MODELING TRANSPORTATION IMPACTS OF NATURAL DISASTERS

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by

DAEYEOL CHANG

Dr. Praveen Edara, Dissertation Supervisor

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

MODELING TRANSPORTATION IMPACTS OF
NATURAL DISASTERS

Presented by Daeyeol Chang

A candidate for the degree of Doctor of Philosophy

And hereby certify that, in their opinion, it is worthy of acceptance.

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Dr. Praveen Edara

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Dr. Carlos Sun

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Dr. Timothy Matisziw

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Dr. Yaw Adu-Gyamfi

DEDICATION

To my wife Jiwon Lee, who is a true helper to me.

To my parents, Hyunbong Chang and Joowon Lee.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my academic advisor, Dr. Praveen Edara, for his encouragement, guidance, and support throughout my doctoral research in University of Missouri-Columbia. I also would like to thank my doctoral committee members: Dr. Carlos Sun, Dr. Timothy Matisziw, and Dr. Yaw Adu-Gyamfi. I want to thank other university faculty I have had the privilege to interact with over the past years and my colleagues in the ZouTrans.

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Daeyeol Chang

Dr. Praveen Edara, Dissertation Supervisor

ABSTRACT

Natural disasters such as hurricanes and pandemics cause significant disruption in people's lives. This research aims to model such disasters' transportation impacts using state-of-the-art simulation methods, statistical and machine learning algorithms. Specifically, two case studies of disasters were studied. First, the effects of various travel demand management and network control strategies on hurricane evacuation of the Hampton Roads region in Virginia were modeled. A mesoscopic simulation model was updated using demand data generated from a household survey effort. The results indicated that phased evacuation scenarios performed the best in terms of travel times, evacuating volumes, and clearance times. Also, the use of lane-reversal on a major interstate evacuation route was shown to be effective in several scenarios. The household survey also asked respondents to provide their preferred route types in the event of a hypothetical Category 4 hurricane evacuation. The responses were used to understand better which factors contribute to evacuees selecting freeway vs. non-freeway evacuation routes. A mixed (random parameters) logit model was developed to determine factors that influence evacuees deciding between a freeway and a non-freeway route. The study found that several factors contribute to evacuees choosing a freeway over other routes. In the descending order of importance (i.e., marginal effects), these factors are willing to use the official recommended route, living in a single-family or duplex housing, expected

travel time to reach the destination, being employed, and possessing prior evacuation experience.

Conversely, a few factors had a negative effect on choosing a freeway. These factors are willingness to evacuate two days before landfall and evacuating to a public shelter or a second home. This study's findings can help emergency management and transportation agencies design effective demand management and traffic control plans to evacuate regions during a hurricane safely.

The second case study involved the modeling of travel impacts of COVID-19 pandemic. Using New York County (i.e. Manhattan) as an example, publicly available location-based mobility data from Google and COVID-19 data from government sources were used to build mobility prediction models. Three machine learning algorithms, Regression Tree, Random Forest, and Extreme gradient boosting (XGBoost) were used to develop different models. Among the three models, the Random Forest models performed the best at predicting mobility index with mean absolute percentage errors of 5.3% and 5.8% at transit stations, 6.5% and 7.1 % for retail and recreation activities. These models enable accurate forecasting of expected mobility by taking into account time series data of activity and COVID variables.

1. Introduction

1.1. Overview

As disasters consistently occur, they can cause considerable damage to our society, economy, as well as to the transportation system. There are many types of disasters such as wildfire, earthquake, and hurricanes. The damage from the wildfire has been recently increasing in the United States. From 2011 to 2020, the burnt acreage due to wildfires grew by 15.5 percent (NOAA, 2020). During the same decade, the US also experienced 29 earthquakes with a magnitude of over 5.0, with 48% of those earthquakes occurring in the past three years (USGS, 2020). Hurricanes are another disaster that regularly disrupts life in the US. In the 1990s, there were 25 major hurricanes over a decade; however, that number grew to 36 in the 2000s and 30 in the 2010s (NOAA, 2020).

As these disasters gradually increase in number each year, the disruptions and potential threats to the transportation system continue. According to the United States Code [46 USCS § 70101(6)], the term transportation disruption means "*Any significant delay, interruption, or stoppage in the flow of trade caused by a natural disaster, heightened threat level, an act of terrorism, or any transportation security incident*.".

In transportation, disruptive events affect traffic in various forms ranging from road accidents in small areas to capacity reductions across the road network depending on their type and size. For example, travelers could experience multiple delays due to shrunken capacities and limited route selection in the case of geophysical or climatological natural disasters.

Another type of disaster, epidemic, makes people alter their lifestyle, including travel behavior. In the recent decade, the world has experienced a few epidemics that have exerted significant impacts. For example, the Middle East Respiratory Syndrome (MERS) in 2012 resulted in 858 deaths. The Western African Ebola virus that spread between 2013 and 2016 consumed 11,000 lives. At the end of 2019, a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) called COVID-19 was discovered in Wuhan, China. On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a pandemic. As of October 31, 2020, 45.5 million cases of COVID-19 have been recorded worldwide, with total deaths surpassing 1.2 million (WHO, 2020). Pandemics such as COVID-19 have a considerable impact on mobility and travel patterns.

This research aims to model the transportation impacts of disruptive events such as natural disasters and pandemics using state-of-the-art simulation methods, statistical and machine learning algorithms. A combination of field data and simulation was used to investigate the impact of disruptions. This proposal is organized as follows. Chapter 2 presents the development of the hurricane evacuation simulation model and its use to study the performance of travel demand management and network strategies. Chapter 3 presents the details of the development of a route choice model for hurricane evacuation. Chapter 4 presents the analysis of mobility impacts during the COVID-19 focused on how infected cases and deaths influenced activities on specific locations and predicted the future.

1.2. Research Objectives

The key objectives of this research for each emphasis area are presented below.

1.2.1. Assessing Travel Demand Management and Network Strategies for Hurricane Evacuation

1) To develop a large-scale regional evacuation model for various scenarios, including several types of demands and road network treatments. The study area includes the nine cities of Chesapeake, Hampton, Newport News, Norfolk, Poquoson, Portsmouth, Richmond, Suffolk, and Virginia Beach.
2) To model and evaluate the evacuation scenarios using the developed model. Performance measures such as clearance times, travel times to destinations, and evacuating volumes were used to compare different scenarios.

1.2.2. Evacuation Route Choice Modeling

To develop a household evacuation route choice model based on survey data collected from households in the Hampton Roads region of Virginia. The survey collected socio-demographic information and evacuation-related characteristics related to route selection. A mixed logit (random parameter logit) model was then developed to identify the factors influencing the selection of freeways versus non-freeways.

1.2.3. Travel Impacts of COVID-19 Pandemic

To model the travel impacts of COVID-19 pandemic. Using New York County as an example, impact on activities by mobility – Transit Station and Retail / Recreation – were examined. Publicly available location-based mobility data from Google mobility report and COVID-19 data from USAfacts website (usafacts.org) were used to develop machine learning models for predicting mobility.

2. HURRICANE EVACUATION MODELING OF TRANSPORTATION DISRUPTION

2.1. Introduction

2.1.1. Background on Hurricanes

The United States has been vulnerable to hurricanes originating in the Atlantic and Pacific oceans. The storms pose threats to coastal residents, including heavy rain, flooding, and high winds, adversely affecting property and economy of an entire region. Hurricane threats are not new concerns; however, it needs more attention due to the increased number of major hurricanes in the recent years. On the other hand, according to the U.S. Census Bureau 2016 population data, the population adjacent to the Atlantic Ocean, Pacific Ocean, or the Gulf of Mexico increased from 51.9 million in 2000 to 59.6 million in 2016. The damage inflicted by major hurricanes can be severe. For example, Hurricane Katrina resulted in damage of $108 billion and 1,833 deaths in 2005. The events of recent hurricanes have made evacuation a leading emergency management issue. Many cities near the coastal area frequently seek to evacuate people under major hurricanes to diminish the potential loss of life. The growth of the resident population in coastal regions makes it essential for the state agencies to have well-organized evacuation and response plans. The state emergency management, transportation, and planning agencies develop and refine plans to evacuate the people prior to hurricane landfall. They are discovering ways to increase evacuation route capacity, better manage the evacuation demand, and better distribute traveler information during an evacuation.

In hurricane impacted areas, landing time, hurricane level, and other factors can be estimated using climatological approaches. Concurrently, traffic control strategies can be planned to minimize the travel impacts. Hurricanes are not the only hazardous event that necessitate evacuation. Table 2.1. lists different human-made and natural events that call for evacuation.

Table 2.1. Examples of hazardous events that necessitate evacuations (source: Wilmot, 2001)

Human-made events	**Natural events**
Terrorist attack	Volcanic eruption
Chemical release	Earthquakes
Nuclear accident	Wildfire
Dam failure	Hurricane

Compared to other events shown in Table 2.1, hurricane events typically have longer advance warning times. Therefore, mitigation strategies such as traffic control and enforcement plans can be established before issuing evacuation orders. Emergency management and transportation agencies disseminate recommended evacuation routes and public shelter destinations to the evacuees.

For a hurricane event, the risk area is also known based on the estimated direction and strength of hurricane. In addition, population data and storm characteristics can be used to obtain estimates of impacted population.

2.1.2. Background on Hurricane Evacuation

Because of hurricanes' characteristics, the Federal Emergency Management Agency (FEMA) requires all states to have a comprehensive emergency action plan. Most of the

States take a two-fold approach to emergency planning and response (Wolshon, 2005). The approach consists of monitoring hurricane paths and declaring evacuation. State-level emergency management agencies usually coordinate local emergency management activities and participation of state-level law enforcement, transportation, and other related agencies. Generally, elements such as time to issue an evacuation order, public response, and traffic management play a significant role in determining evacuation effectiveness.

At the first stage, the weather is monitored that has the potential to affect the at-risk area. This stage includes predicting hurricane paths. The forecast system has been improved by the National Hurricane Center (NHS) over several decades.

The next stage is the determination of an evacuation order, which is the time that states or local authorities order an evacuation. By law, Governors in most states have the right to order the evacuation. Hurricane landing time and expected clearance times are considered in issuing evacuation orders. The term *"clearance time"* is the time needed to complete evacuation. It is calculated based on the evacuation population and availability of road capacity.

The order issue time is a substantial part of the response process. If the order is issued too soon, evacuees that leave for their destinations may not be able to reconsider if the hurricane path changes. On the other hand, if the order is issued too late, evacuees may not safely reach their destinations before the hurricane landfall.

The third stage is to start the evacuation process once the evacuation order has been issued. The order issues consider both hurricane category and expected clearance time. The evacuation order is classified into three categories; voluntary, recommended, and

mandatory (Urbina and Wolshon, 2003). In the case of a voluntary evacuation order, there is little or no traffic control during the evacuation. For the recommended evacuation order, there is a high probability that the hurricane would threaten people in a high-risk area. However, evacuees can choose whether to evacuate or not. When a mandatory evacuation order is issued, most of the infrastructure and human resources are used to manage the traffic system efficiently. However, many states do not issue mandatory evacuation orders due to the difficulty in forcing people to leave their homes. As an example, when hurricane Irma (2017) happened, some residents refused to evacuate even facing flood conditions in Florida.

In terms of managing the traffic during the evacuation, road capacity is one of the critical constraints. Strategies that optimize the use of existing infrastructure are necessary to improve evacuation efficiency. There have been some practical approaches currently used by DOTs. For example, lane reversal, also known as contra-flow increases the road capacity by reversing inbound lanes for use as in the outbound direction. One study shows that reversing one lane could provide about 30% additional capacity (FEMA, 2000). Contra-flow is also used to cater to the high travel demand during special events such as sports games and festivals. Currently, there is no standard as to where to start the contraflow lanes for hurricane evacuation. The termination strategy of contraflow design also varies due to the difference in geometrics and route conditions. For example, one practice is to have the regular lane traffic divert to an auxiliary route, and the traffic in the reversed lane would then cross into the regular lane.

The capacity improvement due to contraflow lanes could help reduce clearance time. For example, the use of contraflow in New Jersey resulted in reducing clearance times from

36 to 20 hours in Cape May county, from 38 to 20 hours in Atlantic county, from 22 to 15 hours in Ocean County, and 20 to 15 hours in Monmouth County (Augustiniak 2001). While contraflow lanes add additional capacity, they come with some implementation issues. They almost always need human resources in the form of DOT or law enforcement personnel to operate them. Contraflow lanes can also be confusing to drivers as they will be driving in the opposite direction.

Effective exchange of traveler information is also an essential factor during an evacuation. The data is necessary for planners and engineers to make appropriate decisions, such as routing strategies. Intelligent Transportation Systems (ITS) have been aiding in monitoring and disseminating traffic information during a hurricane evacuation. Traffic sensors and Closed-circuit television (CCTV) cameras also help collect timely and accurate traffic information during the evacuation.

On the other hand, highway advisory (HAR) and dynamic message signs (DMS) could disseminate the travel and weather information to all evacuees while en-route.

The primary goal of an evacuation plan is to transport people to their destinations in a timely manner. During an evacuation, millions of people evacuate from urban areas, resulting in significant congestion. Thus, it is critical to estimate evacuation performance measures such as travel times, clearance time, and possible congestion locations. In this study, simulation modeling takes into account accurate estimation of evacuation performance measures.

2.2. Method

2.2.1. Evacuation Modeling

The Federal Emergency Management Agency (FEMA), in partnership with the U.S. Army Corps of Engineers (USACE) and National Oceanic and Atmospheric Administration (NOAA) provides assistance to local and state agencies in developing hurricane evacuation plans. Hurricane evacuation studies (HES) are conducted to provide information necessary for agencies to make decisions in the event of a hurricane. The intent of HES is not to replace the operational plans of cities and counties but instead to complement the existing plans by providing information on critical factors that need to be considered for successful hurricane preparedness and response.

One study shows that there are six crucial modeling steps in hurricane evacuations (Tampa Bay Regional Planning Council, 2006) as shown in Figure 2.1. In the first step, the development of evacuation zones and data are used to identify who is likely to evacuate. The second step is the trip generation of how many evacuees will evacuate during a particular scenario. Destinations for the evacuee trips are obtained in the next step. The development of road network should be specified at the same step. The next step is the traffic assignment which determines routes chosen by evacuees to reach their destinations. Clearance times are defined in the last step.

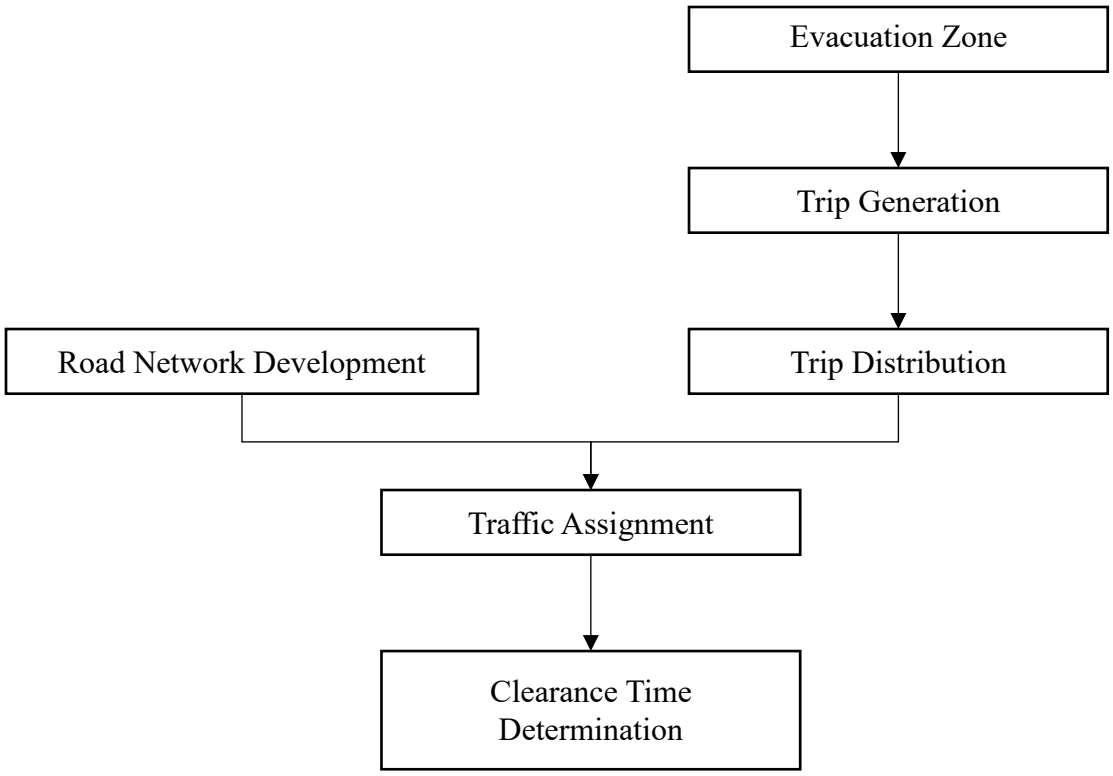


Figure 2.1. Evacuation Modeling Steps (Source: Tampa Bay Regional Planning Council, 2006)

Traffic simulation can be used for planning and analysis of evacuation. It can provide an assessment of the network conditions and the effectiveness of traffic control measures. Simulation models consider network strategies such as road closures, access restrictions, and contraflow lanes and generate performance measures for decision-makers. In previous research, simulation has been used to study hurricane evacuation. For example, Brown et al. (2009) proposed a dynamic assignment model for determining the performance of primary evacuation routes for the Greater Houston area in Texas; Balakrishna et al. (2008) developed a simulation-based system Ocean City, Maryland. The scenarios were compared with different levels of demand and various traffic control

plans. Dixit et al. (2011) showed various statistics considered for the validation procedure of a simulation model used for assessing evacuation strategies.

2.2.2. Traffic Simulation Models

Traffic simulation models are ideal for evaluating different evacuation plans and strategies. The impact of emergency evacuation on road networks has been researched using simulation models since the 1980s (Sheffi et al., 1982). Simulation studies provide information that supports decision-makers with planning, scheduling, and allocating resources for emergency evacuations. Performance measures such as network clearance times, potential bottleneck locations, anticipated travel times are attained as simulation models' outputs.

Traffic simulation models are typically classified into macroscopic, microscopic, and mesoscopic models based on their resolutions.

1) Macroscopic model: Large regional networks have been analyzed using macroscopic traffic modeling. This kind of analysis provides approximate evacuation clearance time and delay estimates. However, these models' low resolution does not understand bottlenecks and associated traffic impacts (e.g., queuing). Examples of macroscopic simulation programs are TransCAD, Cube, and Emme.
2) Microscopic model: Unlike the macroscopic model, microscopic models have the highest simulation fidelity level but require vast data and resources for model development and calibration. They are computationally demanding and are therefore suited for small networks or short simulation periods. Examples of

microscopic simulation programs are VISSIM, CORSIM, AIMSUN, and Cube Dynasim.

3) Mesoscopic model: Mesoscopic models allow for a detailed representation of vehicles (individual or group of individuals) similar to the micro models but update the vehicle's positions using macroscopic traffic flow theory equations. It not only gives considerable detailed information about network and vehicle characteristics but is also capable of simulating strategies on large-scale networks over long periods. Examples are DynusT, DYNASMART, and Cube Avenue.

In this study, a mesoscopic simulation program, Dynamic Urban Systems for Transportation (DynusT) was used to assess evacuation strategies. As a mesoscopic model, DynusT is capable of simulating a large-scale network with large demand. Vehicle positions are updated through a link-based, queue server model but not using car-following logics as in a microscopic model. That is to say, individual parameters such as headway distance or lane change behavior are not represented in the model. DynusT provides a rich description of network traffic performance but avoids individual traveler properties. The users of DynusT include government agencies such as Texas DOT, Federal Highway Administration, consulting firms like URS, PTV America, and also universities or research institutions like Arizona State University, University of British Columbia. The study areas covered North America and even some other countries (Chiu and Nave 2012). DynusT has been used in prior research to study evacuation in various regions including, Arizona (Noh et al. 2009, Zheng et al. 2010), Houston-Galveston region, Texas (Chiu et al. 2008), Jackson, Mississippi (Wang et al. 2009), Dallas, Texas

(Gao et al. 2010), Minneapolis, Minnesota (Kwon and Pitt 2005), Fort Worth, Texas (Sbayti and Mahmassani 2006), and Knox County, Tennessee (Yuan et al. 2006).

The methodological framework of DynusT is shown in Figure 2.2 (Chiu and Bustillos, 2009). First, the network is initialized with initial path assignments for each Origin-Destination (OD) pair given the time-dependent OD trip tables. In the next step, the path assignments are used to simulate traffic using an Anisotropic mesoscopic simulation model, and measures of effectiveness such as travel times and densities are obtained. If the convergence criterion is not met, the path assignments are updated for the next iteration using a gap function vehicle-based (GFV) gradient-like procedure. The vehicles are simulated again with the updated paths. This iterative procedure of path updating using GFV and simulation is repeated until the convergence criterion is met. More details on the framework are provided in Chiu and Bustillos (2009).

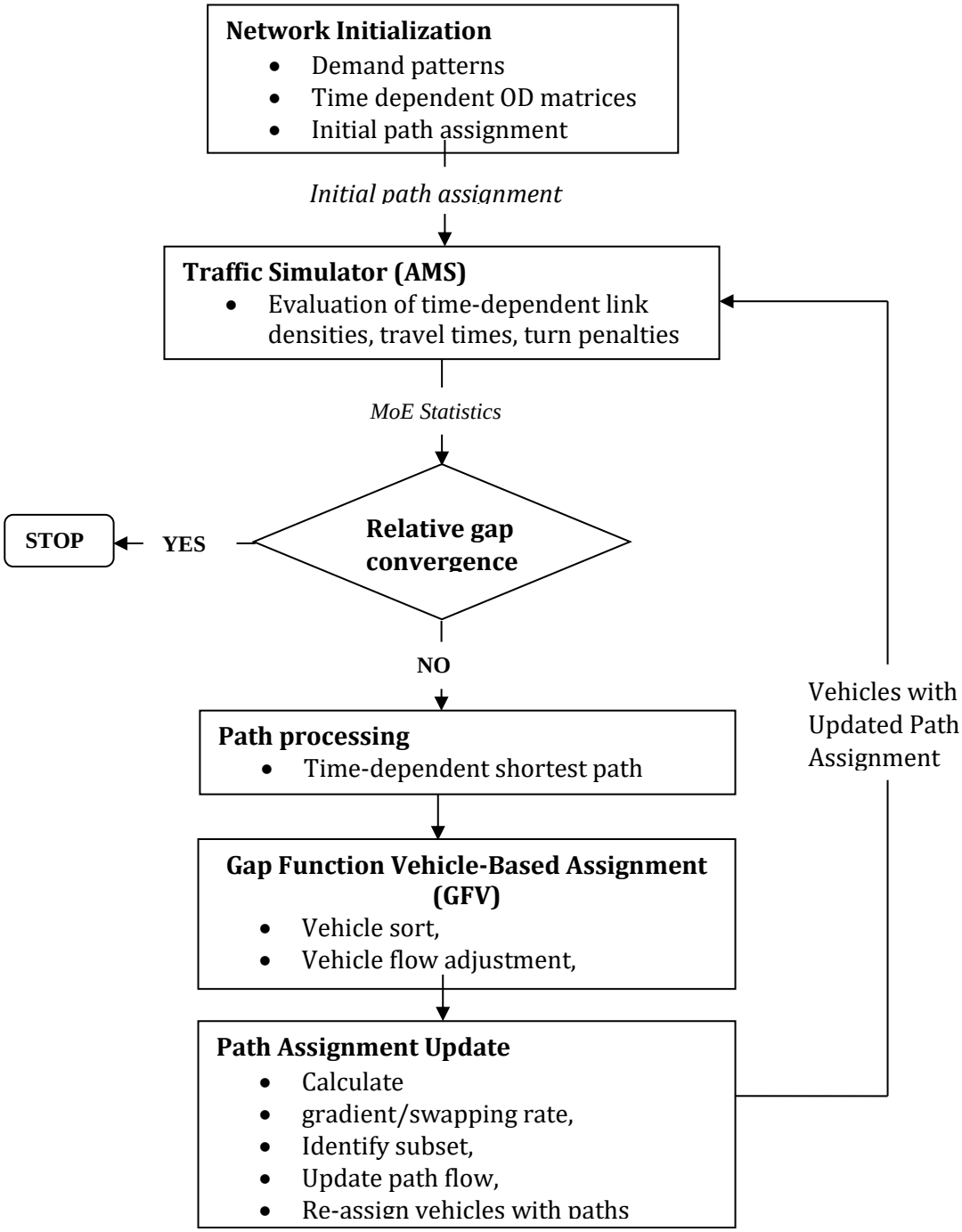


Figure 2.2. The Solution Algorithm for DynusT

(Adapted from Chiu and Bustillos, 2009)

2.2.3. Simulation Model Assumptions

In this study, the following assumptions were made in applying the mesoscopic simulation approach.

1) User-equilibrium (UE) assignment is used for route assignment unless otherwise stated. Under this assumption, each driver would choose the route that has the shortest cost. The UE conditions are assumed to occur when drivers are allowed to experiment with their paths and learn based on trial and error. However, such experimentation may not be possible for evacuation conditions since evacuation events seldom happen. Despite this limitation, UE is still commonly used in evacuation studies due to two reasons – 1) there is no other universally accepted route assignment model for evacuation, 2) the UE assignment results reliable to treat as an optimistic or best-case scenario.
2) The demand input consists only of passenger cars. Public transit, both rail and buses, and trucks are not considered in this research. Thus, evacuees using modes other than passenger cars, although important, are not within the scope of this dissertation.
3) Any existing high occupancy vehicle (HOV) lanes on freeways are treated as regular purpose lanes during evacuation. Thus, all evacuating vehicles had access to the HOV lanes.
4) During the evacuation, there is a chance that incidents, such as crashes, occur and have an impact on the evacuation. Such incidents could cause additional bottlenecks on the evacuation routes. However, this study does not model any incident effects.

5) In addition to the household survey data, information provided by a technical review panel consisting of stakeholders from state and local evacuation agencies within the study area was utilized for making assumptions in generating demand data.

2.2.4. Case study of the Hampton Roads region of Virginia

1) Previous research

Several hurricane evacuation studies were conducted for the Virginia region. The Virginia Center for Transportation Innovation and Research (VCTIR) conducted a research project in 2006 (McGhee and Grimes, 2006) that investigated the operational performance of the interstate evacuation routes described in Virginia Department of Transportation's (VDOT) then Traffic Control Plan (TCP). The evaluation found that the TCP performed well for evacuating traffic under Category 1 and 2 storm intensities. Due to the unavailability of information on background traffic, the study assumed that background traffic would not use interstate routes during evacuation conditions. For more intense storm categories, Categories 3 and 4, the TCP was found to be not as effective. The ramp closures and metering rates on open ramps alleviated congestion on the mainline but created backups on-ramps and adjacent arterial streets. The study recommended implementing lane reversal on I-64 for category 4 or higher storm intensities and strongly consider it for a Category 3 storm. When lane reversal is adopted, the authors suggested increasing the metering rates on-ramps to operate capacity on the mainline efficiently.

In a subsequent study conducted by Edara and McGhee (2008), a microscopic simulation model was developed to analyze the traffic control plan in further detail. The purpose of the study was to determine where bottlenecks might occur based on ramp loading, mainline congestion, or other operational difficulties and to provide an opportunity to address them prior to the implementation of an evacuation of the Hampton Roads region. The main distinction from the previous study (McGhee and Grimes, 2006) was the study area's scope and the inclusion of background traffic in the analysis. The study modeled all major evacuation routes (I-64, I-264, US 58, US 460, Rt. 10, Rt. 60, Rt. 17) and the collector arterials and local streets that carry traffic onto the evacuation routes in nine cities in the Hampton Roads region and the city of Richmond. The impact of evacuations that involve a lane reversal of I-64 on the Richmond region was also evaluated for varying levels of background traffic. As the final analyses were being completed in the spring of 2008, a new set of evacuation parameters were released by the USACE. These parameters had a tremendous impact on the number of evacuating vehicles under each of the storm scenarios. Therefore, the study conclusions did not
reflect the updated traffic projections. A macroscopic simulation evaluation of the Hampton Roads evacuation plan was conducted by Virginia Modeling, Analysis, and Simulation Center (VMASC) of Old Dominion University (VMASC, 2008). The main conclusions of the VMASC study were:

1) The existing emergency response plan is only useful if it goes into effect earlier than anticipated in the plan, 2) The efficient removal of affected residents from risk areas depends on

achieving a proper separation of the two evacuation phases, and 3) The effect of accidents and incidents on the total network evacuation times are not significant (5% or less); however, the effects on traffic conditions local to the incident locations can be substantial. Some of the recommendations for future research suggested in the study included: 1) Inclusion of arterial and local streets leading to the primary evacuation routes in the model, 2) Evaluation of contraflow operations using a microscopic simulation tool instead of the HCM-based analytical tool used in their study and 3) Inclusion of background traffic in regions outside of Hampton Roads to better estimate the impacts of incidents. A compromise between the detailed analysis capabilities of microscopic models and faster execution times of macroscopic models can be achieved by using a mix of macroscopic and microscopic modeling concepts. Mesoscopic models are the middle ground between microscopic and macroscopic models. These models allow for a detailed representation of vehicles (individual or group of individuals) similar to the microscopic models but update the vehicle's positions using macroscopic traffic equations. Because there are no car-following and lane-changing algorithms that need to be evaluated during every time interval, the simulations are much faster than the corresponding microscopic models. The MOEs that are generated from mesoscopic models are not as detailed as the microscopic MOEs but are usually sufficient to evaluate the traffic impacts of evacuations.

In a subsequent research project (Edara 2012), hurricane evacuation of the Hampton Roads region of Virginia was investigated using large-scale mesoscopic simulation models. Fourteen evacuation scenarios consisting of various combinations of storm categories and traffic control strategies were evaluated. Some of the scenarios were

unique and have not been evaluated in previous studies. These scenarios include US 58 lane reversal, a second crossover to the I-64 reversed lanes from I-664 and opening of Monitor-Merrimac Memorial Bridge-Tunnel (MMMBT). The primary goal of the project was to evaluate the impacts of different strategies on evacuation performance. The study area consisted of all the cities in the Hampton Roads region and the city of Richmond. The traffic volume forecasts for hurricane evacuation for the Hampton Roads region from VHES (2008) were used. The evaluation of scenarios provided information on the bottleneck locations, congestion durations, evacuation times, and clearance times. The majority of the evacuation routes send traffic to or through Richmond and the impact of this added traffic on Richmond was assessed.

The primary findings of the scenario evaluations reported in Edara and Fang (2012) include: 1) the status of MMMBT (open or close) did not have any impact on the evacuation performance in a category 1 or 2 storm evacuation. In category 3 storm evacuations, the performance improved when MMMBT was open to traffic, 2) the differences in participation rates (100% versus 70%) did not impact the clearance times in a category 1 storm evacuation. However, in a category 3 storm evacuation, the clearance times for 70% participation rate were significantly lower than those observed in 100% participation rate scenarios, 3) the I-664 crossover onto reversed lanes of I-64 did not improve the evacuation performance in terms of clearance times, average travel times, and bottleneck durations in neither category 2 nor category 3 storm evacuations. Therefore, the additional entrance to I-64 contraflow lanes did not improve the overall evacuation performance, 4) the lane reversal on US-58 did not significantly enhance evacuation performance in a category 2 storm evacuation. However, the US-58 reversal

resulted in significant improvements in both clearance times and average travel times in a category 3 storm evacuation, and 5) the clearance times, average travel times, and bottleneck durations in a category 4 storm evacuation were significantly higher than those in a category 3 evacuation.

Another recent research (Edara 2015) investigated the performance of different network treatments in incidents during hurricane evacuation in the Hampton Roads region. The major findings of the scenario evaluations reported in the Edara (2015) study include: 1) the contraflow of I-64 and US-58 improved clearance time and reduced congestion, 2) limited access US-460 highway and US-58 lane reversal plan helped network in terms of reducing clearance time, 3) the clearance times and average travel times shows that the addition of the US-58 reversal helped the overall evacuation performance during incidents.

2) Study scope

In this study, the Hampton Roads region of Virginia consisting of the following jurisdictions was modeled: York County, City of Poquoson, City of Hampton, City of Newport News, City of Portsmouth, City of Chesapeake, City of Norfolk, City of Virginia Beach, Isle of Wight County, City of Suffolk, and Surry County. When faced with a hurricane threat, the expected response of a population is determined through behavioral analysis. A combination of household surveys was used to estimate the proportions of the population that will evacuate, their possible destinations, and the extent of use of personal vehicles. Information on the type of destinations, including public shelters, homes of friends and relatives, hotels, and out-of-region destinations, were

derived from VHES (2008). The traffic volume was used to combine evacuation demand and background demand developed in VHES (2008).

Figure 2.3 shows the map of the road network modeled in DynusT. The at-risk Hampton Roads region is in the southeast portion of the map. The outbound evacuation routes carry evacuees towards Richmond (northwest) and Washington DC (north). The framework of the evacuation simulation model is shown in Figure 2.4. It consists of three phases. In phase 1, demand data is generated and coded into the simulation model. In phase 2, adjustments to the demand based on travel demand management scenarios (e.g., use of Phased evacuation strategy) are made. Network treatments such as ramp closures and contraflow lanes are implemented in Phase 3.

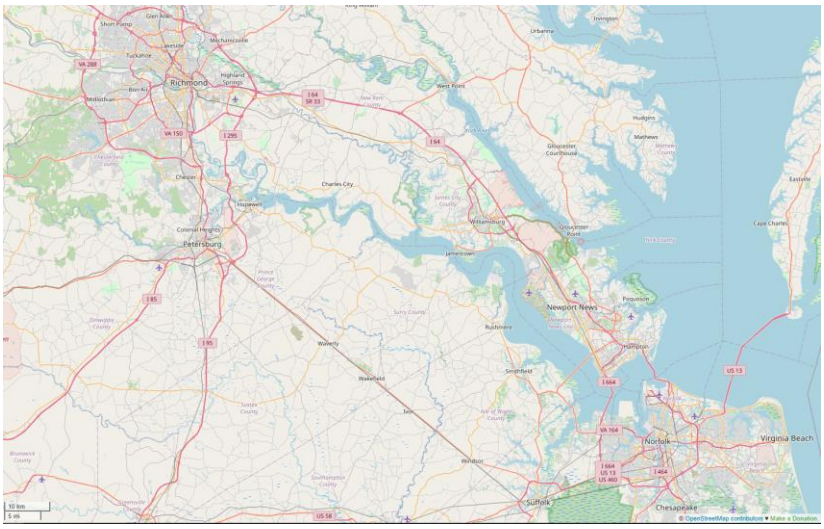


Figure 2.3. Hampton Road Region of Virginia Hurricane Evacuation Area (Sources: Open street Maps)

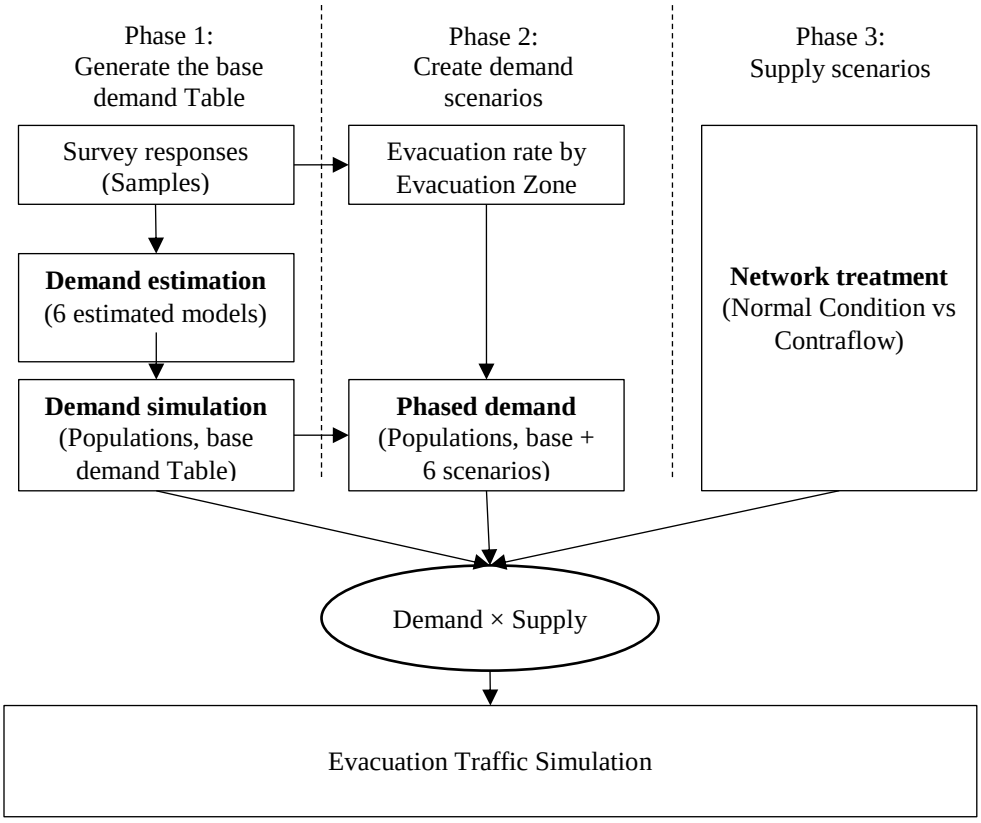


Figure 2.4. The Framework of Evacuation Simulation with Demand and Supply

2.3. Evacuation Demand

2.3.1. Traffic analysis zone

The study region was divided into evacuation zones for trip generation and distribution. The zone boundaries were obtained from the VHES study's graphics reference document (VHES, 2008). A total of 212 generation zones were created in DynusT. Some of the generation zones also serve as destination zones. Additional zones were created for evacuee destinations both inside and outside the study region. Evacuees were headed to one of the three destination types – public shelters, friends/family/hotel/motel

destinations within the Hampton Roads region (in-region trips), or destinations outside the Hampton Roads region (out-of-region trips). The total numbers of zones of each type are shown in Table 2.2. Each destination zones had a designated node for assigning trips. The location of public shelters provided by VHES (2008) study.

Table 2.2. Zones in the study region

Zones	Total number of Zones
Trip generation	212
Public Shelter	94
Friends/family/hotel/motel	43
Out-of-regions	18
Richmond background	16
Total	383

2.3.2. Generating demand

The total number of evacuees and vehicles are dispersed zone to zone by applying the socioeconomic and behavioral assumptions to the zonal data. This produces a 383x383 OD matrix consisting of two parts: the evacuation OD and the background traffic OD. Background traffic does not evacuate but is presented in the road network and adds to the traffic levels. The composition of the total demand is shown in Figure 2.5.

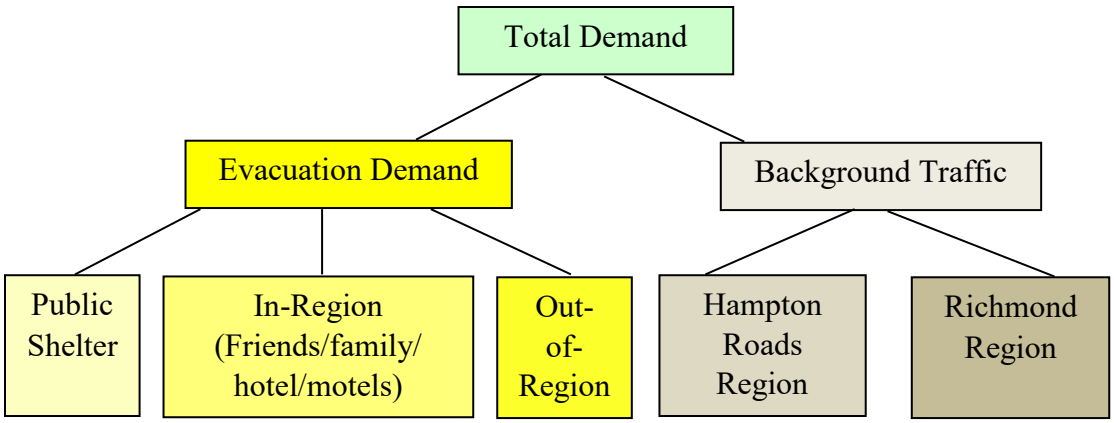


Figure 2.5. Hurricane Evacuation Demand Composition (Source: Edara and Chang, 2015)

The background traffic demand was used from the previous study (Edara and Chang, 2015). It is divided into two parts; one is for Hampton roads region, the other is around Richmond. The Hampton Roads region was generated using the regular day travel demand forecasting model. The daily OD trip Tables were extracted from VDOT's statewide travel forecasting model in the CUBE program. Trip Tables were obtained for home-based work, home-based other, and non-home-based trip types. Based on the technical review panel's recommendation, 5% of home-based work, 15% of home-based other, 10% of non-home-based trips made during a normal day in the region were used as background traffic during evacuation. For Richmond, regions were computed using traffic data obtained from VDOT's continuous count detector stations for a typical weekday by averaging data obtained for Tuesday, Wednesday, and Thursday during a week. The following stations were used: I295 near Exit 15, 9B, 49; I95 near Exit 75, 73, 69, 95; I64 near Exit 197, 205; Highway 288 west of I95, Woodridge Rd, Patterson Ave, W Broad St. This background traffic data was also used in a previous study that used microscopic simulation (Edara and McGhee 2008).

2.3.3. Demand simulation

The seven models estimated above are applied to the total population residing in the Hampton Roads area, VA. Total population data were synthesized based on the Public Use Microdata Sample (PUMS) and the American Community Survey (ACS). Synthesis means generating the entire household/population data of a region based on sampled household/population data from this region (PUMS) and data of census zones within this region (ACS) (Paul et al., 2020).

In OD matrices, each row in the Table stands for an origin, which is a census tract within the study area. Each column in the Table stands for one of the five superzone destinations. Each cell's value stands for the total amount of traffic traveling from an origin to a destination. The base demand Table is then broken into several OD matrices by conducting temporal and spatial distribution. The process is shown in Figure 2.6.

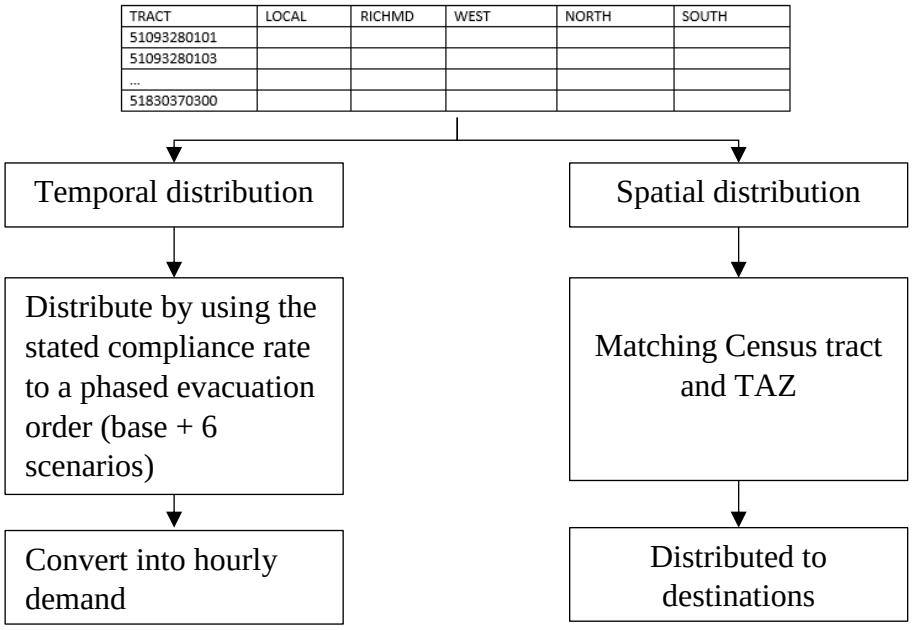


Figure 2.6. Convert Demand Table into OD Matrices

The five destination super zones are LOCAL, RICHMOND, WEST, NORTH, and SOUTH. Demand is further distributed within each destination as described below.

- Local trips are divided across four destinations - two shelters and two family/friend/hotel locations. Local trips stay within the Hampton Roads region.
- Richmond trips are distributed across three destinations within the City of Richmond.
- Trips to the South and North are destined to two locations, while the trips to West are only headed to one destination.

Temporal distribution refers to distributing the total amount of traffic from an origin to a destination by hour, which requires the estimated departure time model (which gives traffic in 6-hour intervals) and a curve fitting model (which distributes 6-hour traffic to each hour). Spatial distribution refers to distributing generated trips from temporal demands to various destinations. In this study, it means reassigning the traffic by DynusT traffic analysis zone (TAZ).

2.3.4. Phased demand

The process mentioned above gives a group of base OD matrices generated based on the estimated models. We created six additional scenarios based on the compliance rate to a phased evacuation order to compare with different scenarios. The compliance rate is from the Hampton Roads survey. Demand from the designated Evacuation Zones (A to D and Out) is distributed over time based on when each Evacuation Zone receives an evacuation

order (VDEM, 2020). Figure 2.7 shows these evacuation zones; Red area is Zone A, Orange area is Zone B, Yellow area is Zone C, and Blue area is Zone D.

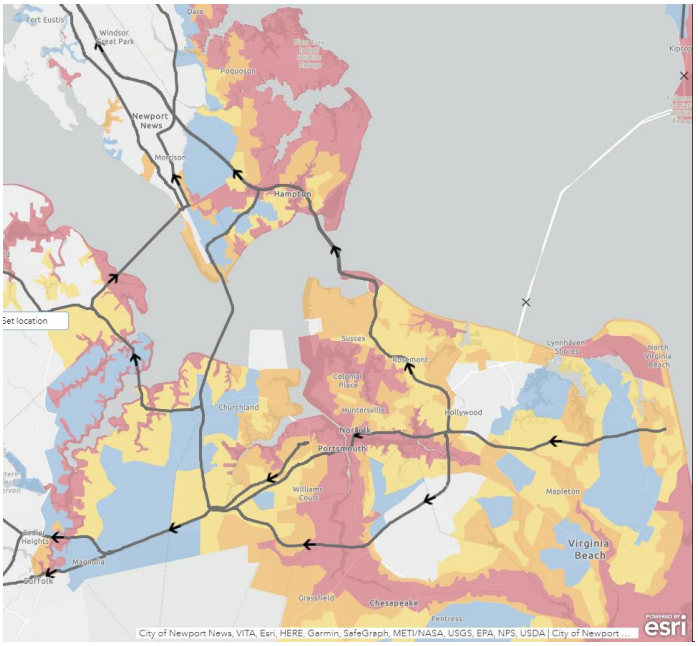


Figure 2.7. Evacuation Zone in the State of Virginia (Source: Virginia know your zone)

Based on our survey responses, we generate phased evacuation scenarios by using the following approach:

- 24.6% evacuate without considering the phased evacuation order (Note: this is the case of evacuating at respondents' own time)
- 8.6% evacuate when the first phased evacuation order is issued to a zone (Note: the first phased evacuation order is issued between 6 am and noon at 3 days before the storm landfall)
- 66.8% evacuate at (or later than) the time when a phased evacuation order is issued to the zone they reside (Note: demand is distributed across time intervals based on proportions we estimated from the survey responses)

We also assumed that a phased evacuation order is only issued between 6 am and 6 pm, allowing for daytime evacuation.

Six phased evacuation scenarios were created based on issuing evacuation orders to different evacuation zones at different times. Following is a description of each scenario.

- Scenario 1 (evacuate zones separately, 6-hour interval): each zone receives the order at different time intervals. The time between two issued orders is at least 6 hours.
- Scenario 2 (evacuate zones separately, 12-hour interval): each zone receives the order at different time intervals. The time between two issued orders is at least 12 hours.
- Scenario 3 (evacuate zone A and B together, 6-hour interval): evacuation zone A and B receive the order at the same time interval. The time between two issued orders is at least 6 hours.
- Scenario 4 (evacuate zone A and B together, 12-hour interval): evacuation zone A and B receive the order at the same time interval. The time between two issued orders is at least 12 hours.
- Scenario 5 (evacuate zone A, B, and C together, 6-hour interval): evacuation zone A, B, and C receive the order at the same time interval. The time between two issued orders is at least 6 hours.

- Scenario 6 (evacuate zone A, B, and C together, 12-hour interval): evacuation zone A, B, and C receive the order at the same time interval. The time between two issued orders is at least 12 hours.

Figure 2.8 shows the distribution of hourly traffic generated for the seven scenarios (baseline + 6 phased scenarios).

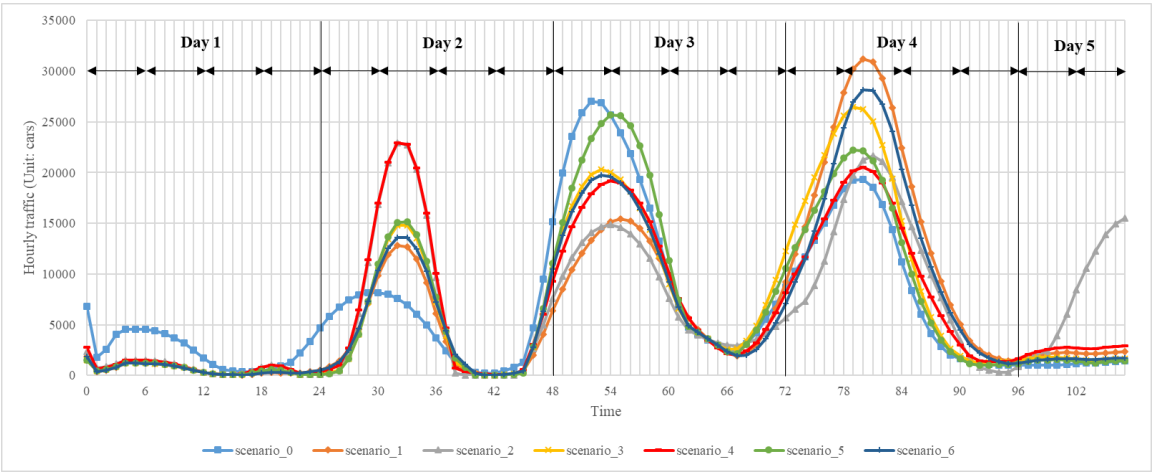


Figure 2.8. Hourly Traffic Volume for all Seven Scenarios

2.3.5. Compressed demand

The demand horizon in the previous seven scenarios was 108-hours. An additional set of scenarios when the same demand evacuates in half the time was also analyzed. The demand horizon for the compressed demand is 54-hours for each scenario. The hourly demand was created by merging the demand for successive time intervals from the 108 hour time horizon. The compressed demand is shown in Figure 2.9.

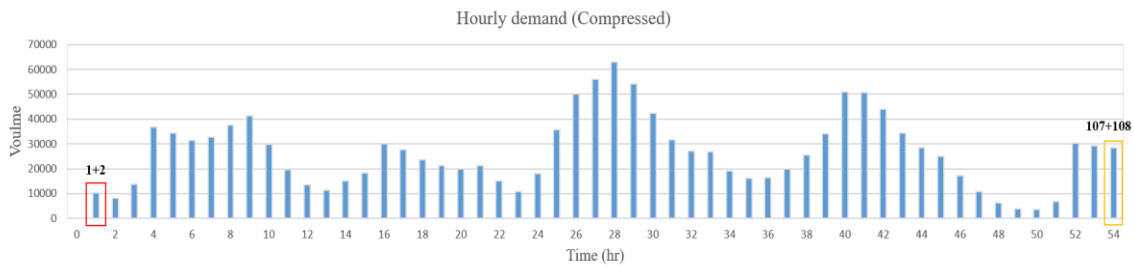
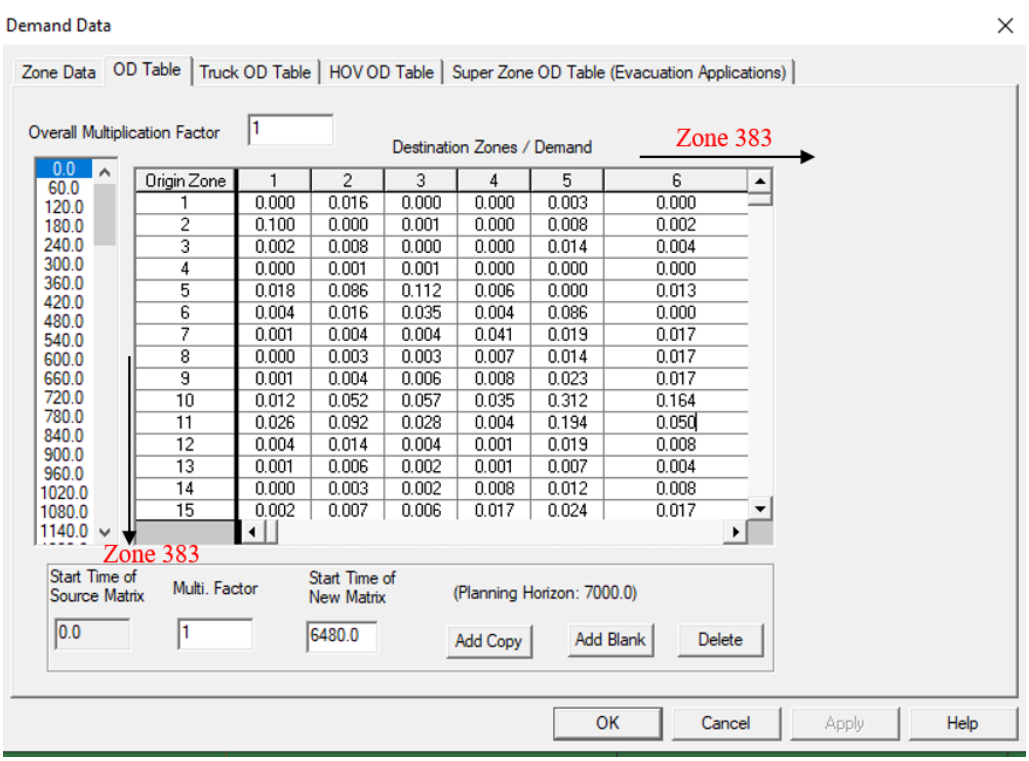


Figure 2.9. Compressed Demand Configuration

Hourly demand were generated by matching the census tract and TAZ in DynusT. US census bureau provides the Tiger/Line shapefiles compatible with GIS software, including road and census tract information. In this study, we mapped demand from 397 census tracts onto 383 zones. Figure 2.10 shows a screenshot of the OD table inputted into DynusT. The demand is entered for each hour separately for all 108 hours.



Origin Zone	1	2	3	4	5	6
1	0.000	0.016	0.000	0.000	0.003	0.000
2	0.100	0.000	0.001	0.000	0.008	0.002
3	0.002	0.008	0.000	0.000	0.014	0.004
4	0.000	0.001	0.001	0.000	0.000	0.000
5	0.018	0.086	0.112	0.006	0.000	0.013
6	0.004	0.016	0.035	0.004	0.086	0.000
7	0.001	0.004	0.004	0.041	0.019	0.017
8	0.000	0.003	0.003	0.007	0.014	0.017
9	0.001	0.004	0.006	0.008	0.023	0.017
10	0.012	0.052	0.057	0.035	0.312	0.164
11	0.026	0.092	0.028	0.004	0.194	0.050
12	0.004	0.014	0.004	0.001	0.019	0.008
13	0.001	0.006	0.002	0.001	0.007	0.004
14	0.000	0.003	0.002	0.008	0.012	0.008
15	0.002	0.007	0.006	0.017	0.024	0.017

Figure 2.10. Demand Table for Evacuation Simulation

2.4. Network Treatment

Three road network treatments were evaluated using the previously discussed demand scenarios. These treatments are shown in Table 2.3. In Network X, there is no lane reversal or ramp closure. In Network Y, I-64 contraflow lanes start near 4th View St. Interchange and terminate near the I-295 interchange in Richmond. The contraflow lanes of I-64 can only be accessed using one entry point (i.e. near 4th view St); no other intermediate crossover locations were available (i.e. I-664 crossover). The MMMBT was open to traffic in all three treatments. In Network Z, contraflow lanes were also operational for US-58 in addition to I-64. VDOT Eastern Region provided detailed traffic control plan including the entrances, termination, and other ramp closure information. Figure 2.11 shows a map that describes the limits of I-64 lane reversal plan. Figure 2.12 shows a US 58 lane reversal plan map, including the two entrances and one termination location. For calibration of network model, the link parameters optimized for the same network in a previous study (Edara and Chang, 2015) were used. These parameters included speed limit, saturation flow, and the traffic flow model.

Table 2.3. Network treatments evaluated in this study

Network	Traffic Control
X	No Reversal in the entire network
Y	I-64 Reversal without I-664 crossover, MMMBT open
Z	I-64 Reversal without I-664 crossover, MMMBT open, US 58 reversal

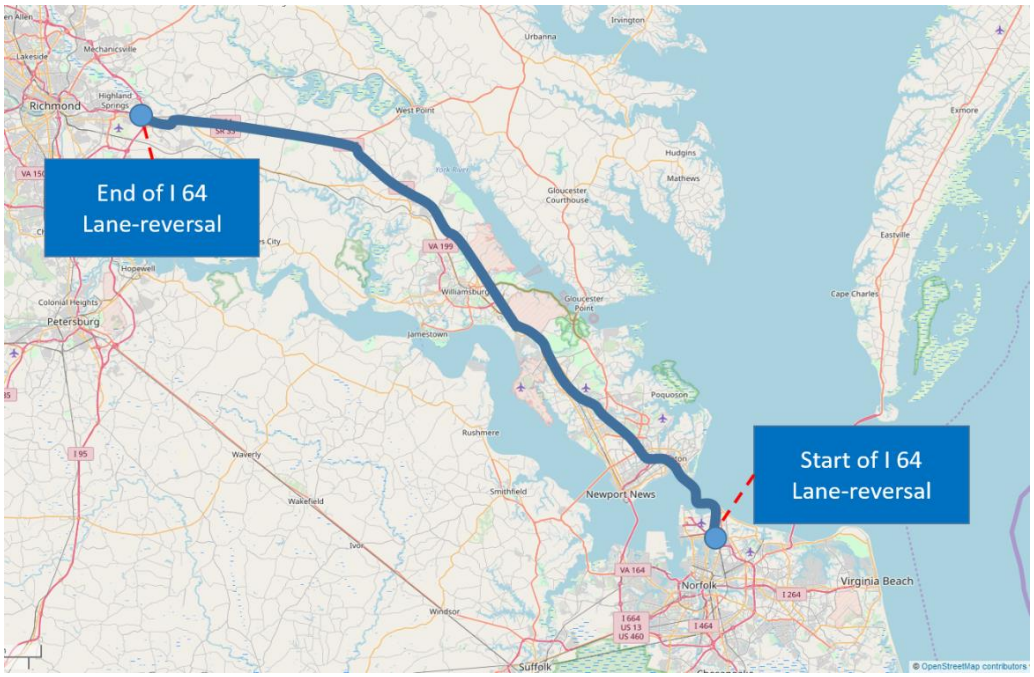


Figure 2.11. I-64 Reversal Plan in Network Y (source: OpensteetMap)

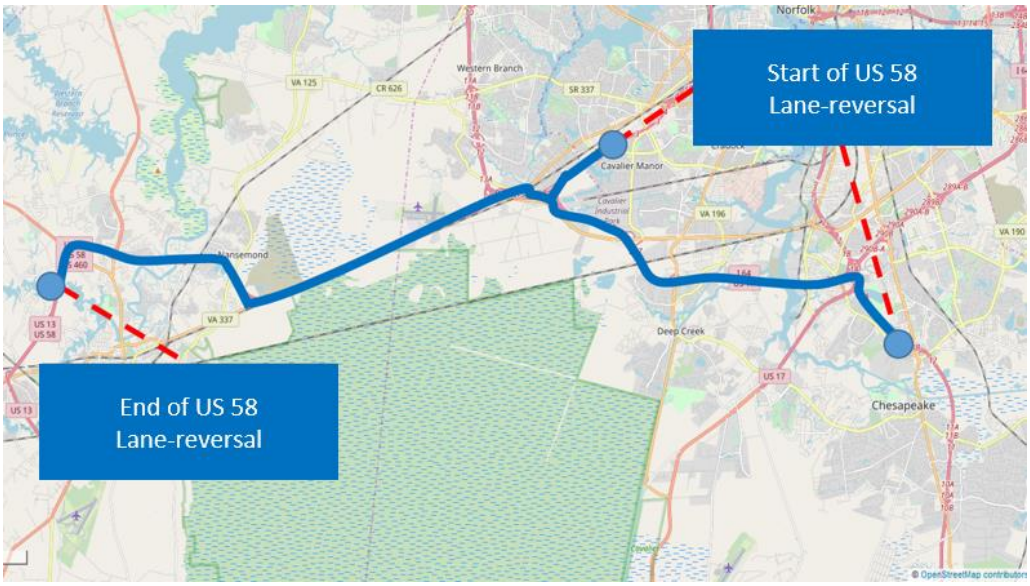


Figure 2.12. US 58 Reversal Plan in Network Z (source: OpensteetMap)

2.5. Simulation Scenarios

The seven demand scenarios and three network treatments resulted in 21 unique simulation scenarios. The compressed demand added another 21 scenarios that were evaluated. Each scenario was simulated in DynusT using the iterative assignment method for reaching the User-Equilibrium condition. Several measures of effectiveness were derived for each scenario from the simulation model. In evacuation studies, clearance time for a given evacuation route at a specified location indicates the time at which the last vehicle using the route has cleared the location. Figure 2.13 shows the selected locations of designated routes from the VHES (2008) study. We compared the evacuation volume and clearance time between different networks with several demand scenarios based on the selected location by each routes. For example, evaluating the percent change of evacuating volume between Network X and Network Y was calculated as follows equation 2.1:

$$\Delta V_i = \{\frac{(Volume\ at\ location\ i\ in\ Network\ Y - Volume\ at\ location\ i\ in\ Network\ X)}{Volume\ at\ location\ i\ in\ Network\ X} \times 100\} \qquad (2.1)$$

Similarly, the percentage difference in clearance time, ΔCT_i, for a location i was calculated as shown in equation 2.2:

$$\Delta CT_i = \{\frac{(Clearance\ time\ at\ location\ i\ in\ Network\ Y - Clearance\ time\ at\ location\ i\ in\ Network\ X)}{Clearance\ time\ at\ location\ i\ in\ Network\ X} \times 100\} \qquad (2.2)$$

Along with the clearance times, the total numbers of vehicles using the evacuation routes were also determined. Network-level measures such as average travel time and average stop time were also extracted from the simulation.

Figure 2.13. Measurement Locations for Evacuating Volumes and Clearance Times

2.6. Evaluation

2.6.1. Standard demand scenarios

1) Network-level measurement

In standard demand scenarios, the simulation time horizon was set to 10,000 minutes for 108 hours of demand to allow sufficient time for all vehicles to reach safety. For

evaluating network-level performance, we extracted average travel time and average stop time for each scenario for all vehicles. The average travel time and stop time for the standard demand scenarios are shown in Tables 2.4 and 2.5. The results showed that scenario 2 (phased evacuation with 12-hour interval) outperformed other scenarios, whereas scenario 1 (phased evacuation with 6-hour interval) performed the worst. For the comparison of network treatments, Network Y produced better outcomes than X. There was little difference in average travel times (and stop times) between Network Y and Z.

Table 2.4. Average travel time for standard demand scenarios (Unit: Minute)

Network	Scenario Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
X	98.69	113.25	83.57	96.63	86.92	102.77	99.57
Y	84.83	99.23	77.13	86.08	78.22	86.84	87.79
Z	84.92	98.93	77.55	86.57	78.66	86.87	88.73

Table 2.5. Average stop time for standard demand scenarios (Unit: Minute)

Network	Scenario Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
X	18.54	25.51	5.6	11.91	7.72	19.31	12.68
Y	5.55	14	2.76	5.68	3.06	6.02	6.29
Z	5.85	13.9	2.85	6.16	3.58	5.93	7.1

2) Evaluating evacuation volumes and clearance time

Evacuating volumes were extracted from vehicle trajectory data. Table 2.6 presents the evacuation volume of several evacuation routes for each scenario. In Network X, there are no evacuating vehicles in I-64 reversal lane due to no traffic controls.

Table 2.6. Evacuating vehicles for the standard demand scenarios

Evacuating Vehicles								
Scenario	Network	Location						
		I64REG	I64REV	US60	RT10	US460	US58	US17
Base	X	238,369	NA	80,364	59,119	73,747	48,070	76,337
	Y	202,491	78,637	68,283	57,760	44,342	45,324	76,264
	Z	202,552	75,383	68,856	59,834	44,883	47,500	76,414
1	X	238,546	NA	79,282	63,041	68,228	59,184	76,596
	Y	186,711	92,037	66,966	61,064	49,032	54,364	77,395
	Z	194,090	92,890	59,153	58,537	49,813	55,558	76,453
2	X	239,309	NA	88,410	65,357	58,363	48,056	76,891
	Y	205,343	86,187	68,284	58,969	33,761	43,032	77,073
	Z	204,388	86,913	69,907	57,093	35,004	42,820	76,641
3	X	225,361	NA	83,193	61,530	73,687	59,728	76,435
	Y	192,412	87,779	64,032	54,287	51,331	51,946	76,971
	Z	186,448	89,634	69,396	55,880	50,317	49,497	76,146
4	X	229,047	NA	82,440	63,941	73,826	53,487	76,625
	Y	198,107	90,065	72,541	56,934	34,291	42,905	76,353
	Z	192,222	92,090	75,813	57,291	34,660	42,676	76,573
5	X	217,493	NA	87,648	61,727	82,262	56,451	76,738
	Y	189,987	88,102	69,505	54,422	47,634	50,039	76,727
	Z	191,427	87,006	66,779	53,714	50,646	51,428	76,950
6	X	224,672	NA	78,899	62,516	75,925	61,028	76,883
	Y	186,531	88,708	67,273	55,246	50,886	52,713	76,696
	Z	185,926	91,410	66,339	55,698	50,310	50,444	76,520

a. Comparison of evacuating vehicles by route of each scenario

Table 2.7 shows the percentage difference in the total number of evacuating vehicles between Network X and Y for all demand scenarios. Evacuation volumes on US 460, I-64 Regular, and US60 decreased. Table 2.8 shows the comparison between Networks X and Z. Evacuation volumes on US 460, I-64 Regular, and US60 all decreased. Only minor percentage differences were observed between Network Y and Z as shown in Table 2.9, thus, implying only a minor improvement due to the addition of US 58 lane reversal in Network Z.

Table 2.7. Percentage differences of evacuating vehicles between Network X and Y (standard demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I-64	17.9%	16.9%	21.8%	24.3%	25.8%	27.9%	22.5%
US60	-15.0%	-15.5%	-22.8%	-23.0%	-12.0%	-20.7%	-14.7%
RT10	-2.3%	-3.1%	-9.8%	-11.8%	-11.0%	-11.8%	-11.6%
US460	-39.9%	-28.1%	-42.2%	-30.3%	-53.6%	-42.1%	-33.0%
US58	-5.7%	-8.1%	-10.5%	-13.0%	-19.8%	-11.4%	-13.6%
US17	-0.1%	1.0%	0.2%	0.7%	-0.4%	0.0%	-0.2%

Table 2.8. Percentage differences of evacuating vehicles between Network X and Z (standard demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I-64	16.6%	20.3%	21.7%	22.5%	24.1%	28.0%	23.4%
US60	-14.3%	-25.4%	-20.9%	-16.6%	-8.0%	-23.8%	-15.9%
RT10	1.2%	-7.1%	-12.6%	-9.2%	-10.4%	-13.0%	-10.9%
US460	-39.1%	-27.0%	-40.0%	-31.7%	-53.1%	-38.4%	-33.7%
US58	-1.2%	-6.1%	-10.9%	-17.1%	-20.2%	-8.9%	-17.3%
US17	0.1%	-0.2%	-0.3%	-0.4%	-0.1%	0.3%	-0.5%

Table 2.9. Percentage differences of evacuating vehicles between Network Y and Z (standard demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	0.0%	0.0%	-0.2%	0.1%	0.1%	0.1%	0.1%
I64REV	0.3%	-2.4%	-0.1%	0.0%	-0.8%	0.2%	-0.1%
US60	-0.6%	0.5%	0.6%	0.0%	0.2%	0.0%	0.3%
RT10	0.5%	-0.1%	0.1%	0.2%	0.0%	-0.2%	0.0%
US460	0.0%	1.2%	-0.1%	0.6%	0.9%	0.0%	0.0%
US58	0.8%	-0.5%	0.0%	0.4%	-0.3%	0.5%	1.4%
US17	-0.4%	0.0%	0.0%	0.6%	0.0%	0.2%	-0.4%

b. Comparison of clearance times on evacuation routes of each scenario

The comparison of clearance times between networks X and Y, X and Z, and Y and Z are shown in Tables 2.10. Table 2.11, Figure 2.14, and Figure 2.15 indicate the percentage differences of clearance time between Network X and Y. Specifically; scenario 1 showed the reduction of clearance time on US 60 and US 460 with Network Y than X.

Table 2.12, Figure 2.16, and 2.17 show the percentage differences of clearance time between Network X and Z. Again; scenario 1 discovered the reduction of clearance time on US 60 with Network Z than X.

Table 2.13, Figure 2.18, and Figure 2.19 indicate the percentage differences of clearance time between Network Y and Z. I64 reversal lane improved clearance time with Network Z than Y.

Table 2.10. Clearance times for the standard demand scenarios

Clearance Times (Hours)								
Scenario	Network	Location						
		I64REG	I64REV	US60	RT10	US460	US58	US17
Base	X	104.39	NA	101.62	98.88	86.41	89.44	96.11
	Y	104.75	89.47	102.8	98.62	87.08	89.38	95.26
	Z	104.78	89.71	102.17	99.13	87.06	90.06	94.89
1	X	105.84	NA	107.09	105.86	94.17	94.99	101.94
	Y	105.75	98.32	104.04	105.85	91.95	95.62	101.95
	Z	105.73	96.01	104.56	105.71	93.03	95.12	102
2	X	108.91	NA	108.39	108.76	108.85	108.93	107.86
	Y	108.38	108.93	108	108.73	108.87	109	107.8
	Z	108.16	108.84	108.6	108.86	108.79	109.02	107.79
3	X	104.92	NA	102	102.68	89.65	90.69	99.92
	Y	105.25	90.41	103.29	103.9	88.71	91.87	99.38
	Z	105.32	90.44	103.24	104.15	89.24	92.23	100
4	X	105.97	NA	103.48	106.73	88.73	99.24	102.93
	Y	105.93	101.68	103.67	106.96	91.79	100.56	103.37
	Z	106.03	100.89	103.93	106.99	92.57	100.24	103.35
5	X	104.85	NA	101.59	100.94	88.14	89.61	98.29
	Y	105	89.48	102.87	102.53	87.68	89.75	98
	Z	105.11	89.66	102.83	102.28	87.69	90.22	98.18
6	X	105.07	NA	101.55	102.96	91.74	93.7	99.58
	Y	105.29	92.04	103.41	103.88	91.27	92.51	99.82
	Z	105.38	91.95	103.74	103.83	91.23	93.76	99.45

Table 2.11. Percentage differences of clearance time between Network X and Y (standard demand)

Scenario /Route	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	0.4%	-0.1%	-0.5%	0.3%	0.0%	0.1%	0.2%
US60	1.2%	-2.9%	-0.4%	1.3%	0.2%	1.3%	1.8%
RT10	-0.3%	0.0%	0.0%	1.2%	0.2%	1.6%	0.9%
US460	0.8%	-2.4%	0.0%	-1.0%	3.5%	-0.5%	-0.5%
US58	-0.1%	0.7%	0.1%	1.3%	1.3%	0.2%	-1.3%
US17	-0.9%	0.0%	-0.1%	-0.5%	0.4%	-0.3%	0.2%

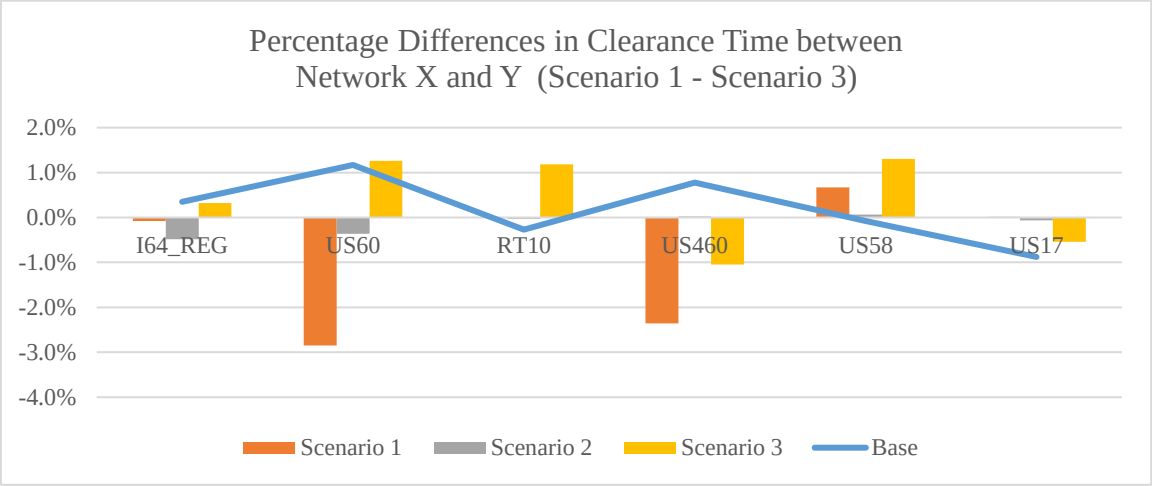


Figure 2.14. Percentage Differences in Clearance Time between Network X and Y (Standard, Scenario 1 to 3)

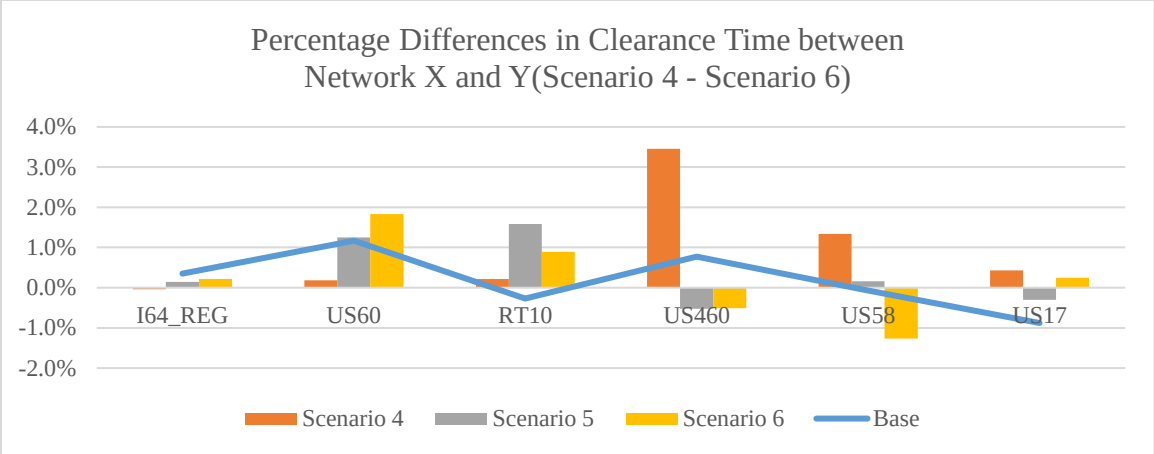


Figure 2.15. Percentage Differences in Clearance Time between Network X and Y (Standard, Scenario 4 to 6)

Table 2.12. Percentage differences of clearance time between Network X and Z (standard demand)

Scenario /Route	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	0.4%	-0.1%	-0.7%	0.4%	0.1%	0.3%	0.3%
US60	0.5%	-2.4%	0.2%	1.2%	0.4%	1.2%	2.2%
RT10	0.2%	-0.1%	0.1%	1.4%	0.2%	1.3%	0.9%
US460	0.7%	-1.2%	0.0%	-0.5%	4.3%	-0.5%	-0.6%
US58	0.7%	0.1%	0.1%	1.7%	1.0%	0.7%	0.1%
US17	-1.3%	0.1%	-0.1%	0.1%	0.4%	-0.1%	-0.1%

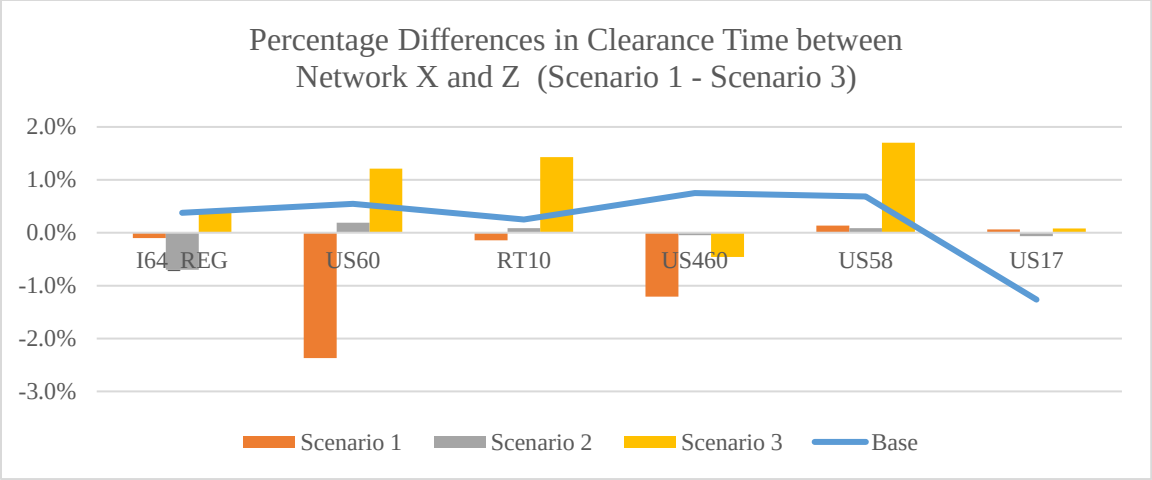


Figure 2.16. Percentage Differences in Clearance Time between Network X and Z

(Standard, Scenario 1 to 3)

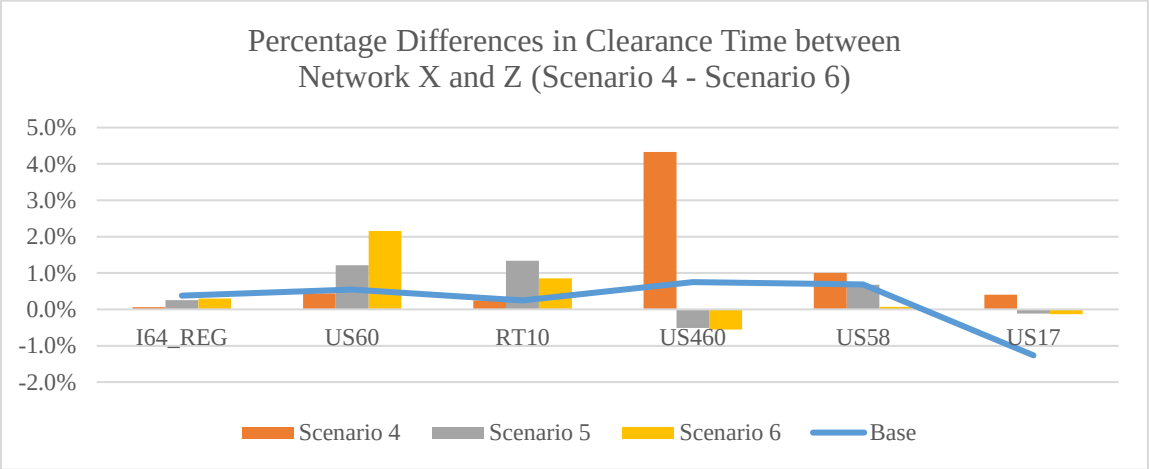


Figure 2.17. Percentage Differences in Clearance Time between Network X and Z

(Standard, Scenario 4 to 6)

Table 2.13. Percentage differences of clearance time between Network Y and Z (standard demand)

Scenario /Route	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	0.0%	0.0%	-0.2%	0.1%	0.1%	0.1%	0.1%
I64REV	0.3%	-2.4%	-0.1%	0.0%	-0.8%	0.2%	-0.1%
US60	-0.6%	0.5%	0.6%	0.0%	0.2%	0.0%	0.3%
RT10	0.5%	-0.1%	0.1%	0.2%	0.0%	-0.2%	0.0%
US460	0.0%	1.2%	-0.1%	0.6%	0.9%	0.0%	0.0%
US58	0.8%	-0.5%	0.0%	0.4%	-0.3%	0.5%	1.4%
US17	-0.4%	0.0%	0.0%	0.6%	0.0%	0.2%	-0.4%

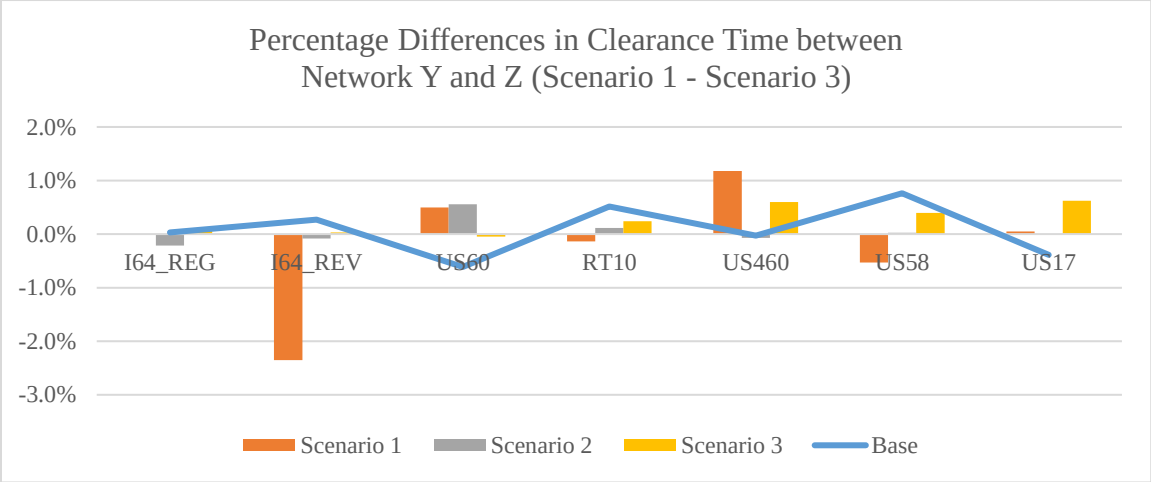


Figure 2.18. Percentage Differences in Clearance Time between Network Y and Z (Standard, Scenario 1 to 3)

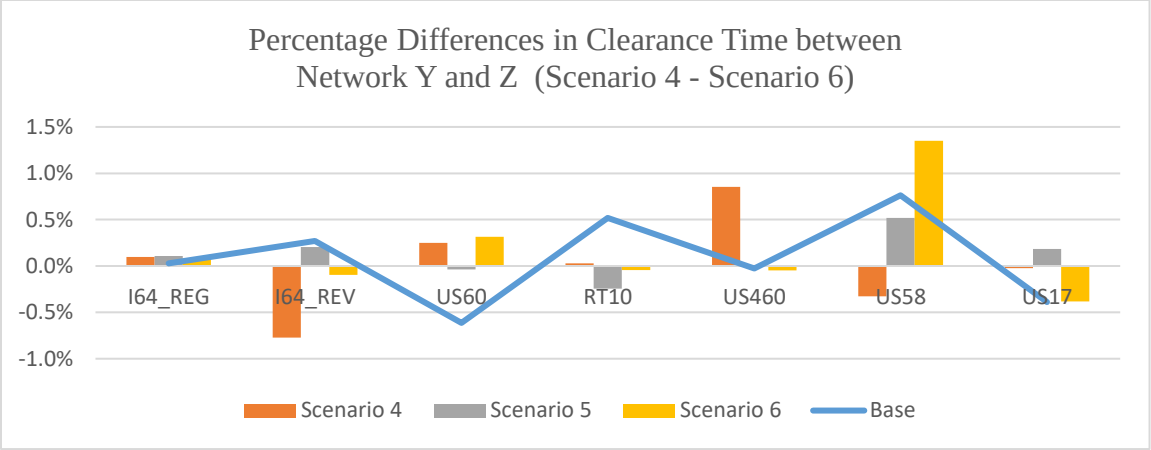


Figure 2.19. Percentage Differences in Clearance Time between Network Y and Z (Standard, Scenario 4 to 6)

2.6.2. Compressed demand scenarios

1) Network-level measurement

In compressed demand scenarios, the simulation time horizon was set to 7,000 minutes for 54 hours of demand loading. The same performance measures used for the 108-hour demand profile were also used for the compressed demand scenarios. For evaluating network-level performance, average travel time and average stop time are reported in Tables 2.14 and 2.15. The results showed that scenario 2 (phased evacuation with 12-hour interval) performed the best. For the comparison of network treatments, Network Y produced better outcomes than X except in scenario 1. Once again, only minor differences were observed between the performance of network Y and Z.

Table 2.14. Average travel time for compressed demand scenarios (Units: Minute)

Network	Scenario Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
X	236.66	228.69	182.58	262.14	223.29	235.38	236.76
Y	201.6	241.53	153.2	206.93	200.48	207.71	199.14
Z	239.41	213.9	185.93	217.28	213.06	239.46	205.29

Table 2.15. Average stop time for compressed demand scenarios (Unit: Minute)

Network	Scenario Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
X	121.55	108.89	76.06	135.5	100.07	113.97	113.53
Y	83.4	120.24	44.77	87.48	80.68	89.07	76.91
Z	112.54	94.56	77.92	95.77	91.93	119.22	83.56

2) Evaluating evacuation volumes and clearance time

Evacuating volumes of compressed demand scenarios were also extracted from vehicle trajectory data. Table 2.16 shows the evacuation volume of several routes for each scenario.

Table 2.16. Evacuating vehicles for the compressed demand scenarios

Scenario	Network	Location						
		I64REG	I64REV	US60	RT10	US460	US58	US17
Base	X	186,351	NA	92,528	57,617	94,252	71,078	76,708
	Y	169,207	73,558	67,441	47,638	86,348	64,570	76,329
	Z	166,728	79,013	67,724	48,526	72,338	69,373	76,251
1	X	190,234	NA	87,448	51,285	120,521	64,470	76,625
	Y	175,729	82,648	60,284	54,524	84,084	59,810	76,783
	Z	196,008	80,511	55,760	46,328	77,258	56,767	76,378
2	X	178,460	NA	88,781	46,928	133,769	62,310	76,583
	Y	180,377	77,437	61,703	56,375	74,459	54,881	76,765
	Z	171,331	83,796	75,736	45,377	74,175	58,027	76,477
3	X	204,462	NA	65,334	45,271	121,866	68,969	76,213
	Y	178,866	87,226	59,572	52,892	74,938	60,467	76,171
	Z	176,452	95,996	60,815	46,408	75,587	60,731	76,317
4	X	210,706	NA	82,791	53,370	108,252	62,884	76,278
	Y	173,133	86,198	62,885	52,387	80,153	57,124	76,601
	Z	183,074	83,482	56,924	50,124	82,558	59,073	76,663
5	X	227,133	NA	62,625	44,934	118,419	65,242	76,192
	Y	175,342	84,765	57,178	60,314	75,602	60,337	76,813
	Z	167,478	82,512	64,900	55,010	79,307	65,309	76,616
6	X	200,323	NA	73,648	47,689	127,591	65,518	76,560
	Y	179,967	90,621	60,009	46,454	81,531	56,388	77,216
	Z	176,837	88,313	61,882	49,882	76,536	63,652	76,739

a. Network comparison of evacuating vehicles of each scenario

Percentage differences in evacuating vehicles between network pairs are reported in this section. Table 2.17 compares networks X and Y, Table 2.18 compares networks X and Z, and Table 2.19 compares networks Y and Z. Evacuation volumes on US 460, I-64 Regular, and US60 were lower in networks Y and Z than in network X. This relief comes from the addition of extra capacity in the form of contraflow lanes in the network Y and

Z. Between networks Y and Z, with the exception of scenario 1, the usage of US 58 and US 60 increased in network Z due to the implementation of contraflow lanes on US 58.

Table 2.17. Percentage differences of evacuating vehicles between Network X and Y (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	-9.2%	-7.6%	1.1%	-12.5%	-17.8%	-22.8%	-10.2%
US60	-27.1%	-31.1%	-30.5%	-8.8%	-24.0%	-8.7%	-18.5%
RT10	-17.3%	6.3%	20.1%	16.8%	-1.8%	34.2%	-2.6%
US460	-8.4%	-30.2%	-44.3%	-38.5%	-26.0%	-36.2%	-36.1%
US58	-9.2%	-7.2%	-11.9%	-12.3%	-9.2%	-7.5%	-13.9%
US17	-0.5%	0.2%	0.2%	-0.1%	0.4%	0.8%	0.9%

Table 2.18. Percentage differences of evacuating vehicles between Network X and Z (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	-10.5%	3.0%	-4.0%	-13.7%	-13.1%	-26.3%	-11.7%
US60	-26.8%	-36.2%	-14.7%	-6.9%	-31.2%	3.6%	-16.0%
RT10	-15.8%	-9.7%	-3.3%	2.5%	-6.1%	22.4%	4.6%
US460	-23.3%	-35.9%	-44.5%	-38.0%	-23.7%	-33.0%	-40.0%
US58	-2.4%	-11.9%	-6.9%	-11.9%	-6.1%	0.1%	-2.8%
US17	-0.6%	-0.3%	-0.1%	0.1%	0.5%	0.6%	0.2%

Table 2.19. Percentage differences of evacuating vehicles between Network Y and Z (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	-1.5%	11.5%	-5.0%	-1.3%	5.7%	-4.5%	-1.7%
I64REV	7.4%	-2.6%	8.2%	10.1%	-3.2%	-2.7%	-2.5%
US60	0.4%	-7.5%	22.7%	2.1%	-9.5%	13.5%	3.1%
RT10	1.9%	-15.0%	-19.5%	-12.3%	-4.3%	-8.8%	7.4%
US460	-16.2%	-8.1%	-0.4%	0.9%	3.0%	4.9%	-6.1%
US58	7.4%	-5.1%	5.7%	0.4%	3.4%	8.2%	12.9%
US17	-0.1%	-0.5%	-0.4%	0.2%	0.1%	-0.3%	-0.6%

b. Comparison of clearance times of each scenario

The changes in clearance times between different network pairs are shown in Tables 2.20.

Table 2.21, Figure 2.20, and Figure 2.21 present the percentage difference of clearance time between network X and Y. The results present that clearance time improved on Scenario 2 and 3 with major routes (I64, US60, and US460).

Similarly, Table 2.22, Figure 2.22, and Figure 2.23 show the percentage difference of clearance time between network X and Z. The results indicate that clearance time reduced with several scenarios on US460 and US58.

Lastly, Table 2.23, Figure 2.24, and Figure 2.25 present the percentage difference of clearance time between network Y and Z. The results reveal no considerable difference between network Y and Z; however, clearance time reduced US60 and US58 with Scenario 1.

Table 2.20. Clearance times for the compressed demand scenarios

Clearance Times (Hours)								
Scenario	Network	Location						
		I64REG	I64REV	US60	RT10	US460	US58	US17
Base	X	56.76	-	65.35	59.27	57.52	57.51	49.66
	Y	55.27	49.22	58.99	52.62	52.35	51.27	50.29
	Z	58.14	49.64	61.93	55.38	50	48.62	49.4
1	X	63.77	-	78.07	59.68	66.64	60.57	53.16
	Y	61.62	54.73	70.37	60.34	55.76	56.82	52.56
	Z	66.25	53.35	65.34	55.15	54.17	53.46	53.12
2	X	57.33	-	98.2	57.55	64.3	62.96	57.82
	Y	58.15	55.99	55.03	62.19	55.32	57.49	55.53
	Z	58.5	56.44	97.78	57.86	54.77	56.04	56.46
3	X	103.56	-	65.63	62.57	70.02	65.29	53.91
	Y	61.85	58.19	59.99	57.91	55.47	54.1	53.24
	Z	73.44	58.25	67.63	56.13	54.03	54.06	52.42
4	X	62.58	-	87.44	60.61	62.7	59.36	54.54
	Y	60.79	58.25	63.33	59.43	56.99	57.8	52.5
	Z	61.6	55.94	67.93	56.85	58.11	54.28	52.71
5	X	75.72	-	58.66	63.37	63.41	58.42	54.19
	Y	61.41	56.72	62.01	64.11	55.69	55.28	52.51
	Z	62.94	55.77	64.69	60.39	56.47	54.84	52.32
6	X	60.88	-	58.68	63.59	64.98	59.23	53.49
	Y	61.17	59.37	61.14	56.05	56.01	54.99	52.71
	Z	62.67	58.21	64.24	55.92	53.74	53.1	53.24

Table 2.21. Percentage differences of clearance time between Network X and Y (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	-2.6%	-3.4%	1.4%	-40.3%	-2.9%	-18.9%	0.5%
US60	-9.7%	-9.9%	-44.0%	-8.6%	-27.6%	5.7%	4.2%
RT10	-11.2%	1.1%	8.1%	-7.4%	-1.9%	1.2%	-11.9%
US460	-9.0%	-16.3%	-14.0%	-20.8%	-9.1%	-12.2%	-13.8%
US58	-10.9%	-6.2%	-8.7%	-17.1%	-2.6%	-5.4%	-7.2%
US17	1.3%	-1.1%	-4.0%	-1.2%	-3.7%	-3.1%	-1.5%

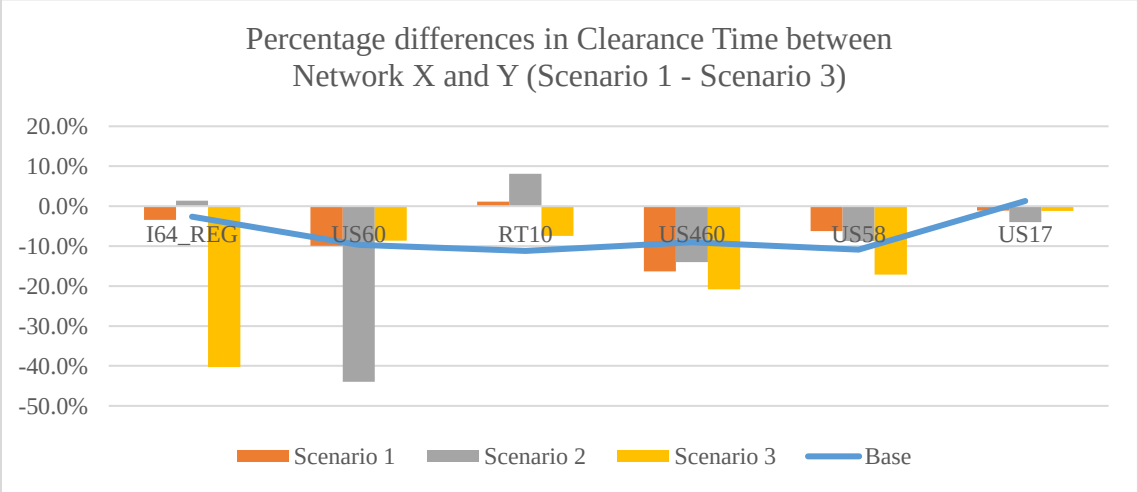


Figure 2.20. Percentage Differences in Clearance Time between Network X and Y (Compressed, Scenario 1 to 3)

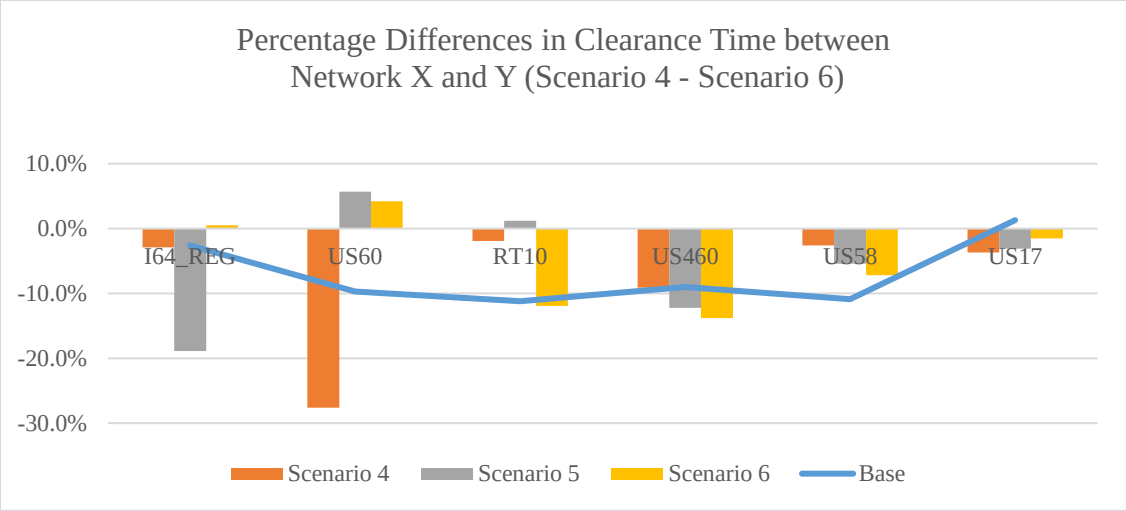


Figure 2.21. Percentage Differences in Clearance Time between Network X and Y (Compressed, Scenario 4 to 6)

Table 2.22. Percentage differences of clearance time between Network X and Z (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	2.4%	3.9%	2.0%	-29.1%	-1.6%	-16.9%	2.9%
US60	-5.2%	-16.3%	-0.4%	3.0%	-22.3%	10.3%	9.5%
RT10	-6.6%	-7.6%	0.5%	-10.3%	-6.2%	-4.7%	-12.1%
US460	-13.1%	-18.7%	-14.8%	-22.8%	-7.3%	-10.9%	-17.3%
US58	-15.5%	-11.7%	-11.0%	-17.2%	-8.6%	-6.1%	-10.3%
US17	-0.5%	-0.1%	-2.4%	-2.8%	-3.4%	-3.5%	-0.5%

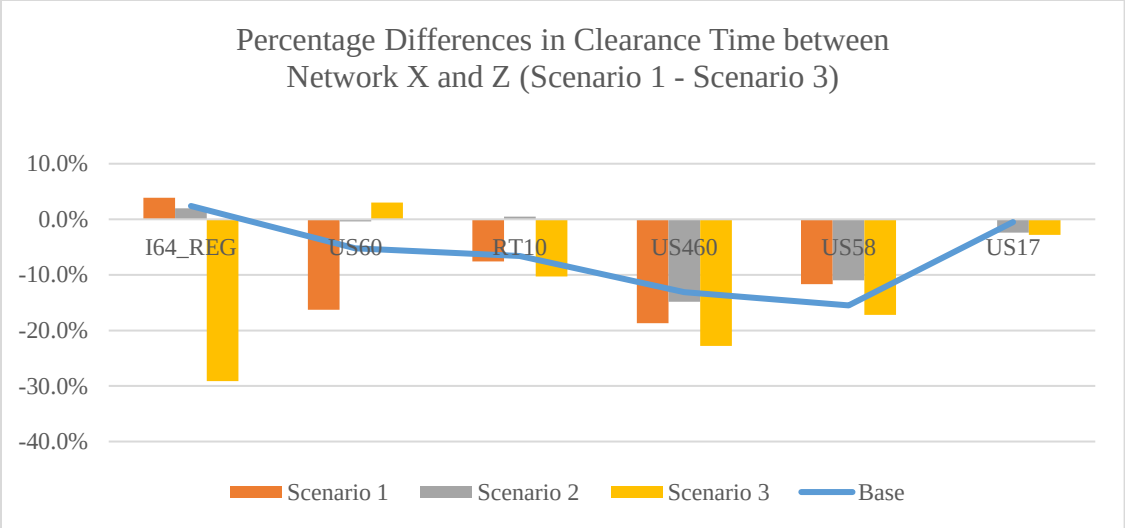


Figure 2.22. Percentage Differences in Clearance Time between Network X and Z

(Compressed, Scenario 1 to 3)

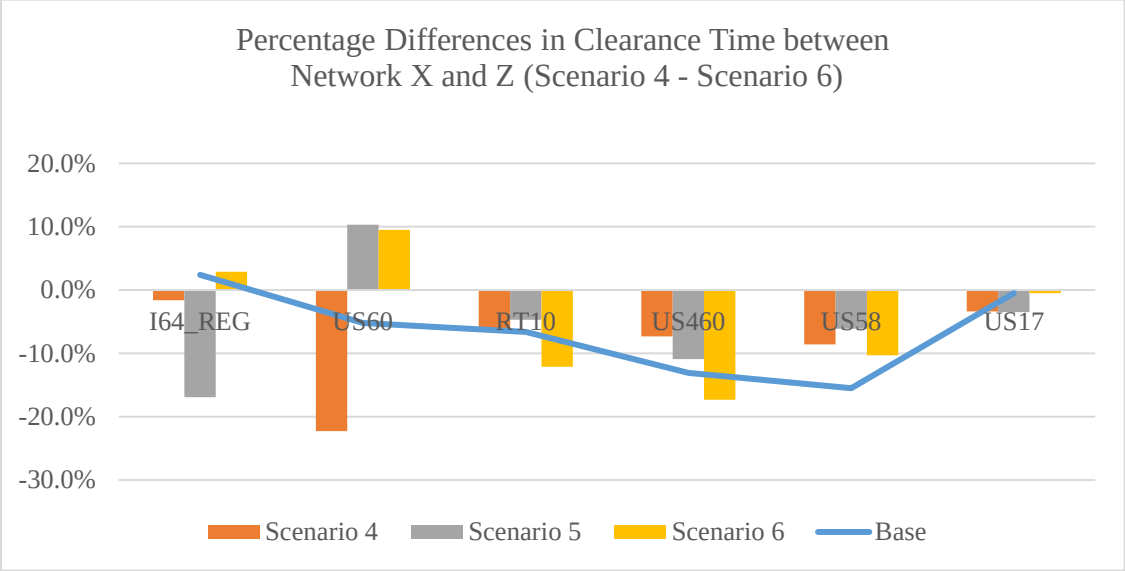


Figure 2.23. Percentage Differences in Clearance Time between Network X and Z

(Compressed, Scenario 4 to 6)

Table 2.23. Percentage differences of clearance time between Network Y and Z (compressed demand)

Location	Base	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
I64REG	5.2%	7.5%	0.6%	18.7%	1.3%	2.5%	2.5%
I64REV	0.9%	-2.5%	0.8%	0.1%	-4.0%	-1.7%	-2.0%
US60	5.0%	-7.1%	37.7%	12.7%	7.3%	4.3%	5.1%
RT10	5.2%	-8.6%	-7.0%	-3.1%	-4.3%	-5.8%	-0.2%
US460	-4.5%	-2.9%	-1.0%	-2.6%	2.0%	1.4%	-4.1%
US58	-5.2%	-5.9%	-2.5%	-0.1%	-6.1%	-0.8%	-3.4%
US17	-1.8%	1.1%	1.7%	-1.5%	0.4%	-0.4%	1.0%

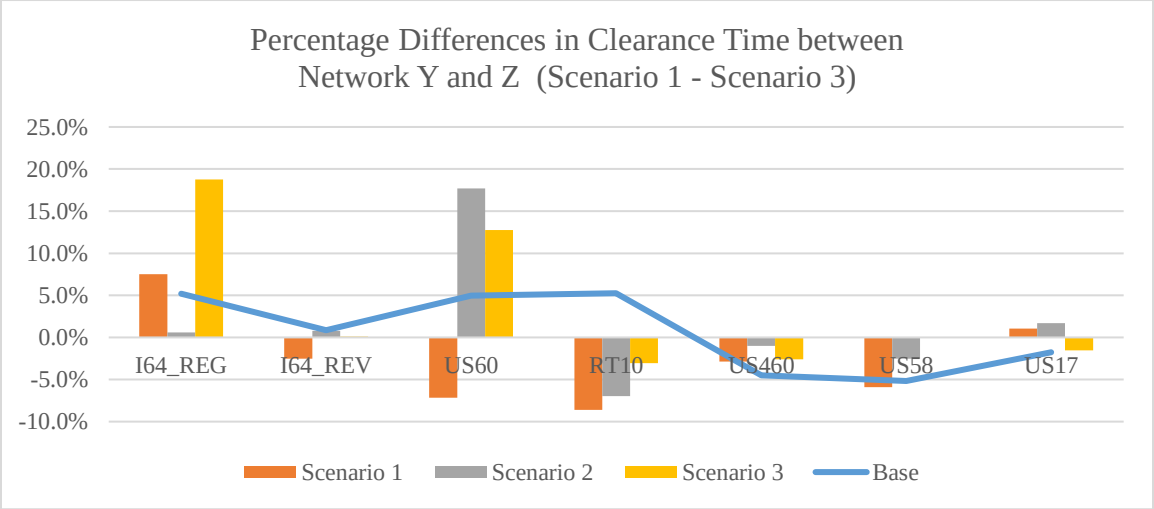


Figure 2.24. Percentage Differences in Clearance Time between Network Y and Z (Compressed, Scenario 1 to 3)

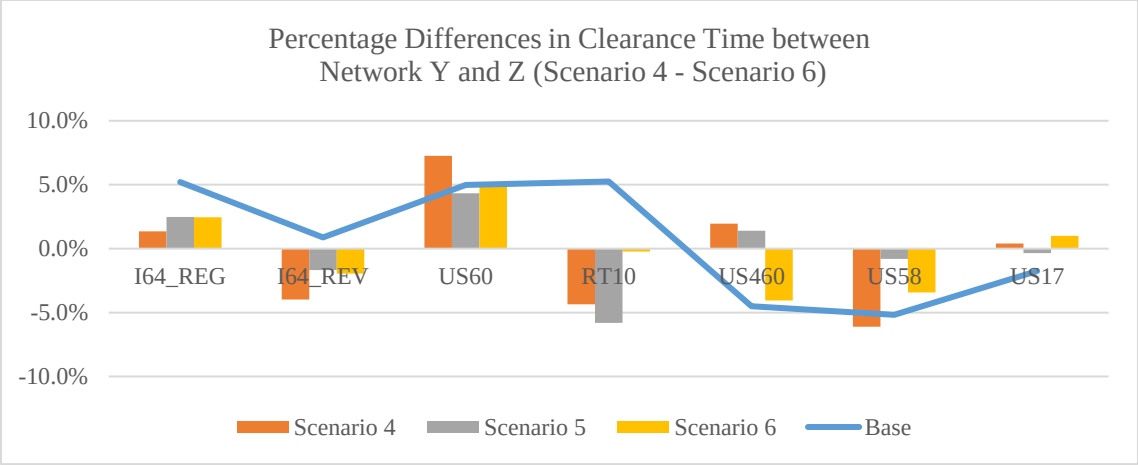


Figure 2.25. Percentage Differences in Clearance Time between Network Y and Z (Compressed, Scenario 4 to 6)

2.7. Findings and Conclusion

A phased evacuation was found to be a highly effective travel demand management strategy for managing demand during an evacuation.

- Scenario 2 (12-hours interval phased evacuation order) outperformed the baseline and other phased evacuation scenarios. Compared to the different scenarios, the evacuation demand profile of scenario 2 was more evenly dispersed than others.
- Scenario 4 (evacuate zone A and B together with 12-hours interval phased evacuation order) performed the following best.
- Scenario 1 (evacuate zones separately with a 6-hour interval order issue) performed the worst among all evaluated scenarios. The hourly demand curve

was unbalanced with a large spike from time interval 72 hours to 96 hours, immediately before hurricane landfall.

Lane reversal was found to produce considerable improvement in the evacuation performance.

- Network Y (lane-reversal on I-64) showed a better performance than Network X (no lane-reversal) in terms of average travel time and clearance time.
- Network Z (lane-reversal on I-64 and US 58) also showed better performance than Network X (no lane-reversal) in terms of average travel time and clearance time.
- Only minor differences were observed between the performance of networks Y and Z. Thus, a step-wise lane reversal implementation policy that implements lane reversal on one route at a time should be considered part of evacuation traffic control plans.

3. MODELING ROUTE SELECTION DURING HURRICANE EVACUATION

3.1. Introduction

The 2018 hurricane season emphasized the substantial role of evacuation in hurricane-prone areas. For example, many people were stuck in gridlock over several hours on the North Carolina Interstate highways during Hurricane Florence (CBS News, 2018). Gridlock could lead to significant injuries and property damage if a storm makes landfall while drivers are still on the road (Lindell et al., 2005). Understanding evacuees' travel behavior is critical to the design of effective traffic management plans. Within engineering models, evacuee travel behaviors typically include the evacuate/stay decision, destination choice, departure time, mode choice, and route choice. Evacuation route choice is the primary focus of this study. A better understanding of intended route choice behavior allows planners and policymakers to design more realistic evacuation plans. Route choice is also a critical input to simulation models used to test evacuation traffic management plans and traffic control strategies. Developing such models with more detailed human behavioral data will improve their value.

Simulation models are often based on aggregate assumptions of behavior. The most famous of these is the system optimum, which minimizes the collective travel time for all vehicles, and user equilibrium, in which each traveler minimizes his/her individual travel time (Wardrop, 1952). System optimum is generally considered an ideal, which cannot be currently obtained. User equilibrium is more practically obtained through repeated

experience with the transportation network under similar conditions and travel information systems. Fang and Edara (2013) reported the sensitivity of evacuation performance estimates to evacuee route choice behavior. Because of the lack of repeated experience with evacuation traffic conditions, proper equilibrium is unlikely to be obtained in reality. To better understand the conditions that may emerge from individual preferences, models of route selection developed from disaggregated data can identify factors influencing this choice.

Evacuation processes are complex and involve a series of related decisions. Homeowners must choose to evacuate or stay; they must decide when to go, how many cars to take, where to seek accommodations, a destination, and a route(s) that would help them reach their destination efficiently. State transportation agencies typically work to influence those decisions with communications and planning efforts, such as designating evacuation routes. The intersections between homeowners and agency choices are essential for life and livelihood. To better understand those choices, social scientists have developed a number of theoretical models of the related behavioral choices and their influences on the action, including the Protective Action Decision Making (Lindell and Perry, 2012), Warning Processing (Mileti and Sorensen, 1990), and Risk Interpretation and Action (Eiser et al., 2012). While this particular analysis was not developed with one theoretical model in mind, in building the survey on which this analysis was based, we controlled for or considered a broad range of survey items that influence evacuations decisions as represented in these models. For example, variations in the information provided by official agencies and other sources, access to information, environmental cues, social cues, prior

experiences, impediments such as limited income, demographic differences, and many other factors.

Using the data described above, this chapter's objective is to develop a household evacuation route choice model based on survey data collected from households in the Hampton Roads region of Virginia. The study area includes the nine Chesapeake, Hampton, Newport News, Norfolk, Poquoson, Portsmouth, Richmond, Suffolk, and Virginia Beach cities. The survey collected socio-demographic information and evacuation-related characteristics related to route selection. A mixed logit (i.e., random parameter logit) model was then developed to identify the factors influencing the choice of freeways versus non-freeways.

3.2. Literature Review of Route Choice during Hurricane Evacuation

Evacuees select an initial route before beginning their evacuation trips. While en-route, they may continually re-evaluate their choice based on the traffic they are currently experiencing and traffic information from a variety of sources, such as mobile navigation applications, variable/dynamic/ changeable message signs (VMS/DMS/CMS), and radio traffic reports. Since the data in this study comes from a behavioral intention survey, this literature review focuses on pre-trip route selection.

Evacuees often base their pre-trip route choice on their regular routes to their destinations (Lindell et al., 2018). Familiarity with the route and believing that it will be the fastest or shortest have been cited as reasons for choosing a particular route during Hurricanes Ivan, Katrina (Murray-Tuite et al., 2012), and Lili (Lindell et al., 2011). Freeways typically have higher design speeds and greater capacities than lower classifications of roadways,

suggesting that many evacuees will select freeways when provided a choice. Dow and Cutter (2002) found that this inherent preference can lead to a severe imbalance of traffic where freeways are over-utilized and other routes are underutilized. Chiu and Mirchandani (2008) also found a preference for freeways in a stated preference questionnaire.

However, some evacuees with prior evacuation experience anticipate severe congestion on their regular routes and may select other routes, expecting them to be less congested (Lindell et al., 2018). Lindell et al. (2001) study of five hurricane areas in Texas indicates that between 9 and 37 percent of potential evacuees intended to use unofficial evacuation routes. While the exact methodology for defining evacuation routes is not readily available in published literature, they tend to be high-capacity roadways perpendicular to the hazard when possible (Lindell et al., 2018).

A route's designation as an evacuation route by a transportation agency is not necessarily the governing reason for its use. Not all evacuees have information about the official routes (e.g., only 26 percent of Hurricane Bret evacuees received such information (Zhang et al., 2004). As discussed above, evacuees select their routes based on familiarity and belief that it will be the fastest, at least partially aligning with user equilibrium assumptions. In addition to these criteria, Prater et al. (2001) found that 69 percent of their respondents (Hurricane Bret) thought their route was the most logical, 4 percent followed hurricane evacuation maps, 3 percent followed official recommendations, 24 percent based their decisions on other reasons. Similarly, in a study of Hurricane Katrina and Rita evacuees, Wu et al. (2012) found that evacuees relied on the following sources from most to least: experience, en-route traffic conditions, recommendations from news media,

recommendations from local authorities, and written evacuation guidance. However, Carnegie and Deka (2010) found a much higher percentage (81) of survey respondents who were likely to self-evacuate would “very likely” follow route instructions.

These differing reasons for selecting routes, information provision, personal familiarity, and prior experience suggest that individual route selection can be complex to predict. When modeling the major bridge Miami Beach residents intended to use for a hurricane evacuation with a random parameter (mixed) multinomial logit model, Sadri et al. (2015) found a mixture of evacuation characteristics, evacuee characteristics, and distance to the evacuation destination to be significant. Evacuees tended to prefer closer bridges. Race, gender, prior evacuation experience, type of accommodations, evacuation timing (number of days before landfall and time of day), and transportation mode influenced bridge choice (Sadri et al., 2015). These authors also used Hurricane Ivan survey data and random parameters (mixed), multinomial logit models, to select among the routing strategies of familiar routes and recommended routes, where the familiar routes also included those usually used and thought to be the fastest (Sadri et al., 2014). Variables with mixed effects for at least one utility expression had the number of years of residence in the current home, accommodation type, channel (Lindell and Perry, 2012; Lindell and Perry, 2004) of evacuation notice number of days before landfall that the evacuee departed. Variables with fixed effects included geographic home location, evacuation distance, income categories, number of children in the household, and the evacuee's age (Sadri et al., 2014). Our study tests related variables to the extent that they are present in both the current and prior surveys.

3.3. Method

In this study, we assume that an individual who has decided to evacuate can choose from a choice set of two routes –a freeway or a non-freeway (i.e., arterial/local roads). Logit models comprise an analytical framework for modeling individual preferences towards alternatives. However, in the derivation and application of a standard logit model, one assumes that the parameters or coefficients of variables are fixed across all individuals. When this assumption does not hold, parameter estimates will be inconsistent with reality, and the outcome probabilities would be erroneous (Washington et al., 2010). In such instances, a methodological approach that allows for the variation of parameters is more appropriate and can help capture the variance present in the sociodemographic and evacuation-related attributes of various evacuees. Previous research (Revelt and Train, 1998; McFadden and Train, 2000) has also demonstrated the effectiveness of such a methodological approach that can explicitly account for parameter variability.

The methodological framework for this study is illustrated in Figure 3.1. In the first step, a household survey was conducted to collect data pertaining to the route selection preferences of potential evacuees. The survey responses were processed by removing incomplete responses and using data encoding procedures to prepare socio-demographic and evacuation-specific data. The next step involved using the prepared data to estimate logit models for route choice. A backward stepwise method was used in the R statistical computing software to select variables. For variable selection, several goodness of fit measures were utilized, including improvements to adjusted R-square, Akaike information criterion (AIC), and Bayesian information criterion (BIC), as well as the significance of each variable (Zhang, 2016). Two binary logit models were estimated

using the selected variables; one is a standard logit (fixed-parameter logit) model, the other is a mixed logit (random parameter logit) model. The methodology's final step involved model validation, interpretation, and comparison of the fixed and mixed logit model results.

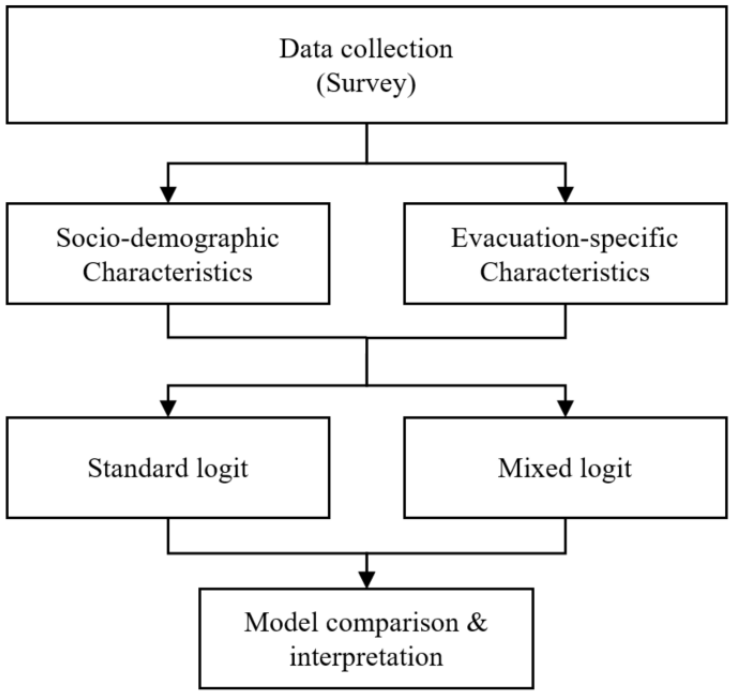


Figure 3.1. Modeling Framework

The route choice function for evacuee *n* is presented in Equation 3.1 (Washington et al., 2010):

$$RS_{i,n} = \beta_i X_{i,n} + \varepsilon_{i,n} \quad (3.1)$$

where,

$RS_{i,n}$ = route choice function determining the route type *i*.

$X_{i,n}$ = vector of explanatory variables (see Table 3.1).

β_i = vector of estimable parameters.

$\varepsilon_{i,n}$ = error term.

If $\varepsilon_{i,n}$ are assumed to be generalized extreme value distributed (Manski and McFadden, 1981), the binomial logit model results in $P_n(i)$, the probability of route choice type *i* among all the types *I* for evacuee *n* shown in Equation 3.2:

$$P_n(i) = \frac{\exp(\beta_i X_{i,n})}{\sum_I \exp(\beta_i X_{I,n})} \quad (3.2)$$

To consider the variations of parameters across different evacuees, a mixed logit model is used to compute the route choice probabilities (Train, 2009) as shown in Equation 3.3:

$$P_n(i) = \int \frac{\exp(\beta_i X_{i,n})}{\sum_I \exp(\beta_i X_{I,n})} f(\beta|\varphi) d\beta \qquad (3.3)$$

Where,

$P_n(i)$ = probability of route choice type *i* (among all types *I*).

$f(\beta|\varphi)$ = density function of β.

Φ= vector of estimates of the density function (mean and variance).

The β can now allow evacuee-specific variations of the effects of X on route choice probabilities, and the density function $f(\beta|\varphi)$ is used to determine β. A weighted average then obtains the mixed (random parameter) logit probabilities for different values of β across evacuees where some factors of the vector β may be fixed and some may be randomly distributed (Gkritza and Mannering, 2008). Simulation approaches are commonly used to estimate the maximum likelihood of mixed logit models. One of the

simulation-based approaches considers Halton draws which provide a better distribution of draws for numerical integration than purely random draws (Bhat, 2003). McFadden and Ruud (1994) and Stern (2006) provide further details about the simulation-based maximum likelihood approaches. In this study, we considered 200 Halton draws, which are usually sufficient for accurate estimation under the assumption that parameters are typically distributed (Bhat, 2003).

3.4. Data

In this study, data were used from a household survey of the Hampton Roads region in Virginia conducted by the research team in May 2018. The group consisted of researchers from University of Delaware, Virginia Tech, Clemson, and University of Missouri. The University of Delaware researchers led the design and deployment of the IRB-approved survey with support from other partner universities. The survey results were then shared with University of Missouri researchers. The Hampton Roads region has a population exceeding 1.6 million residents. The survey was distributed following the best practices from social science literature. Dillman (2007) recommends five elements for achieving high survey responses rates: respondent-friendly surveys, four contacts through first-class mail, stamped return envelopes, personalization of correspondence, and prepaid financial incentives (p. 150-153). The survey respondents were presented with a hypothetical scenario of a Category 4 storm with wind speeds between 130 and 156 mph forcing a mandatory evacuation of the region. The survey was sent to a random sample of 2,500 households in the Hampton Roads region and was returned by 415 households.

The response rates for the general survey were AAPOR Response Rate 2 =19%, AAPOR Cooperation Rate= 96%, AAPOR Refusal Rate 1= 1%, AAPOR Contact Rate 1= 20%.

After checking the reliability of the survey responses, 22 observations were removed due to respondents choosing 'I don't know' for the route and another 28 observations were removed due to missing responses to one or more questions. Thus, data from 365 (of 415) observations were deemed to be valid for the analysis. Sixty-four percent of the households (232 out of 365) that responded to the survey said they would choose a freeway to evacuate, while the remaining 36% (133 of 365) said they would use a non-freeway route. Sadri et al. (2015) show that evacuees are more likely to use the usual or familiar route during their evacuation. For evacuees traveling to destinations out of the region, they may prefer to use a freeway as they would in normal conditions for long trips. The stepwise selection process resulted in 11 explanatory variables. The variables include household socio-demographic information and evacuation-related characteristics such as employment status, evacuation accommodation, expected travel time to the destination, the time and day of the evacuation, and previous evacuation experience. Table 3.1 shows the variables used in the final model specification and their descriptive statistics. Table 3.2 shows the correlations between variables. The correlation values in most cases were less than 0.2 (threshold commonly used for variable selection) (Mukaka, 2012). There was only one correlation value of -0.229 that slightly exceeded the 0.2 thresholds. In terms of the correlation between the dependent and independent variables, evacuation accommodation, expected travel time to reach destination on a normal day, and dwelling type had the highest correlation to the dependent variable of route choice.

Table 3.1. Descriptive statistics for explanatory variables

Variable Number	Variable Description	Mean	SD	Type	Range
Response variable					
1	Evacuation route type (if use freeway 1; if not 0)	0.636	0.482	Dichotomous	[0,1]
Socio-demographic characteristics					
2	Evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.288	0.453	Dichotomous	[0,1]
3	Employment status (if employed 1; otherwise 0)	0.559	0.497	Dichotomous	[0,1]
4	Dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	0.868	0.338	Dichotomous	[0,1]
Evacuation-specific characteristics					
5	Evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	0.082	0.275	Dichotomous	[0,1]
6	Evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	0.345	0.476	Dichotomous	[0,1]
7	Willingness to use recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	0.888	0.316	Dichotomous	[0,1]
8	When asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	0.203	0.403	Dichotomous	[0,1]
9	Willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.447	0.498	Dichotomous	[0,1]
10	Expected travel time to reach destination on a normal day (hours)	3.838	3.254	Continuous	[0.16, 18]
11	Willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.318	0.466	Dichotomous	[0,1]
12	Evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0)	0.301	0.459	Dichotomous	[0,1]

Table 3.2. Correlation matrix between variables

#	1	2	3	4	5	6	7	8	9	10	11	12
1		0.13	0.16	0.18	-0.23	-0.01	0.16	0.09	0.04	0.19	0.10	0.14
2	0.13		-0.09	-0.01	-0.06	0.11	0.07	0.01	0.01	0.01	-0.01	-0.10
3	0.16	-0.01		0.14	-0.06	0.03	0.05	0.02	-0.01	0.07	-0.02	0.14
4	0.18	-0.01	0.14		-0.12	-0.01	0.02	-0.05	0.07	0.04	0.04	0.04
5	-0.22	-0.06	-0.06	-0.12		-0.05	0.01	-0.05	0.05	-0.14	-0.03	-0.04
6	-0.01	0.11	0.03	-0.01	-0.05		-0.02	0.14	-0.07	0.18	-0.01	0.13
7	0.16	0.07	0.05	0.02	0.01	-0.02		-0.17	-0.12	0.02	0.08	0.10
8	0.10	0.01	0.02	-0.05	-0.05	0.14	-0.17		-0.04	0.06	-0.01	-0.01
9	0.04	0.01	-0.01	0.07	0.05	-0.07	-0.12	-0.04		-0.11	0.01	-0.07
10	0.19	0.01	0.07	0.04	-0.14	0.18	0.02	0.06	-0.11		-0.07	0.09
11	0.10	-0.01	-0.02	0.04	-0.03	-0.01	0.08	-0.01	0.01	-0.08		0.04
12	0.14	-0.10	0.14	0.04	-0.04	0.13	0.10	-0.01	-0.07	0.09	0.04	

3.5. Results

3.5.1. Fixed logit model

Past studies have used the logit model to identify factors for route preference during an evacuation. Sadri et al. (2014) and Sadri et al. (2015) developed mixed logit (random parameter) model to reflect the heterogeneity of preference of evacuees. In this study, we used a mixed logit model and compared it to a fixed logit model. Validation was performed using bootstrapping (Kohavi, 1995). Giancristofaro and Salmaso (2007) describe the validation process as having three steps - exclude a sub-sample of observations, develop a model using remaining samples, and then test the model on the initially excluded sub-

sample. Efron and Tibshirani (1997) and Steyerberg et al. (2004) show that bootstrap is a more efficient internal validation process than the data-splitting, repeated data-splitting jack-knife method, in terms of variance and low bias.

Table 3.3 shows the results of the fixed logit model and validation using the bootstrap method. The results included all the explanatory variables were significant at the 10% level of significance. Also, the bootstrap results (of variable significance) were consistent with those in the estimated model, thus validating the model.

Table 3.3. Estimation and validation results for standard logit model of evacuation route choice

Explanatory variables	Fixed parameter model			Bootstrap	
	β	P-value	Marginal effect	Bias	P-value
Constant	2.588	0.000		0.141	0.000
Indicator variables for evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.731	0.010	0.136	0.036	0.014
Indicator variables for employment status (if employed 1; otherwise 0)	0.543	0.028	0.101	0.011	0.039
Indicator variables for dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	0.899	0.011	0.167	0.046	0.022
Indicator variables for evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	-1.529	0.001	-0.284	-0.084	0.012
Indicator variables for the evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	-0.506	0.059	-0.094	-0.021	0.073
Indicator variables for willingness to use the recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	1.153	0.003	0.215	0.062	0.006
Indicator variables when asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	0.888	0.009	0.165	0.055	0.011
Indicator variable for willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.451	0.075	0.084	0.025	0.087
Expected travel time to reach destination on a normal day (hour)	0.139	0.002	0.026	0.008	0.002
Indicator variable for willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.486	0.070	0.090	0.019	0.094
Indicator variable for evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0) (Standard deviation of the parameter estimate)	0.561	0.049	0.104	0.028	0.085

3.5.2. Mixed logit model

A mixed logit model with random parameters was also estimated in this study. Table 3.4 shows that most of the variables included in the random-parameter model are statistically significant (at a 10% level of significance) with plausible signs. Only two variables were not significant at the 10% significance level; willingness to use multiple personal vehicles (p-value of 0.11) and willingness to evacuate early when expecting delay (p-value of 0.11). Nevertheless, these two variables were kept in the model due to their potential influence on evacuee's preference to choose a freeway (as evidenced by their positive coefficient signs). The parameters of departure hour produced statistically significant standard deviations for their assumed (normal) distributions. All other variables have fixed parameters. The positive value means that evacuees are more likely to choose a freeway than a non-freeway.

Table 3.4. Estimation results of mixed logit model for evacuation route choice

Explanatory variables	Random parameter model		
	β	P-value	Marginal effect
Constant	3.096		
Indicator variables for evacuation experience (if evacuated in a previous storm 1; otherwise 0)	0.858	0.008	0.036
Indicator variables for employment status (if employed 1; otherwise 0)	0.698	0.016	0.055
Indicator variables for dwelling type (single family home, duplex, or townhouse 1; otherwise 0)	1.078	0.009	0.142
Indicator variables for evacuation accommodation (if evacuees likely to evacuate to shelter or second home 1; otherwise 0)	-1.944	0.001	-0.020
Indicator variables for the evacuation day (if evacuee is most likely to evacuate 2 days before landfall 1; otherwise 0)	-0.648	0.042	-0.034
Indicator variables for willingness to use the recommended route (if evacuees are willing to use recommended route from emergency officials 1; otherwise 0)	1.360	0.002	0.181
Indicator variables when asked to wait to evacuate until a later time (if evacuees evacuate without considering recommended start times 1; otherwise 0)	1.109	0.006	0.029
Indicator variable for willingness to use multiple personal vehicles (if evacuees are willing to use multiple personal vehicles 1; otherwise 0)	0.463	0.114	0.031
Expected travel time to reach destination on a normal day (hour)	0.167	0.001	0.087
Indicator variable for willingness to evacuate early when a one-hour delay is expected to result in arriving at destination around the same time as hurricane landfall (if evacuees are willing to evacuate early 1; otherwise 0)	0.502	0.111	0.023
Indicator variable for evacuation departure hour (if evacuees is most likely to evacuate 12:00 a.m. to 6:00 a.m. 1; otherwise 0) (Standard deviation of the parameter estimate)	1.771 (3.217)	0.104 (0.073)	0.001

3.5.3. Model validation

The performance of the fixed and mixed logit models was compared. A likelihood ratio (LR) was computed using the difference between the log-likelihood values of the mixed logit model and fixed logit model as shown in Equation (3.4) (Sadri et al., 2015):

$$\text{LR} = -2[LL(\beta_{random}) - LL(\beta_{fixed})] \qquad (3.4)$$

Where LL(β_{random}) is the log-likelihood at the convergence of the mixed logit (random-parameter) and LL(β_{fixed}) is the log-likelihood at the convergence of the standard logit (fixed-parameter) model. LR is χ^2- distributed with degrees of freedom equal to the difference in the number of parameters in both the models. The value of LR is 4.996, and the critical value of $\chi^2_{0.05,1}$ (5% significance level and degrees of freedom equal to 1) is 3.841. As a result, the null hypothesis of no random parameters can be rejected (Sadri et al., 2015). The goodness-of-fit measure, McFadden's pseudo R square (ρ^2), for both models are reported in Table 3.5. The ρ^2 value ranges between 0 and 1, with a value close to 1 indicating the best fit. Domencich and McFadden (1975) described that the ρ^2 values between 0.2 and 0.4 are considered to be an excellent fit for logit models. The ρ^2value for the mixed logit model (0.17) was slightly better than the ρ^2value of 0.159 for the fixed logit model.

The estimated models were also validated using the likelihood ratio test as implemented in Sadri et al. (Sadri et al., 2014). The dataset was split into two equal samples. After breaking the data, two separate models were analyzed with the same specification using these two samples. The likelihood ratio test statistic is shown in Equation 3.5.

$$\text{LR} = -2[LL(\beta_{Full}) - LL(\beta_{sample1}) - LL(\beta_{sample2})] \qquad (3.5)$$

Where, $LL(\beta_{Full})$ is the log-likelihood at the convergence of the model estimated using the entire data and $LL(\beta_{sample1})$ is the log-likelihood at the convergence of the model estimated using sample 1, which is equal to -93.702, $LL(\beta_{sample2})$ is the log-likelihood at the convergence of the model estimated using sample 2, which is equal to -97.358. According to Equation 3.5, the LR value is 15.417 and the degrees of freedom are equal to 13. Since $\chi^2_{0.05,13}$ is equal to 22.362, the test could not reject the null hypothesis that the parameters across different samples are equal. As a result, this test validates the model specification applied in this study.

Table 3.5. Goodness-of-fit measures for the random and fixed parameter logit models

Goodness-of-fit Measures	Random Parameters	Fixed Parameters
Number of parameters	13	12
Log likelihood at zero, LL (0)	-252.998	-252.998
Log-likelihood at convergence, LL (β)	-198.768	-201.266
ρ^2	0.170	0.159
LR $test^2$	Random versus fixed parameters	
LR $= -2[\mathrm{LL}(\beta_{random}) - LL(\beta_{fixed})]$	4.996	
Number of observations	365	

3.6. Discussion

In this section, the results of the mixed logit model shown in Table 3.4 are discussed. The parameter for the evacuation experience indicator variable has a positive sign. From the average marginal effect, for evacuees who have prior evacuation experience, the probability of selecting freeways increases by 0.036 (or 3.6%). These individuals may have experienced congestion during their prior evacuation and anticipate that freeways will provide faster travel times in their next evacuation.

Being employed also increased the chance of someone choosing a freeway for evacuation by 0.055 (5.5%). Under normal conditions, too, Chang and Sohn (2015) reported that commuters are more likely to use freeways when traveling to work. Thus, familiarity with using freeways could be a contributor to their use during evacuation. The dwelling type variable demonstrated that individuals living in a single-family home, duplex, or townhome had a higher preference (14.2%) towards freeways.

The negative parameter for accommodation type shows that those who want to evacuate to a shelter or a second home prefer non-freeways rather than freeways. The marginal effect only shows a slightly decreased preference (2.0%) for freeways. Shelters may be located relatively close to the evacuee's home, making freeway use less practical. Another variable with a negative parameter was the lead time for an evacuation. Suppose evacuees were to depart two days in advance of landfall, their probability of using non-freeway routes over freeways increases by 3.4% (marginal effect) compared to individuals leaving earlier or later. Potentially, those leaving closer to landfall perceive freeways as providing a faster travel time, needed to arrive safely at their destination before hurricane hazards arrive.

Two interesting trends were observed with respect to the response to evacuation recommendations from emergency officials. Those individuals willing to use the recommended route exhibited a higher probability, of 18.1%, to use freeways. On the other hand, freeways were also preferred by individuals who would not comply with the recommended departure times. The marginal effect was 2.9% higher for choosing a freeway for these individuals compared to those who believed they would comply with the recommended evacuation time. Those respondents who said they would use multiple personal vehicles to evacuate also expressed a 3.1% higher preference for choosing a

freeway. Expected travel time to reach the destination on a typical day was positively associated with a preference for freeways. Respondents show an 8.7% higher probability of choosing freeways for every 1% increase in travel time. Potentially, longer normal travel times indicate a farther destination, for which freeways may be more direct than other routes. When asked if the route preference would depend on early departure due to expected congestion, there was a 2.3% higher preference to choose a freeway to evacuate among those that said they would depart early to avoid reaching their destination at the same time as hurricane landfall. The hour of departure variable was modeled using a random parameter. With a mean of 1.771 and a standard deviation of 3.217 (assuming a normal distribution of the parameter), it indicates that 17% of the evacuees who departed from their homes between midnight and dawn (6:00 a.m.) results in a lower probability of using freeways, whereas the remaining 83% have a higher probability of using freeways.

Thus, in summary, several factors contribute to evacuees choosing a freeway over other routes. In the descending order of marginal effects, these factors are: willingness to use the official recommended route, living in a single-family or duplex housing, expected travel time to reach the destination, being employed, and possessing prior evacuation experience. Conversely, a few factors had a negative effect on choosing a freeway. These factors are: willingness to evacuate two days prior to landfall and evacuating to a public shelter or a second home.

3.7. Conclusion

Freeway facilities carry large amounts of vehicular traffic in urban areas. They play a critical role in regional evacuations. In this study, factors influencing individual preferences for choosing a freeway were investigated. There are some practical implications of the study findings. Knowledge of factors that positively affect freeway route selection can help agencies better optimize the evacuation process. If freeways are expected to be underutilized during an evacuation, an agency might target one or more of the above factors to motivate individuals to use freeways. For example, an agency can recommend the use of freeways to evacuees who plan to leave two days before landfall, reinforcing their innate preference. Capacity enhancing strategies such as contraflow lanes and use of hard shoulders could also be implemented for this time period for high-demand areas. On the other hand, if freeways are expected to be overutilized, the agency can design countermeasures based on the same factors to encourage local roads and arterials (i.e., non-freeways). Countermeasures such as traffic signal coordination in the outbound direction can be implemented on arterial streets and have public informed about the improvements. Conversely, ramp closures can be strategically determined to improve local streets' utilization and reduce overcrowding of freeways. Finally, the factors that contribute to evacuees choosing a freeway found in this study could be used as contextual variables when modeling the performance of evacuation strategies using normative performance measurement models.

4. PREDICTING TRAFFIC MOBILITY DURING COVID-19

4.1. Introduction

Since 2010, humanity has been exposed to three epidemics that have exerted significant impacts. The Middle East Respiratory Syndrome (MERS) that occurred in 2012 resulted in 858 deaths. The Western African Ebola virus that spread between 2013 and 2016 consumed 11,000 lives. At the end of 2019, a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) called COVID-19 was discovered in Wuhan, China. On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a pandemic. As of October 31, 2020, 45.5 million cases of COVID-19 have been recorded worldwide, with total deaths surpassing 1.2 million (WHO, 2020). Pandemics such as COVID-19 have a considerable impact on mobility and travel patterns.

Many countries have been making efforts to mitigate the virus spread by implementing various policies such as stay-at-home, termination of transit service, and self-quarantine. Restricting social contact is expected to help lower the probability of spreading the virus. At the same time, several national and international health organizations are making efforts to discover other factors affecting virus spread. In epidemiology, many researchers have evaluated the connection between travel and transmission of COVID-19. Published research has focused on how to accurately predict the number of confirmed cases and not on the overall travel impacts of the pandemic. This study analyzes the mobility trends resulting from the effects of COVID-19. Using New York County as an example, the impact on various location mobility – activities on Transit station and activities on Retail / Recreation – were examined. Publicly available location-based

mobility data from Google and the USA facts were used to develop mobility prediction models. Three machine learning algorithms, Regression Tree, Random Forest, and Extreme gradient boosting (XGBoost). The developed models can assist transportation agencies in planning transit and bike-sharing services during a pandemic through accurate estimation of demand.

4.2. Review of Relevant Literature

The outbreak of COVID-19, for its severity and global reach, has had an unprecedented negative influence over the society and the economy. Due to the newness of the pandemic, research on the travel impacts is limited. One study in mainland China examined the effect of travel constraints on the spread of COVID-19 and found that travel quarantine postponed the spread of infection from Wuhan to other mainland China areas (Chinazzi et al., 2020). In Budapest, Hungary, public transport ridership declined by 90% in March 2020 after movement restrictions were announced (Busky, 2020). Haas et al. (2020) show that 80% of people in the Netherlands reduced their outdoor activities, with a more substantial decrease observed for the elderly. Also, they found that the total number of trips reduced by 55% after the implementation of lockdown. In the United Kingdom, a 73% reduction in road travel was reported by Carrington (2020). A recent study in Seoul, South Korea, identified the subway ridership variations related to risk perception of COVID-19. They showed that daily subway passengers decreased by 40% in the first week of March compared to January 2020 (Park, 2020).

In the United States, the first case of COVID-19 occurred on March 1, 2020, in New York State. Eleven days later, New York City announced a State of Emergency with limiting occupation of spaces and allowing remote-working and flexible workers'

schedules. These changes translated into reduced mobility at specific places. On March 20th, New York City declared stay-at-home order with the closure of all non-essential businesses. Even with the stay-at-home order in place, the cases and deaths of COVID-19 kept increasing until the beginning of April.

Teixeira and Lopes (2020) found that bike-sharing ridership is more resilient than subway ridership during the pandemic period in New York City. Ali et al. (2020) investigated changes in mobility habits due to COVID-19 in the Chicago area using a survey. People perceived high-risk modes in the following order: transit, pooled ride-hailing, taxi, and ride-hailing, shared scooters, shared bike, walking, personal bike, and personal vehicle. Survey respondents reported going to gyms and hospitals as high-risk activities.

4.3. Data

In this study, publicly available data for New York County was used to examine the mobility trends before and during COVID-19. First, we investigated mobility change with travel data from the Bureau of Transportation Statistics to examine how trip patterns changed due to the epidemic. The Daily Travel data were collected for the Bureau of Transportation Statistics by the Maryland Transportation Institute and Center for Advanced Transportation Technology Laboratory at the University of Maryland. The daily travel estimates are from a mobile device data panel from merged multiple data sources that address the geographic and temporal sample variation issues often observed in a single data source. In this study, we focused on the duration from March 1, 2020, which is the first day of COVID-19 cases in New York State, to October 31, 2020, which is the day before the vaccine news was first released.

Figure 4.1 shows New York County's total trips from March 1, 2020, to October 31, 2020. The trips started to decrease from March 23, when the State of New York declared stay-at-home order. The daily trips gradually increased from May 10, and the total daily trips remained consistent after that.

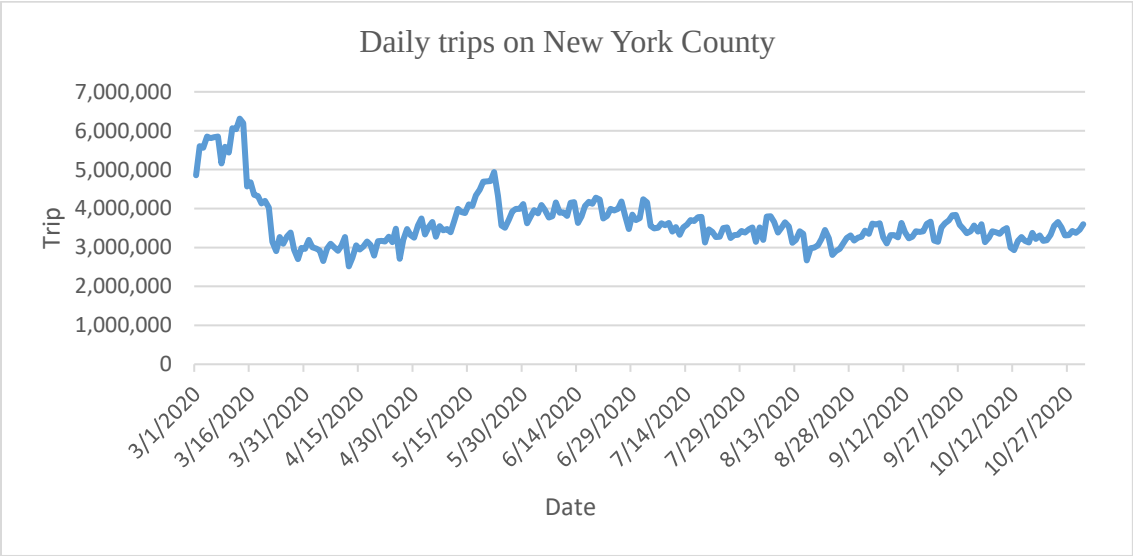


Figure 4.1. Daily trips of New York County (Source: Bureau of Transportation Statistics)

The mobility prediction model data was obtained from two resources: 1) Google mobility data and 2) COVID-19 data. The descriptive statistics of the data are shown in Table 4.1.

The Google mobility data show movement trends by region across different categories of places. According to Google, the median value from the 5 week period from the 3rd of January to the 6th February 2020 was set as the baseline value. The mobility data shown in Table 4.1 are the relative change compared to the baseline. For example, the mobility at Transit Station areas decreased, on average, by 60.82% compared to the baseline.

COVID-19 data of daily new cases and deaths is reported by the USAfacts.org website.

Table 4.1. Descriptive statistics of data for New York County

Data type	Variable	Mean	S.D	Min	Max
Google mobility data (baseline: 0)	Transit Station	-60.82	16.10	-83.00	-1.00
	Retail and Recreation	-65.69	17.98	-89.00	3.00
	Grocery and Pharmacy	-30.36	13.27	-63.00	20.00
	Parks	-34.49	21.44	-80.00	34.00
	Workplaces	-53.51	20.76	-80.00	7.00
	Residential	18.04	8.87	0.00	35.00
COVID-19 data	COVID-19 daily new cases	149.84	200.04	0.00	1737.00
	COVID-19 daily new deaths	13.16	30.38	0.00	345

4.3.1. Google mobility data

On March 29, 2020, Google released mobility data, aggregated from mobile device location information covering the period from Feb 15, 2020. The mobility trends for the following six travel categories are available.

1) Transit station: public transport hubs such as subway, bus, and train stations.
2) Retail and Recreation: places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters
3) Grocery and Pharmacy: places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies
4) Parks: places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
5) Residential: places of residence.
6) Workplaces: places of employment.

Figure 4.2 shows the Google mobility data in New York County from March to October 2020. Except for residential locations, the mobility values for all other categories drastically reduced during this period. Mobility related to Retail and Recreation activities fell the most, followed by activities at Transit Stations. The stay-at-home order and remote-work meant the residential activity increased.

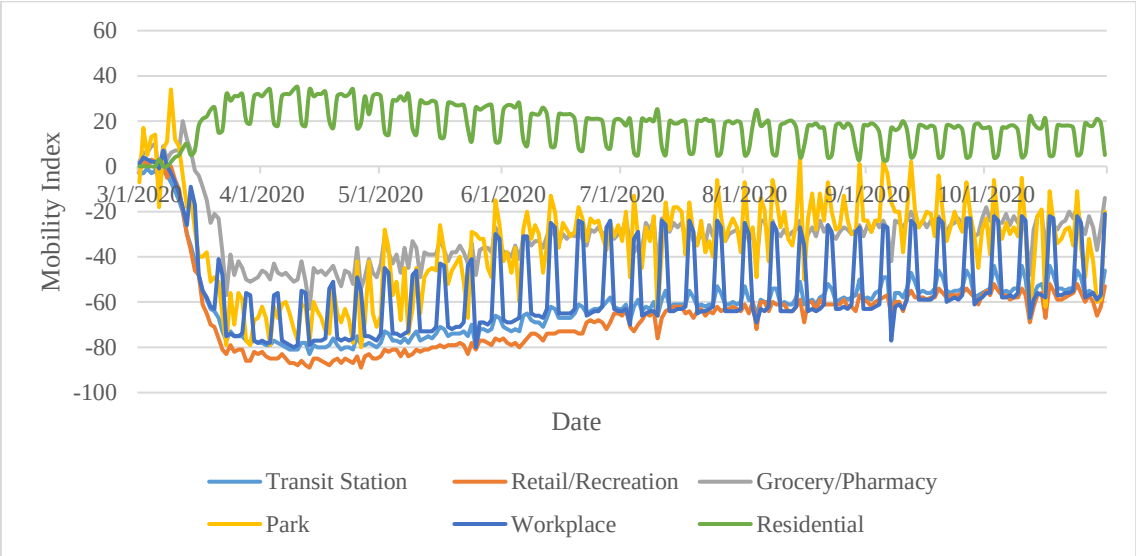


Figure 4.2. Google Mobility Trends for New York County (Source: Google mobility report, google.com/covid19/mobility)

4.3.2. COVID-19 data

Most countries and cities provide daily updates of COVID-19 cases and deaths. In this study, COVID-19 data was extracted from the USAfacts.org website. The cumulative number of daily new cases and daily new deaths from March 2020 to October 2020 are plotted in Figure 4.3. The cases and deaths reached their peak during early April (steep

slope in Figure 4.3) and started to decrease after the middle of April (flattening of slope in Figure 4.3).

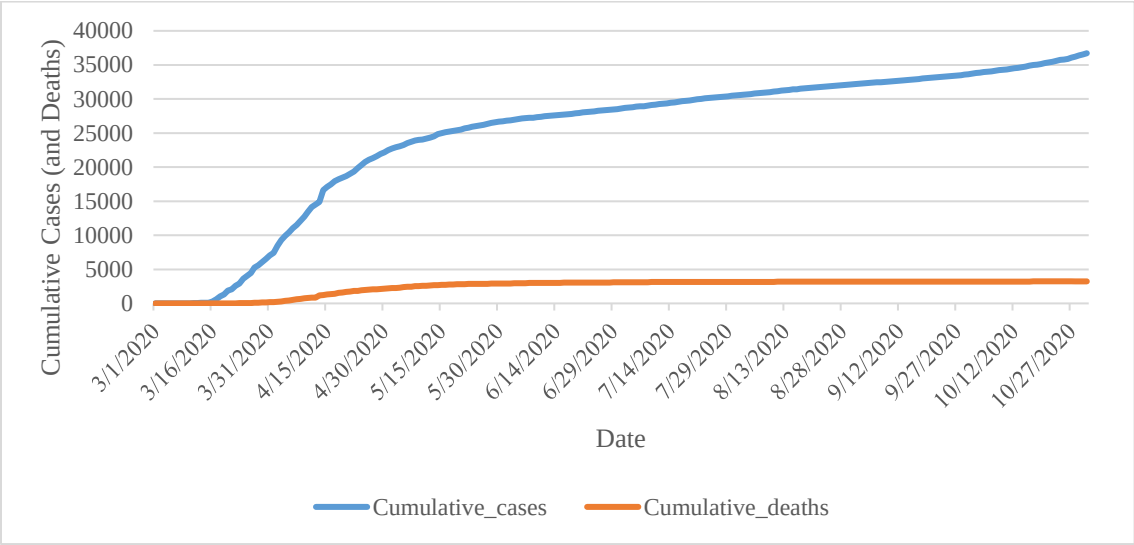


Figure 4.3. Cumulative COVID-19 Cases and Deaths in New York County

(Source: USA Facts)

4.3.3. Correlation matrix of variables

The correlation between mobility variables and COVID-19 variables was computed. Figure 4.4. shows a correlation matrix. COVID-19 'daily cases' and 'daily deaths' are negatively correlated to the mobility of all categories except residential activity. The negative relationship could be due to people feeling reluctant to go outside not to risk getting infected due to the high prevalence of COVID in the community.

Among the categories, Transit station and Retail/Recreation mobilities were highly correlated. Mobility at parks had the highest correlation to COVID-19 cases (-0.63) and deaths (-0.53) than other activities.

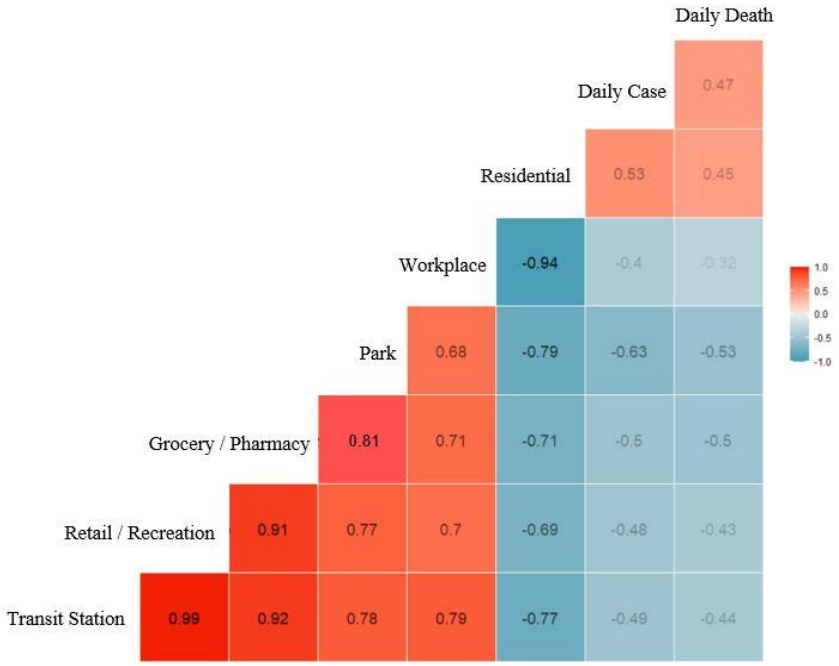


Figure 4.4. Correlation Matrix for Mobility and COVID-19 Variables

4.4. Method

This study developed prediction models for three categories: Transit Station mobility, Retail and Recreation mobility, and Workplace mobility. In addition, prediction models were developed for two prediction horizons – one day ahead i.e., predicting d+1 (a day after) and one week ahead (d+7 or a week later) where d is the current date when the prediction is being made. Inputs to the models include daily new COVID-19 cases and deaths for recent three days - d-1, d-2, and d-3, average daily cases and fatalities over last

seven days (d-7 to d-1). Time-series mobility data for d-1 and d-6 were also used in developing the model.

In terms of methodology, different tactics were used to predict the mobility index as a function of the variables mentioned above. Specifically, three methods were discovered- Regression Tree, Random Forest, and Extreme Gradient Boosting.

4.4.1. Classification and Regression Tree

A Classification and Regression Tree is a statistical approach based on tree-building algorithms to classify or predict problems. This method was first proposed by Breiman et al. (1984). The rules are built by recursively splitting the data into smaller groups with binary separations based on a single predictor variable. A thorough search process inspects splits for all of the predictors. For regression trees, the designated split is the one that maximizes the homogeneity of the resulting groups regarding the response variable, although other options can be available. The output is a tree drawing with the branches determined by the splitting rules and a series of terminal nodes that contain the mean response. The procedure initially grows maximal trees and then uses cross-validation techniques to prune the overfitted tree to an optimal size.

The Regression tree analysis can be carried out in four main steps: tree building, tree-building stop, tree pruning, and optimal tree selection (Lewis et al. 2000).

a) Tree building

This step is stated with a root node, and then the Regression tree checks all possible splitting variables to find the best possible variable for splitting the root node into two child nodes.

b) Tree building stop

Node splitting is repeated for each child node until one of three following conditions occurs 1) each of the child nodes has only one observation and 2) observations inside each child node have the same distribution of input variables

c) Tree pruning

The “cost-complexity” method is used to simplify trees by the cutting of essential nodes. When the complexity parameter increases, more and more nodes are pruned away, resulting in simpler and simpler trees.

d) Optimal tree selection

This step aims to discover the maximal tree that fits the learning dataset with the highest accuracy compared to other trees. It is based on finding the correct complexity parameter, which the information in the training dataset is suitable but not over-fitting.

Regression Tree has clear benefits over statistical methods. It is effective in discover structure in data with hierarchical or non-additive variables. Also, it allows for the possibility of interactions and non-linearity among variables. Lastly, it is easy to understand and interpret as no worry about tuning a large number of parameters. However, the method leads to high variance results and makes over-fitting easily. These issues could be improved by bagging methods such as Random Forest.

4.4.2. Random Forest

Random Forest (RF) is a supervised learning method and extensively used to solve classification or numeric problems, which was first introduced by Breiman (2001).

Random Forest is a bagging technique, not a boosting. There is no correlation between trees while building the trees.

Random Forest is similar to Bagging tree that bootstrapping are drawn to perform multiple trees. The difference is that each tree is created with a randomized subset of predictors. A large number of trees are grown, thus a “forest” of trees. The number of predictors used to find the optimal partition at each node is a randomly selected subset of the predictors' total number. Like a Bagging tree, the tree grows to its maximum size without pruning and is aggregated through tree averaging. There is no need to perform a test set or cross-validation using discharged samples to calculate the unbiased error rate and variable importance. Since many trees grow, there is a limited generalization error, which means that overfitting is impossible, a handy feature for prediction.

Suppose K trees are generated in bagging with positive correlation ρ, and each with variance σ^2.

The average variance is calculated as below equation 4.1:

$$\rho\sigma^2 + \frac{1-\rho}{K}\sigma^2 \qquad \text{(Equation 4.1)}$$

With the increase of K, the second term approach to zero, but the first term remains, and the pairwise correlation of bagged trees limits averaging benefits. This process results in diminishing the variance of bagging by reducing the correlation between the trees. The tree growing process is achieved by random selection of the input variables.

The random forest's critical feature is the out-of-bag (OOB) estimate, which is described as follows. For each data case (x,y) in the training set, aggregate the votes or take the average only over those trees built on bootstrap training sets that do not contain (x,y).

While Random forests are more of a "black box" approach than bagging trees because they would not be checked individually, it provides some metrics to help with interpretation. Variable importance is evaluated based on how much worse the prediction will be if the predictor's data is randomly permissive. This can draw a conclusion based on the relative importance between predictors. Thus, this procedure is much more interpretable than a neural network-like approach.

4.4.3. Extreme gradient boosting

The Extreme gradient boosting (XGBoost) is a tree-based ensemble method used for both regression and classification. It was first proposed by Chen and Guestrin (2016). It is built on gradient boosting framework principles and designed to “push the extreme of the computation limits of machines to provide a scalable, portable and accurate library.”

The concept of XGboost is extended from a gradient boosting decision tree (GBDT). GBDT is an iterative algorithm for decision trees. GBDT builds the tree classifier in a serial manner, where each tree tries to gradient reduction of the loss function of the previous model. XGBoost is the optimized version of the traditional gradient boosting trees. As with other boosting methods, it is a stepwise method that generalizes by optimizing arbitrary differential loss functions. In other words, XGBoost is one of the implementations of the concept of Gradient Boosting, but what makes XGBoost unique is that it uses more normalized model formalization to control overfitting, thereby providing better performance and helping to reduce overfitting.

4.5. Results

The afore described methods were used to develop prediction models for the mobility index for transit and recreation/retail trips. The dataset was separated into training (70%) and testing (30%). This section presents the results of the prediction models.

4.5.1. Transit station model

1) Prediction model with target d+1

The prediction accuracy for the three models, CART, Random Forest, and XGBoost are shown in Table 4.3. Random Forest performed the best with MAPE of 5.281%.

As a baseline, time series model without COVID-19 variables were conducted by using Random Forest, the accuracies were 6.902% (target of d+1) and 7.127% (target d+7).

Table 4.2. Accuracy of Transit Station model for different methods (MAPE: %)

Target	CART	Random Forest	XGBoost
d+1	8.189%	5.281%	6.774%
d+7	8.667%	5.811%	6.993%

The relative importance of variables in the Random Forest prediction model are plotted in Figure 4.5. The top two important variables are the mobility at the transit station at d-1 and d-6 The average daily cases and deaths in the past seven days were the next two important variables followed by daily cases and deaths for previous three days (d-1,d-2, and d-3). The percentage importance of these variables are reported in Table 4.3.

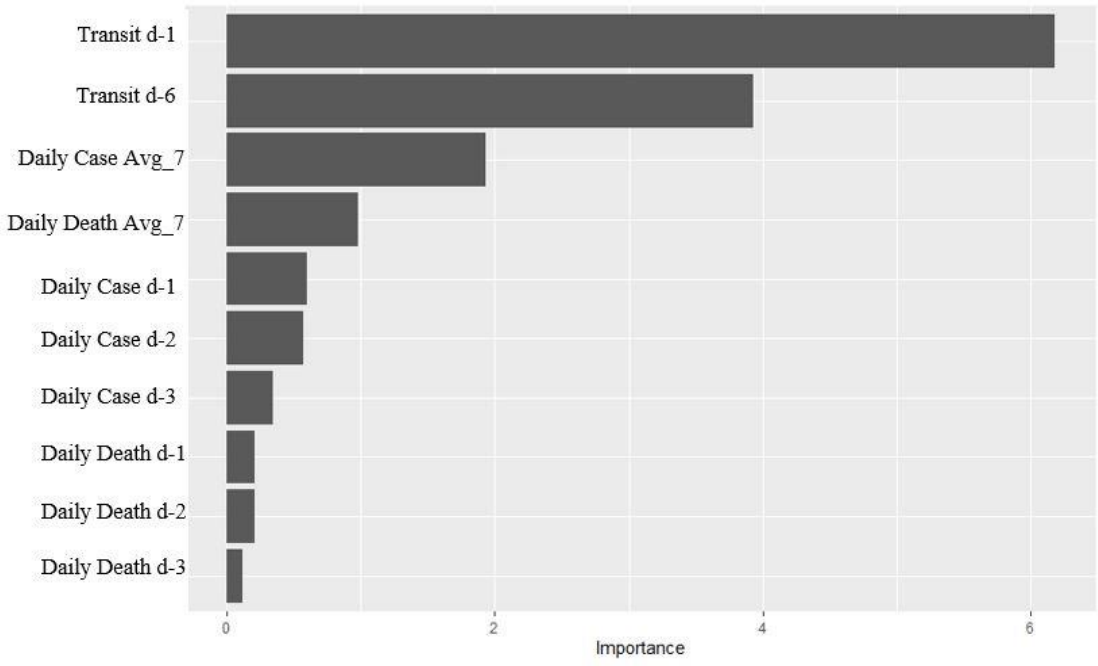


Figure 4.5. Importance view in RF for Transit Station Model (Target: d+1)

Table 4.3. Variables importance for prediction models of Transit Station activity

#	Transit Station Model (d+1)		Transit Station Model (d+7)	
1	Transit d-1	19.7%	Transit d-1	21.5%
2	Transit d-6	15.3%	Daily Case Avg_7	14.2%
3	Daily Case Avg_7	12.3%	Transit d-6	11.1%
4	Daily Death Avg_7	9.2%	Daily Case d-2	9.7%
5	Daily Case d-1	7.9%	Daily Case d-1	9.4%
6	Daily Case d-2	7.2%	Daily Death d-1	8.6%
7	Daily Case d-3	6.4%	Daily Death Avg_7	8.3%
8	Daily Death d-1	5.3%	Daily Case d-3	7.3%
9	Daily Death d-2	4.1%	Daily Death d-2	7.3%
10	Daily Death d-3	3.4%	Daily Death d-3	7.2%

2) Prediction model with target d+7

The prediction accuracy for the three models, CART, Random Forest, and XGBoost are shown in Table 4.3. Once again, Random Forest performed the best with MAPE of 5.811%.

Figure 4.6 shows the variable importance plot of Random Forest prediction model with a target date of d+7. The most important variable was found to be the transit activity at d-1, followed by average daily cases over the past seven days. Table 4.3 shows the percentage importance of each of the independent variables.

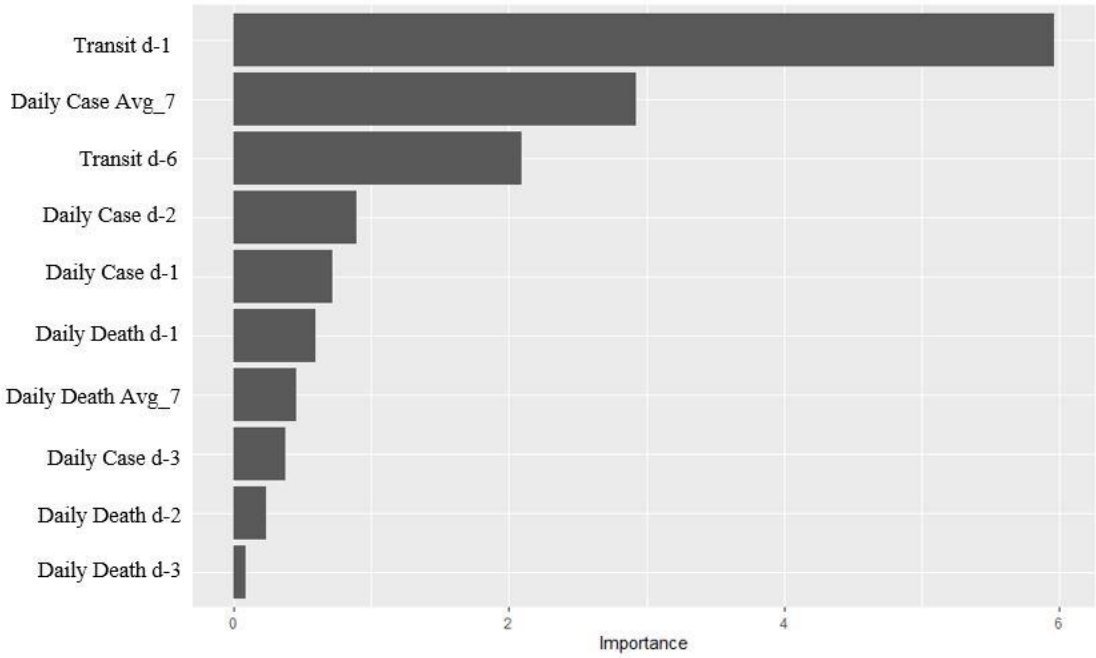


Figure 4.6. Importance view in RF for Transit Station Model (Target: d+7)

4.5.2. Retail and recreation model

1) Prediction model with target d+1

The prediction accuracy for three models, CART, Random Forest, and XGBoost are shown in Table 4.4. Random Forest performed the best with MAPE with 6.547%. Time series model without COVID-19 variables were conducted by using Random Forest as a baseline, the accuracies were 9.583% (target of d+1) and 10.328% (target d+7).

Table 4.4. Accuracy of Retail/Recreation model for different methods (MAPE: %)

Target	CART	Random Forest	XGBoost
d+1	9.674%	6.547%	8.329%
d+7	10.367%	7.139%	9.095%

The relative importance of variables in the Random Forest prediction model are plotted in Figure 4.7. The most important variable is the mobility at the retail and recreation at d-1, followed by average daily cases in the past seven days and the mobility at retail and recreation at d-6. The percentage importance of these variables are shown in Table 4.5.

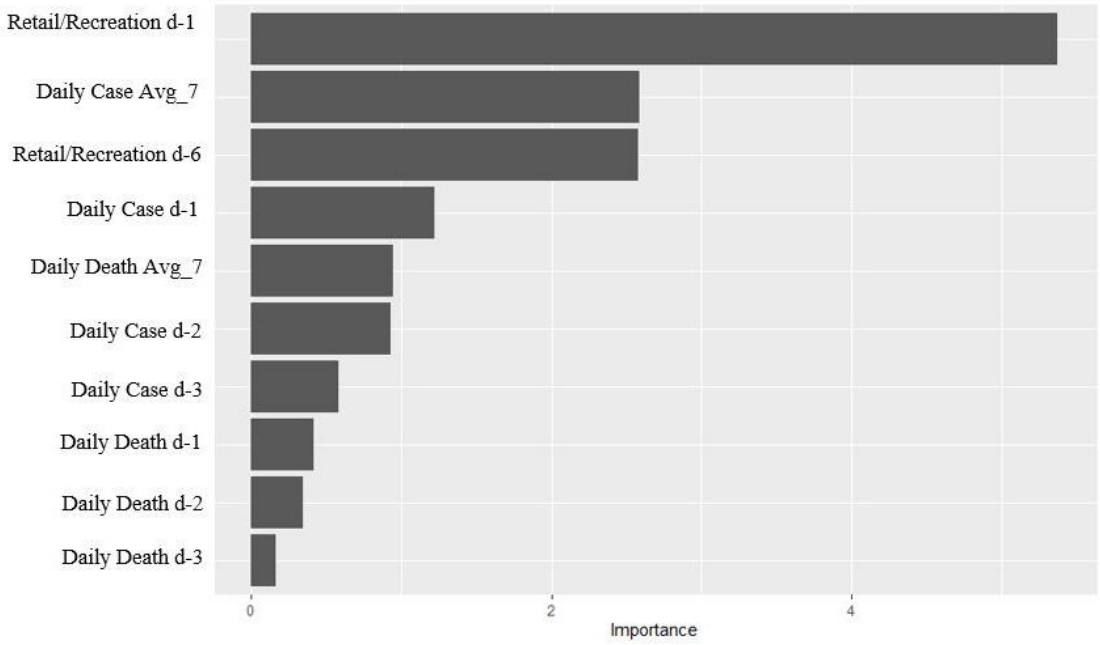


Figure 4.7. Importance view in RF for Retail/Recreation Model (Target: d+1)

Table 4.5. Variables importance for prediction models of Retail and Recreation activity

#	Retail/Recreation Model (d+1)		Retail/Recreation Model (d+7)	
1	Retail/Recreation d-1	15.6%	Retail/Recreation d-1	18.3%
2	Daily Case Avg_7	11.1%	Daily Case Avg_7	14.1%
3	Retail/Recreation d-6	10.5%	Daily Case d-1	12.3%
4	Daily Case d-1	9.6%	Retail/Recreation d-6	11.2%
5	Daily Death Avg_7	9.4%	Daily Case d-3	11.1%
6	Daily Case d-2	8.6%	Daily Case d-2	7.4%
7	Daily Case d-3	7.1%	Daily Death Avg_7	6.9%
8	Daily Death d-1	6.9%	Daily Death d-1	6.1%
9	Daily Death d-2	6.3%	Daily Death d-2	5.3%
10	Daily Death d-3	5.8%	Daily Death d-3	5.2%

2) Prediction model with target d+7

The prediction accuracy for three models, CART, Random Forest, and XGBoost are reported in Table 4.4. Once again, Random Forest performed the best with MAPE with 7.139%. Figure 4.8 presents the variable importance plot of Random Forest prediction model with a target date of d+7. The most important variable was found to be the retail and recreation activity at d-1, followed by average daily cases over the past seven days. Table 4.5 shows the percentage importance of each of the independent variables.

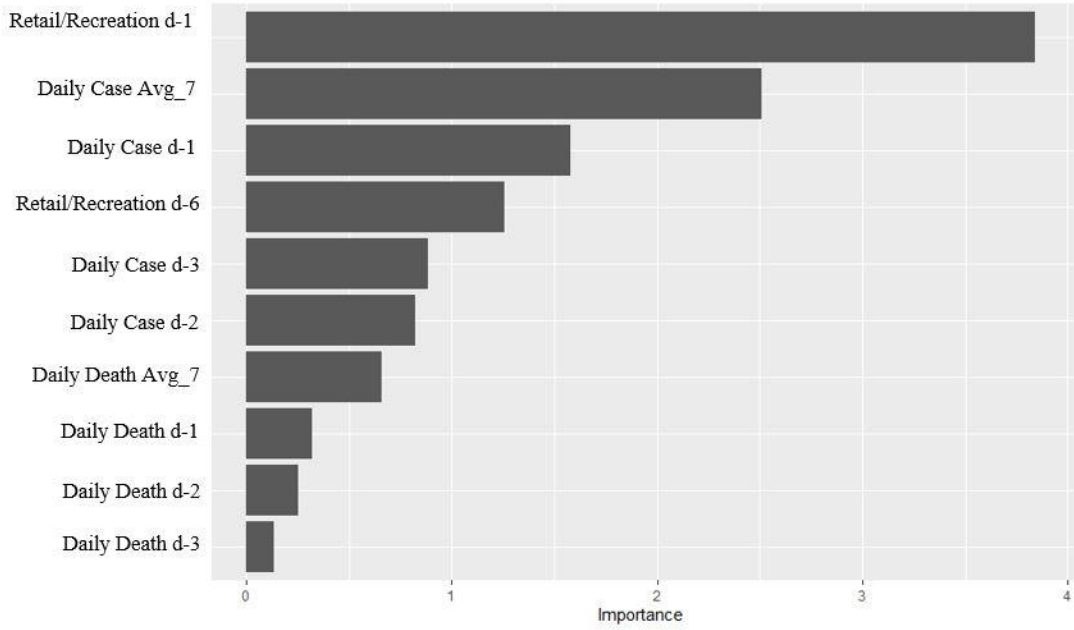


Figure 4.8. Importance view in RF for Retail/Recreation model (target: d+7)

4.5.3. Workplace model

1) Prediction model with target d+1

The prediction accuracy for the three models, CART, Random Forest, and XGBoost are shown in Table 4.7. None of the models were able to predict the outcome with high accuracy. Time series model without COVID-19 variables were conducted by using Random Forest as a baseline, the accuracies were 36.697% (target of d+1) and 39.512% (target d+7).

The MAPE values ranged between 27.944% for Random Forest and 35.785% for CART. One possible reason for this poor performance is the sensitivity of workplace activity to employer decisions (e.g., work from home policies) that are not captured in the input variables.

Table 4.6. Accuracy of Workplace model for different methods (MAPE: %)

Target	CART	Random Forest	XGBoost
d+1	35.785%	27.944%	29.667%
d+7	38.694%	29.039%	32.648%

The relative importance of variables in the Random Forest prediction model are shown in Figure 4.9. The most important variable is the mobility at the workplaces at d-6, followed by the activity at the workplace at d-1. The percentage importance of these variables are reported in Table 4.7.

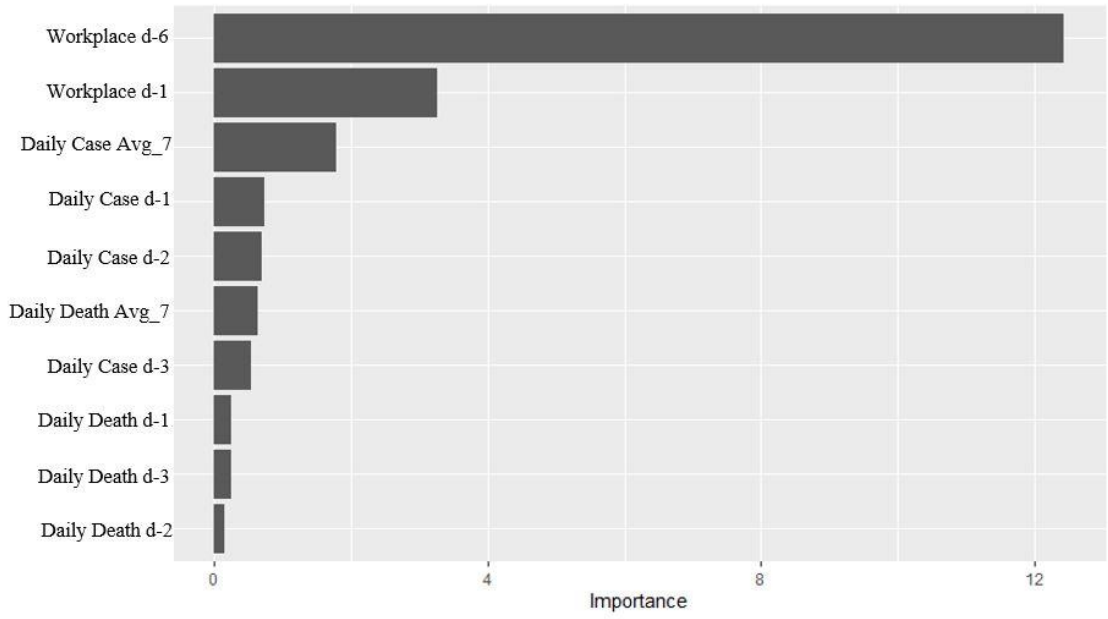


Figure 4.9. Importance view in RF for Workplace model (Target: d+1)

Table 4.7. Variables importance for prediction models of Workplace activity

#	Workplace Model (d+1)		Workplace Model (d+7)	
1	Workplace d-6	52.3%	Workplace d-1	59.1%
2	Daily Case Avg_7	11.6%	Daily Case Avg_7	12.0%
3	Workplace d-1	10.5%	Daily Death Avg_7	8.8%
4	Daily Death Avg_7	9.8%	Daily Case d-1	8.4%
5	Daily Case d-1	8.5%	Daily Death d-1	8.1%
6	Daily Case d-3	8.1%	Workplace d-6	7.9%
7	Daily Case d-2	7.1%	Daily Case d-2	7.4%
8	Daily Death d-3	6.3%	Daily Case d-3	7.3%
9	Daily Death d-2	5.7%	Daily Death d-3	6.3%
10	Daily Death d-1	5.4%	Daily Death d-2	5.8%

2) Prediction model with target d+7

The performance of the three models for d+7 were similar to the poor performance observed for d+1. Figure 4.10 shows the variable importance plot of Random Forest prediction model with a target of d+7. The most important variable was found to be the workplace activity at d-1, followed by the average daily cases in the past seven days and the workplace activity at d-6.

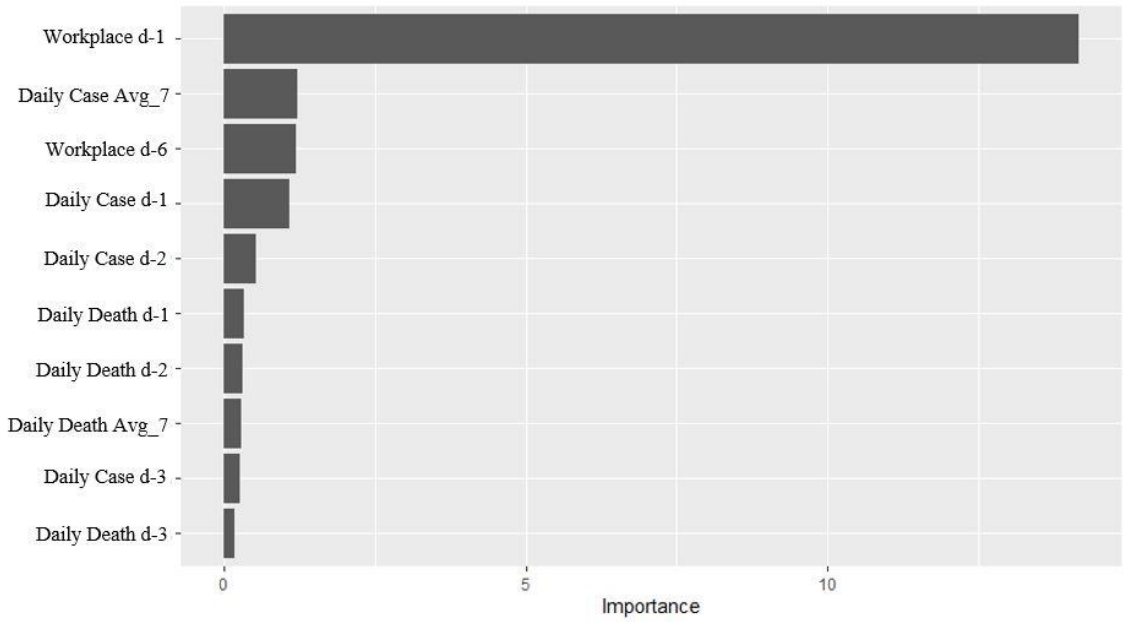


Figure 4.10. Importance view in RF for Workplace model (Target: d+7)

4.5. Conclusion

This study examined mobility data during COVID-19 to ascertain the pandemic's travel impact in one major metropolitan area in the US. Among the three machine learning methods, Random Forest models developed to predict the mobility index values of two different locations (transit station and retail/recreation) were found to be reasonably

accurate with MAPE values between 5.2 and 5.8% for Transit Station Model and 6.5 and 7.1% for Retail / Recreation Model for forecasting one day in advance and seven days in advance. The important predictors in both models were found to be activities at target locations on d-1 and d-6. The average daily new cases of COVID-19 within the past week was also a key predictor. Also, COVID-19 daily cases were found to be a more important predictor than number of COVID-19 deaths. While the prediction models produced satisfactory performance for transit and recreation and retail activity forecasts, they all failed at accurately predicting workplace mobility index, presumably due to the variability in the workplace policies adopted by employers in the New York County region.

There are a few limitations to this study. First, the mandatory stay at home orders were not explicitly included as independent variables in the modeling. Second, the performance of the models with only the timeseries values of the mobility index was not computed. In future research, a baseline prediction can be established using only the timeseries data.

5. CONCLUSION

This dissertation investigated ways to assess the traffic impacts of two natural disasters – hurricanes and epidemic. As was shown, different types of traffic analysis approaches are required to study disruptive events' effect on traffic operations. These approaches include traffic simulation (with various demand and traffic controls), statistical modeling (mixed logit model), and machine learning algorithms (Regression Tree, Random Forest, and XGBoost).

The study findings can assist stakeholders and practitioners in a few ways. The proposed traffic simulation model for hurricane evacuation was capable of studying various phased evacuation and traffic control management techniques such as contraflow and ramp closure. Mesoscopic simulation methods were demonstrated to be effective at assessing various travel demand scenarios and network control strategies. These methods generate performance measures such as clearance times, delays, and travel times that are easily understood by emergency management personnel. The findings in Chapter 2 can help decision-makers compare different scenario outcomes to establish evacuation policies. Using household survey data, we found that evacuee route choice (between freeway vs. non-freeway) depends on socioeconomic characteristics, evacuation destination, evacuation experience, and storm features. The findings in Chapter 3 enable transportation agencies effectively manage the supply side by adopting appropriate traffic management strategies (e.g. signal coordination, freeway ramp metering).

Finally, the mobility prediction in Chapter 4 enables planners to accurately forecast future travel patterns during an epidemic. Predicting travel index values one week in advance were found to be nearly as accurate as predicting one day in advance. The

dissertation tried to utilize numerous tools, including programming languages and transportation software, to better model the impacts of disruptions. Programming languages, including open source languages (e.g., Python and R) and commercial languages (e.g., MATLAB, Visual Basic for Application (VBA)), have facilitated easier implementation of machine learning algorithms and large-scale simulations.

Future research can be conducted in two areas. First, other types of transportation disruptions such as earthquakes and flooding could be explored using traffic simulation methods. For example, studying a no-notice evacuation of an earthquake occurring in the New Madrid Seismic Zone can help with the emergency preparedness and disaster response. Safely evacuating the most impacted people from the southeast part of Missouri will help save lives and reduce human suffering. A second natural extension of this dissertation research is related to the study of COVID-19 impacts using other datasets such as transit-card data, bike data, detector data, and survey responses.

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APPENDIX

A. Hampton Road Evacuation Survey Questionnaire

Note: If you are not the decision-maker for evacuation-related decisions in your household, please give this survey to the household member who does make those decisions.

1. Are you at least 18 years old?
   ☐ Yes ☐ No

2. How likely is that you and your family will be impacted by a hurricane in the next five years?
   ☐ Very unlikely ☐ Unlikely ☐ Not sure ☐ Likely ☐ Very likely

3. If a hurricane were to impact you and your family, how likely is it that you would experience the following?

	Not At All Likely	Not Very Likely	Some-what Likely	Very Likely	I Don't Know
A. Property damage	☐	☐	☐	☐	☐
B. Disruption to your daily life	☐	☐	☐	☐	☐
C. Injury and/or death	☐	☐	☐	☐	☐

4. Have you ever experienced a hurricane?
   ☐ Yes, In what year was your most recent hurricane experience (it is ok to estimate):_____
   ☐ No

5. If you have experienced a hurricane before, did you have any of the following happen to you?

	Yes	No
A. Property damage	☐	☐
B. Disruption to daily life	☐	☐
C. Injury to self and/or injury or death of a friend or relative	☐	☐

6. What is your best estimate of how many times you have evacuated in the past?
   _____

7. What is your best estimate of how many times you have chosen *not* to evacuate when evacuation was recommended for your area? _____

8. To what extent do you agree or disagree that, in general, evacuation is an effective way to protect you from hurricanes?
   ☐ Strongly Disagree ☐ Disagree ☐ Neutral ☐ Agree ☐ Strongly Agree
9. Do you think you could prevent or reduce damage to your property if you stayed on your property during a hurricane?
   ☐ Yes, and I would probably choose not to evacuate for that reason
   ☐ Yes, but I don't think it is worth the risk to myself/my family, so I would evacuate
   ☐ No, I don't think I could significantly reduce the damage by staying on my property
   ☐ I don't know

10. Which of the following best describes your current level of planning for a hurricane?
    ☐ I haven't done any planning
    ☐ I have some general ideas about what I would do
    ☐ I have a complete plan for what I would do

11. If a hurricane was going to impact your neighborhood, what would you be most likely to do?
    ☐ Evacuate
    ☐ Shelter in my home
    ☐ Other, specify_____
    ☐ I don't know

12. Where would you go? (please write the city and state)
    _____

13. What kind of place would you go to?
    ☐ Relative's home
    ☐ Friend's home
    ☐ Hotel/motel/inn
    ☐ Second home/property
    ☐ Shelter
    ☐ Other
    ☐ I don't know
    ☐ I don't have a place to go

14. On a normal day (when there is not an evacuation happening), approximately how long (in hours) would it take you to travel to your chosen evacuation destination?
    _____

15. Approximately how long (in hours) do you think it would take you to travel to your destination *during an evacuation*? _____

16. How long before the predicted arrival of the hurricane would you most likely begin your evacuation?
    ☐ The same day
    ☐ The day before
    ☐ Two days before
    ☐ Three or more days before
    ☐ I don't know

17. When do you think you would be most likely to leave?
    - ☐ Early morning (12:00 am – 5:59 am)
    - ☐ Morning (6:00 am – 11:59 am)
    - ☐ Afternoon (12:00 pm – 5:59 pm)
    - ☐ Evening/night (6:00 pm – 11:59 pm)
    - ☐ I don't know

For the next few questions, please imagine that you decided to evacuate, even if you think you are more likely not to evacuate. Assuming you made that choice, select the response to each question below that best captures what you think you would do.

18. Which type of road would you mostly travel on?
    - ☐ Freeway (road with on/off ramps and no stop lights/signs)
    - ☐ Major roads (may have stop lights or stop signs)
    - ☐ Any other local or back roads
    - ☐ I don't know

19. If officials recommend using a particular evacuation route, would you use that route?
    - ☐ I definitely would use the recommended route
    - ☐ I probably would use the recommended route
    - ☐ I probably would not use the recommended route
    - ☐ I definitely would not use the recommended route
    - ☐ I don't know

20. Who do you think is responsible for the safety of individual people?
    - ☐ More an individual/household responsibility
    - ☐ Shared equally between households and the government
    - ☐ More a government responsibility
    - ☐ I don't know

21. To what extent do you think each is responsible for ensuring people have the resources to evacuate?
    - ☐ More an individual/household responsibility
    - ☐ Shared equally between households and the government
    - ☐ More a government responsibility
    - ☐ I don't know

22. If you had to evacuate today, how much money do you think the evacuation would cost (consider travel costs, a place to stay, lost income, food, and fuel)?

    _____

23. If you had to evacuate today, how much money (cash, savings, credit card, money you could borrow) do you have available to spend on evacuation?

_____

24. Imagine you had participated in an evacuation. If you were later asked to rate how "good" your evacuation experience was, how important would each of the following factors be for your rating?

	Not Important At All	Not Very Important	Some-what Important	Very Important
A. Injuries or death of someone in your household	☐	☐	☐	☐
B. Damage to your property	☐	☐	☐	☐
C. If you were in physical danger from the hurricane	☐	☐	☐	☐
D. If you had a car accident while evacuating	☐	☐	☐	☐
E. If you were physically uncomfortable during the evacuation	☐	☐	☐	☐
F. How worried you were during the evacuation	☐	☐	☐	☐
G. Access to resources like restrooms, fuel, food, etc.	☐	☐	☐	☐
H. The time you could begin your evacuation	☐	☐	☐	☐
I. How much time it took to evacuate	☐	☐	☐	☐
J. How fast traffic was moving	☐	☐	☐	☐
K. How far you had to travel	☐	☐	☐	☐
L. The cost of evacuating	☐	☐	☐	☐
M. How much gasoline/fuel it took to evacuate	☐	☐	☐	☐
N. How many days you were away from your home	☐	☐	☐	☐
O. How many days you were away from your job/school	☐	☐	☐	☐
P. How many days your normal routine was disrupted	☐	☐	☐	☐
Q. How afraid you were during the evacuation	☐	☐	☐	☐

25. Considering the factors described in the previous question, how much risk or hardship would you be willing to endure if you know that it means more people will be safe?
    - ☐ None. I'm only concerned about myself and my family.
    - ☐ I can put up with a little hardship if I know it means other people will be safe.
    - ☐ I can put up with a lot of hardship if I know it means more people will be safe.
    - ☐ I'll put up with whatever hardship is necessary if I know it means more people will be safe

26. How many personal vehicles does your household have available to use in an evacuation?
    - ☐ None
    - ☐ One
    - ☐ Two
    - ☐ Three
    - ☐ More than three
    - ☐ I don't know

27. How many licensed drivers are there in your household?
    - ☐ None
    - ☐ One
    - ☐ Two
    - ☐ Three
    - ☐ More than three
    - ☐ I don't know

28. About how much fuel is in your household's primary vehicle right now?
    - ☐ Full tank
    - ☐ ¾ tank
    - ☐ ½ tank
    - ☐ ¼ tank
    - ☐ Near empty tank
    - ☐ I have an electric car
    - ☐ I don't know
    - ☐ I don't have any vehicles

29. Do you think this is enough fuel for you to reach the place you think you would evacuate to?
    - ☐ Yes
    - ☐ No
    - ☐ I don't know
    - ☐ I don't have any vehicles

30. Do you have family or friends outside of your household that would be willing to let you evacuate with them?
    - ☐ Yes
    - ☐ Maybe
    - ☐ No
    - ☐ I don't know

31. Do you have access to the things you think you need to evacuate?
    - ☐ Yes
    - ☐ Maybe
    - ☐ No
    - ☐ I don't know

Hurricane Scenario Please Read!!!

For the rest of the survey, we want you to imagine that it is the middle of the summer, and that a Hurricane is threatening your area. Multiple sources you trust say that next Thursday morning, a category 4 hurricane (130-156 mph wind speeds) will affect your neighborhood. A mandatory evacuation order has been given for your neighborhood. Please keep this scenario in mind as you answer the remaining questions.

32. Given the scenario described above, would you evacuate?
    ☐ Yes, I would evacuate ☐ No, I would not evacuate ☐ I don't know

33. How frequently would you check for updated information on the hurricane and/or the evacuation?
    - ☐ About every 30 minutes
    - ☐ About every hour
    - ☐ About every two hours
    - ☐ About every six hours
    - ☐ About every 12 hours
    - ☐ About once a day
    - ☐ I would not check for updated information

If you answered in question #32 that you would not evacuate, please skip ahead to question # 43.

If you answered yes please answer the next few questions based on what you would do given the scenario above.

34. How many days before the projected arrival of the hurricane would you leave your home?
    - ☐ More than three days before the hurricane's arrival
    - ☐ Three days before the hurricane's arrival
    - ☐ Two days before the hurricane's arrival
    - ☐ One day before the hurricane's arrival
    - ☐ The day of the hurricane's arrival
    - ☐ I don't know

35. In what part of the day are you most likely to begin your evacuation?
    - ☐ Early morning (12:00 am – 5:59 am)
    - ☐ Morning (6:00 am – 11:59 am)
    - ☐ Afternoon (12:00 pm – 5:59 pm)
    - ☐ Evening/night (6:00 pm – 11:59 pm)
    - ☐ I don't know

36. If officials asked that different areas/zones start evacuating at different times, but your area/zone is asked to wait for a later slot, which of the following are you most likely to do?
    - ☐ Evacuate with the first group
    - ☐ Evacuate at the recommended time for my zone
    - ☐ Evacuate later than recommended for my zone
    - ☐ Evacuate without considering the recommended start times
    - ☐ Decide not to evacuate
    - ☐ I don't know

37. Where would you most likely begin your evacuation from?
    - ☐ Home
    - ☐ Someone else's home
    - ☐ Work
    - ☐ Children's school
    - ☐ Store
    - ☐ Other_____

38. What cross-street or intersection is closest to where you would begin your evacuation from?
    _____

39. Which of the following options would you be most likely to use to evacuate?
    - ☐ Personal vehicle
    - ☐ Get a ride from family or friends
    - ☐ Mass Transit
    - ☐ Walk
    - ☐ Ride a bike
    - ☐ I don't know

40. If you and your household are most likely to use one or more personal vehicle(s) to evacuate, how many vehicles would you use?
    - ☐ One
    - ☐ Two
    - ☐ Three or more
    - ☐ I would not evacuate by personal vehicle
    - ☐ I don't know

41. If you would use all of your household's available vehicles to evacuate, which of the following are reasons you would use all of the vehicles? Check all that apply.
    - ☐ Concerns the vehicles would be damaged or stolen if left behind
    - ☐ Cannot afford to repair/replace damaged vehicles
    - ☐ To have enough seats for all of my household
    - ☐ To have enough space for the belongings I would bring
    - ☐ To have enough space to bring my pets
    - ☐ Because my household has enough drivers to bring all the vehicles
    - ☐ My household only has one vehicle
    - ☐ I would not use all of my household's available vehicles
    - ☐ Other (specify):_____

42. If you would not use all of your household's available vehicles to evacuate, which of the following are reasons you would use fewer vehicles? Check all that apply.
    - ☐ To have multiple drivers for the vehicles I would use
    - ☐ Not enough drivers for all of the vehicles
    - ☐ Concerns about the reliability of the vehicle(s) I would not use
    - ☐ To keep my family together as much as possible
    - ☐ To save on fuel costs
    - ☐ Concerns about traffic
    - ☐ No real reason to take all of the vehicles
    - ☐ I would use all of my household's available vehicles
    - ☐ Other (specify):_____

We would like to know if any of the following scenarios would make you change your evacuation decisions. For each question, please mark the box for any change(s) you would make. You can select as few or as many as you like.

43. If there was a **six hour traffic delay** and you would arrive at your destination **before** the hurricane made landfall, you would…
    - ☐ Decide not to evacuate
    - ☐ Evacuate earlier that day
    - ☐ Evacuate later that day
    - ☐ Evacuate a day sooner
    - ☐ Evacuate a day later
    - ☐ Change my route
    - ☐ Use more vehicles
    - ☐ Use fewer vehicles
    - ☐ Change my destination
    - ☐ Not change anything
44. If there was a **six hour traffic delay** and you would arrive at your destination **around the same time** the hurricane made landfall, you would…
    - ☐ Decide not to evacuate
    - ☐ Evacuate earlier that day
    - ☐ Evacuate later that day
    - ☐ Evacuate a day sooner
    - ☐ Evacuate a day later
    - ☐ Change my route
    - ☐ Use more vehicles
    - ☐ Use fewer vehicles
    - ☐ Change my destination
    - ☐ Not change anything

45. If there was a **six hour traffic delay** and you would arrive at your destination **after** the hurricane made landfall, you would…
    - ☐ Decide not to evacuate
    - ☐ Evacuate earlier that day
    - ☐ Evacuate later that day
    - ☐ Evacuate a day sooner
    - ☐ Evacuate a day later
    - ☐ Change my route
    - ☐ Use more vehicles
    - ☐ Use fewer vehicles
    - ☐ Change my destination
    - ☐ Not change anything

46. If there was a **three hour traffic delay** and you would arrive at your destination **before** the hurricane made landfall, you would…
    - ☐ Decide not to evacuate
    - ☐ Evacuate earlier that day
    - ☐ Evacuate later that day
    - ☐ Evacuate a day sooner
    - ☐ Evacuate a day later
    - ☐ Change my route
    - ☐ Use more vehicles
    - ☐ Use fewer vehicles
    - ☐ Change my destination
    - ☐ Not change anything

47. If there was a **three hour traffic delay** and you would arrive at your destination **around the same time** the hurricane made landfall, you would…
    - ☐ Decide not to evacuate
    - ☐ Evacuate earlier that day
    - ☐ Evacuate later that day
    - ☐ Evacuate a day sooner
    - ☐ Evacuate a day later
    - ☐ Change my route

☐ Use more vehicles
☐ Use fewer vehicles
☐ Change my destination
☐ Not change anything

48. If there was a **<u>three hour traffic delay</u>** and you would arrive at your destination **<u>after</u>** the hurricane made landfall, you would…
    ☐ Decide not to evacuate
    ☐ Evacuate earlier that day
    ☐ Evacuate later that day
    ☐ Evacuate a day sooner
    ☐ Evacuate a day later
    ☐ Change my route
    ☐ Use more vehicles
    ☐ Use fewer vehicles
    ☐ Change my destination
    ☐ Not change anything

49. If there was a **<u>one hour traffic delay</u>** and you would arrive at your destination **<u>before</u>** the hurricane made landfall, you would…
    ☐ Decide not to evacuate
    ☐ Evacuate earlier that day
    ☐ Evacuate later that day
    ☐ Evacuate a day sooner
    ☐ Evacuate a day later
    ☐ Change my route
    ☐ Use more vehicles
    ☐ Use fewer vehicles
    ☐ Change my destination
    ☐ Not change anything

50. If there was a **<u>one hour traffic delay</u>** and you would arrive at your destination **<u>around the same time</u>** the hurricane made landfall, you would…
    ☐ Decide not to evacuate
    ☐ Evacuate earlier that day
    ☐ Evacuate later that day
    ☐ Evacuate a day sooner
    ☐ Evacuate a day later
    ☐ Change my route
    ☐ Use more vehicles
    ☐ Use fewer vehicles
    ☐ Change my destination
    ☐ Not change anything

51. If there was a **<u>one hour traffic delay</u>** and you would arrive at your destination **<u>after</u>** the hurricane made landfall, you would…
    ☐ Decide not to evacuate
    ☐ Evacuate earlier that day
    ☐ Evacuate later that day
    ☐ Evacuate a day sooner
    ☐ Evacuate a day later
    ☐ Change my route
    ☐ Use more vehicles
    ☐ Use fewer vehicles
    ☐ Change my destination
    ☐ Not change anything

52. In the chart below, please indicate whether each of the factors would make you more or less likely to evacuate.

	More Likely to Evacuate	Less Likely to Evacuate	Makes No Difference	I Don't Know
A. If the hurricane hit on a weekday	☐	☐	☐	☐
B. If the hurricane hit on a weekend	☐	☐	☐	☐
C. If the hurricane was at the end of the month	☐	☐	☐	☐
D. If you had to take care of someone who was sick	☐	☐	☐	☐
E. If your friends and family decide not to evacuate	☐	☐	☐	☐
F. Concerns for protecting your home from damage	☐	☐	☐	☐
G. Concerns about your job.	☐	☐	☐	☐
H. Concerns about how inconvenient the evacuation would be	☐	☐	☐	☐
I. Concerns for how expensive the evacuation would be	☐	☐	☐	☐
J. Concerns about having fuel while evacuating	☐	☐	☐	☐
K. Concerns about being caught on the road during the hurricane	☐	☐	☐	☐
L. Concerns about being injured or killed during the evacuation	☐	☐	☐	☐

53. How would this influence the likelihood that you will evacuate?
    - ☐ It would make me much more likely to evacuate
    - ☐ It would make me somewhat more likely to evacuate
    - ☐ This information would not influence my evacuation decision
    - ☐ It would make me somewhat less likely to evacuate
    - ☐ It would make me much less likely to evacuate
    - ☐ I don't know

54. How would this influence the likelihood that you will use the interstate highways to evacuate?
    - ☐ It would make me much more likely to use the interstate
    - ☐ It would make me somewhat more likely to use the interstate

- ☐ This information would not influence my evacuation decision
- ☐ It would make me somewhat less likely to use the interstate
- ☐ It would make me much less likely to use the interstate
- ☐ I don't know

55. How would this influence the time that you would begin your evacuation?
    - ☐ I would want to leave before the emergency measures were implemented
    - ☐ It would not affect the time I would begin my evacuation
    - ☐ I would want to leave after the emergency measures were implemented
    - ☐ I don't know

56. How would this influence your choice of evacuation destination?
    - ☐ I would choose a different destination
    - ☐ It would not affect my choice of destination
    - ☐ I don't know

57. How would this influence the number of vehicles your household would use?
    - ☐ It would make me more likely to use more vehicles to evacuate
    - ☐ It would make me more likely to use fewer vehicles to evacuate
    - ☐ It would not affect how many vehicles I would use
    - ☐ I don't know

58. What year were you born?_____

59. How many people live in your household who are…
    A. under the age of 18? _____
    B. age 18-64? _____
    C. age 65 or older? _____

60. How many people live in your household who have…
    A. Seriously impaired hearing?_____
    B. Seriously impaired vision even with glasses? _____
    C. Serious difficulty concentrating, remembering, or making decisions? _____
    D. Serious difficulty walking/climbing stairs? _____
    E. Difficulty dressing or bathing? _____
    F. Difficulty doing errands alone such as visiting a doctor's office or shopping? _____

61. How many pets (if any) live in your household? _____

62. If you have pets, what kind of animals are they? _____

63. What is the highest level of education you have completed?
- ☐ Did not finish high school
- ☐ High school graduate or GED
- ☐ Vocational/ Technical School after High School
- ☐ Some College (without finishing a degree)
- ☐ 2 year college degree (Associate)
- ☐ 4 year college degree (Bachelor)
- ☐ Graduate degree (Master's or Ph.D.)
- ☐ Professional degree (D.D.M., J.D., M.D., etc.)

64. Which of the following best describes your marital status?
- ☐ Married
- ☐ Single/Never married
- ☐ Widowed
- ☐ Separated
- ☐ Divorced

65. Which category best describes your race/ethnicity?
- ☐ Caucasian/White
- ☐ African American/Black
- ☐ Asian
- ☐ American Indian
- ☐ Pacific Islander
- ☐ Multi-racial
- ☐ Hispanic

66. Which of the following best describes your gender?
- ☐ Male
- ☐ Female
- ☐ Other:_____

67. Which of the following best describes your current employment status?
- ☐ Employed full-time
- ☐ Employed part-time
- ☐ Unemployed
- ☐ Homemaker
- ☐ Student
- ☐ Retired
- ☐ Unable to work

68. Which of the following best describes your home?
- ☐ Single family home,
- ☐ Duplex, or townhouse
- ☐ Manufactured home or trailer
- ☐ Apartment or condominium
- ☐ Some other kind of structure
- ☐ I don't know

69. Do you (or your family) own your residence or do you rent?

- ☐ Own
- ☐ Rent
- ☐ Other

69. How many years have you lived in the Hampton Roads area? _____

70. Please mark the income range that best describes your annual household income from all sources. This is before taxes and other deductions.

- ☐ $0 - $14,999
- ☐ $15,000 - $34,999
- ☐ $35,000 - $49,999
- ☐ $50,000 - $74,999
- ☐ $75,000 - $99,999
- ☐ $100,000 - $149,999
- ☐ $150,000 - $249,999
- ☐ $250,000 +

B. Glossary of Terms

Term	Definition
Average travel time	Travel time from the origin to the destination.
Bootstrap	A type of resampling where large numbers of smaller samples of the same size are repeatedly drawn, with replacement, from a single original sample.
Clearance time	Time needed to complete evacuation at a certain point.
Contraflow lane	A lane in which traffic flows in the opposite direction of the surrounding lanes.
Freeway	An expressway with fully controlled access
Goodness-of-fit	Statistical tests aiming to determine whether a set of observed values match those expected under the applicable model.
High occupancy vehicle	A motor vehicle carrying more than a specified minimum number of people and therefore permitted to use a traffic lane reserved for such vehicles
Intelligent transportation system	an advanced application which aims to provide innovative services relating to different modes of transport and traffic management and enable users to be better informed and make safer, more coordinated, and 'smarter' use of transport networks
Marginal effect	It measures the impact that an instantaneous change in one variable has on the outcome variable while all other variables are held constant.
Mean absolute percentage error	The measure of prediction accuracy of a forecasting method in statistics
Traffic analysis zone	The unit of geography most commonly used in conventional transportation planning models
User-equilibrium	States that the journey times in all routes actually used are equal and less than those that would be experienced by a single vehicle on any unused route

VITA

Daeyeol Chang received B.S. degree in urban engineering from Chung-Ang University, South Korea and the M.S. degree in transportation engineering from Chung-Ang University, South Korea. He entered the Graduate School at University of Missouri-Columbia in August 2016 to purse the degree of Doctor of Philosophy in Civil Engineering. During this time as a graduate student as well as a research assistant, Daeyeol was involved with several funded research projects by NSF and MoDOT. He received several awards for his work in student competitions, conferences, and journal publications.