes	99. DNR

5. **You consider to divert during an incident if you travel is mostly for:** (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

1.	2.	3.	4.
Regular Commute trips	Regular non-commute trips	Infrequent trips	First time trips

6. **How many times in last three months during an incident did you divert?** (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

7.	6.	5.	4.	3.	2.	1.	99.
100% of the times	80 – 99%	60 – 79%	40 – 59%	20 – 39%	1 – 19%	Never	DNR

7. **How much increase in delay of your trip will make you consider divert?** (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

1.	2.	3.	4.	5.	6.	7.	99.
<10% (up to 6 minutes for a hour trip)	11 – 20% (7 to 12 minutes for a hour trip)	21 – 30% (13 to 18 minutes for a hour trip)	31 – 40% (19 to 24 minutes for a hour trip)	41 – 50% (25 to 30 minutes for a hour trip)	>50% (more than 30 minutes for a hour trip)	Never divert	DNR

8. **How much travel time savings trigger you to diverted to an alternative route during an incident?** (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

1.	2.	3.	4.	5.	6.	7.	99.
<10% (up to 6 minutes for a hour trip)	11 – 20% (7 to 12 minutes for a hour trip)	21 – 30% (13 to 18 minutes for a hour trip)	31 – 40% (19 to 24 minutes for a hour trip)	41 – 50% (25 to 30 minutes for a hour trip)	>50% (more than 30 minutes for a hour trip)	Never divert	DNR

9. **What percentage of your trips do you follow the route suggested by the app?** (CIRCLE ONLY ONE APPROPRIATE RANGE. READ IF NEEDED)

7.	6.	5.	4.	3.	2.	1.	99.
100% of trips	80 – 99%	60 – 79%	40 – 59%	20 – 39%	1 – 19%	Never	DNR

10. **When you do not follow the suggested route, what is your primary reason?** (READ LIST. CIRCLE ONLY ONE.)

1. Travel time savings is not enough	4. Do not trust the app's route	6. Other __________
2. Avoiding neighborhoods	5. App route is too complicated	99. DNR
3. Prefer my typical route		

11. **Do you think the use of such apps changes PEOPLE'S USAGE (time they drive on) the following types of roads?** (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Freeways	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Major Roads	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
	5.	4.	3.	2.	1.	99.
Neighborhood Streets (30 mph or less)	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR

12. **How do you think the apps change the characteristics of neighborhood streets in the following areas?** (READ LIST. CIRCLE ONLY ONE IN EACH ROW.)

	5.	4.	3.	2.	1.	99.
Speed	Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR
Driver Alertness	5.	4.	3.	2.	1.	99.

Large Increase	Small Increase	Neither Increase nor Decrease	Small Decrease	Large Decrease	DNR

13. **What is your home zip code?** _______________ (ENTER FIVE-DIGIT NUMBER)

14. What best describes the type of residence you currently live in? (READ LIST. CIRCLE ONLY ONE)

5.	4.	3.	2.	1.	99.
Detached (free-standing) home	Attached home / duplex / townhouse	Apartment / condo building	Dormitory	Other _____________	DNR

15. Which of the following categories best represents your age? (CIRCLE ONLY ONE)

1. 18-24	3. 35-44	5. 55-64	7. 75 or Over
2. 25-34	4. 45-54	6. 65-74	99. DNR

16. What is your gender?

1. Male	2. Female	3. Other	4. DNR

17. What is the highest level of education you have completed? (CIRCLE ONLY ONE)

1. Less than 9th grade	4. Some college but no bachelor's degree	99. DNR
2. From 9th grade to 12th grade	5. Bachelor's degree	
3. High school graduate	6. Graduate work or postgraduate degree	

18. **How many persons, including children, are in your household?** _________ 99. DNR

19. **How many of these persons in your household are children under the age of 18?** ________ 99. DNR

20. Do you have other comments related to the use of navigational apps?

____

____

____

THANK YOU!!

APPENDIX F – SUMMARY OF ACCOMPLISHMENTS

a. *Student and faculty accomplishments such as awards, etc.*
   - Dr. Mohammed Hadi received the College of Engineering Faculty Research Award, 2017-2018
   - Lei Bu received her Ph.D. degree in Transportation Engineering from Jackson State University with this research as part of her thesis.

b. *Products developed as a consequence of this project*

   The code for creating a website to receive "Google Location History" data has been published to GitHub at: https://github.com/gti-gatech/navigation_apps

c. *Publications and presentations*
   - Tariq, M.T., R.C. Saha, and M. Hadi, Methodology to Derive Route Diversion during Freeway Incident Condition, Presented at the Transportation Research Board's 98th Annual Meeting, Washington, D.C., 2019
   - Bu, L., F. Wang, X. Zhou, and C. Yin. Managed gating control strategy for emergency evacuation, Transportmetrica A - Transport Science, Issue 10, Vol. 14, November 2018. https://doi.org/10.1080/23249935.2018.1552336
   - Kiriazes, R., Watkins, K., Guin, A., Hunter, M. Impact of Smartphone Applications on Trip Routing, Presented at the Transportation Research Board's 99th Annual Meeting, Washington, D.C., 2020

d. *Articles in the news related to this project (please provide links to articles)*

   NA

e. *Results and activities undertaken that support the mission of this grant*

   The results of the project were presented at a professional conference, the ITS Georgia Annual meeting on October 7 in Athens Georgia. The presentation was very well accepted by the Georgia Department of Transportation Representatives and the consultant community and piqued considerable interest in the results. (Meeting website: http://www.itsga.org/event/2019-annual-meeting-and-exposition/)