REAL-TIME RECOMMENDATIONS FOR TRAFFIC CONTROL IN AN ITS SYSTEM DURING AN EMERGENCY EVACUATION

FINAL REPORT

JUNE 2022

AUTHORS

Lauren Davis, Xiuli Qu, Younho Seong

North Carolina A&T State University (NCAT)

US DEPARTMENT OF TRANSPORTATION GRANT 69A3551747125

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title: Real-Time Recommendations for Traffic Control in an Intelligent Transportation System (ITS) During an Emergency Evacuation Subtitle: Phase II Studies		5. Report Date December 2020 6. Source Organization Code
7. Author(s) : Qu, Xiuli; Davis, Lauren; Seong, Younho; Alabi, Miriam; Meda, Harshitha; Parvez, Mahmud		8. Source Organization Report No. CATM-2022-R4-NCAT
9. Performing Organization Name and Address Center for Advanced Transportation Mobility Transportation Institute 1601 E. Market Street Greensboro, NC 27411		10. Work Unit No. (TRAIS) 11. Contract or Grant No. 69A3551747125
12. Sponsoring Agency Name and Address University Transportation Centers Program (RDT-30) Office of the Secretary of Transportation–Research U.S. Department of Transportation 1200 New Jersey Avenue, SE Washington, DC 20590-0001		13. Type of Report and Period Covered Final Report: May 2020 – August 2021 14. Sponsoring Agency Code USDOT/OST-R/CATM
15. Supplementary Notes:		

16. Abstract

Recent hurricanes caused mass evacuations and brought the public attention to the issues occurring during these mass evacuations. To address these issues, the project team has investigated significant cues for hurricane evacuation planners' decisions, built the Rule-based Lens Model (RLM) using Monte-Carlo simulation and supervised machine learning (SML) algorithms to analyze decision-making behavior during a hurricane evacuation, and developed an agent-based hurricane evacuation simulation model using the MATSim framework to estimate evacuation traffic volumes and patterns under different scenarios. Our results show that one cue (wind speed) contributes to evacuation planners' decisions, and the percentage of families choosing shelter-in-place slightly affects evacuation traffic. We have also proposed and tested the quantitative methods to quantify a hurricane disruption to the US airport network, to reroute disrupted flights, and to recommend multimodal routes for affected passengers. Our results show that the proposed methods can identify the airports to be disrupted by an approaching hurricane and feasible airports for flight rerouting, and suggest hiring buses to transfer passengers affected by a hurricane. These models, methods and findings can support the deployment of an effective evacuation, rescheduling of airline flights and passengers affected, and improve the mobility of the people during a hurricane.

17. Key Words Hurricane Evacuation, Air Transportation, Road Transportation, Multimodal Transportation, Decision Making, Rescheduling, Lens Models, Supervised Machine Learning, MATSim, Optimization		18. Distribution Statement Unrestricted; Document is available to the public through the National Technical Information Service; Springfield, VT.	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 95	22. Price …

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

TABLE OF CONTENTS

EXECUTIVE SUMMARY

In recent years natural disasters such as hurricanes, floods, and winter storms, have caused significant losses and disruptions to infrastructure, communities, and the economy. Effective preparation and quick response to natural disasters is very important for the mitigation of such losses and disruptions. As an important part of natural disaster preparation and response, evacuations often occur before or after a natural disaster. However, an effective evacuation involves complex planning, preparation, and operations. Moreover, diverse human evacuation behavior, such as staying or evacuating from home, taking public transportation or driving private vehicles, and different times and routes to leave from the affected area, complicates the management of mass evacuations.

In the second phase of this CATM project, we proposed and tested the quantitative methods to quantify a hurricane disruption to the United States (US) airport network, to identify feasible airports to reroute flights from a disrupted airport, and to recommend personalized multimodal options for passengers stranded due to a hurricane. Our results showed that the proposed quantitative methods can identify the airports to be disrupted by an approaching hurricane, potential airports for rerouting flights from the disrupted airports, and road transportation services to be utilized for rescheduling passengers. Our experimental results revealed that hurricane impact distance and forecast track affect identifying potential disruptors, their disruptees and potential airports to reroute to from a disrupted airport. In addition, our results implied that it is advisable to hire buses to transfer passengers when a disruptive event is anticipated to occur at a particular airport.

For hurricane evacuation, we investigated significant cues for Evacuation Planners' decisions during a hurricane evacuation, built the Rule-based Lens Model (RLM) to analyze decision-making behavior during an emergency evacuation in an incomplete information environment, and developed an agent-based hurricane evacuation simulation model to examine evacuation traffic volumes under different scenarios. Our analysis results showed that only one (wind speed) of the seven cues tested contributes to Evacuation Planners' decision. Our experimental results demonstrated that Monte-Carlo simulation was 66% accurate in simulating ecological data, and the supervised machine learning (SML) algorithms are capable of modeling both ecology and judgment policy. Our simulation results

showed that optimized individual evacuation plans considering traffic conditions can reduce the average evacuation trip duration by about 10% when compared to taking the shortest path, and the percentage of families choosing shelter-in-place slightly affects evacuation traffic and travel time.

The proposed graph theoretical and rerouting methods can support airports and airlines administrators to recognize the airports that might be affected beforehand, which in turn can aid in planning for a disruption. The planning for rescheduling of airline passengers based on a hurricane forecast path may alleviate the problem of passenger disruption. The RLM combining the ecological and judgment models can quantify evacuee decision making when limited information is available for data-supported models, which can support disaster management. The developed hurricane evacuation simulation model can estimate evacuation traffic volumes and average travel time given a hurricane evacuation scenario, which could provide insights for hurricane evacuation planning and management. This simulation model can be used as a tool to support hurricane evacuation planning by comparing different traffic control policies under different hurricane evacuation scenarios.

Our results of the second phase of this CATM project have been published as one peer-reviewed conference paper and presented as posters and oral presentations at national professional conferences and regional transportation symposiums. One journal paper has been submitted. In addition, four graduate students (including two female students) and one African American undergraduate student have been involved in this CATM project. Two of the four graduate students working on this project have graduated with the dissertation research in Transportation. The participation of these students can contribute to the diversity of the US transportation workforce in the future.

DESCRIPTION OF PROBLEM

As part of natural disaster preparation and response, evacuations often occur before or after natural disasters such as hurricanes and earthquakes. For example, nearly seven million Florida residents evacuated from the state during Hurricane Irma (2017), making it the largest hurricane evacuation in the US and causing significant traffic congestion and fuel shortage in Florida. Hurricane Irma also caused significant disruption to air transportation in Florida. Nearly 4000 flights were cancelled according to one report by Flight Aware. In addition to canceling and diverting flights, airlines also added flights to get passengers out of the storm's path and moved their planes (some of which cost $100 million) to other safe cities. United Airlines, Delta, and American added flights in advance of the hurricane to help get stranded passengers out of the storm's path. The ripple effects of the storm were felt in other cities like Atlanta, where Delta canceled nearly 1000 flights resulting in many passengers stranded at the airport.

During Hurricane Florence (2018), evacuation orders were issued to 25 counties in North Carolina and South Carolina, causing approximately one million Carolinians to evacuate from their homes. However, some residents chose shelter-in-place despite mandatory evacuation issued in their counties. Traffic congestion and fuel shortages occurred in the eastern coastal areas in North Carolina even though the state government prepared for evacuation by closing public schools and issuing evacuation orders three days before landfall, arranging evacuation paths and providing evacuation guide. A worse issue was that some people could not evacuate due to the closure of a bridge when they chose to evacuate later. Therefore, it is obvious that effective and proper traffic control is crucial during a mass evacuation.

Recently, information and communication technologies (ICT) have been incorporated in the NC transportation infrastructure to build intelligent transportation systems (ITSs), which include smart actuated signals, dynamic message signs, the roadway weather information system, reversible lane systems, and the traveler information management system. These ITSs provide us with opportunities to improve the effectiveness and efficiency of emergency response. For example, smart traffic signals and the traffic coordination network enable emergency vehicles to respond to incidents rapidly. During natural disasters, ITSs can also play an important role in mass emergency evacuations. In this CATM project, we aimed to develop and integrate ecological models for human evacuation behavior prediction and hurricane evacuation traffic control in intelligent transportation infrastructure. The ultimate goal is to create a human-centered intelligent traffic control recommendation system to support mass evacuations. The research questions of the second phase of our CATM project are:

- What are the differences in network structure among the US airlines, and to what extent are these differences correlated with the consequences of severe weather disruptions to airline flight schedules?
- How should airline carriers recommend personalized, multi-modal options for passengers whose flights are cancelled due to severe weather? We consider various transportation modes to get the passengers to their destinations.
- How do human make decisions to evacuate on emergency?
- Can the Monte Carlo simulation be used to replace the unavailable ecological environment?
- Can machine learning algorithms outperform traditional logistic regression models to evaluate and predict human judgment?
- How does the percentage of families choosing to shelter-in-place affect evacuation traffic and the average evacuation travel time?
- How can optimized individual evacuation plans affect evacuation traffic and individuals' evacuation travel time?

METHODOLOGY AND RESULTS

In this CATM project, we conducted studies addressing hurricane evacuation and weather-related flights recovery. Before we conducted these studies, we investigated the components of North Carolina's Intelligent Transportation System (ITS) and identified the potential actions that are supported by the smart components in the current NC road transportation system that can be used to improve traffic control during a hurricane evacuation. We also requested and collected historical data related to hurricane evacuations from different sources to support our CATM studies. The methodology and results of five studies in Phase 2 of this CATM project are described in detail in the following subsections.

Study 1 – A Graph Theoretical Approach Integrating Geospatial Information to Analyze Airport Network Disruptions

1.1 Research Problem

Air transportation is one of those complex systems that needs to function across multiple organizations and departments. Besides its intricate functionality, it is often subjected to different types of disruptions such as aircraft technical issues, human planned attacks, airport damage, airport congestion, industrial strikes, and severe weather conditions among others. These disruptions influence the operational stability of the airport network system [1]. Moreover, weather disruptions account for over 50% of the delays in the US National Airspace (NAS) [2]. In this study, we analyzed weather related disruptions on an airport network.

Weather-related disruptions are a common occurrence in an air transportation system. Due to their stochastic nature, they can be hard to predict accurately, even though we have forecasting tools [3-5]. It is not always possible to eliminate the source of disruptions, especially if they are weather-related events such as hurricanes and tropical storms. However, to mitigate the impact of weather-related disruptions, there might be a necessity to develop robust planning and recovery mechanism tools or methods [6]. Nonetheless, to either plan for a hurricane disruption or to provide opportunities for recovery when disturbances cannot be avoided, locating airports that can be impacted is essential. Besides, there may be airports that, in turn, can be affected due to these originally impacted ones. Therefore, capturing these two types of airports and understanding their roles beforehand in either an overall airport or a single airline network can help us efficiently plan, reschedule, and recover both flights and passengers before, during, and after a hurricane disruption.

Generally, during hurricanes and tropical storms, a forecast is issued for a three-day or five-day period. Utilizing this time frame, we developed a graph theoretical approach using network theory to classify airports ahead of a hurricane from two different perspectives: “Disruptor” and “Disruptee.” Disruptor and Disruptee is a pair of airports where disruptor is a hurricane affected airport. Whereas, disruptee is an airport impacted by a disruptor. The meaning of Disruptor and Disruptee is explained in detail in the following sections. Making use of this classification, we further developed a method to discover airports for rerouting to minimize passenger travel disruption, delays, and cancellations during a hurricane. An attempt in minimizing any of these aforementioned events can also be of great economic value as it can decrease different types of costs. However, during a hurricane there are certain factors that vary per day, time, and location: one is forecast track of a hurricane issued by the National Hurricane Center (NHC); second is impact of a hurricane, i.e., effect of a hurricane can differ based on time and location due to change in its path and intensity as days progress. Therefore, it is crucial to analyze the influence of these two factors on our theoretical approach’s functionality. From our results, we are able to identify potential disruptors and their respective disruptees in the US airport network for a hurricane scenario. Moreover, we provided alternate airport choices to reroute from the disrupted airports. We are also able to deduce that the geographical element of the theoretical approach influence identification of disrupted airports and their rerouting choices. In addition, we provided analysis to identify disruptees and their rerouting choices for different hurricane impact distances and forecast track.

The goal of developing the graph theoretical approach is to minimize hurricane-related passenger disruption. The specific **research objectives** are:

- to understand the ability of airline passengers to get rerouted from a hurricane impacted airport;
- to understand the effect of a change in the forecast track of a hurricane on identifying disruptors, disruptees, and rerouting airport choices;

- to understand the effect of a change in the hurricane impact distance on identifying disruptees and discovering rerouting choices for an airport classified as a disruptor.

1.2 Methodology

As a part of our approach, we developed two mathematical equations to classify an airport as either a disruptor or disruptee. In this study, we also proposed an approach to rerouting from hurricane affected airports. In this section, “Disruptor” and “Disruptee” are defined, and the two equations to classify an airport are presented with the assumptions to drive the two equations. After that, the approach to rerouting passengers from affected airports is presented.

1.2.1 Disruptor equation

An airport is defined as a *disruptor* if it gets affected during an event and impacts flight routes connecting from and through this airport along with other flight routes. For a hurricane disruption, we considered the following three different scenarios to classify an airport as a disruptor.

- The first scenario captures all immediate connections from an airport.
- The second scenario captures flight routes for which an airport serves as an intermediate connection.
- The third scenario considers the geospatial element, i.e., flight routes that are supposed to go through a disrupted airport zone.

We captured these three scenarios by developing an equation that quantifies the extent to which airports in a network can be disruptors. The disruptor equation consists of three components: the immediate, the intermediate, and the geospatial components. The immediate component captures all immediate connections from an airport, whereas the intermediate component captures flight routes for which an airport is an intermediate connection. The geospatial element captures flight routes that lie within a disrupted airport zone. The higher value of the disruptor equation indicates a highly disrupted airport. To develop the disruptor equation, we use the degree centrality measure for immediate connection scenarios, as well as simple paths for intermediate and geospatial scenarios. For the details of driving the disruptor equation, please refer to Meda's dissertation [7].

1.2.2 Disruptee equation

A *disruptee* is an airport that is impacted by a disrupted airport, i.e., disruptor. To classify an airport as a disruptee, we explored the three scenarios discussed in section 1.2.1 in a slightly different way. We used simple paths of length up to three to capture these three scenarios. In this study, we developed an equation to quantify the extent to which airports in a network can be disruptees when a particular airport serves as a disruptor. The effect on a disruptee can be either due to disruptor's importance as a direct or intermediate connection for flights of the disruptee airport, or due to the geographical location of the disruptor. Thus, the disruptee equation consists of three components: the destination component, the transition component, and the geographical component. The destination component captures the number of flight paths originating from an airport that are affected due to a disruptor airport being their final destination. The transition component captures flight routes from an airport for which disruptor airports act as an intermediate connection. The geographical component estimates the flight paths from an airport that fall under the disrupted zone of the airport. For the details of driving the disruptee equation, please refer to Meda's dissertation [7].

1.3 Experimental Design

The US airports network data and the hurricane forecast data are required in the experiment. Figure 1.1 illustrates the data extraction process for the US airports network data. We referred to an open and online source "openflights.org" to obtain worldwide airlines routes data [8]. This dataset consists of 67663 routes between 3321 airports on 548 airlines spanning worldwide as of June 2014. Since we want to restrict these route data to the US airports, we extracted calendar year 2018 enplanements data from the Federal Aviation Administration (FAA) website. The routes data is further filtered using commercial and primary service airports information present in the enplanements dataset [9]. The routes data filtering resulted in 2465 routes between 354 US airports on 60 airlines. Using this data, an undirected airport network is constructed with airports as nodes and direct flights between each pair of airports as edges.

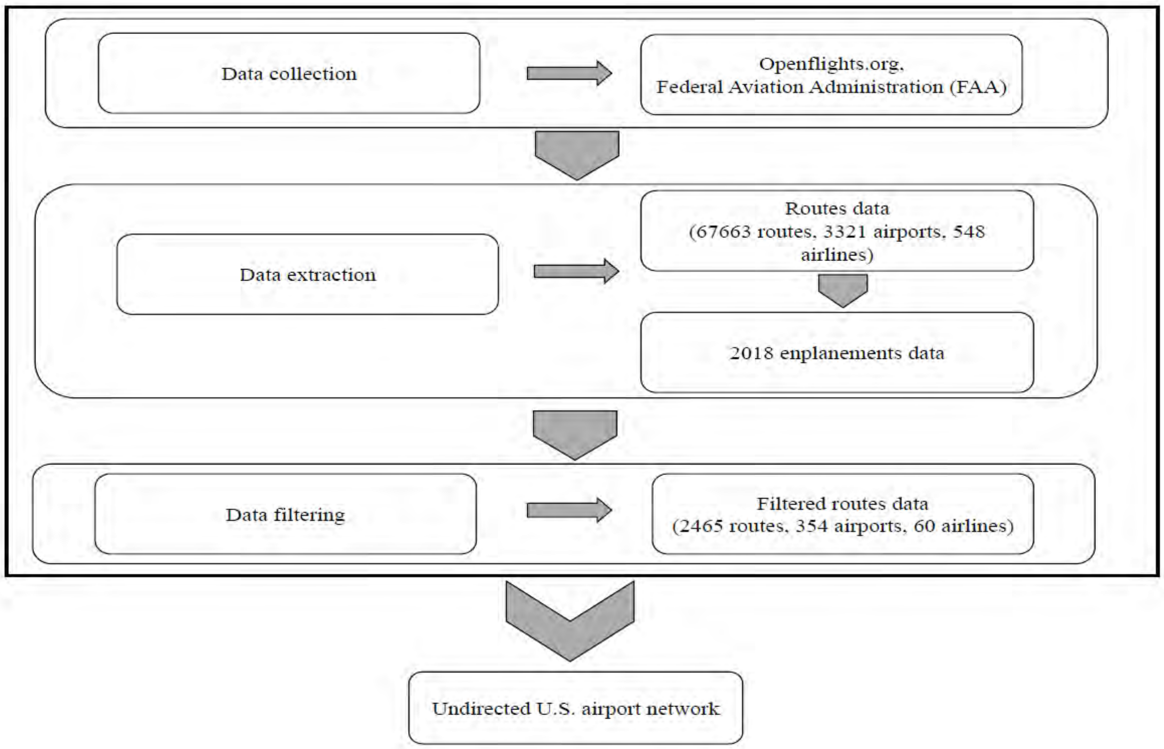


Figure 1.1: Data extraction process for the US airport network.

During every hurricane, NHC issues hurricane forecasts every six hours. This forecast is usually for an entire three-day or five-day path of a storm or cyclone and it utilizes 2/3 probability circle radii, which are based on the historical forecast records over five years. The circle radii at different forecast hours are set in a way such that two-thirds of historical official forecast errors over a five-year sample lie within the circle. This also means that the probability of a cyclone or storm to fall within the cone of uncertainty is 67%. Table 1.1 shows the radii of NHC and Central Pacific Hurricane Center (CPHC) cone circles for 2020, which are based on forecast errors from years 2015-2019. The hurricane forecast data is available in text file format and can be retrieved from the archives of NHC. Based on time of forecast and the radii of NHC and CPHC cone circles for the year 2020, we can estimate forecast period and match them with respective cone circle radius (both in nautical miles and miles).

Table 1.1: Radii of NHC and CPHC cone circles for the year 2020

Forecast period (hours)	Atlantic basin (NM)	EN Pacific basin (NM)	CN Pacific basin (NM)
12	26	25	34
24	41	38	49
36	55	51	66
48	69	65	81
60	86	78	95
72	103	91	120
96	151	115	137
120	196	138	156

Note: EN stands for eastern north, CN for central north, and NM for nautical miles.

In the experiment, we selected Hurricane Matthew 2016 and extracted its forecast data from NHC archives. Hurricane Matthew 2016 had its impact on the US during the period October 7th, 2016 to October 9th, 2016. We examined the forecast path and data three days ahead of this time period, i.e., starting from October 4th, 2016. Since this hurricane occurred in the Atlantic basin, NHC cone radii for year 2020 pertaining to this basin were used. For any airport that lies within a hurricane forecast cone radius, it is necessary to identify hurricane impact distance to compute disruptor and disruptee equation values. Therefore, in this study, we assumed NHC cone radius as a hurricane impact distance for an airport that lies within a forecast specific radius.

1.4 Results and Discussion

In the experiment, the disruptor equation values for different hurricane impact distances were computed at NHC's 2020 cone radii of the Atlantic basin. In Figure 1.2, the weights for each component of the equation show that the intermediate component plays a vital role to classify an airport as a disruptor followed by the immediate and the geospatial components. Table 1.2 shows the 20 airports with high disruptor equation values for different hurricane impact distances. The results in the table reveal that Chicago O'Hare airport (ORD) is the top disruptor irrespective of the hurricane impact distance. It is accompanied by Denver airport

(DEN) and Atlanta Hartsfield-Jackson airport (ATL). Moreover, most of the top 20 disruptors are common across each distance. Further, to understand the significance of each airport's disruptor equation value, we classify all airports values into three categories: higher risk, moderate risk, and lower risk. Table 1.3 shows the ranges of the disruptor equation values for three risk categories at each hurricane impact distance (i.e., cone radius). The lower end for higher risk category at each distance starts at a value greater than 0.13768; for medium risk category at a value greater than 0.06922. Thus, based on the forecast path of a hurricane and three categories of disruptor values, an airport can be classified as a disruptor.

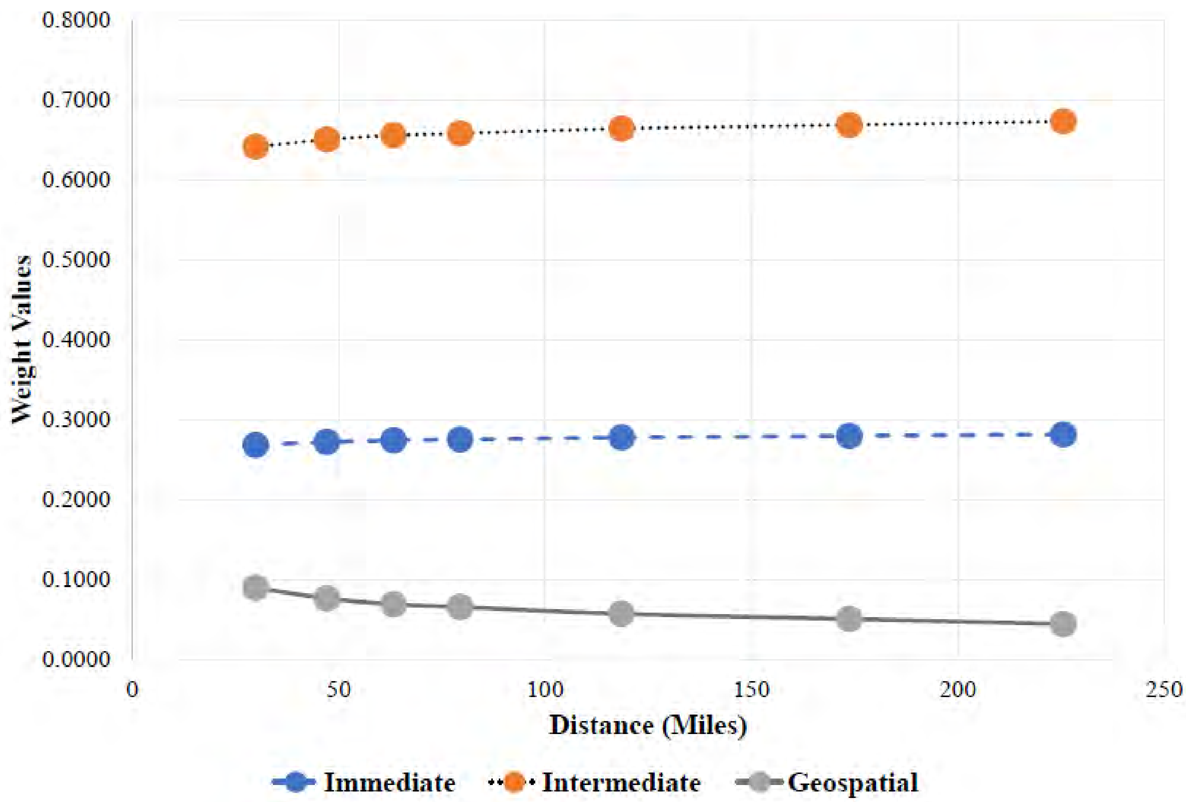


Figure 1.2: Weights for each component in the disruptor equation for different distances (NHC's 2020 Cone Radii).

Table 1.2: 20 airports with high disruptor equation values for different distances

29.926 miles	47.191 miles	63.305 miles	79.419 miles	118.553 miles	173.801 miles	225.596 miles
ORD	ORD	ORD	ORD	ORD	ORD	ORD
ATL	ATL	ATL	ATL	DEN	ATL	ATL
DEN	DEN	DEN	DEN	ATL	DEN	DEN
DFW	DFW	DFW	DFW	DFW	DFW	DFW
MSP	MSP	MSP	MSP	MSP	MSP	MSP
LAS	LAS	LAS	LAS	LAS	DTW	DTW
DTW	DTW	DTW	DTW	DTW	LAS	CLT
CLT	CLT	CLT	CLT	CLT	CLT	LAS
SLC	SLC	SLC	SLC	SLC	SLC	IAH
IAH	IAH	IAH	IAH	IAH	IAH	SLC
PHL	PHL	PHL	PHL	PHL	PHL	PHL
SEA	SEA	SEA	SEA	SEA	SEA	SEA
LAX	LAX	LAX	LAX	LAX	LAX	LAX
DCA	DCA	DCA	DCA	DCA	DCA	DCA
IAD	IAD	IAD	IAD	IAD	IAD	IAD
PHX	PHX	BOS	BOS	PHX	BOS	BOS
BOS	BOS	PHX	PHX	BOS	PHX	PHX
MCO	MCO	MCO	MCO	MCO	MCO	EWR
EWR	EWR	EWR	EWR	EWR	EWR	MCO
MDW	SFO	SFO	SFO	SFO	SFO	SFO

Table 1.3: Ranges for three risk categories of the disruptor equation values

Distance	Lower		Moderate		Higher	
(in miles)	Lower end	Upper end	Lower end	Upper end	Lower end	Upper end
29.926	0.00076	0.06922	0.06922	0.13768	0.13768	0.20614
47.191	0.00077	0.07069	0.07069	0.14060	0.14060	0.21051
63.305	0.00078	0.07147	0.07147	0.14217	0.14217	0.21287
79.419	0.00078	0.07195	0.07195	0.14311	0.14311	0.21428
118.553	0.00079	0.07350	0.07350	0.14621	0.14621	0.21892
173.801	0.00109	0.07528	0.07528	0.14947	0.14947	0.22366
225.596	0.00131	0.07638	0.07638	0.15145	0.15145	0.22653

In the experiment, we examined the effect of the hurricane impact distance, hurricane forecast track, and rerouting choices for the impacted airports. Our results revealed that change in hurricane impact distance and forecast track impact recognizing potential disruptors and in turn their disruptees. In addition, this affects identifying potential airports to reroute to from a disrupted airport. This may result in inefficient planning/rescheduling to handle disruption due to a hurricane. For the details of the experimental results and analyses, please refer to Meda's dissertation [7].

In the experiment, we made certain assumptions regarding knowing the data of single and multiple flight itineraries. In reality, this may not always be possible to obtain this segregated passenger itinerary data, and one of the future areas of research is to consider this aspect and refine the methods for classification of airports as disruptors and disruptees. We also assumed that passengers opt for flights that have a maximum of two connections. Nevertheless, this may not be the case every time as passengers can opt for a flight with more than two connections. Furthermore, the disruptor equation values for airports in the US airport network are smaller and none of them are close enough to one. One of the reasons for this could be normalization factors, which could be further explored in the future. Additionally, identifying the most important group of airports that might be affected during a hurricane is another interesting area to investigate as airports present in one region might be affected the most during a disruption than the ones that are present in a different area.

Study 2 – Multimodal Approach for Rescheduling Airline Passengers

2.1 Research Problem

The passengers play a major role during a disruption and should be at the core of the air transportation system [10,11]. Disruptions can cause loss both financially and in terms of passenger good will to airlines. However, the availability of resources on existing flights to reschedule passengers may not be sufficient. To ensure passengers reach their destinations safely, it may be necessary to explore the usage of alternative sources of transportation. There is limited research that has explored multimodal resources for disruption recovery.

The focus of this work is to design and understand the extent to which multimodal rescheduling of airline passengers during a predicted hurricane disruption can alleviate passenger inconvenience. The two primary aims of this study are (1) to develop a multi-commodity network flow (MCNF) model for multimodal rescheduling of airline passengers, and (2) to test the proposed model and obtain managerial insights for rescheduling during a hurricane disruption. In doing so, we utilized certain network theory concepts and incorporated some of the methods from our graph theoretical approach study. As a part of our second aim, we examined our model for different airline network topologies. Our results indicated that network topologies of airlines may affect multimodal rescheduling. We also observed that different modes of transportation can be utilized in multimodal rescheduling of airline passengers.

2.2 Methodology

When a disruption occurs at an airport, the general goal is to reschedule all the affected outgoing passengers that may get affected to their respective destinations. Hence, for multimodal rescheduling, we considered two other sources of transportation apart from scheduled flights (S: source 1). They were spare aircrafts (SA: source 2) for initiating a new flight service and charter buses (B: source 3) for road transportation. In this study, we did not consider rail as an alternative means for re-accommodating passengers because the rail system in the US does not have access to a majority of the important airports. In one of the multimodal research studies, it was reported that some of the airlines found it more flexible to hire buses using contacts [12,13]. For each source of transportation, the number and set of arcs varied and we made the following assumptions in setting up the network for rescheduling.

- We assumed the airport network constructed based on steady state flow data as a scheduled flights network.
- For road transportation service, we identified the rerouting airports from a disrupted airport were within a certain distance from source and destination airports. These were included as first mile options, and we added a directed arc in the road transportation network from the disrupted airport to each one of these rerouting airports.
- Likewise, there may be close airports to destinations within a certain radius to where passengers could fly and then travel by road. We included these last mile possibilities in the road transportation network and added directed arcs to the respective destinations from these rerouting airports.
- We set up network for initiating a new flight service in such a way that we

added directed arcs where scheduled flights and road transportation service arcs existed. This is because we assumed that it was difficult to initiate a new flight service where there was no existing flight route. Moreover, we added arcs from the origin to every other airport present in the network. This provided an option to transfer passengers to any airport in the network from the disrupted airport using a new flight service when there was no other possible way for rescheduling.

An example of a multi-commodity network is shown in Figure 2.1.

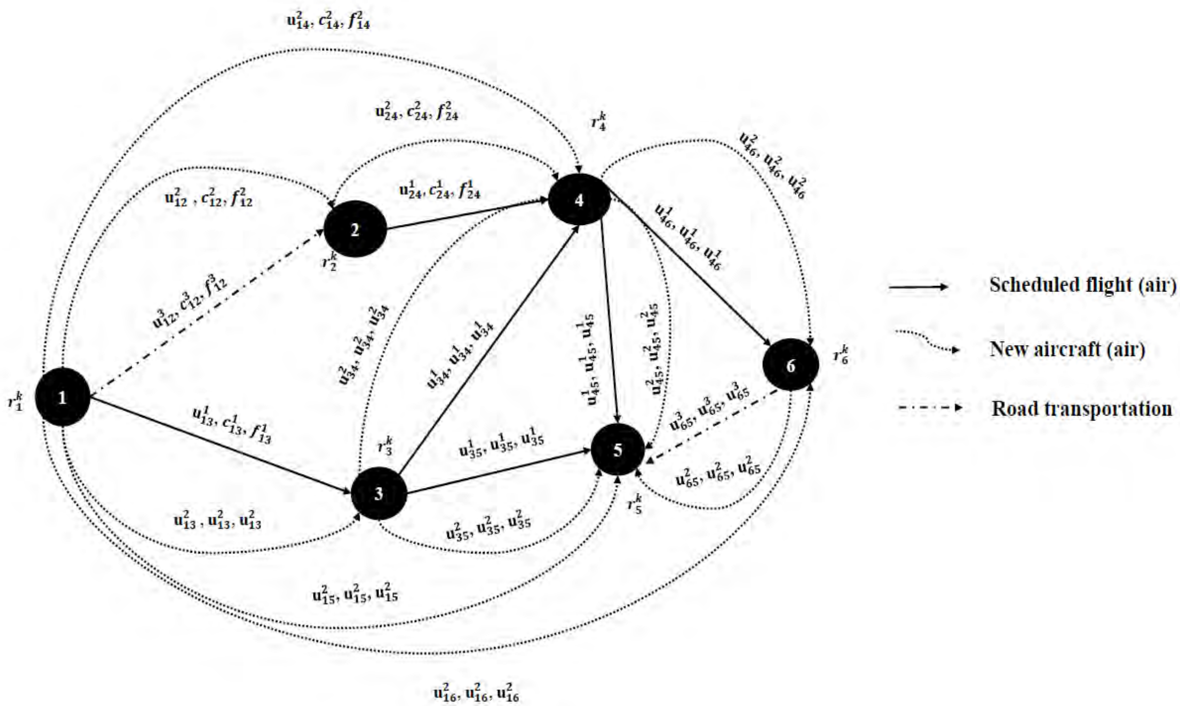


Figure 2.1: An example of a multi-commodity network.

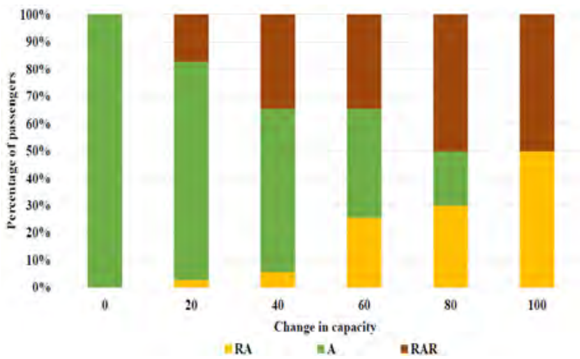
2.3 Results and Discussion

Figure 2.2 presents the distribution of rescheduled passengers using multi-mode vs single-mode transportation. The multi-mode is a combination of usage of air and road transportation services for rescheduling disrupted passengers. There are different possibilities through which multi-mode rescheduling can be achieved. These include: by air followed by road (AR); by road followed by air (RA); by air followed by road and then by air (ARA); and by road followed by air and then by road (RAR). Whereas, the single-mode rescheduling includes either road (R) or air (A) transportation. However, the air transportation can be a combination of scheduled flights and spare aircrafts utilization. We observed that first mile and last mile options can be activated at every scenario except for base case. This implies that alternate sources of transportation (especially road transportation) are utilized in rescheduling disrupted passengers. Apart from air transportation, RA and RAR are the most used multi-mode rescheduling options for the toy network example.

In this study, we tested the proposed MCNF model on a simulated network and four real-world carrier networks. Our results show that for both simulated and carrier networks, road transportation is utilized for rescheduling passengers when such option is available. This indicates that when a disruptive event is anticipated to occur at a particular airport, it is advisable to hire buses to transfer passengers. Figure 2.3 shows the average number of passengers that may have to travel using multi-mode and single-mode. The results in the figure show that for three of the four carrier networks (JetBlue, Frontier and Spirit), more than 80% of passengers get rescheduled with single-mode. The single-mode is traveling by either air or road transportation, whereas the multi-mode rescheduling utilizes both air and road transportation. However, traveling by air may comprise usage of combination of scheduled and new flights. The spare aircrafts are utilized in rescheduling for certain changes in available capacity and increases in number of affected passengers. Our analysis on the four carriers shows that the airports in northeastern region of the US may play a major role as connections for multimodal rescheduling. Some of these airports serve as either operating bases or focus cities for the airlines. For the details of the analyses, please refer to Meda's dissertation [7].

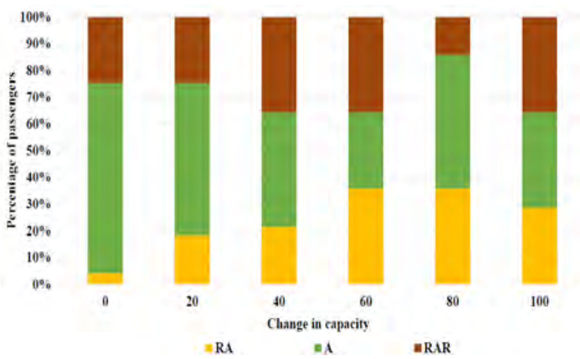
We also proposed a utility function to estimate the passengers' satisfaction. Figure 2.4 displays the average passenger satisfaction utility for the four carrier networks. The results in the figure show that Southwest Airline passengers may experience more inconvenience when compared to its competitors. Moreover, the comparison of the average rescheduling cost in Figure 2.5 shows that the cost for Southwest Airline passenger rescheduling is higher than the other three carriers. The airport network topology can be the reasons for these findings.

However, this needs to be validated further by conducting more experiments with different airports as disruptors.

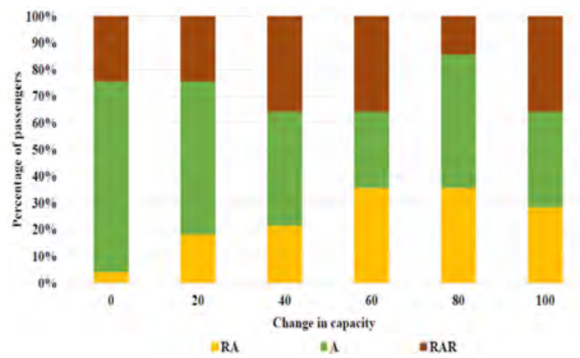


(a) No change in demand

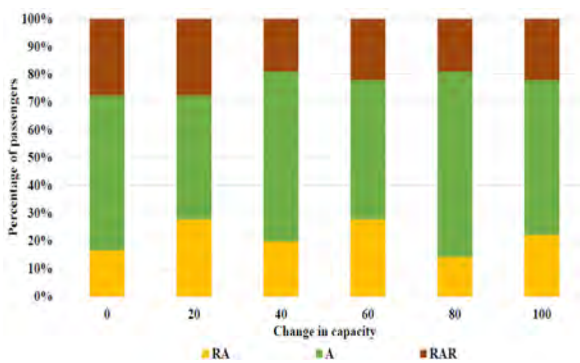
(b) 20% increase in demand



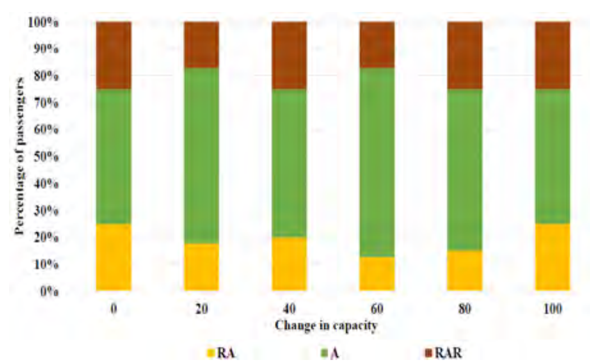
(c) 40% increase in demand



(d) 60% increase in demand



(e) 80% increase in demand



(f) 100% increase in demand

Figure 2.2: Distribution of passengers onto different means of transportation with increase in demand and change in capacity.

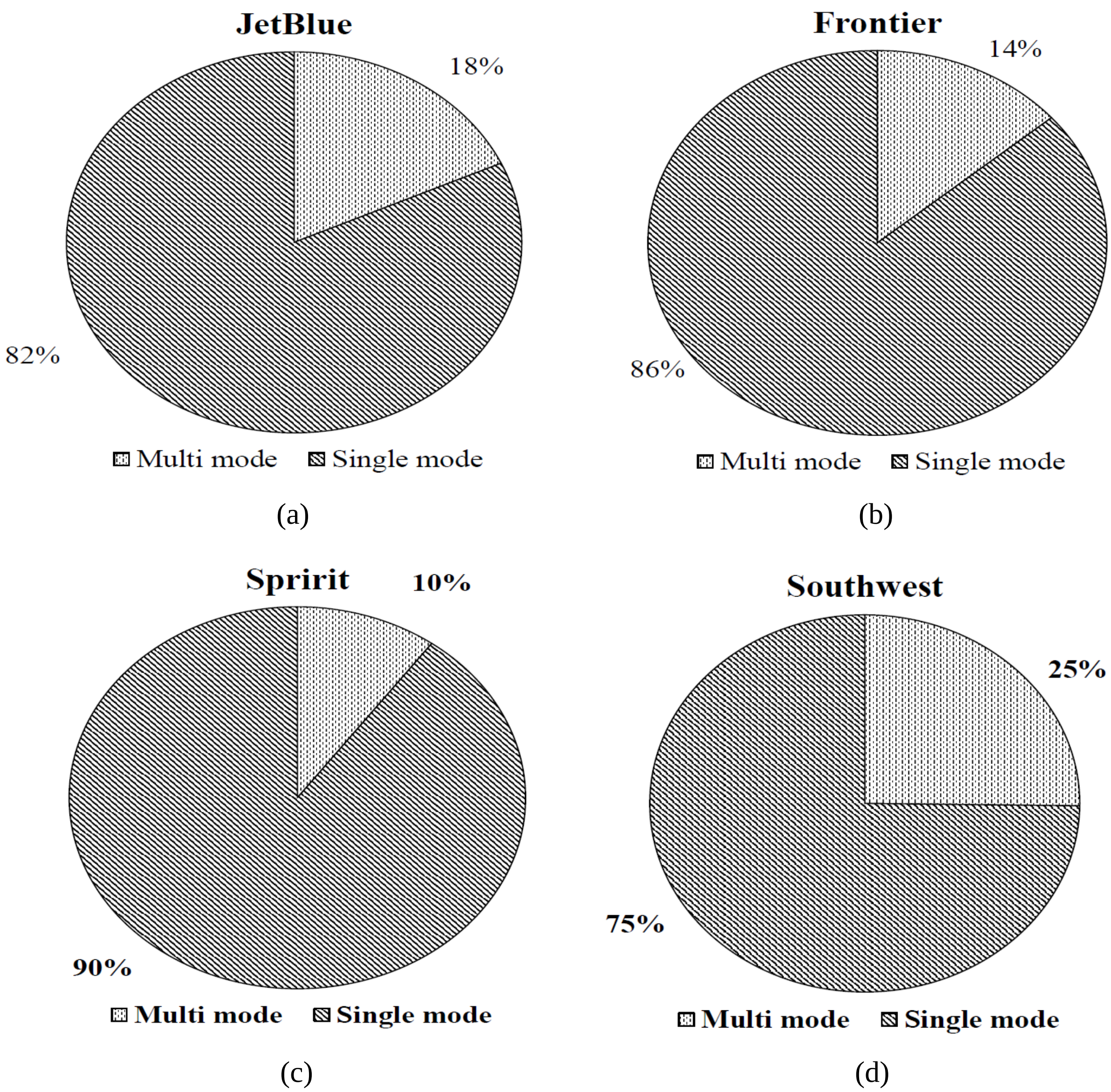


Figure 2.3: Single-mode and multi-mode operations for four airline networks.

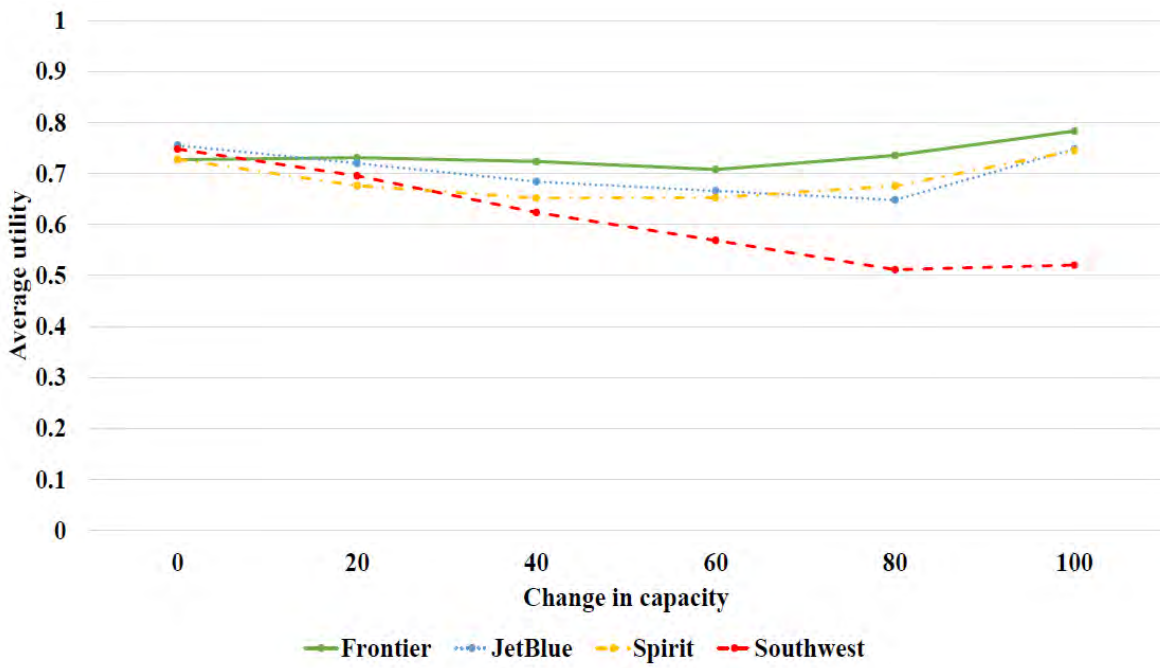


Figure 2.4: Average passenger satisfaction utility for four airline networks.

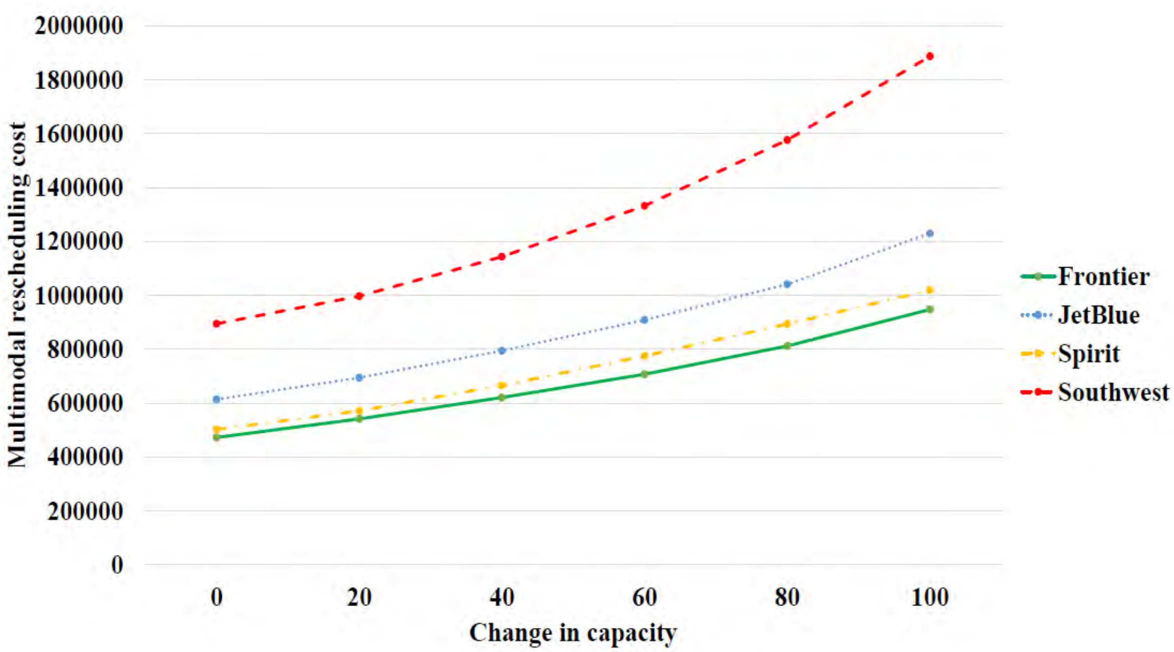


Figure 2.5: Average multi-modal rescheduling costs for four airline networks.

Study 3 – A Simulation Study of Hurricane Evacuations in Eastern North Carolina

3.1 Research Problem

Over the last decade, the number and intensity of hurricanes affecting the US have increased notably, causing significant disruptions and damages to the communities and infrastructure in the Atlantic and Gulf coasts. For example, recent major hurricanes such as Harvey (2017), Irma (2017), Florence (2018), Michael (2018), Dorian (2019), Laura (2020), Zeta (2020), and Ida (2021) caused many casualties and damaged thousands of houses in the US, and significantly disrupted critical infrastructures in the coastal areas. These hurricanes also caused mass emergency evacuations, in which millions of people traveled from the affected areas to safe locations before landfall. The issues, such as severe traffic congestion and fuel shortage, occurred during the recent mass hurricane evacuations bringing the public attention to the challenges of managing an effective hurricane evacuation.

Over the years, government agencies have guided millions of people for hurricane evacuations through road transportation systems and tried many policies to improve hurricane evacuation management. Meanwhile, researchers have proposed policies, models and tools to support hurricane evacuation management [14-16]. However, the issues occurred during the recent hurricane evacuations revealed that better traffic control and better resource and supply preparation are very important for an effective mass evacuation. To identify better traffic control policies and predict resources needed during a hurricane evacuation, the first step is to estimate the evacuation traffic volume and pattern. To meet this need, in this study, we developed a hurricane evacuation simulation model to estimate the traffic volume and the average trip duration under an evacuation scenario. Using the hurricane evacuation simulation model developed, we investigated the impact of the percentage of families choosing shelter-in-place and optimized individual evacuation plans on evacuation traffic and the average evacuation travel time.

3.2 Methodology

3.2.1 Assumptions for the hurricane evacuation simulation model

In North Carolina (NC), when an approaching hurricane is forecasted, the disaster management agency activates and then coordinates all hurricane emergency preparation and response activities. One of the critical activities is to prepare and manage an effective evacuation in the potentially affected region. In response to an approaching hurricane, the NC governor issues mandatory or voluntary evacuation orders to the potentially affected counties two or three days before the forecasted landfall. The NC government agencies provide evacuation guides, recommend evacuation routes in the evacuation zone, deploy more emergency response resources along the recommended evacuation routes, and open shelters as needed to accommodate some residents evacuating from their homes. Usually, the NC government does not provide public transportation services for hurricane evacuation.

A majority of NC residents in the affected region choose to evacuate from the region before landfall. They may follow the recommended evacuation routes or choose their own evacuation routes based on the online real-time traffic information. However, some residents choose shelter-in-place despite mandatory evacuation in their counties. As most families choose staying or evacuating together [16], in the hurricane evacuation simulation model, a family is assumed to evacuate together by one vehicle or stay home together. The model simulates individual vehicles traveling through the highway transportation system to evacuate from the evacuation zone in eastern NC. Figure 3.1 shows the evacuation zone in eastern NC, which includes 35 NC counties affected by many past major hurricanes, and the highways in the zone usually used for hurricane evacuation [17]. During the period of a hurricane evacuation (usually 72 hours before landfall), regular traffic volumes gradually decrease. Thus, we assumed a three-day hurricane evacuation period in this study. During the three-day evacuation period, a constant percentage of road capacity is assumed for evacuation traffic on each day, but the percentage of road capacity for evacuation traffic increases from one day to the next.

3.2.2 Simulation model

An open-source agent-based transport simulation (MATSim) framework [18] was used to develop the hurricane evacuation simulation model that captures the trips of individual evacuation vehicles given an evacuation scenario. The MATSim-based simulation model consists of three main modules: population and departure generation module, network generation module, and scenario generation module. Figure 3.2 illustrates the relationship among the three modules and the steps in each module.

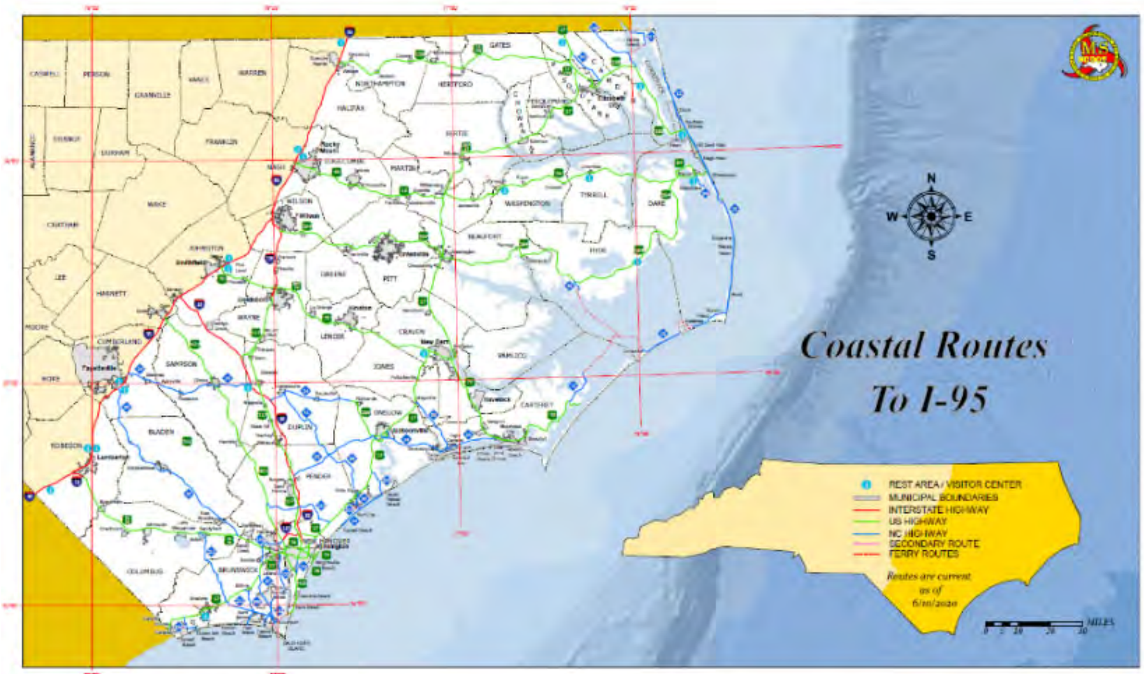


Figure 3.1: Evacuation zone and routes for evacuation in eastern North Carolina [17].

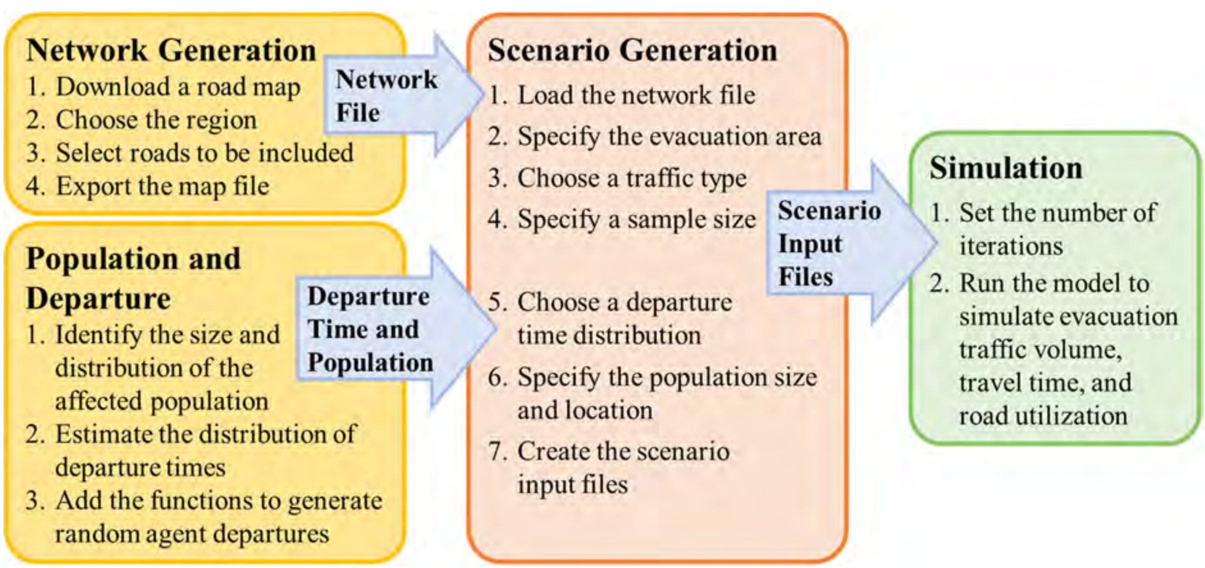


Figure 3.2: Procedure to build the MATSim-based hurricane evacuation simulation model

In the MATSim platform, agents represent individual evacuees (persons or vehicles), and the population contains all agents. Each agent has a list of evacuation plans, and each plan consists of a list of activities and legs that describe the planned actions in the plan. The main activities include pre-evacuation, post-evacuation, and routing activities such as departure, entering a link, leaving from a link, arrival, and so on. Each activity is performed on a specific links, and associated with an end time or a duration. A leg describes how to travel from one location to the next. Each leg is assigned a transport mode, a route (i.e., a sequence of links), and an expected travel time. Each evacuation plan is associated with a score, which is calculated and updated after each simulation iteration based on the results of the mobility simulation. Each agent selects one evacuation plan by comparing the scores of its plans, and all selected evacuation plans are executed by the mobility simulation in the next iteration. Over the simulation iterations, agents keep improving their evacuation plans by selecting a plan with a better score or creating new plans more responsive to the change in traffic pattern.

The MATSim platform includes three built-in options (Dirac-delta, normal, and log-normal) to generate agents' departure times [18]. One of the three built-in options can usually capture the distribution of departure times in a short-notice or no-notice emergency evacuation, such as a building or city evacuation due to a local disaster. However, none of the three built-in options can properly generate agents' departure times during a hurricane evacuation. During a major hurricane, the residents in the affected region usually evacuate from the region within 12–72 hours before landfall. More residents choose to evacuate during the daytime than the nighttime, and some residents choose staying home instead of evacuating from the region. To capture the distribution of departure times during a hurricane evacuation, we modified the population and departure generation module in the MATSim platform by adding the new functions that generate departure times equally distributed with a higher departure rate during the daytime and a lower rate during the nighttime. The functions also enable us to assign the percentage of agents choosing to stay.

The network in the simulation model represents the road network through which evacuees (or agents) travel to safe locations. The network consists of nodes and links. Nodes represent locations (or points) separating roads into segments, while directional links represent road segments. Each link is associated with attributes such as length, capacity, free flow speed, the number of lanes, and so on. The network generation module extracts the highway network in the NC evacuation zone from the NC map available at Geofabrik Downloads [19], and saves the network in OpenStreetMap (OSM) format as one of the inputs to the scenario generation module.

In this study, MATSim Evacuation-GUI [18] was used to create a simulation scenario and evacuate the simulation model. To create a simulation scenario, the OSM-format network is loaded first, and then the evacuation area and the population locations are indicated on the network using polygons. After that, the population sizes are loaded and attached to the corresponding locations. Finally, the simulation scenario needs a specific traffic type, a reasonable sample size, a departure time distribution selected, and a directory to store the scenario input files and simulation output files. The input files generated for the simulation scenario are loaded to the MATSim simulation engine, which runs the simulation model for a given number of iterations.

3.2.3 Simulation outputs

The MATSim platform reports the cumulative number of agents evacuated, en-route agents and arrivals per time interval, and the average trip duration for each iteration. These performance metrics can be used to compare traffic volumes and travel time under different evacuation scenarios. The utilization of links is recorded every ten iterations, which can be used to estimate traffic volumes and pattern and identify the major evacuation routes.

3.3 Case Study and Results

3.3.1 Study area and scenarios

In the case study, the MATSim-based hurricane evacuation simulation model was populated using the highway transportation system in eastern NC, and tested using the Hurricane Florence evacuation in NC. Figure 3.3 shows the highway network for the evacuation in the study area, which includes interstate highways, US routes and NC routes in the NC evacuation zone. During Hurricane Florence, evacuation orders were issued to the 16 NC counties (shown in Table 3.1) three days before landfall. Figure 3.4 illustrates the evacuation area and the distribution of potential vehicles evacuating from the 16 counties, and Table 3.1 presents the country seats, the populations and the estimated numbers of families in the 16 counties. The number of families was estimated based on the average NC family size of 2.98 [20]. The total number of vehicles that may evacuate from a county equals the number of families in the county because of the assumption that a family evacuates together by one vehicle.

Figure 3.3: Highway network for evacuation

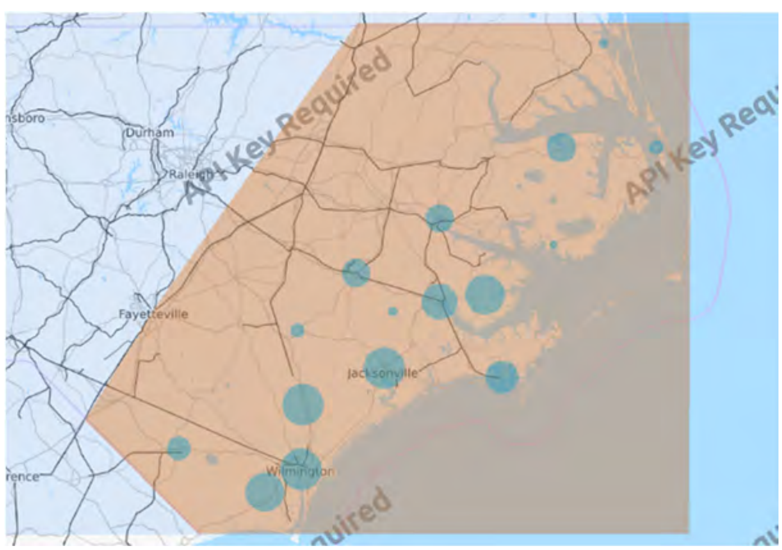


Figure 3.4: Evacuation area and the distribution of potential vehicles evacuating from the 16 North Carolina counties

During Hurricane Florence, most NC families in the affected region chose to evacuate before landfall. However, some families chose shelter-in-place. Therefore, in the case study, we examined two scenarios representing two percentages (5% and 10%) of families choosing shelter-in-place. The departure time distribution and the road capacity for evacuation traffic are assumed to be the same in both scenarios. Table 3.2 summarizes the settings for the two scenarios. Each scenario was evaluated three times using the simulation model with 10% sample size and 100 iterations.

Table 3.1: North Carolina countries with evacuation orders during Hurricane Florence

County Name	County Seat [1]	Population in 2019 [2]	Number of Families	County Name	County Seat [1]	Population in 2019 [2]	Number of Families
Beaufort	Washington	47,168	15,829	Hyde	Swan Quarter	5,213	1,750
Brunswick	Bolivia	131,815	44,234	Jones	Trenton	9,594	3,220
Carteret	Beaufort	69,070	23,178	Lenoir	Kinston	56,756	19,046
Columbus	Whiteville	56,068	18,815	New Hanover	Wilmington	227,938	76,490
Craven	New Bern	102,491	34,393	Onslow	Jacksonville	195,069	65,460
Currituck	Currituck	26,363	8,847	Pamlico	Bayboro	12,701	4,263
Dare	Manteo	36,222	12,156	Pender	Burgaw	60,399	20,269
Duplin	Kenansville	58,967	19,788	Tyrell	Columbia	4,131	1,387

[1] It is assumed that vehicles evacuate from the area around county seats.

[2] The population was retrieved from https://www.northcarolina-demographics.com/counties_by_population.

Table 3.2: Two scenarios in the cast study

<table>
<tr><th colspan="2"></th><th>Scenario 1</th><th>Scenario 2</th></tr>
<tr><td colspan="2">Percentage of families choosing shelter-in-place</td><td>5%</td><td>10%</td></tr>
<tr><td rowspan="3">Departure and available road capacity</td><td>48–72 hours before landfall</td><td colspan="2">8% of families and 10% road capacity</td></tr>
<tr><td>24–48 hours before landfall</td><td colspan="2">20% of families and 28% road capacity</td></tr>
<tr><td>Within 24 hours before landfall</td><td>67% families and 90% road capacity</td><td>62% families and 90% road capacity</td></tr>
<tr><td>Departure time distribution</td><td colspan="3">95% evacuees depart during the daytime (6AM – 6PM)
5% evacuees depart during the nighttime (6PM – 6AM)
Uniform distributions with two departure rates for the daytime and nighttime, respectively</td></tr>
</table>

3.3.2 Model validation

Hourly traffic data in eastern NC during Hurricane Florence were collected and provided by the traffic survey group of the NC Department of Transportation. The data set includes hourly traffic volumes at 38 locations, half of which are in the study area. However, hourly traffic data with 72 hours before the landfall are missing at the most locations in the study area due to the sensor failures caused by the flood during Hurricane Florence. Only one sensor located in Wayne County collected hourly traffic data within 24-72 hours before the landfall. We compared the observed and simulated daily evacuation traffic volumes at this location to validate our hurricane evacuation simulation model. The comparison results in Table 3.3 show that the observed daily evacuation traffic volumes are within the 95% intervals of the simulated daily evacuation traffic volumes.

Table 3.3: Comparison of the observed and simulated daily evacuation traffic volumes

	Observed daily evacuation traffic	Simulated daily evacuation traffic		
		Average	Standard error	95% interval
48–72 hours before landfall	234	232	17	[199.68, 265.32]
24–48 hours before landfall	348	357	11	[335.44, 378.56]

3.3.3 Results and discussion

Figure 3.5 shows that for each simulation run, the average trip duration converges to a steady value after 80 iterations. This implies that all agents' evacuation plans have been optimized under a random evacuation travel demand after 80 iterations. Our results show that optimized individual evacuation plans can reduce the average trip duration by 8% – 12%, comparing to taking the shortest path without considering traffic conditions (Iteration 0). Figure 3.6 shows that less evacuation vehicles are on route within 48–72 hours before landfall. However, Figure 3.5 reveals that the average duration of evacuation trips within 48–72 hours before landfall is significantly longer than that within 48 hours before landfall. This is because the road capacity for evacuation within 48–72 hours is much lower. The results in Figures 3.5 and 3.6 also reveal that a higher percentage of families choosing shelter-in-place slightly reduces the amount of en-route evacuation vehicles and the average duration of evacuation trips.

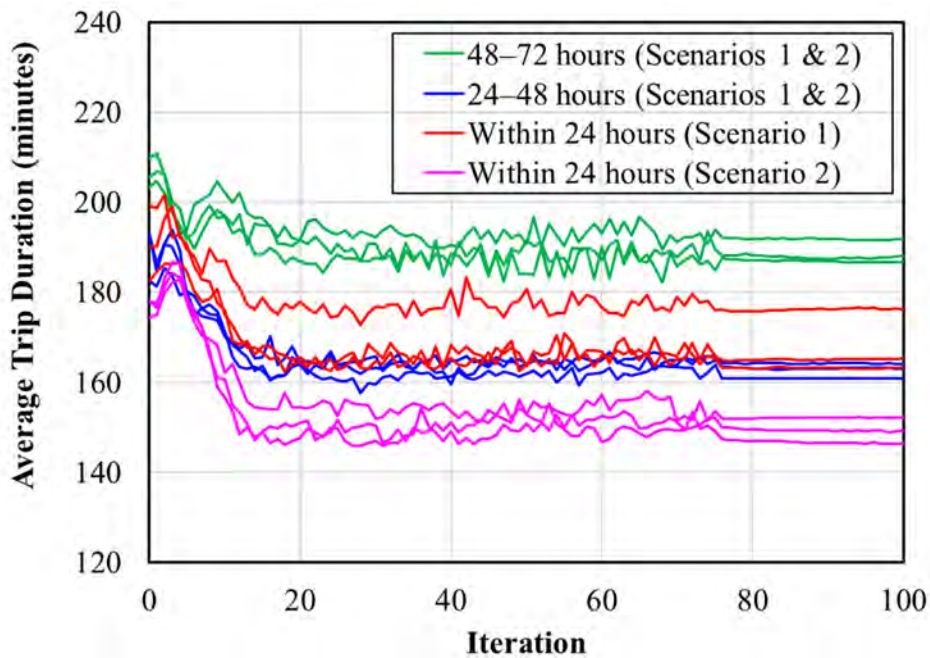


Figure 3.5: Convergence of the average trip duration

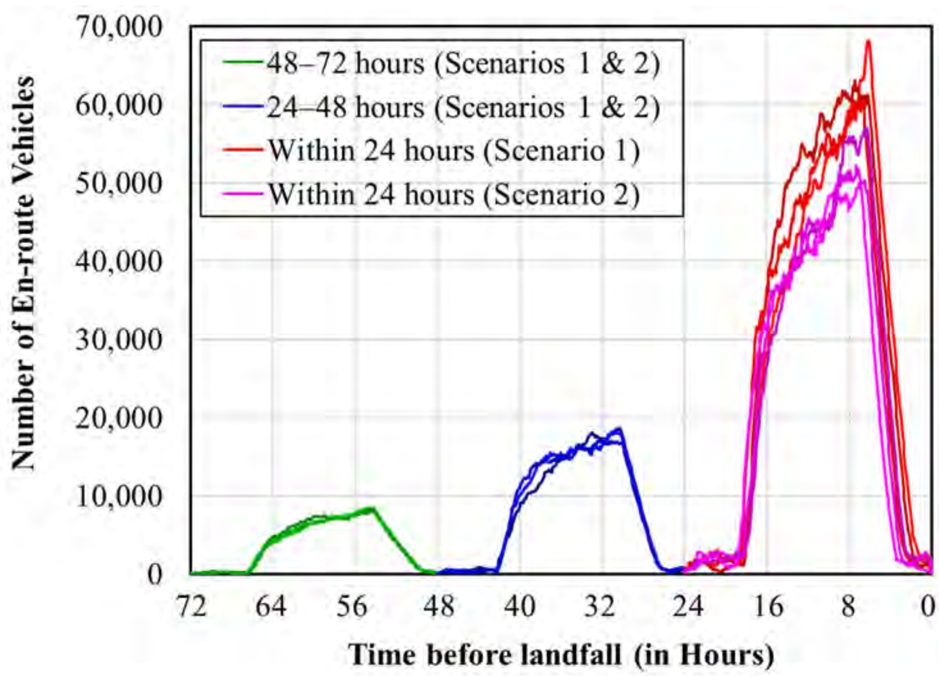


Figure 3.6: En-route evacuation traffic over time

Study 4 – Judgment Characterization for Emergency Evacuation Using Lens Model: A Machine Learning Approach

4.1 Research Problem

Intelligent Transportation Systems play an important role in mass emergency evacuations. In dealing with all humanitarian aspects of emergencies, emergency preparedness and disaster management are essential. Evacuation Planners (EP) and individuals' decisions during emergency preparation involve complex behavioral factors [21]. In this study, we proposed to characterize EPs' decision-making behavior during emergency evacuation using machine learning algorithms and statistical methods. In doing so, a decision-making tool, the Brunswik Lens model, was used to describe the correlation between the environment and the behavior of organisms in the environment. Additionally, identifying significant cues for residents to decide dynamic evacuation routes under an uncertain environment and having incomplete information is somewhat limited due to how stochastic decision-making can be.

4.2 Methodology and Results

In the modeling process, a judgment model is created with cues influencing the judgment. In the previous studies [22-24], the researchers considered the variables including wind speed, rainfall, number of households affected, flood level, median household income, and the poverty level. These variables (cues) were found to influence evacuation in NC while preparing for an impending hurricane. The goal is to create a judgment model for an emergency to gain insight into the decision behavior of the various entities involved when the environment presents multiple cues.

The judgment data about Hurricane Matthew was retrieved from multiple federal, state governments and other websites. All data collected are related to counties that were affected by Hurricane Matthew in NC. The weather-related data were collected from October 8th to 9th, 2016, when the hurricane approached. Socio-economic data such as poverty, median household income level, poverty level data, and disaster data were obtained for the year 2016 from the United States Census Bureau (USCB), United States Department of Agriculture Economic Research Service (USDA), and WebEOC [25], respectively.

Weather data was mainly taken from National Oceanic and Atmospheric Administration (NOAA) and United States Geological Survey, respectively. The data collected consisted of seven variables and 42 observations (counties). All seven variables examined were numerical and normally distributed.

4.2.1 Hypotheses development

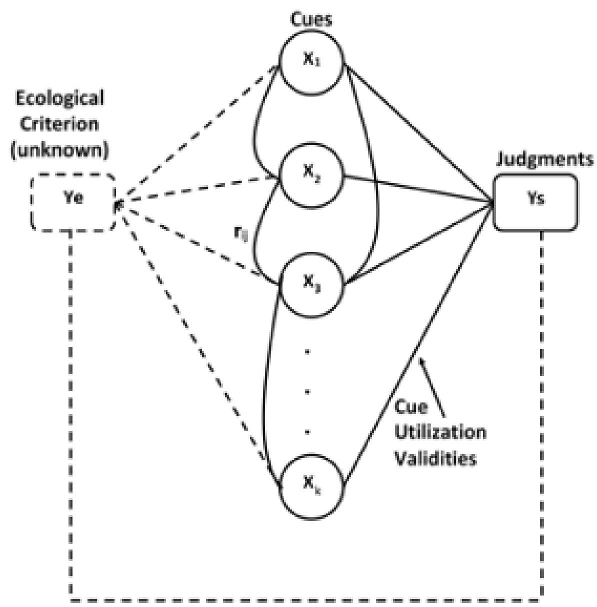
The lens model framework has been used to describe the decision-making behavior of experts in different domains from the perspective of both the organism (expert) and the environment (domain area). This model uses primarily statistical methods (linear regression) to quantify judgment tasks. Furthermore, machine learning (ML) techniques have been proven to be a valuable tool in capturing the decision-making behavior of judges with higher accuracy than the standard regression model in some domains [26].

Hypothesis 1a (H1a): ML algorithms can quantify the decision-making behavior of experts in an emergency evacuation with incomplete information with satisfactory performance.

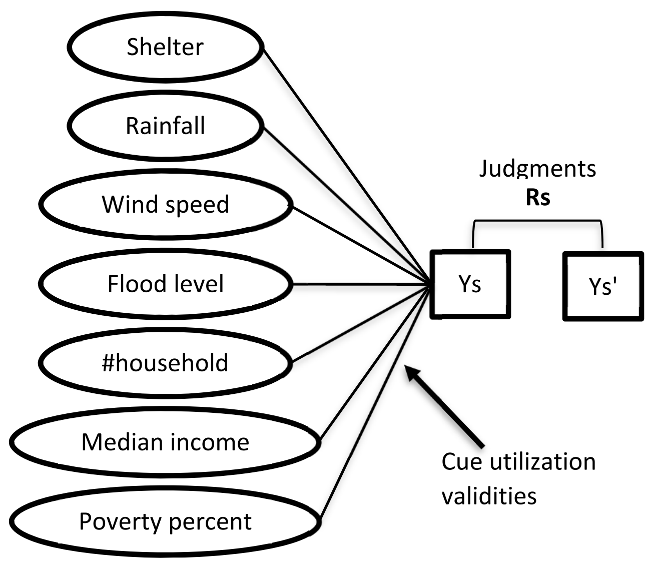
Hypothesis 1b (H1b): ML algorithm models can/will outperform statistical approaches in characterizing the decision-making behavior of experts in an emergency evacuation situation.

4.2.2 Brunswik Lens model

Figure 4.1 shows the Brunswik Linear Lens Model representation of single-system design (ecological criterion unavailable or not of interest) [27]. The Lens Model framework and its related parameters can capture and quantify judgment policies. Figure 4.1(a) represents the model of the criterion or environment. This model describes the relationship between the ecological criterion value (e.g., individuals' decision to evacuate or not) and the cue values accessible at the time a judgment is made. Figure 4.1(b) represents the judge's policy or strategy. It describes the relationship between the cue values and the criterion value. In Figure 4.1(b), the judgments are related to each cue, known as cue utilization validity. The pattern of cue utilization demonstrated by a judge determines the judgment policy, Y_S, represents the EPs' judgment and is modeled as a linear combination of a set of k cues ($X_i, i = 1, \dots., k$).



(a)



(b)

Figure 4.1: Brunswik Linear Lens Model representation of single system design (ecological criterion unavailable or not of interest).

$$Y_S = \sum_{i=1}^{k} \beta_{si} X_i + e \quad (1)$$

In Equation (1), the β_{si} denotes the weights of the cues that contribute to the judge's decision, and e represents the scope to which the cognitive model misses the actual value when trying to predict the judgment, Y_S [27]. Thus if $\hat{Y}_S$ denotes the cognitive model, then

$$Y_S = \hat{Y}_S + e \quad (2)$$

The correlation between Y_S and $\hat{Y}_S$, denoted by R_s, measures the cognitive control with which a judgment strategy is executed. Consistency refers to the similarity between judgments made to repeated profiles of cue information [27].

$$R_s = \text{corr}\ (Y_s, \hat{Y}_s) \quad (3)$$

4.2.3 Machine learning algorithms

Supervised learning is a machine learning technique that uses computational learning theory, pattern recognition, and algorithm construction to map inputs to the output. Six (6) machine learning algorithms were also used to create the judgment model, namely linear discriminant analysis (LDA), K-nearest neighbor (KNN), logistic regression (LR), classification and regression tree (CART), Naive-Bayes (NB), support vector machine (SVM). Python packages provide algorithms built in their libraries. Figure 4.2 shows the steps in Machine Learning.

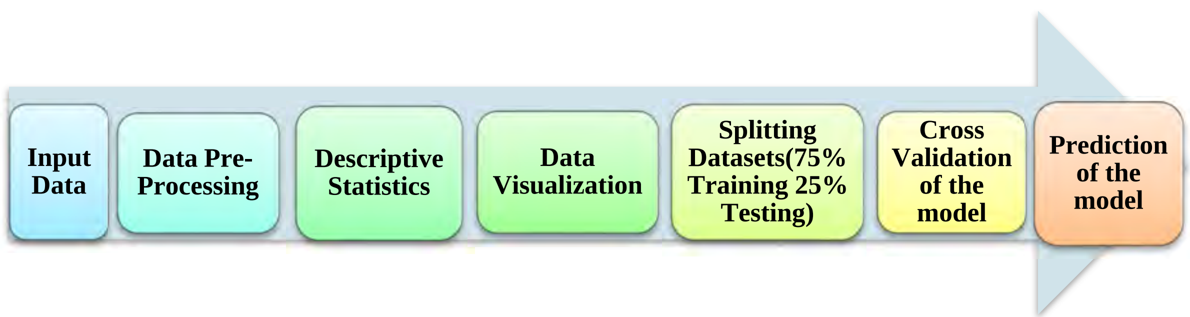


Figure 4.2: Steps in machine learning.

4.2.3 Evaluation metrics

The two-performance metrics for the evaluation of models were Cross-Validation Accuracy (CVA) and Prediction/Model Accuracy (Accuracy). A ten-fold cross-validation is used in this study, and the accuracy is defined as:

$$Prediction\ Accuracy\ (PA)\ =\ \frac{TP+TN}{TP+TN+FP+FN}\ , \tag{4}$$

where TP, TN, FP and FN represent true positive, true negative, false positive, and false negative, respectively.

4.2.4 Lens model parameter, ($\hat{Y}_S$) and R_s

The supervised machine learning techniques: LR, LDA, KNN, CART, NB, SVM as shown in Figure 4.3, also represented interesting accuracies but did not perfectly estimate the judgment model since model accuracies were 0.66, 0.72, 0.69, 0.6, 0.65 and 0.76, respectively. Figure 4.3 displays the cross-validation accuracy for all the machine learning models and data types after 75% of the judgment data is used in training them, and the model accuracy after 25% of the data is used to test the model. In the Judgment model, SVM generated a high CVA of approximately 73%, and LR, LDA and NB generated a PA of 72.7%.

The Lens model parameters are computed using the Logistic regression for the judgment model. This technique is used as an idiographic-statistical approach to understanding the characteristics and conditions of individuals' behavior. This approach also helps to capture judgment policies as well as aspects of the judgment process. Logistic Regression provides a statistical model that, in its basic form, uses a logistic function to model a dichotomous dependent variable.

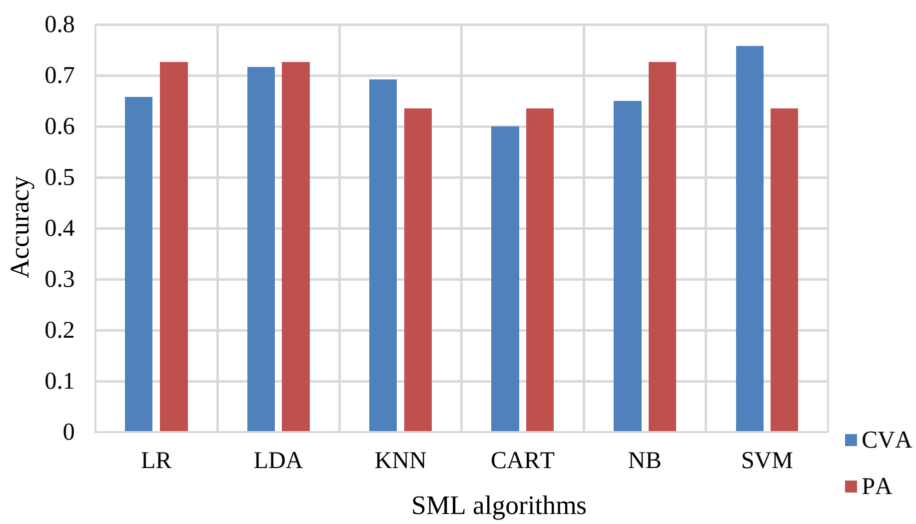


Figure 4.3: Accuracies of the six machine learning algorithms

Dependent Variable

In regression analysis, logistic regression (or logit regression) estimates the parameters of a logistic model (a form of binary regression). Mathematically, logistic regression estimates a multiple linear regression function defined as:

$$\left(\frac{p(y=1)}{1-(p=1)}\right) = \beta_o + \beta_1 . x_{12} + \beta_2 x_{12} + \cdots \beta_p x_{in} \text{ for } i = 1,\ldots, n. \quad (5)$$

In the selection of cues, backward elimination regression was used. In the backward elimination method, all the cues are initially used to build the model. Subsequently, the cue with the highest p-value is eliminated if the p-value is greater than the significance level (0.05). This is repeated, and a single cue is eliminated for each iteration until the cue shows a p-value less than 0.05. However, in this application, all the cues were eliminated except the wind speed. This means that only one of the cue weights contributed well enough to the model. The pseudo-R^2 value validates the performance of the model.

Figure 4.4 shows the results of logistic regression for judgment when all cues were used. Figure 4.4 shows the R^2 for the judgment model ($\hat{Y}_S$) and a correlation (r) of 50.2%. For the judgment model ($\hat{Y}_S$), R^2 values were very low indicating that the cues were not able to produce the best model. Table 4.1 shows the weighting applied to each cue that contributed to the EPs' judgment. These weights explain how the judge's policy was made based on the cue utilization validities.

```
                           Logit Regression Results
==============================================================================
Dep. Variable:               evacuate   No. Observations:                   42
Model:                          Logit   Df Residuals:                       34
Method:                           MLE   Df Model:                            7
Date:                Mon, 30 Nov 2020   Pseudo R-squ.:                  0.2528
Time:                        19:21:34   Log-Likelihood:                -17.224
converged:                       True   LL-Null:                       -23.053
                                        LLR p-value:                    0.1124
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
const             -1.5887      0.504     -3.150      0.002      -2.577      -0.600
Shelters           0.4428      0.590      0.751      0.453      -0.713       1.599
Wind_Speed         1.1022      0.526      2.096      0.036       0.072       2.133
Rainfall          -0.6706      0.595     -1.128      0.260      -1.836       0.495
Households         0.4337      0.538      0.806      0.420      -0.621       1.488
Flood_Lvl_ft      -0.0491      0.497     -0.099      0.921      -1.023       0.925
Median _Income     0.0962      0.813      0.118      0.906      -1.498       1.691
Poverty_Percent    0.2831      0.637      0.444      0.657      -0.966       1.532
```

Figure 4.4: Logistic regression output for judgment when all cues were used

Table 4.1: Cue weights

Cues	Relative(cue) weight
Shelters	0.144
Wind speed (mph)	0.358
Rainfall (in)	0.217
Households	0.141
Food level (ft)	0.016
Median Income ($)	0.031
Poverty Percentage (%)	0.092

Independent variables

The total number of independent variables, also known as the cues in this context, is seven (7), as shown in Appendix A. Checking the correlation between the variables (cues) helps eliminate all redundant cues. The correlation between two variables is defined as:

$$r_{xy} = \frac{\sum (X_i - \underline{X})(y_i - \underline{y})}{\sqrt{\sum (X_i - \underline{X})^2 \sum (y_i - \underline{y})^2}}, \quad (6)$$

where

- r_{xy} the correlation coefficient of the linear relationship between the variables x and y
- X_i – the values of the x-variable in a sample
- $\underline{X}$ – the mean of the values of the x-variable
- y_i – the values of the y-variable in a sample
- $\underline{y}$ – the mean of the values of the y-variable

There were no high positive correlations among cues, as shown in Figure 4.5, indicating that all cues are independent and can be used for prediction

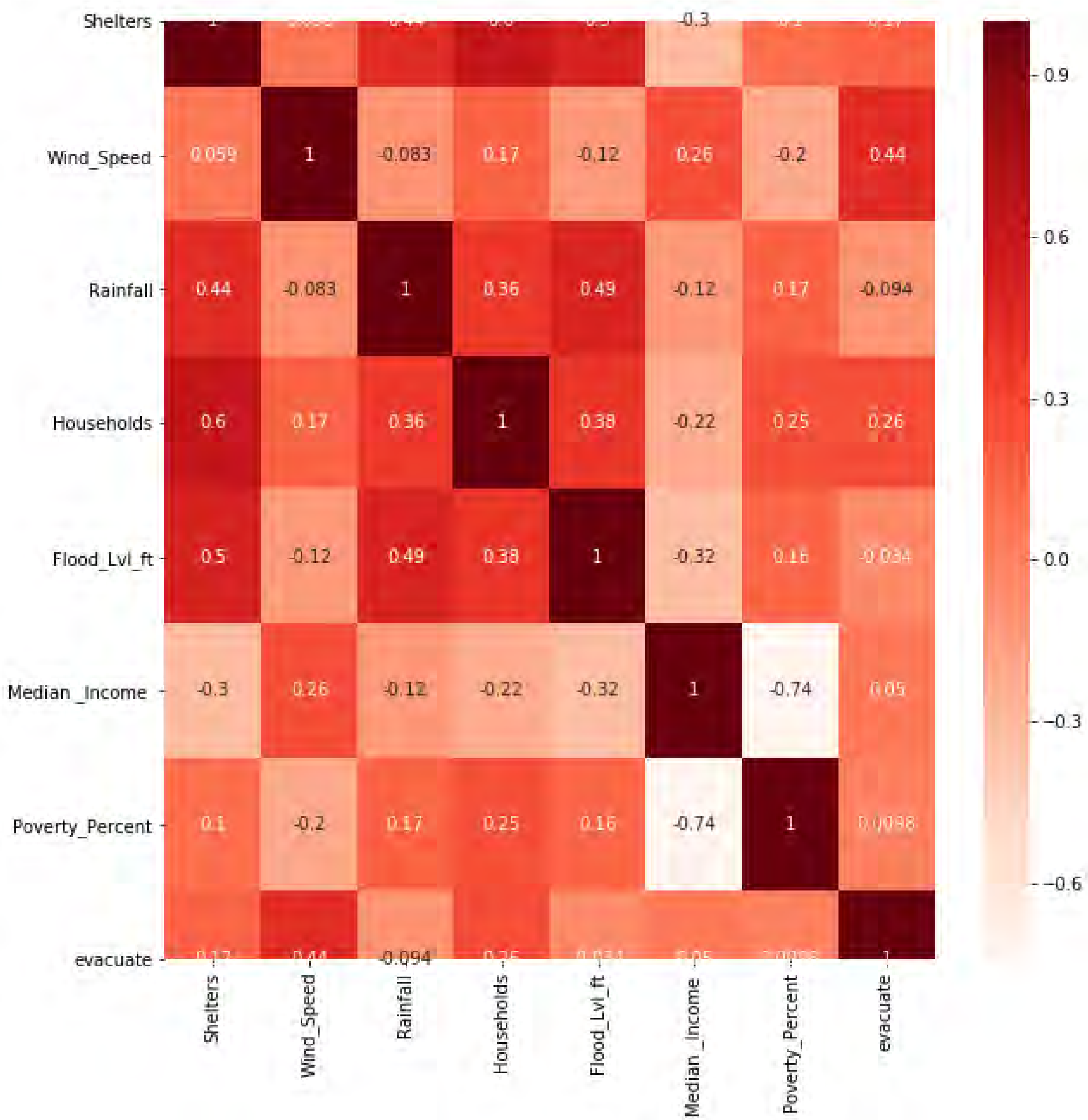


Figure 4.5: Correlation matrix for the cues

Study 5 – Decision-Making Model for Emergency Evacuation Based on the Lens Model Using Machine Learning and Monte-Carlo Simulation for Incomplete Information Environment

5.1 Research Problem

As an extension of Study 4, the ecology data of the Lens Model (LM) is unknown, and the LM is designed as a single system (design with incomplete information). Because there is no data to create an ecological model, there are limitations within the LM framework in terms of understanding and determining how judgments correspond to the ecology.

To simulate unknown data, Monte-Carlo Simulation (MCS), a broad class of computational algorithms based on repeated random sampling to get numerical results, is often used in conjunction with the law of large numbers. LLN (law of large numbers) explains how many times the same experiment can be performed through probabilistic theory. As a result of this law, the average outcome of a large number of trials should lead a simulated dataset to be close to the true value or expected value. The simulated data was used to test and train the ecological model. Using MCS, we analyzed decision-making behavior during an emergency evacuation in an incomplete information environment. First, the available ecology/criterion data was simulated so a judgment model could be developed completely. Secondly, the nonlinear SML algorithms and LM parameters were tested and compared to validate their performance.

5.2 Methodology

In this section, we explain how hypotheses were developed, how data was collected, how models were developed (machine learning and LM), and how predictions were made. We also assess the performance of nonlinear machine learning algorithms as well as LM parameters.

According to Cooksey [27], the double-system LM represents the Rule-based Lens Model (RLM) paradigm in which the right side of the model describes the judge's cognitive system, and the left side is overtly compared to an ecology system. In this study, deciding whether to evacuate or not is a continuous judgment of the organism, which is the basis for the ecology-judgment model. Matching frequencies are employed by the RLM to predict judgment. Here, the nonlinear Supervised Machine Learning (SML) algorithms were applied to predict both cognitive and ecology models in the LM using matching frequencies.

LM parameters (r_a, G, C, R_e, and R_s) describe the judgment performance of human operators, their knowledge of the environment, their unmodeled knowledge, their ability to predict the environment, and their cognitive control respectively, all of which can be extracted by machine learning models via Equations (7)–(11). MCS was used to obtain the actual criteria (Y_e), while historical data was used to obtain the judgment values (Y_s).

$$r_a = \text{corr}\,(Y_e, Y_s) \tag{7}$$

$$G = \text{corr}\,(\hat{Y}_e, \hat{Y}_s) \tag{8}$$

$$C = \text{corr}\,(Z_s, Z_e) \tag{9}$$

$$R_e = \text{corr}\,(Y_e, \hat{Y}_e) \tag{10}$$

$$R_s = \text{corr}\,(Y_s, \hat{Y}_s) \tag{11}$$

In these equations, Z_e and Z_s indicate the residual values for the ecology and the judgment, respectively; $\hat{Y}_e$ and $\hat{Y}_s$ obtained through the Machine Learning models indicate the predicted values for ecology and judgment, respectively.

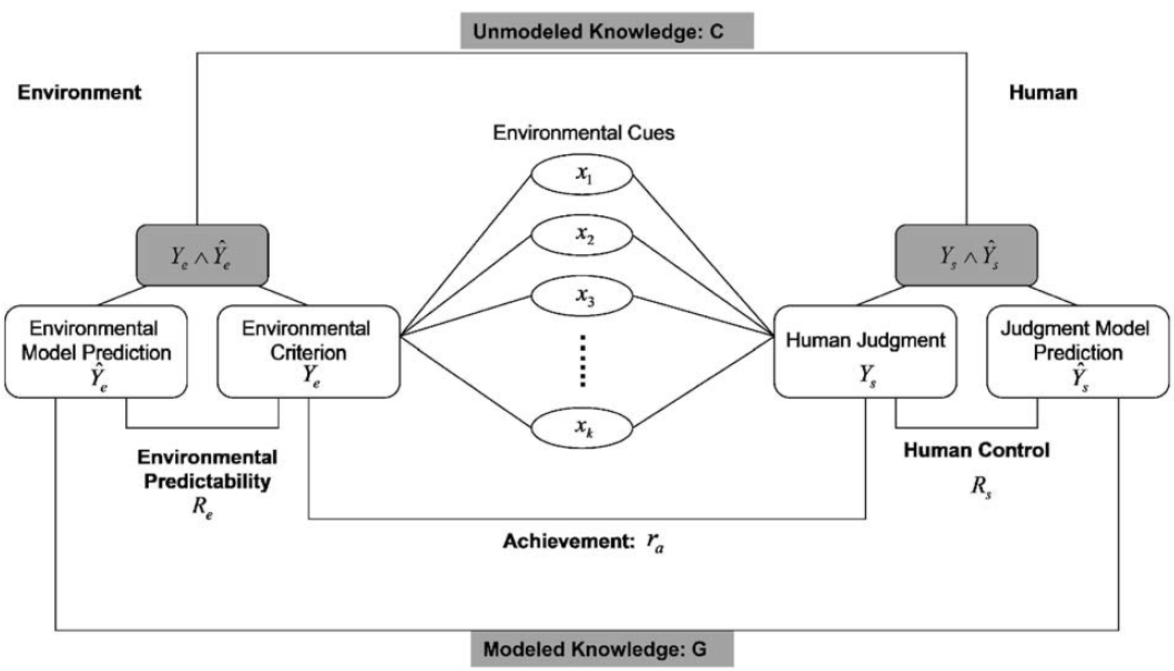


Figure 5.1: The Rule-based Lens Model framework proposed by Yin & Rothrock [28].

5.2.1 Hypothesis development

The Brunswik approach to understanding the relationship between the organism and the environment was probabilistic functionalism that formed the idiographic representation of the organism's model of the environment. Therefore, it is logical to suggest that an expert of an environment has the inherent knowledge of the environment that governs its judgment. Hence, we proposed the following hypothesis:

Hypothesis 2 (H2): The output of an expert judge can be used to estimate the ecology in the case where the output of the ecology is unknown (that is, in the case of a single system design).

Hypothesis 3 (H3): Based on H2, data simulation based on the theory of large numbers can approximate the ecology from the information inherent in the output of the expert judgment.

The ecology simulated from the judge's domain knowledge allows fully characterizing the emergency evacuation using ML algorithms models. Therefore, the hypothesis below was proposed:

Hypothesis 4 (H4): Can ML algorithm models fully characterize an emergency evacuation situation using the judgment output and the simulated ecology.

Given these models, the incomplete information created by the single system design is bridged by the simulated ecology that results in a double system design for the complete description of the judgment analysis related to an emergency evacuation.

5.2.2 Data collection, modeling, and prediction

Judgment data about Hurricane Matthew were gathered from several federal, state, and other government websites. As part of Study 4, all data collected relate to counties in NC that were affected by Hurricane Matthew. A total of seven variables were examined, all of which were numerical and normally distributed.

Due to the lack of Ecology data, Monte-Carlo simulation was used to generate the data, which were then used to develop the ecology model. To generate simulated data, packages in Python, pandas-montecarlo, were used to utilize the judgment data as historical data. Parameters are typically calculated by integrating random instances of parameter values taken from probability distribution functions defined by users.

Five Supervised Machine Learning (SML) models were used to classify each model, and prediction accuracies and LM parameters were computed. These SML models were used to predict ecological criterion, $\hat{Y}_e$, and human judgment, $\hat{Y}_s$.

5.2.3 Machine learning model development

There are algorithms built into Python packages. Supervised learning is a method of machine learning where algorithms are used to learn how to map an input to an output. The judgment model was also created using five nonlinear machine learning algorithms: K-nearest neighbor (KNN), Classification and Regression Tree (Decision Tree) (CART), Naive Bayes (NB), Support Vector Machine (SVM), Stochastic Gradient Boosting (GB), Adaptive Boosting-Adaboost (AB).

An analysis of nonlinear machine learning algorithms (classifications) is presented in this study, as well as the methodology used to develop ecology-judgment data. Using the classification method, there are four steps involved: data description, preprocessing, feature extraction, and classification. Preprocessing involves transforming the data before it is fed into the algorithm. It is not feasible to analyze the data since it was gathered in raw form from different sources. To remove outliers and standardize the dataset, we used two different data preprocessing techniques for machine learning. Since there was no missing data in the dataset, Equation (12) was used to eliminate outliers. This means that the dataset has a normal distribution, where most of the data values fall within the Gaussian curve with a maximum of 3σ. Any dataset that falls outside of these limits is defined as an outlier.

5.2.4 Evaluation metrics

Two evaluation metrics were used to evaluate the performance of the models: Cross-Validation Accuracy (CVA) and Prediction Accuracy (recall). CVA is defined as a statistical method used to estimate the precision of machine learning models. The recall is a performance measurement for machine learning classification problems, which can be computed using Equation (12).

$$Recall = TP(TP+FN) \tag{12}$$

where TP is True Positive, and FN is False Negative.

5.3 Results and Discussion

To obtain the actual judgment and criterion (Y_e) values, machine learning algorithms were applied to both ends of the LM: the ecology side, and the judgment side. To represent both judgment and criterion, categorical values were used; “0” for "do not evacuate" and "1" for "evacuate."

5.3.1 Machine learning model evaluation

Figure 5.2 shows that MCS simulates all the factors that affect individuals' decision-making during an emergency evacuation and compares them to observed data. As shown by the results, the parameters (simulations = 20, goal = 0.5) used with MCS were able to maintain both the observed distribution and the ecological dataset derived from the judgment dataset. Figures 5.3 and 5.4 show the estimated mean of the Cross-Validation (CV) accuracy across the Supervised Machine Learning models. Only 80% of the data was used for training the models.

Figure 5.3 shows the cross-validation accuracy of the data, and the machine learning models for the ecology data. For the ecology data, GB generated a CVA of approximately 76%. To test the prediction accuracy of the model, only 20% of the data is used. To evaluate its performance, Recall is used to determine whether 20% of the data could reasonably predict the model. According to Figure 5.3, KNN demonstrated a good prediction accuracy of approximately 89%.

Figure 5.4 shows the cross-validation accuracy of all the machine learning models and data after 80% of the judgment data were used in training. The Judgment model generated a CVA of approximately 68%. Testing Prediction Accuracy (PA) using 20% of the data and then using Recall to evaluate the performance. Figure 5.4 illustrates the predicted values. All models showed fairly high prediction accuracies of approximately 88%.

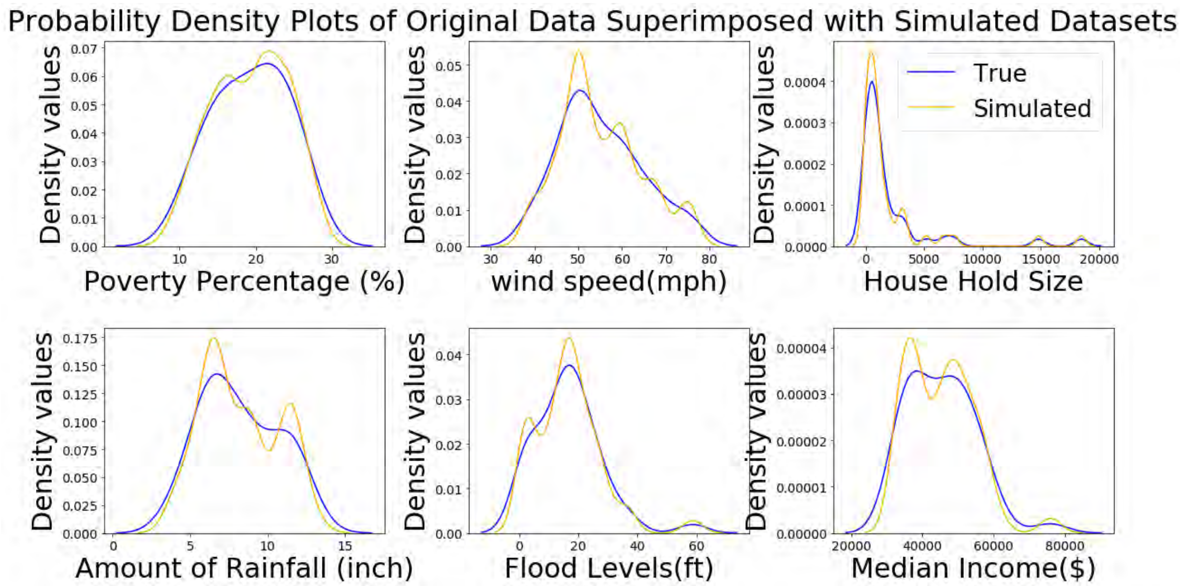


Figure 5.2: Density plot of the simulated and the observed datasets superimposed for each independent variable.

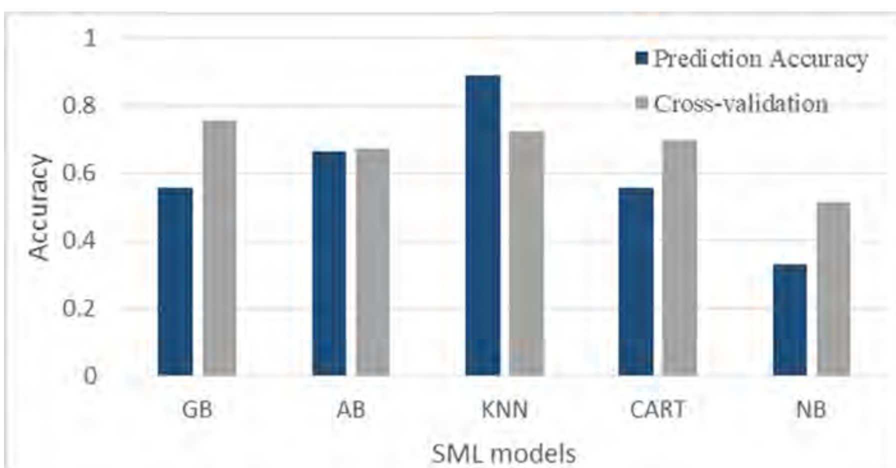


Figure 5.3: Performance of Supervised Machine Learning (SML) models based on Cross-Validation accuracy and prediction accuracy for the Ecology/Criterion data.

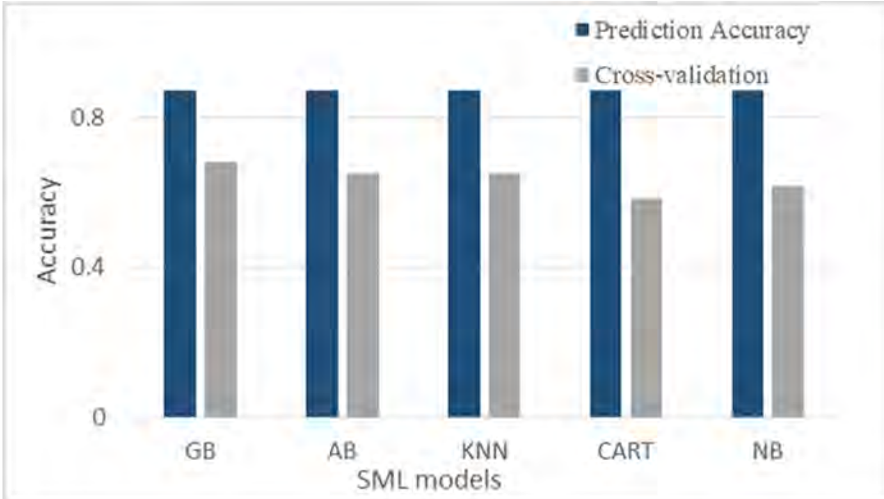


Figure 5.4: Performance of Supervised Machine Learning (SML) models based on Cross-Validation accuracy (CV) and Prediction Accuracy (PA) for the Judgment data.

5.3.2 Lens models parameters

The correlation between the simulated data (data for criterion) and the observed data (judgment data), r_a was 0.66. Table 5.1 shows the LM parameters of the 5 SML models. G explains the correlation between R_e and R_s confirming the relationship and the consistency of the SML models. KNN generated the highest G value of 0.655. R_e and R_s explain the performance in modeling the ecology and capturing the judgment policy, respectively. KNN shows a high R_e value of 0.661 and AB, GB, CART and NB show high R_s results of 0.745. C shows the correlation between the residuals of the criterion and the judgment data. KNN produced the lowest positive C value of 0.143.

Table 5.1: Performance of Supervised Machine Learning (SML) models based on Lens- model parameters (G,C,R_e,R_s)

Data	G	C	R_e	R_s
Adaptive Boosting (AB)	0.258	0.377	0.316	0.745
Gradient Boosting (GB)	0.447	0.378	0.316	0.745
K-nearest neighbor (KNN)	0.655	0.143	0.661	0.654
Classification and Regression Tree (CART)	0.60	0.378	0.316	0.745
Naive-Bayes (NB)	0.447	0.293	0.25	0.745

5.3.3 Discussion

As a result of presented cues, EPs were asked to determine whether to evacuate or not evacuate emergencies. To understand the decisions made by individuals and government (EP) during an emergency evacuation, the full Lens model was used. For the LM parameters to be determined, information (data) from both ends must be available and complete. Since an individual's decisions are unknown and uncertain, the left side of the LM criterion or the left side of the LM is unknown during an emergency evacuation. In terms of understanding and determining how judgments correspond to the criterion, this signifies a single system design and creates drawbacks within the LM framework. We are not aware of any studies that have explored the possibility of switching from a single system to a double system when analyzing emergency evacuations. By simulating the actual criterion with MCS, the first aim was to obtain data. However, in this study, the criterion data were simulated based on judgment data. The parameter r_a measures how well MCS mimics ecological data by maintaining the distribution of observed (judgment) data. Our results indicated that MCS was 66% accurate in simulating ecological data.

To capture the nonlinear strategies in this evacuation decision problem, five nonlinear SML algorithms were used instead of Logistic regression methods within the LM. Multiple SML algorithms were used to confirm data sensitivity, and the best SML algorithm was examined based on its predictive performance when both ends of the LM were joined and correlated. The SML models offer a unique advantage in the development of predictive models for both ends of the LM. Consequently, the prediction accuracy of the individual SML models and the LM parameters were compared, demonstrating that the SML algorithm is capable of modeling both ecology and judgment policy. In terms of modeling the ecology (left side of the LM), KNN outperformed the other SML models at mapping to cues the criterion (ecological validity). In terms of the human judgment side (right side of the LM), all SML models performed equally. Table 5.1 shows that although the *C* values for all the SML models were relatively low, the models were able to capture the non-compensatory strategies that existed in the LM. KNN yielded a low R_s as compared to the other SML models.

FINDINGS, CONCLUSIONS, RECOMMENDATIONS

In the second phase of this CATM project, we

(1) proposed and tested a graph theoretical approach to analyzing the US airport network during a hurricane disruption and a rerouting method to identify feasible airports to reroute passengers from a disrupted airport;

(2) proposed a multi-commodity network flow model with side constraints for multimodal rescheduling of airline passengers through less risky airports and with limited number of connections and tested the model's functionality on a simulated network and four real carrier networks;

(3) developed an agent-based hurricane evacuation simulation model that simulates the trips of individual evacuation vehicles given an evacuation scenario and validated the simulation model using the NC highway system and the Hurricane Florence evacuation in NC;

(4) investigated significant cues for Evacuation Planners' decisions during hurricane evacuation using the Brunswik Linear Lens Model and the six machine learning algorithms; and

(5) extended the Lens model (LM) using Monte-Carlo simulation (MCS) and nonlinear supervised machine learning (SML) algorithms to analyze decision-making behavior during an emergency evacuation in an incomplete information environment.

For rescheduling airline passengers whose flights are cancelled due to severe weather, our results showed that the proposed graph theoretical approach can help recognize the airports that might be affected beforehand, which, in turn, can aid in planning for a disruption, and the planning for rescheduling of airline passengers based on a hurricane forecast path may alleviate the problem of passenger disruption. Our experimental results also revealed that hurricane impact distance and forecast track affect recognizing potential disruptors and, in turn, their disruptees, and also affect identifying potential airports to reroute to from a disrupted airport. This may result in an inefficient planning/rescheduling to handle disruption due to a hurricane. Our findings for multimodal rescheduling indicated that for both simulated and real carrier networks, road transportation is utilized for rescheduling passengers when such option is available. This implied that it is advisable to hire buses to transfer passengers when a disruptive event is anticipated to occur at a particular airport. The spare aircrafts should be also utilized in rescheduling at some circumstances. Our analysis on the four carriers showed that the airports in northeastern US region may play a major role as connections for multimodal rescheduling, and some of these airports serve as either operating bases or focus cities for the airlines.

For hurricane evacuation, our simulation results showed that optimized individual evacuation plans can reduce the average evacuation trip duration by 8% – 12% comparing taking the shortest path without considering traffic conditions, and the percentage of families choosing shelter-in-place slightly affects evacuation traffic and travel time. The developed hurricane evacuation simulation model can estimate evacuation traffic volumes and average travel time, which could provide insights for hurricane evacuation planning and management. This simulation model can be used as a tool to support hurricane evacuation planning by comparing different traffic control policies under different hurricane evacuation scenarios.

Our results of decision making cues for hurricane evacuation showed that among the seven cues we tested, only one cue (wind speed) contributes to Evacuation Planners' decision (i.e., whether to issue an evacuation order). Our experimental results demonstrated that Monte-Carlo simulation was 66% accurate in simulating ecological data, and the SML algorithms are capable of modeling both ecology and judgment policy. In terms of modeling the ecology (left side of the LM), KNN outperformed the other SML models at mapping to cues the criterion (ecological validity). In terms of the human judgment side (right side of the LM), all SML models performed equally. The Rule-based Lens model (RLM) developed by combining the ecological and judgment models can help quantify and understand evacuee decision making. The RLM developed in our study contributes to disaster management literature by describing decision-making when limited information is available for data-supported models.

REFERENCES

1 Kohl, N., Larsen, A., Larsen, J., Ross, A., & Tiourine, S. (2007). Airline disruption management – Perspectives, experiences and outlook. *Journal of Air Transport Management*, 13(3), 149–162. DOI: https://doi.org/10.1016/j.jairtraman.2007.01.001

2 Bureau of Transportation Statistics. Airline On-Time Statistics and Delay Causes. https://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp?pn=1.9. Accessed in March 2021.

3 Chen, J.-H., Lin, S.-J., Magnusson, L., Bender, M., Chen, X., Zhou, L., Xiang, B., Rees, S., Morin, M., & Harris, L. (2019). Advancements in hurricane prediction with NOAA's next-generation forecast system. *Geophysical Research Letters*, 46(8), 4495–4501. DOI: https://doi.org/10.1029/2019GL082410

4 Rappaport, E. N., & Franklin, J. L., Avila, L. A., Baig, S. R., Beven, J. L., Blake, E. S., Burr, C. A., Jiing, J.-G., Juckins, C. A., Knabb, R. D., Landsea, C. W., & Mainelli, M. (2009). Advances and challenges at the National Hurricane Center. *Weather and Forecasting*, 24(2), 395–419. DOI: https://doi.org/10.1175/2008WAF2222128.1

5 Willoughby, H. E., Rappaport, E.N., & Marks, F. D. (2007). Hurricane forecasting: The state of the art. *Natural Hazards Review*, 8(3), 45–49. DOI: https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(45)

6 Humbertson, R. & Sinha, A. (2012). Managing irregular airport operations. *Journal of Airport Management*, 6(4), 318–328.

7 Meda, H. (2021). A Theoretical Approach and Optimization Model integrating Network Theory to Analyze and Mitigate Airport Network Disruption. Dissertation, North Carolina A&T State University, Greensboro, North Carolina.

8 OpenFlights. Airport, Airline and Route Data. https://openflights.org/data.html. Accessed in April 2019.

9 Federal Aviation Administration. Passenger Boarding (Enplanement) and All-Cargo Data for US. https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/. Accessed in December 2020.

10 European Commission, Directorate-General for Mobility and Transport, Directorate-General for Research and Innovation (2011). Flightpath 2050 Europe's vision for aviation: Maintaining global leadership and serving society's needs. DOI: https://data.europa.eu/doi/10.2777/50266
https://ec.europa.eu/transport/sites/transport/files/modes/air/doc/flightpath2050.pdf.

11 European Commission. Roadmap to a single European transport area – Towards a competitive and resource efficient transport system. European Commission. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0144:FIN:EN:PDF. Accessed in June 2022.

12 Marzuoli, A., Boidot, E., Colomar, P., Guerpillon, M., Feron, E., Bayen, A., & Hansen, M. (2016). Improving disruption management with multimodal collaborative decision-

making: A case study of the Asiana crash and lessons learned. *IEEE Transactions on Intelligent Transportation Systems*, 17(10), 2699–2717. DOI: https://doi.org/10.1109/TITS.2016.2536733

13 Zhang, Y., & Hansen, M. (2008). Real-time intermodal substitution: strategy for airline recovery from schedule perturbation and for mitigation of airport congestion. *Transportation Research Record*, 2052(1), 90–99. DOI: https://doi.org/10.3141/2052-11

14 Bayram, V. (2016). Optimization models for large scale network evacuation planning and management: A literature review. *Surveys in Operations Research and Management Science*, 21(2), 63-84. DOI: https://doi.org/10.1016/j.sorms.2016.11.001

15 Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. *Transportation Research Part C: Emerging Technologies*, 42, 44-59. DOI: https://doi.org/10.1016/j.trc.2014.02.015

16 Alawadi, R., Murray-Tuite, P., Marasco, D., Ukkusuri, S., & Ge, Y. (2020). Determinants of full and partial household evacuation decision making in Hurricane Matthew. *Transportation Research Part D: Transport and Environment*, 83, 102313. DOI: https://doi.org/10.1016/j.trd.2020.102313

17 North Carolina Department of Transportation. Evacuation Routes. https://www.ncdot.gov/travel-maps/maps/Pages/evacuation-routes.aspx. Accessed in January 2022.

18 Horni, A., Nagel, K., & Axhausen, K. W. (2016). The Multi-Agent Transport Simulation MATSim. London: Ubiquity Press. DOI: https://doi.org/10.5334/baw

19 Geofabrik Downloads. OpenStreetMap Data Extracts. https://download.geofabrik.de/. Accessed in January 2022.

20 Casey, J. North Carolina Census Data: Households & Families. https://www.census-charts.com/HF/North_Carolina.html#reading. Accessed in January 2022.

21 Simonovic, S. P., & Ahmad, S. (2005). Computer-based model for flood evacuation emergency planning. *Natural Hazards*, 34(1), 25-51. DOI: http://dx.doi.org/10.1007/s11069-004-0785-x

22 Fu, H., & Wilmot, C. G. (2006). Survival analysis–based dynamic travel demand models for hurricane evacuation. *Transportation Research Record*, 1964(1), 211-218. DOI: https://doi.org/10.1177/0361198106196400123

23 Hasan, S., Ukkusuri, S., Gladwin, H., & Murray-Tuite, P. (2011). Behavioral model to understand household-level hurricane evacuation decision making. *Journal of Transportation Engineering*, 137(5), 341-348. DOI: https://doi.org/10.1061/(ASCE)TE.1943-5436.0000223

24 Whitehead, J. C., Edwards, B., Van Willigen, M., Maiolo, J. R., Wilson, K., & Smith, K. T. (2000). Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. *Global Environmental Change Part B: Environmental Hazards*, 2(4), 133-142. DOI: https://doi.org/10.1016/S1464-2867(01)00013-4

25 North Carolina Department of Safety. WebEOC database 2016. www.ncsparta.net/eoc7/default.aspx. Accessed in July 2019.

26 Nuamah, J. K., & Seong, Y. (2019). A machine learning approach to predict human judgments in compensatory and noncompensatory judgment tasks. *IEEE Transactions on Human-Machine Systems*, 49(4), 326-336. DOI: https://doi.org/10.1109/THMS.2019.2892436

27 Cooksey, R. W. (1996). *Judgment analysis: Theory, methods, and applications*. Academic Press.

28 Yin, J., & Rothrock, L. (2006). A rule-based lens model. *International Journal of Industrial Ergonomics*, 36(5), 499-509. DOI: https://doi.org/10.1016/j.ergon.2006.01.012

APPENDIX A: Data for the Judgment Model

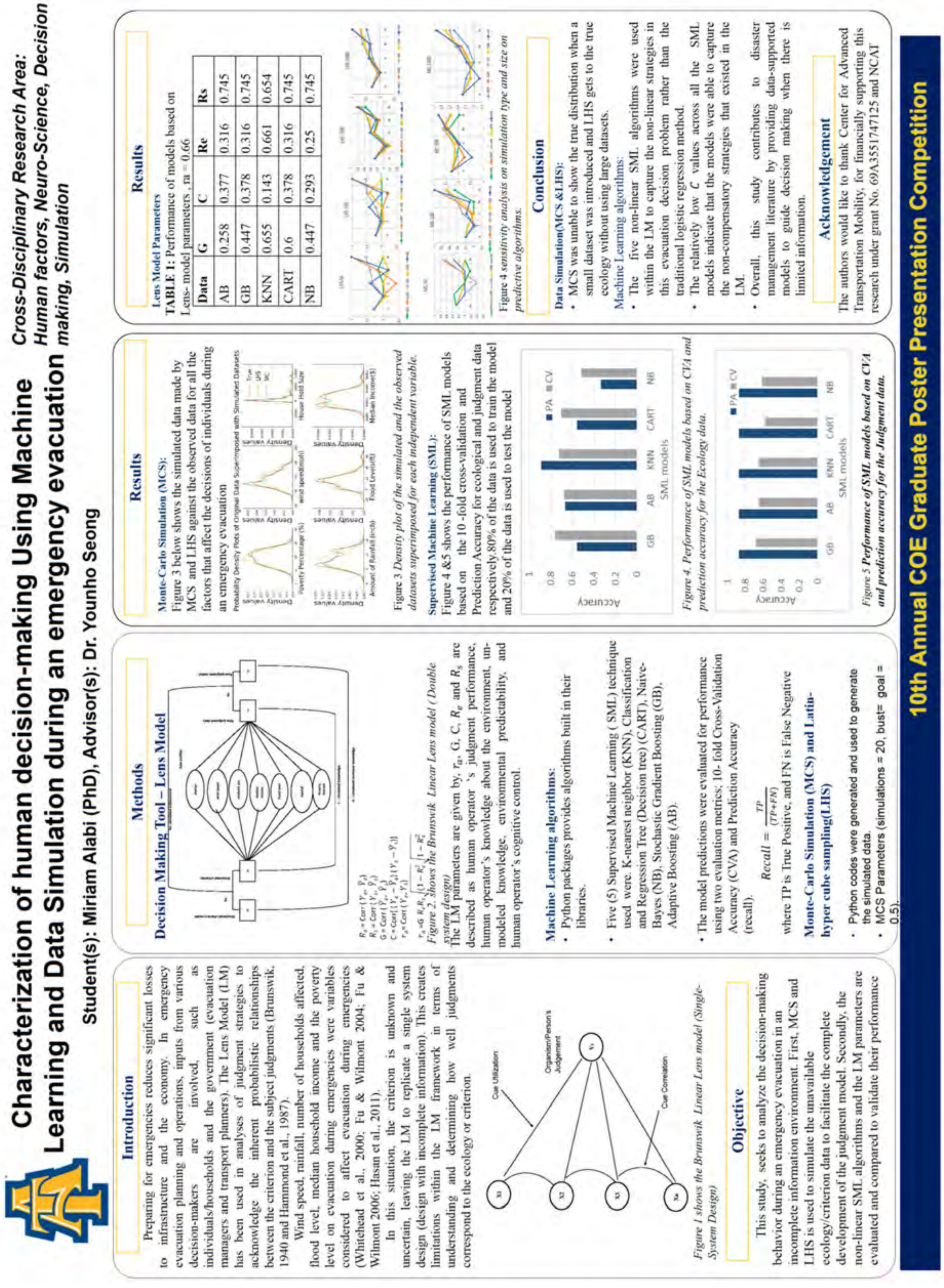
Table A.1: Data obtained from multiple sources for the judgment model

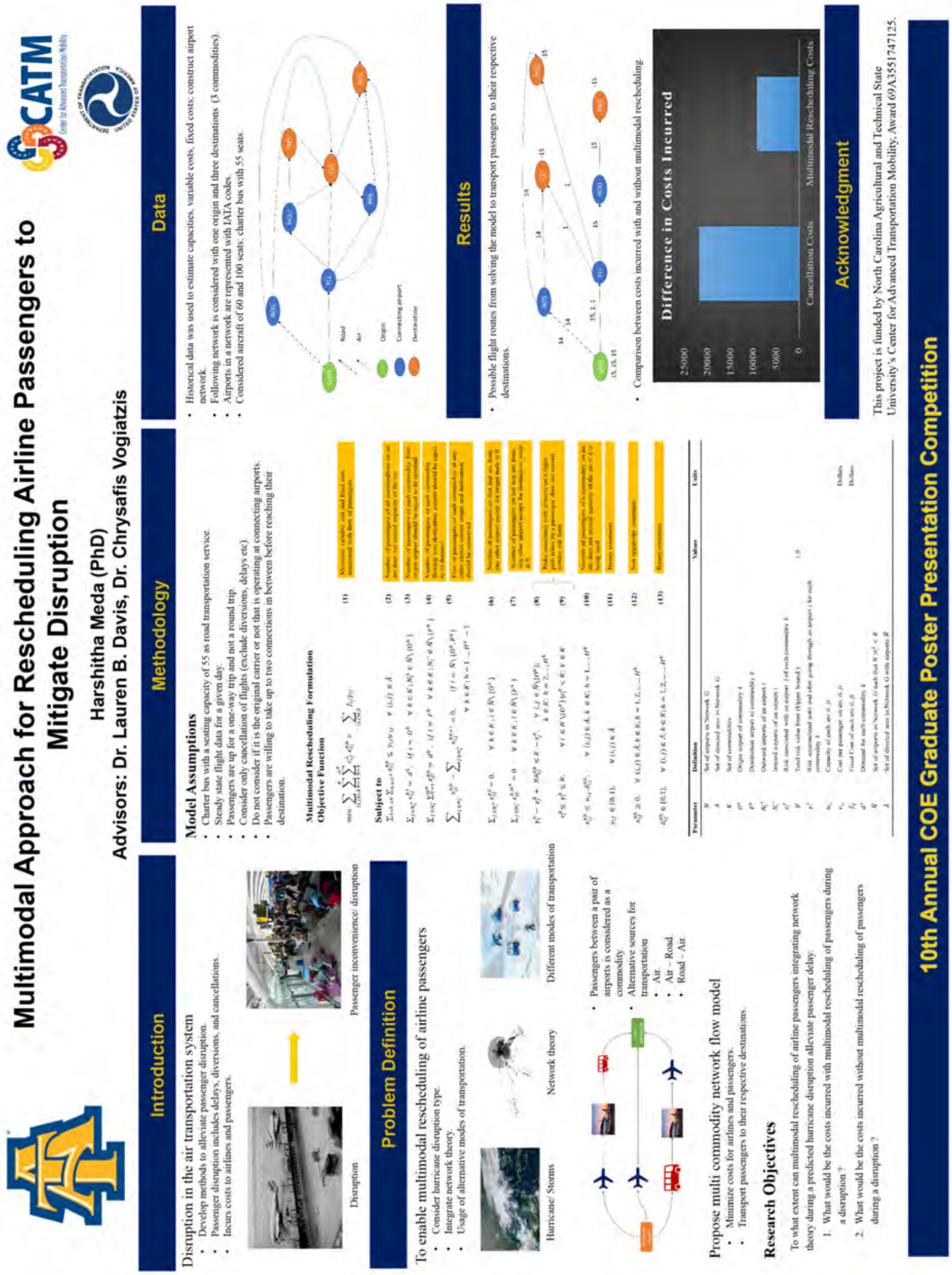
Name of County	No of Shelters	Wind Speed	Rainfall	Households affected	Flood Level (ft)	Median Household Income	Poverty Percent	Evacuate
Anson	1	45	4	74	24.39	33,228	25.1	0
Beaufort	2	50	7.5	850	12.50	45,860	19	1
Bertie	2	40	10.5	1025	16.67	34,127	24.4	0
Bladen	4	39	12	2817	36.34	34,422	26.4	0
Brunswick	3	67	7	784	18.98	47,000	13.8	0
Carteret	2	60	6.5	49	8.48	52,000	12.3	1
Columbus	5	59	11.5	5189	2.00	40,000	24.6	0
Cumberland	6	60	13	14803	58.70	42,107	18.8	0
Dare	0	75	6	1121	3.00	56,489	10.9	1
Duplin	3	49	7	1322	19.92	39,146	21.3	0
Durham	1	60	11.5	850	17.73	54,093	16.1	0
Edgecombe	4	60	11.5	3139	36.15	35,000	23.9	1
Franklin	0	45	8.41	13	23.18	50,000	15.3	0
Gates	0	64	9	158	16.19	49,258	15.2	0
Greene	1	50	9	579	24.18	38,010	23.7	0
Harnett	1	57	7	1683	19.31	51,682	16.1	0
Hyde	0	75	6	194	2.00	56,285	22.3	1
Hertford	1	40	9	453	15.40	37,000	26.1	0
Hoke	1	60	11.5	1786	12.84	45,829	19.5	0
Johnston	3	50	11.5	1683	28.90	57,151	13.2	0
Jones	1	50	6.5	226	18.46	34,005	21.5	0
Lee	1	45	11.5	190	11.44	50,547	16.9	0
Lenoir	1	51	9	3291	28.24	38,000	20.6	1
Martin	1	50	9	213	11.60	35,080	22.5	0
Montgomery	0	50	4	0	10.40	37,800	21.4	0
Moore	1	55	5	343	8.91	56,678	11.4	0
Nash	1	55	7	927	15.26	47,200	16.5	0
New Hanover	1	75	6	23	3.00	56,200	17.3	0
Onslow	6	50	6.5	442	20.55	38,000	13.7	0
Orange	1	45	6.5	850	16.25	61,130	12.8	0
Pamlico	1	50	5	7569	2.00	46,762	18.5	0
Pasquotank	1	64	8.5	476	16.19	45,400	17	0
Pender	3	68	6	957	17.79	50,000	15	1
Pitt	3	69	8	3303	24.46	50,000	21.5	1
Richmond	0	50	6	23	17.60	37,000	24.9	0
Robeson	5	67	11	18482	25.00	33,000	27.8	1

Table A.1: (cont'd)

Name of County	No of Shelters	Wind Speed	Rainfall	Households affected	Flood Level (ft)	Median Household Income	Poverty Percent	Evacuate
Sampson	3	60	12	2236	27.92	38,835	19.6	0
Scotland	0	55	7	500	15.47	52,000	27.6	0
Vance	1	55	5	850	2.00	32,733	24.2	0
Wake	1	45	9	916	5.47	76,000	9.2	0
Wayne	3	50	6.5	6695	2.00	45,000	20.6	1
Wilson	1	52.5	10.5	721	2.00	43,456	22.3	0

APPENDIX B: Posters and Presentation Slides




Multimodal Approach for Rescheduling Airline Passengers to Mitigate Disruption
Harshitha Meda (PhD)
Advisors: Dr. Lauren B. Davis, Dr. Chrysafis Vogiatzis
Introduction
Disruption in the air transportation system
Develop methods to alleviate passenger disruption.
Passenger disruption includes delays, diversions, and cancellations.
Incurs costs to airlines and passengers.
Disruption
Passenger inconvenience/ disruption
Problem Definition
To enable multimodal rescheduling of airline passengers
Consider hurricane disruption type.
Integrate network theory.
Usage of alternative modes of transportation.
Hurricane/ Storms
Network theory
Different modes of transportation
Passengers between a pair of airports is considered as a commodity.
Alternative sources for transportation
Air.
Air – Road.
Road – Air.
Propose multi commodity network flow model
Minimize costs for airlines and passengers.
Transport passengers to their respective destinations.
Research Objectives
To what extent can multimodal rescheduling of airline passengers integrating network theory during a predicted hurricane disruption alleviate passenger delay.
1. What would be the costs incurred with multimodal rescheduling of passengers during a disruption ?
2. What would be the costs incurred without multimodal rescheduling of passengers during a disruption ?
Methodology
Model Assumptions
Charter bus with a seating capacity of 55 as road transportation service.
Steady state flight data for a given day.
Passengers are up for a one-way trip and not a round trip.
Consider only cancellation of flights (exclude diversions, delays etc).
Do not consider if it is the original carrier or not that is operating at connecting airports.
Passengers are willing to take up to two connections in between before reaching their destination.
Multimodal Rescheduling Formulation
Objective Function
Subject to
Parameter
Definition
Values
Units
Dollars
Dollars
Data
Historical data was used to estimate capacities, variable costs, fixed costs; construct airport network.
Following network is considered with one origin and three destinations (3 commodities).
Airports in a network are represented with IATA codes.
Considered aircraft of 60 and 100 seats; charter bus with 55 seats.
Road
Air
Origin
Connecting airport
Destination
Results
Possible flight routes from solving the model to transport passengers to their respective destinations.
Comparison between costs incurred with and without multimodal rescheduling.
Difference in Costs Incurred
25000
20000
15000
10000
5000
0
Cancellation Costs
Multimodal Rescheduling Costs
Acknowledgment
This project is funded by North Carolina Agricultural and Technical State University's Center for Advanced Transportation Mobility, Award 69A3551747125.
10th Annual COE Graduate Poster Presentation Competition

Model-Driven Decision Making for Road Asset Protection before a Hurricane

Sachin Mhatre (Ph.D)

Advisor: Xiuli Qu

Cross-Disciplinary Research Area: Application of OR in disaster management

Methodology

A standard form for a two-stage stochastic integer linear programming (SILP)

$$\min_{\forall x} \; C^T x + E_P\,[Q\,(x,w)]$$
$$Ax = b$$
$$x \in R^{n_1} * Z^{p_1}$$
$$Q\,(x,w) := \min_{\forall y} q^T y$$
$$\text{s.t. } W_y = h - Tx,$$
$$y \in R^{n_2} * Z^{p_2}$$

x – Represents first stage decisions

y – Represents second stage decisions

w – Represents the uncertain data for the second-stage, where the parameters (q, h, t) are actual realization of the random data with known distribution P

R and Z denotes reals and integers respectively

n_1, n_2, p_1, p_2 are non-negative integers

In the model, the first stage decision is the road asset protection plan, i.e., the protection of critical edges and bridges.

The second stage decisions are shortest paths between humanitarian resource locations and shelters under damage scenarios.

The objective of the model is to minimizes the travelling time between essential locations (i.e., resource locations and shelters) after a hurricane.

Experimental Design

Factors and Levels in the Experiment

Factors	Levels
Wind Intensity	Low: Wind intensity of Category-1 hurricanes
	High: Wind intensity of Category-2 hurricanes
Flood Level	Low (3.67 feet): Peak flood level during Hurricane Dorian
	High (12.42 feet): Double the peak flood level during Hurricane Florence
Protection resource	0, 500, 1000,1500, 2000, 3000

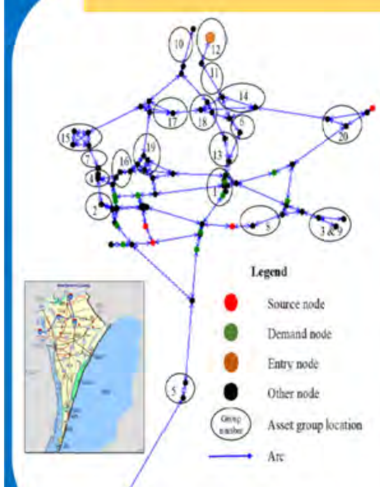
Conclusions

- ❖ Developed stochastic optimization model for road asset protection decision making before a natural disaster
- ❖ Proposed a solution algorithm to solve the stochastic model
- ❖ Examined the impact of experimental factors on the optimal road asset protection plan
- ❖ The model and the solution algorithm can support decision making for road asset protection planning.

Acknowledgment

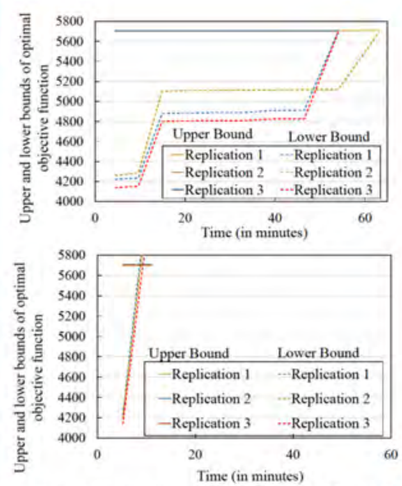
Supported by the Center for Advanced Transportation Mobility (CATM), USDOT grant # 69A3551747125. The views and conclusions in this poster are those of the authors and should not be interpreted as the USDOT policies.

Experimental Results



New Hanover County highway network with asset group locations.

Protection resource (aggregate units)	Sample size (N)	Computational time (min)	Computational time (min) GSD	Optimal objective value (Total traveling time in minutes): Average	Standard error	Average (GSD)	Standard error (GSD)
0	25	1.0	1.1	15432.5	437.8	15432.5	437.9
	50	1.7	2.0	15264.1	450.8	15264.1	450.8
	75	2.5	2.8	15148.2	191.9	15148.2	191.9
	100	3.5	3.7	14941.1	113.3	14941.1	113.3
500	25	1.2	1.3	9576.1	1.3	9576.1	1.3
	50	2.4	2.4	9576.8	0.8	9576.8	0.8
	75	3.6	4.1	9576.2	0.9	9576.2	0.9
	100	5.2	5.3	9575.8	0.9	9575.8	0.9
1500	25	**24.9**	**2.9**	5705.0	2.3	5705.4	2.2
	50	**37.5**	**5.1**	5704.6	1.6	5704.5	1.7
	75	**48.9**	**7.5**	5703.9	1.2	5704.4	1.7
	100	**61.6**	**10.5**	5705.7	1.1	5705.7	1.1
3000	25	1.6	1.6	1817.1	8.5	1815.4	7.6
	50	3.2	3.3	1809.7	6.7	1812.2	9.1
	75	4.8	5.0	1809.8	7.1	1811.5	8.8
	100	7.8	6.8	1807.1	6.5	1810.3	9.8



Algorithms convergence for a sample size of 100 and the instance with protection resource level of 1500

10th Annual COE Graduate Poster Presentation Competition

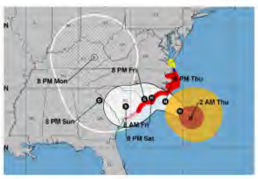
Traffic Analysis for Hurricane Evacuations in Eastern North Carolina: A Simulation Study

Mahmud Parvez and Xiuli Qu

North Carolina A&T State University, Greensboro, NC

Introduction

Recent hurricanes caused mass evacuations. Many issues occurred during these hurricane evacuations, which have been brought to the public attention and attracted researchers to study how to manage an effective hurricane evacuation. Proper traffic control, sufficient emergency responders, and enough evacuation supplies are crucial for an effective hurricane evacuation. Therefore, it is important to estimate evacuation traffic volumes and patterns under different scenarios. To meet this need, we developed a hurricane evacuation simulation model using an open-source agent-based transport simulation (MATSim) framework.



Simulation Scenario

Time Interval	Evacuators	Road Capacity
48–72 hours before the landfall	10% population	10%
24–48 hours before the landfall	40% population	50%
Within 24 hours of the landfall	45% population	90%
Daytime (6AM–6PM)	95% of daily evacuators	
Nighttime (12–6AM & 6–11:59PM)	5% of daily evacuators	
1. Different uniform distributions for daytime and nighttime departures		
2. 5% population choosing "Stay home"		

Fig. 1: Evacuation zone and 16 population locations

MATSim Simulation

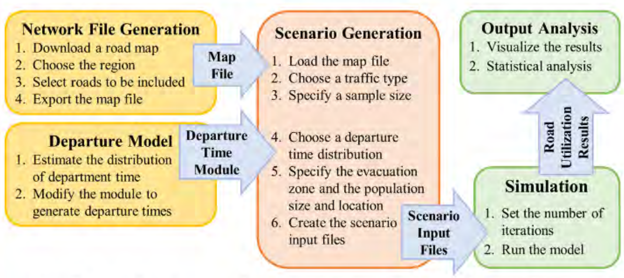
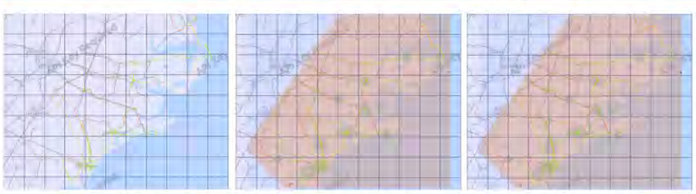


Fig. 2: Procedure to create the evacuation simulation model using MATSim

Conclusion

- Developed an agent-based hurricane evacuation simulation model.
- The model captures the evacuation route selection by individuals.
- The model is populated using the highway transportation system in the eastern NC evacuation zone.
- The model has been tested using the evacuation scenario in NC during Hurricane Florence.
- The simulation model could be used to evaluate traffic volumes under different evacuation scenarios.

Results



(a) 48 – 72 hours (b) 24 – 48 hours (c) Within 24 hours

Fig. 3: Road utilization for evacuation during the three days before the landfall

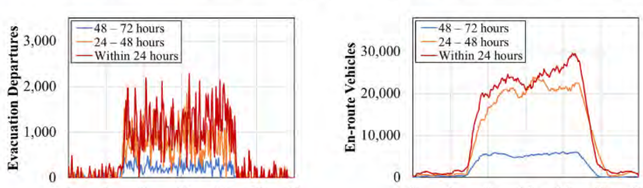


Fig. 4 Numbers of evacuation departures and en-route evacuation vehicles over time

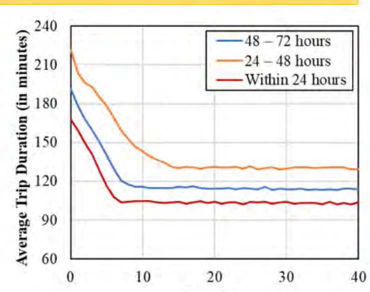
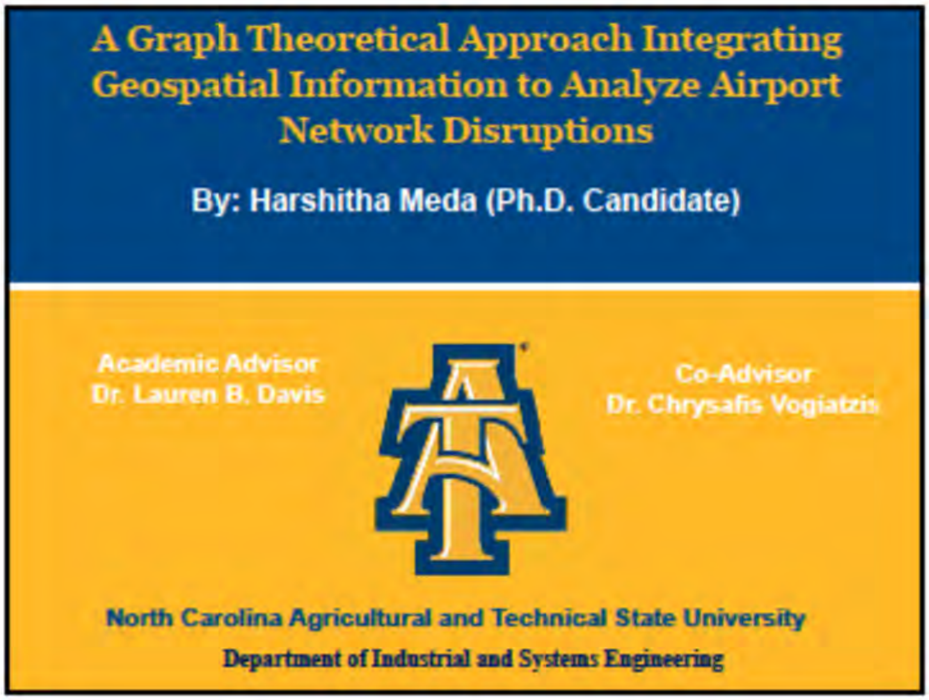


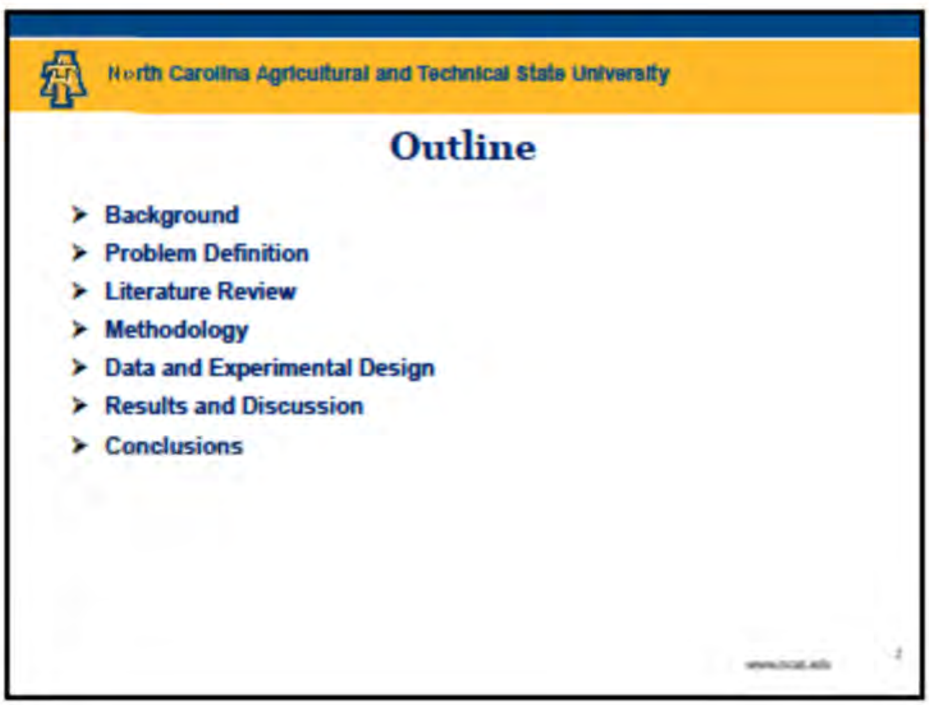
Fig. 5: Average duration of evacuation trips

Acknowledgement

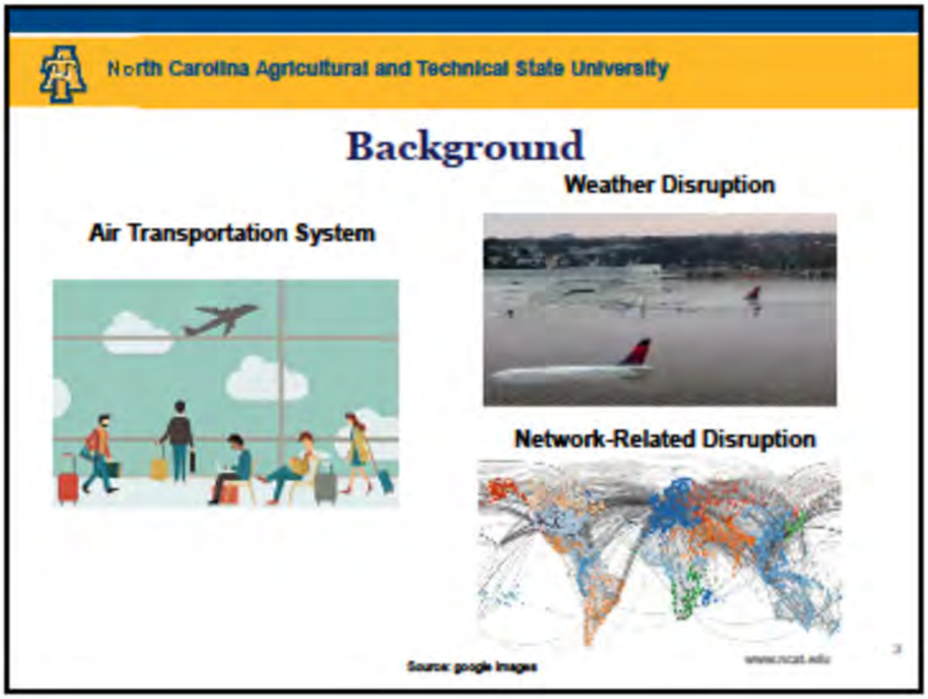
Supported by the Center for Advanced Transportation Mobility (CATM), USDOT grant # 69A3551747125. The views and conclusions in this poster are those of the authors and should not be interpreted as the USDOT policies.


A Graph Theoretical Approach Integrating Geospatial Information to Analyze Airport Network Disruptions
By: Harshitha Meda (Ph.D. Candidate)
Academic Advisor
Dr. Lauren B. Davis
Co-Advisor
Dr. Chrysafis Vogiatzis
North Carolina Agricultural and Technical State University
Department of Industrial and Systems Engineering

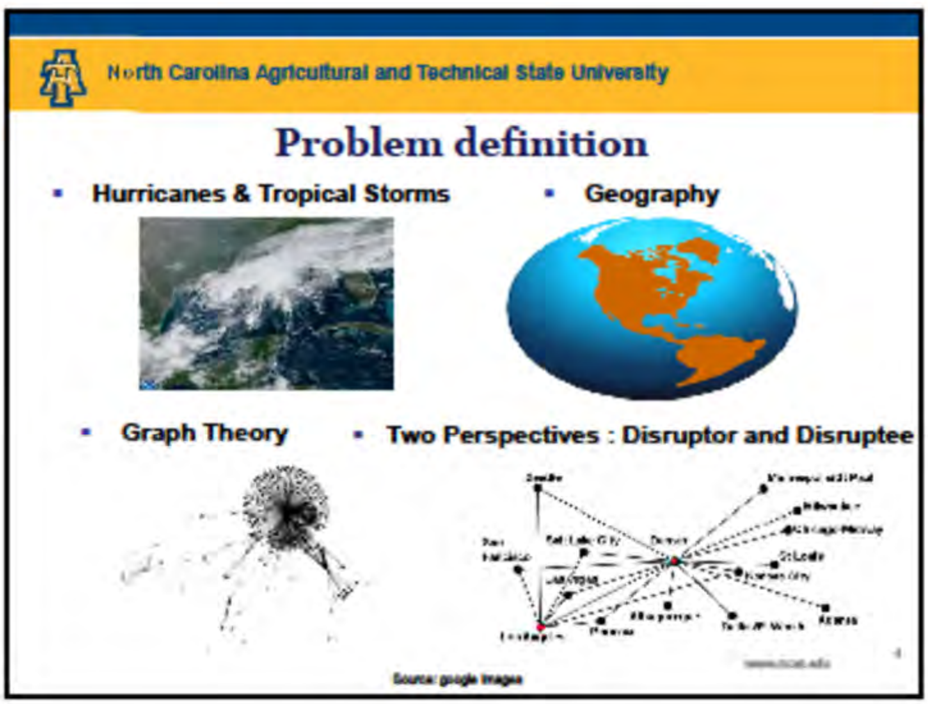
1


North Carolina Agricultural and Technical State University
Outline
Background
Problem Definition
Literature Review
Methodology
Data and Experimental Design
Results and Discussion
Conclusions

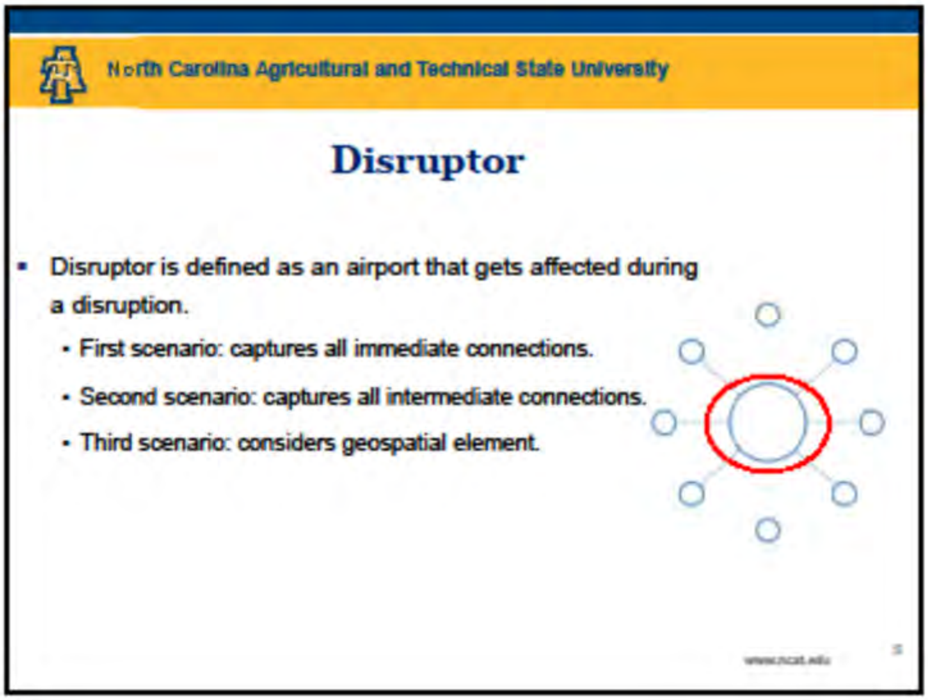
2


North Carolina Agricultural and Technical State University
Background
Weather Disruption
Air Transportation System
Network-Related Disruption
Source: google images
www.ncat.edu

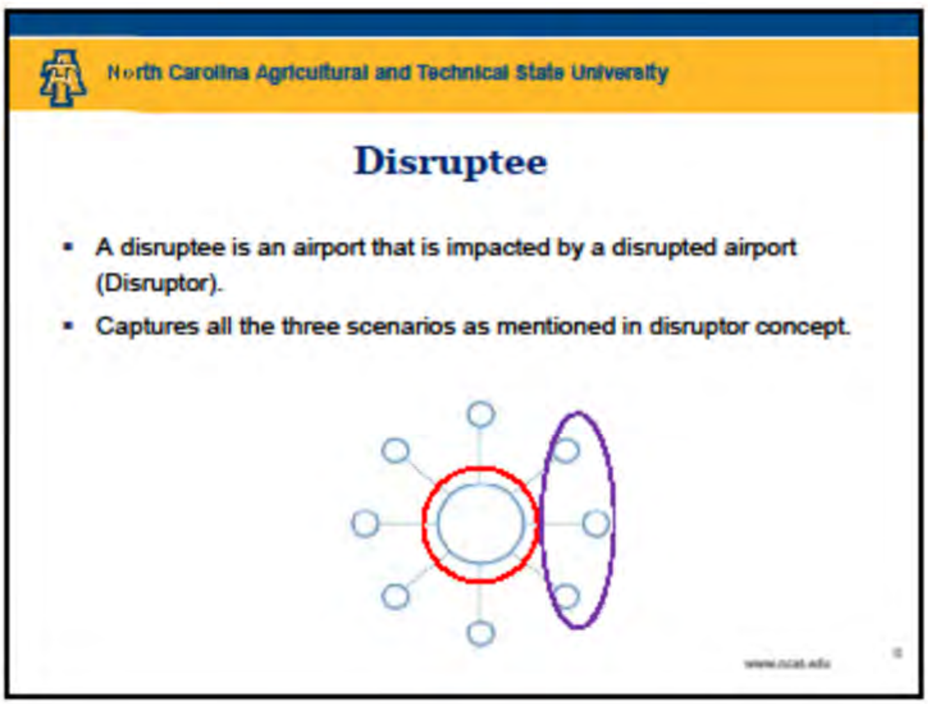
3


North Carolina Agricultural and Technical State University
Problem definition
Hurricanes & Tropical Storms
Geography
Graph Theory
Two Perspectives : Disruptor and Disruptee
Source: google images
www.ncat.edu

4


North Carolina Agricultural and Technical State University
Disruptor
Disruptor is defined as an airport that gets affected during a disruption.
First scenario: captures all immediate connections.
Second scenario: captures all intermediate connections.
Third scenario: considers geospatial element.

5


North Carolina Agricultural and Technical State University
Disruptee
A disruptee is an airport that is impacted by a disrupted airport (Disruptor).
Captures all the three scenarios as mentioned in disruptor concept.

6

North Carolina Agricultural and Technical State University

Problem definition…

- **Objective:**
  - To develop graph theoretical approach integrating geospatial information to capture airports in an airport network from two perspectives: extent of being a disruptor and disruptee.
- **Scope**
  - Hurricane application
  - U.S. airport network

www.ncat.edu 7

7

North Carolina Agricultural and Technical State University

Problem Definition…

- **Research Objectives:**
  1. To understand the ability of airline passengers to get rerouted from a hurricane impacted airport.
  2. To understand the effect of a change in the forecast track of a hurricane on identifying disruptors and disruptees.
  3. To understand the effect of a change in the hurricane impact distance on identifying disruptees for an airport classified as a disruptor.

www.ncat.edu 8

8

North Carolina Agricultural and Technical State University

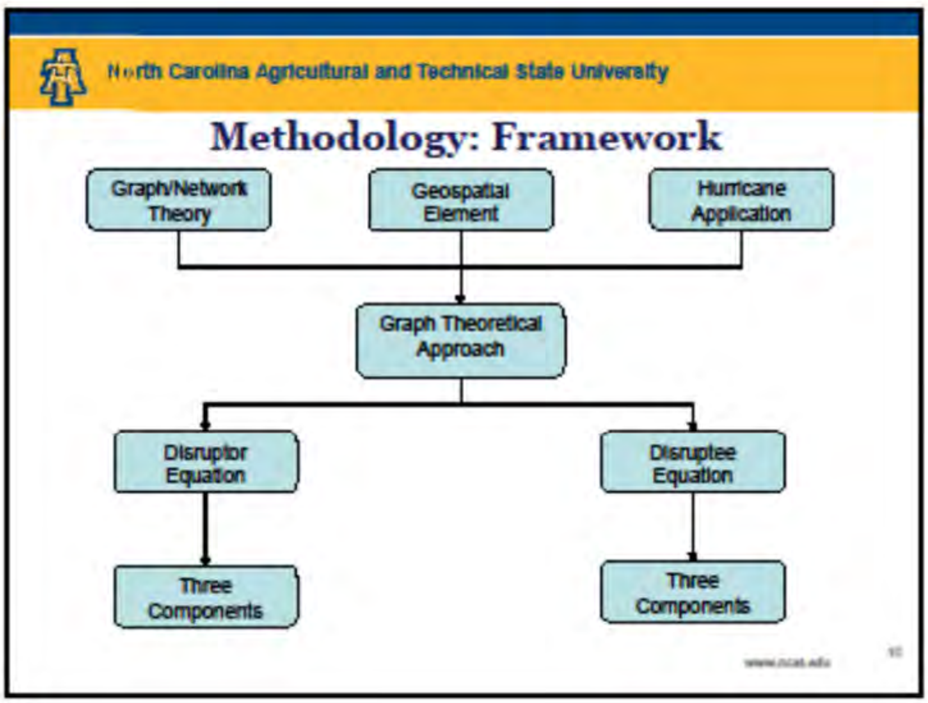
Literature Review

Author	Graph Theory	Centrality Concepts	Geography	Two Perspectives	Realistic Weather Scenario
Wei et al. (1997)	●	●			
Zhenhua Wu et al. (2006)	●	●			
Massimiliano and Fabrizio (2013)	●	●			
Tatsuya Kotegawa et al.(2014)	●	●			
Min and Gi (2017)	●	●			
Proposed Approach	●	●	●	●	●

Source: google images

www.ncat.edu

9



10

North Carolina Agricultural and Technical State University

Methodology

- **Assumptions**
  - We consider simple paths of length up to 3 between every pair of airports.
  - Passenger opts for a maximum of two connections.
  - Single path/itinerary flights operate separately from multiple path/itinerary flights.
  - Undirected and unweighted airport network (static in nature).

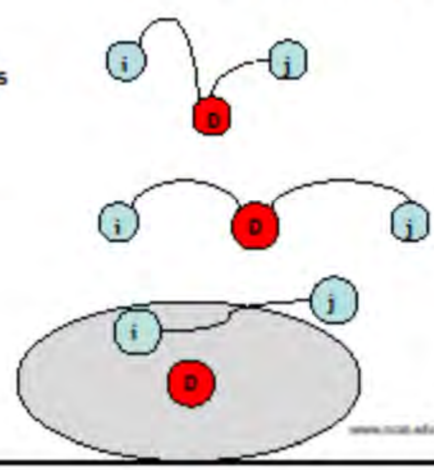
www.ncat.edu 11

11

North Carolina Agricultural and Technical State University

Methodology

- **Disruptor Equation :** Quantifies extent to which an airport can be a disruptor.
  - Three Different Components
    - Immediate Component
    - Intermediate Component
    - Geospatial Component



www.ncat.edu 12

12

North Carolina Agricultural and Technical State University

Methodology

- **Disruptor Equation:** Quantifies extent to which an airport can be a disruptor.

$$F_d(A) = w_M \cdot \frac{1}{N_M} \underbrace{\boxed{\sum_j s_{Aj}^1}}_{\text{Immediate Component}} + w_I \cdot \frac{1}{N_I} \underbrace{\boxed{\sum_{j \neq k; j,k \neq A} \frac{s_{jk}^{1+}(A|I)}{s_{jk}^{1+}}}}_{\text{Intermediate Component}} + w_G \cdot \frac{1}{N_G} \underbrace{\boxed{\sum_{j \neq k; j,k \neq A} \frac{s_{jk}^{1+}(A|G)}{s_{jk}^{1+} - s_{jk}^{1+}(A|I)}}}_{\text{Geospatial Component}} \Leftrightarrow s_{jk}^{1+}(A|I) < s_{jk}^{1+}$$

$$0 \leq F_d(A) \leq 1$$

www.ncat.edu 13

13

North Carolina Agricultural and Technical State University

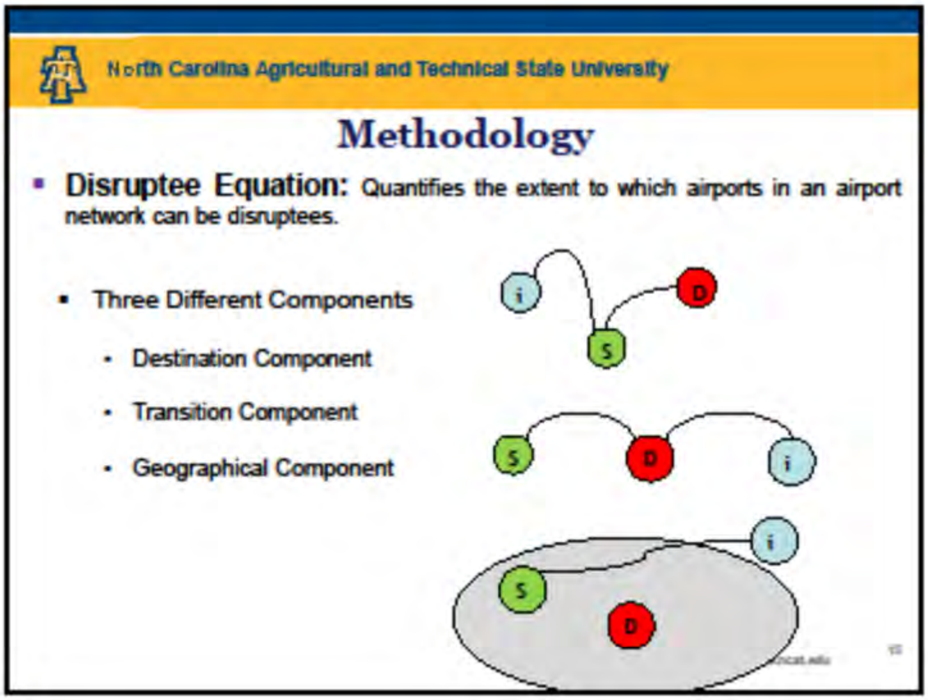
Methodology

- **Disruptor Equation:** Quantifies extent to which an airport can be a disruptor.

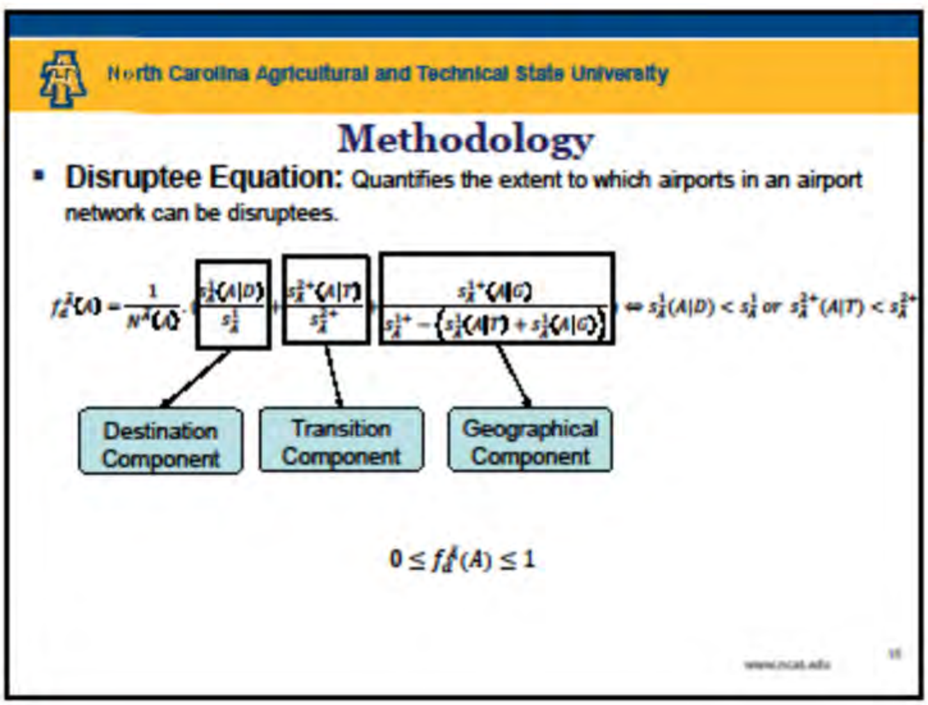
$$F_d(A) = w_M \cdot \frac{1}{N_M} \cdot \sum_j s_{Aj}^1 + w_I \cdot \frac{1}{N_I} \cdot \sum_{j \neq k; j,k \neq A} \frac{s_{jk}^{1+}(A|I)}{s_{jk}^{1+}} + w_G \cdot \frac{1}{N_G} \cdot \sum_{j \neq k; j,k \neq A} \frac{s_{jk}^{1+}(A|G)}{s_{jk}^{1+} - s_{jk}^{1+}(A|I)} \Leftrightarrow s_{jk}^{1+}(A|I) < s_{jk}^{1+}$$

Term	Definition
$F_d(A)$	Extent to which an airport *A* can be a disruptor when hurricane effect is up to distance *d* miles.
s_{AJ}^1	Number of simple paths of length one connecting nodes *A* and *J*.
s_{jk}^{1+}	Number of simple paths of length up to 3 between airports *j* and *k*.
$s_{jk}^{1+}(A\|I)$	Number of simple paths of length up to 3 between airports *j* and *k* that have airport *A* as an intermediate connection.
$s_{jk}^{1+}(A\|G)$	Number of simple paths of length up to 3 between airports *j* and *k* that are geographically impacted due to an airport *A*'s location.
$s_{jk}^{1+} - s_{jk}^{1+}(A\|I)$	Number of simple paths of length up to 3 between airports *j* and *k* that are available for exploring the geospatial element.
N_M, N_I, N_G	Normalization factors for immediate, intermediate, and geospatial components.
w_M, w_I, w_G	Weights for immediate, intermediate, and geospatial components.

14


North Carolina Agricultural and Technical State University
Methodology
Disruptee Equation: Quantifies the extent to which airports in an airport network can be disruptees.
Three Different Components
Destination Component
Transition Component
Geographical Component
i
D
S
S
D
i
i
S
D

15


North Carolina Agricultural and Technical State University
Methodology
Disruptee Equation: Quantifies the extent to which airports in an airport network can be disruptees.
$f_d^2(A) = \frac{1}{N^2(A)} \cdot \left(\boxed{\frac{s_A^1(A|D)}{s_A^1}} + \boxed{\frac{s_A^{2+}(A|T)}{s_A^{2+}}} + \boxed{\frac{s_A^{1+}(A|G)}{s_A^{1+} - \left\{ s_A^1(A|T) + s_A^1(A|G) \right\}}} \right) \Leftrightarrow s_A^1(A|D) < s_A^1 \text{ or } s_A^{2+}(A|T) < s_A^{2+}$
Destination Component
Transition Component
Geographical Component
$0 \le f_d^2(A) \le 1$
www.ncat.edu

16

North Carolina Agricultural and Technical State University

Methodology

- **Disruptee Equation:** Quantifies the extent to which airports in an airport network can be disruptees.

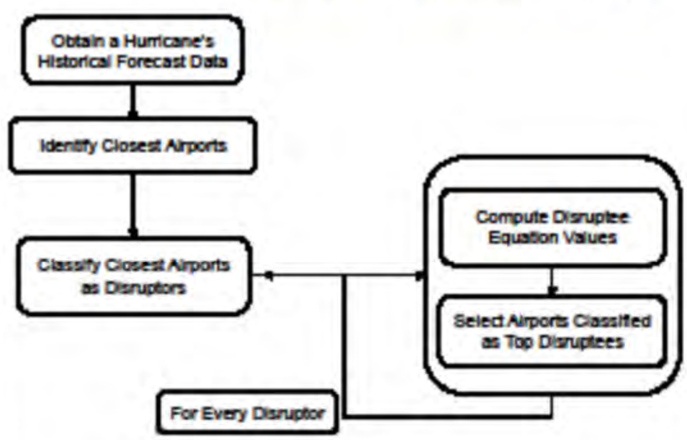
$$f_d^{\bar{A}}(A) = \frac{1}{N^{\bar{A}}(A)} \cdot \left(\frac{s_{\bar{A}}^{1}(A|D)}{s_{\bar{A}}^{1}} + \frac{s_{\bar{A}}^{2+}(A|T)}{s_{\bar{A}}^{2+}} + \frac{s_{\bar{A}}^{1+}(A|G)}{s_{\bar{A}}^{1+} - \left\{ s_{\bar{A}}^{1}(A|T) + s_{\bar{A}}^{1}(A|G) \right\}} \right) \Leftrightarrow s_{\bar{A}}^{1}(A|D) < s_{\bar{A}}^{1} \text{ or } s_{\bar{A}}^{2+}(A|T) < s_{\bar{A}}^{2+}$$

Term	Definition
$f_d^{\bar{A}}(A)$	Extent to which an airport $\bar{A}$ could be a disruptee when an airport A is a disruptor.
$s_{\bar{A}}^{1}$	Number of simple paths of length one with an airport $\bar{A}$ as a source.
$s_{\bar{A}}^{1}(A\|D)$	Number of simple paths of length one with an airport $\bar{A}$ as a source and an airport A as a direct destination.
$s_{\bar{A}}^{2+}$	Number of simple paths of length 2 or 3 with an airport $\bar{A}$ as a source.
$s_{\bar{A}}^{2+}(A\|T)$	Number of simple paths of length 2 or 3 with an airport $\bar{A}$ as a source and an airport A as an intermediate connection or a destination after more than a single hop.
$s_{\bar{A}}^{1+} - \left\{ s_{\bar{A}}^{1}(A\|T) + s_{\bar{A}}^{1}(A\|G) \right\}$	Number of simple paths of length up to 3 with an airport $\bar{A}$ as a source that are available for exploring the geospatial element.
$s_{\bar{A}}^{1+}(A\|G)$	Number of simple paths of length up to 3 with an airport $\bar{A}$ as a source that are geographically impacted due to disruptor airport A's location.
$N^{\bar{A}}(A)$	Normalization factor for the disruptee equation.

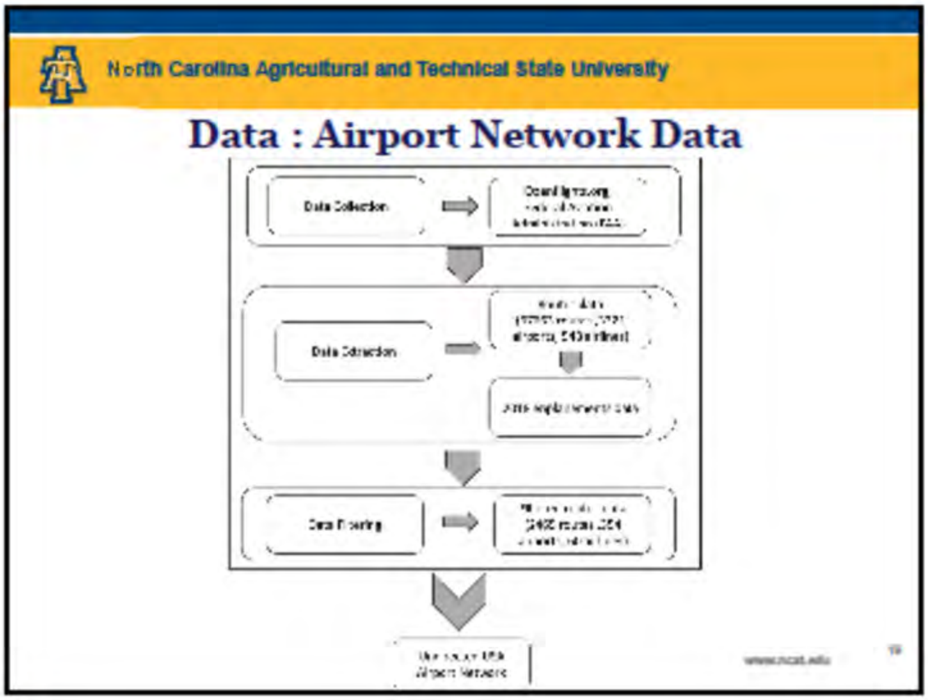
17

North Carolina Agricultural and Technical State University

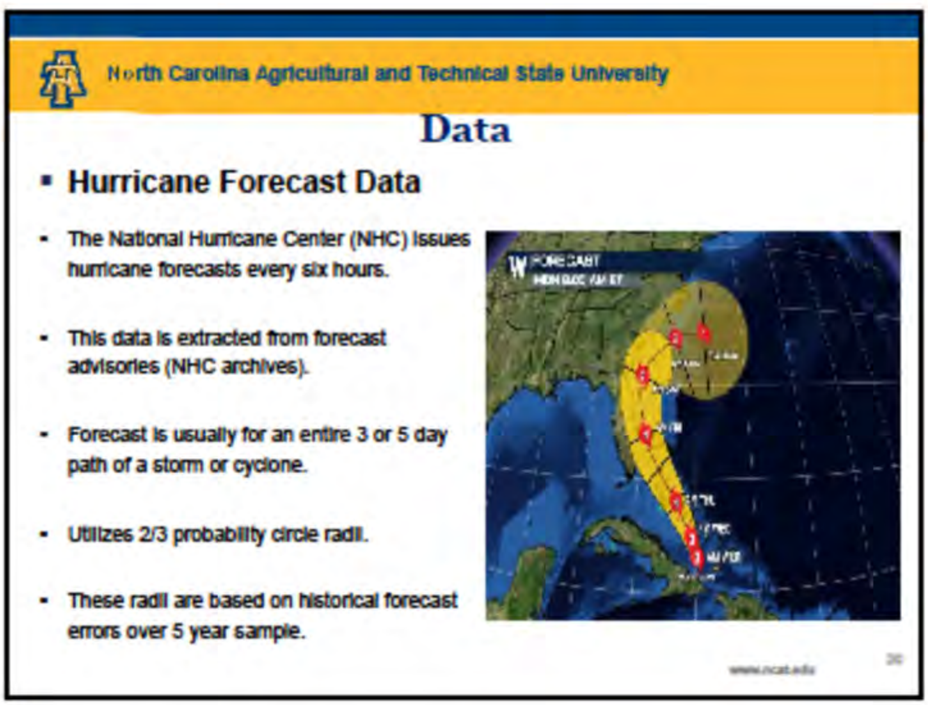
General Methodology



18


North Carolina Agricultural and Technical State University
Data : Airport Network Data
Data Collection
Data Extraction
www.ncat.edu
19

19


North Carolina Agricultural and Technical State University
Data
▪ Hurricane Forecast Data
- The National Hurricane Center (NHC) issues hurricane forecasts every six hours.
- This data is extracted from forecast advisories (NHC archives).
- Forecast is usually for an entire 3 or 5 day path of a storm or cyclone.
- Utilizes 2/3 probability circle radii.
- These radii are based on historical forecast errors over 5 year sample.
FORECAST
www.ncat.edu
20

20

North Carolina Agricultural and Technical State University

Data

- Radii of NHC and CPHC cone circles for the year 2020

Forecast Period (hours)	Atlantic Basin, (NM)	Eastern North Pacific Basin, (NM)	Central North Pacific Basin, (NM)
12	26	25	34
24	41	38	49
36	55	51	66
48	69	65	81
72	103	91	120
96	151	115	137
120	196	138	156

www.ncat.edu 21

21

North Carolina Agricultural and Technical State University

Experimental Design

- Hurricane Matthew 2016: occurred in the North Atlantic basin.
- Impacted U.S. states during period: October 7-9, 2016.
- Considered hurricane forecast issued on October 4, 2016.

www.ncat.edu 22

22

North Carolina Agricultural and Technical State University

Research Objective 1: To understand the ability of airline passengers to get rerouted from a hurricane impacted airport.

23

www.ncat.edu

23

North Carolina Agricultural and Technical State University

Results and Discussion

- Forecast issued on October 4, 2016 at 3:00 am

Forecast on October 4, 2016, 3:00 am

24

www.ncat.edu

24

North Carolina Agricultural and Technical State University

Results and Discussion

- Number of close airports for forecast issued on October 4, 2016 at 3:00 am

www.ncat.edu

25

North Carolina Agricultural and Technical State University

Results and Discussion

- Disruptor Equation (DE) values for close airports for forecast issued on October 4, 2016 at 3:00 am

79.419	Miles	118.563	Miles	173.801	Miles	225.596	Miles
Airport	DE Value	Airport	DE Value	Airport	DE Value	Airport	DE Value
None	None	PBI	0.0198	DAB	0.0099	ILM	0.0144
		FLL	0.0622	JAX	0.0286	MYR	0.0312
		MIA	0.0474	SFB	0.0503	OAJ	0.0134
				BQK	0.0098	EWN	0.0121
				MLB	0.0092	FLO	0.0136
				MCO	0.0825	FAY	0.0161
				GNV	0.0125	CHS	0.0295
						PGV	0.0134
						RDU	0.0461
						CAE	0.0251
						SAV	0.0268

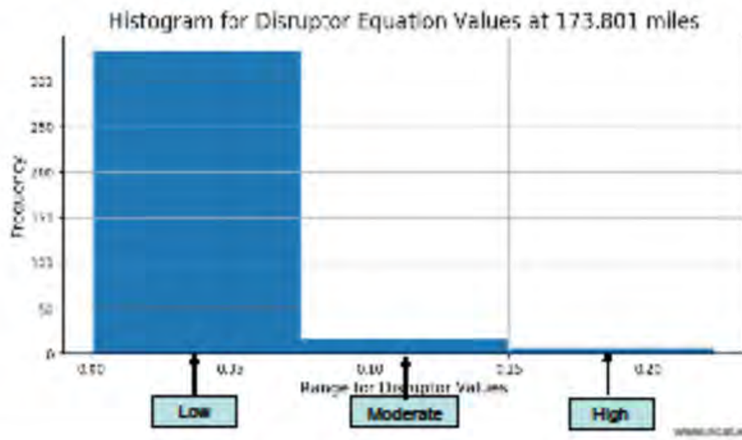
www.ncat.edu

26

North Carolina Agricultural and Technical State University

Results and Discussion

- Histogram for disruptor equation values at a radius (distance) of 173.801 miles



www.ncat.edu

27

North Carolina Agricultural and Technical State University

Results and Discussion

- Disruptor Equation (DE) values for close airports for forecast issued on October 4, 2016 at 3:00 am

78.418	Miles	118.563	Miles	173.801	Miles	226.596	Miles
Airport	DE Value	Airport	DE Value	Airport	DE Value	Airport	DE Value
None	None	PBI	0.0198	DAB	0.0099	ILM	0.0144
		FLL	0.0622	JAX	0.0286	MYR	0.0312
		MIA	0.0474	SFB	0.0503	OAJ	0.0134
				BQK	0.0098	EWN	0.0121
				MLB	0.0092	FLO	0.0136
				MCO	0.0825	FAY	0.0161
				GNV	0.0125	CHS	0.0295
						PGV	0.0134
						RDU	0.0461
						CAE	0.0251
						SAV	0.0268

www.ncat.edu

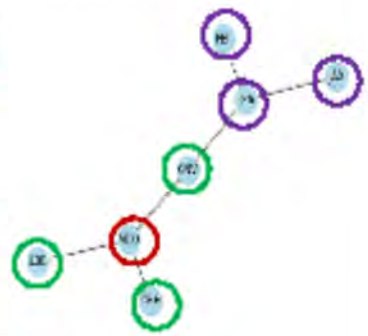
28

North Carolina Agricultural and Technical State University

Results and Discussion

- Disruptee equation values for MCO as a disruptor at a distance of 173.801 miles

Airport	Destination Component	Transition Component	Geographical Component	Disruptee Equation Value
ORH	0.5000	0.5443	1.0000	0.8177
LBE	0.3333	0.4585	0.7438	0.6581
GNV	0.2000	0.2211	1.0000	0.6459
EYW	0.1250	0.1714	0.8810	0.5541
RSW	0.0333	0.0788	1.0000	0.5469
MIA	0.0208	0.0634	0.9997	0.5364
FLL	0.0172	0.0528	0.9997	0.5357
TPA	0.0000	0.0435	1.0000	0.5176
JAX	0.0000	0.0370	1.0000	0.5079
PBI	0.0000	0.0384	1.0000	0.5055



www.ncat.edu

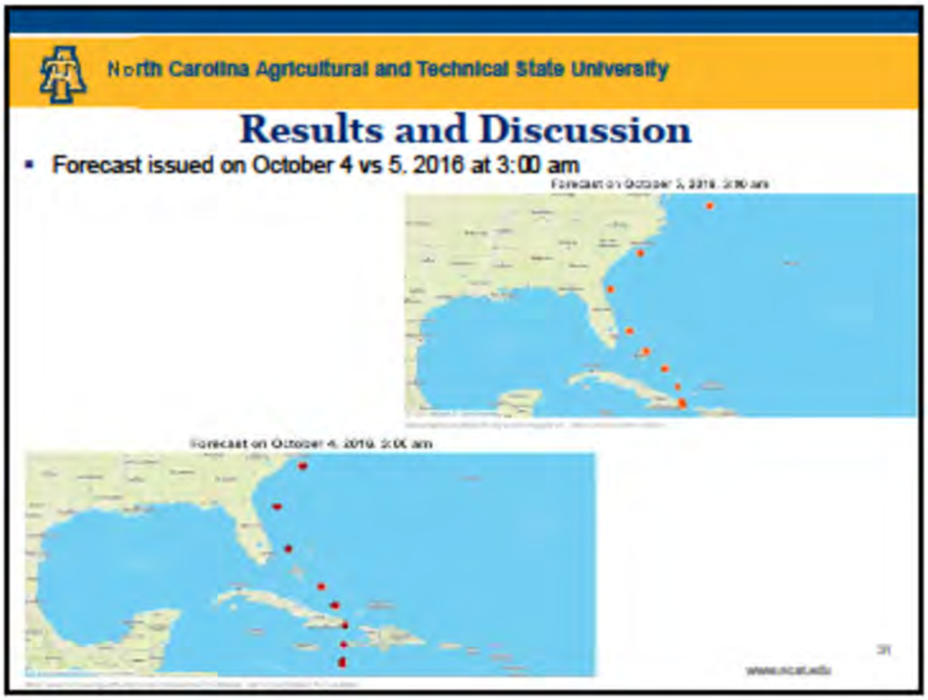
29

North Carolina Agricultural and Technical State University

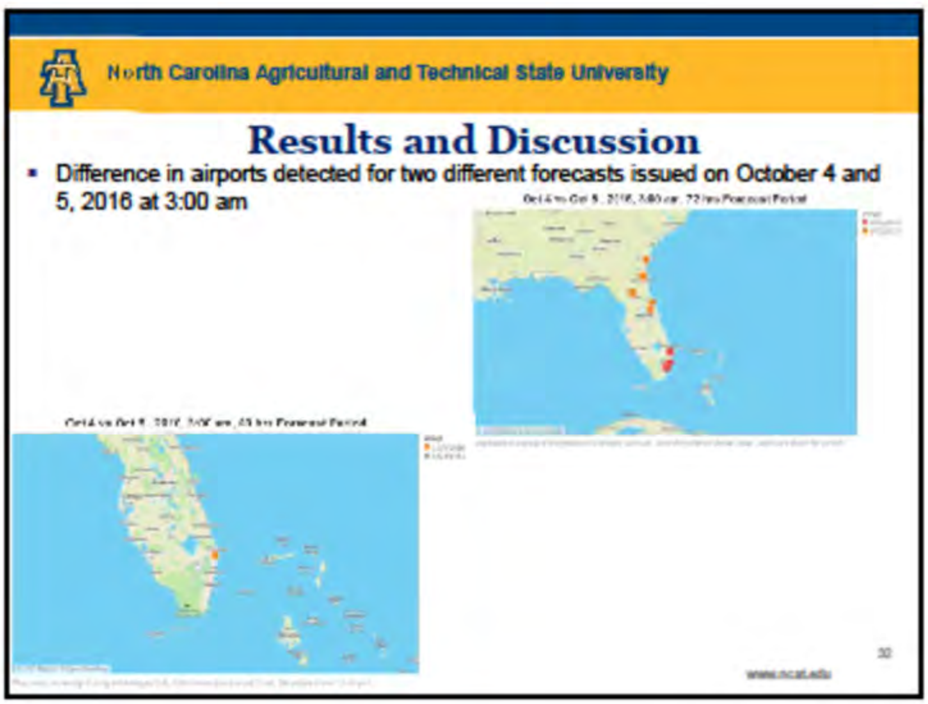
Research Objective 2: To understand the effect of a change in the forecast track of a hurricane on identifying disruptors and disruptees.

www.ncat.edu

30


North Carolina Agricultural and Technical State University
Results and Discussion
Forecast issued on October 4 vs 5, 2016 at 3:00 am
Forecast on October 4, 2016, 3:00 am
31
www.ncat.edu

31


North Carolina Agricultural and Technical State University
Results and Discussion
Difference in airports detected for two different forecasts issued on October 4 and 5, 2016 at 3:00 am
32
www.ncat.edu

32

North Carolina Agricultural and Technical State University

Results and Discussion

- Difference in airports detected for two different forecasts issued on October 4 and 5, 2016 at 3:00 am

33

North Carolina Agricultural and Technical State University

Research Objective 3: To understand the effect of a change in the hurricane impact distance on identifying disruptees for an airport classified as a disruptor.

34

North Carolina Agricultural and Technical State University

Results and Discussion

- Disruptee equation values for different hurricane impact distances

Distance	63.305 miles		118.553 miles		173.801 miles
Airport	Disruptee Value	Airport	Disruptee Value	Airport	Disruptee Value
ORH	0.5770	ORH	0.7559	ORH	0.8177
SFB	0.5044	LBE	0.6565	LBE	0.6581
LBE	0.4666	GNV	0.6459	GNV	0.6459
MCN	0.4173	EYW	0.5198	EYW	0.5541
RSW	0.4151	TPA	0.5176	RSW	0.5460
MLB	0.4143	PBI	0.5059	MIA	0.5364
DAB	0.4143	RSW	0.5053	FLL	0.5357
PGD	0.3536	SFB	0.5044	TPA	0.5176
PSM	0.3369	PIE	0.5022	JAX	0.5079
BLV	0.3369	PGD	0.4948	PBI	0.5059
GNV	0.3335	SRQ	0.4787	SFB	0.5044
SRQ	0.3127	FLL	0.4596	PIE	0.5022
SWF	0.3001	MCN	0.4359	PGD	0.4948
LCK	0.2875	MIA	0.4255	SRQ	0.4787
ACY	0.2702	MLB	0.4143	MCN	0.4421
EYW	0.2574	DAB	0.4143	DAB	0.4143
TLH	0.2490	LCK	0.4049	MLB	0.4143
FLL	0.2476	SWF	0.3932	LCK	0.4049
MIA	0.2402	IAG	0.3712	SWF	0.3985
ISP	0.2307	PSM	0.3369	IAG	0.3726

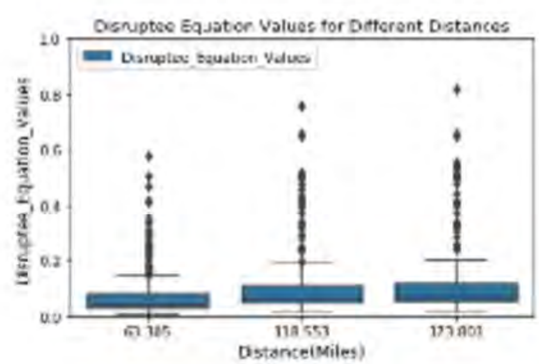
www.ncat.edu

35

North Carolina Agricultural and Technical State University

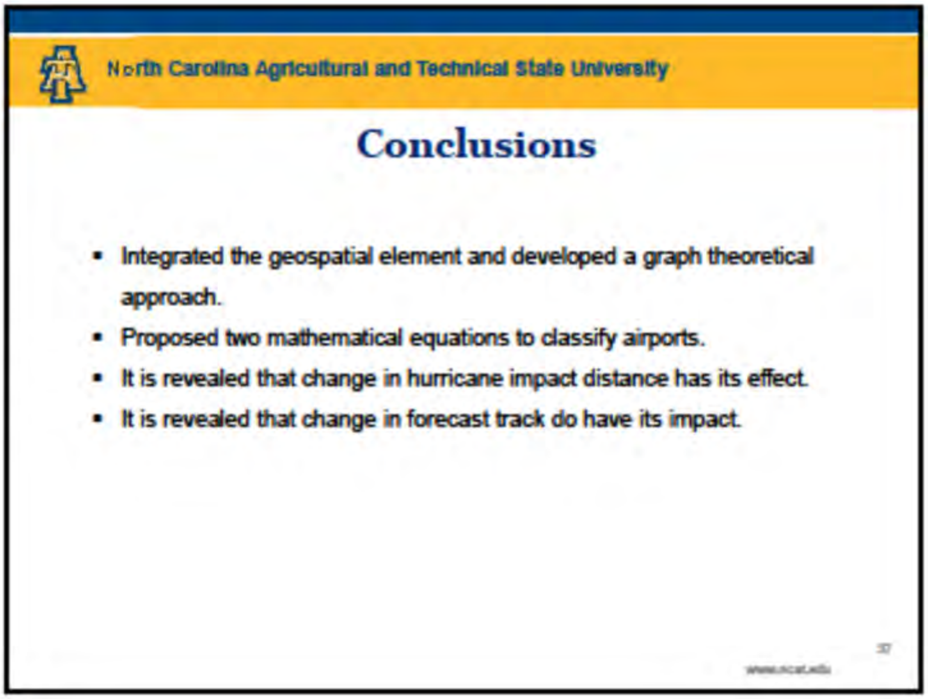
Results and Discussion

- Disruptee equation values for different hurricane impact distances

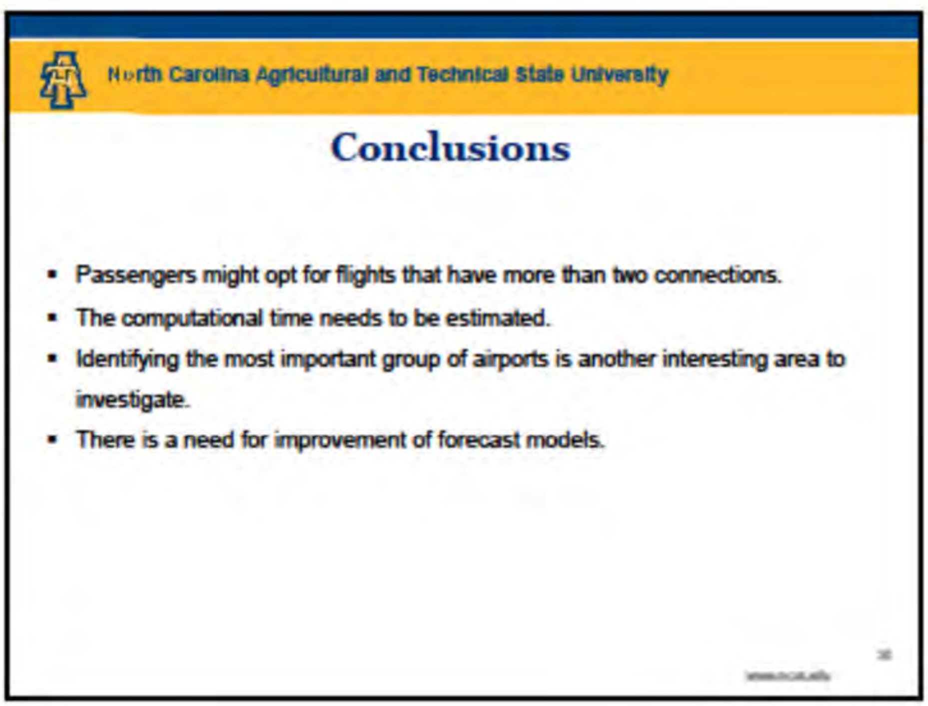


www.ncat.edu

36


North Carolina Agricultural and Technical State University
Conclusions
Integrated the geospatial element and developed a graph theoretical approach.
Proposed two mathematical equations to classify airports.
It is revealed that change in hurricane impact distance has its effect.
It is revealed that change in forecast track do have its impact.

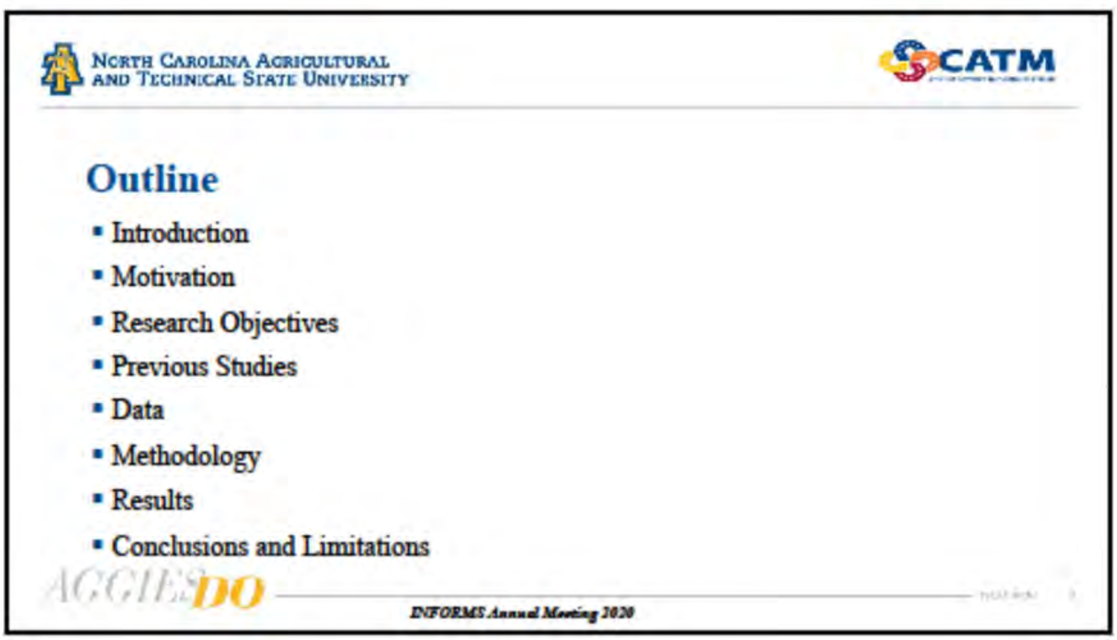
37


North Carolina Agricultural and Technical State University
Conclusions
Passengers might opt for flights that have more than two connections.
The computational time needs to be estimated.
Identifying the most important group of airports is another interesting area to investigate.
There is a need for improvement of forecast models.

38

North Carolina Agricultural and Technical State University
CATM
Traffic Pattern Discovery During Recent Hurricane Evacuations in North Carolina: A Case Study
Sachin Mhatre, Xiuli Qu
Department of Industrial and Systems Engineering
North Carolina A&T State University, Greensboro, NC
INFORMS Annual Meeting 2020
AGGIES DO

1



North Carolina Agricultural and Technical State University
CATM
Outline
Introduction
Motivation
Research Objectives
Previous Studies
Data
Methodology
Results
Conclusions and Limitations
AGGIES DO
INFORMS Annual Meeting 2020

2

North Carolina Agricultural and Technical State University

CATM

Introduction

Overview

- Frequency and intensity of natural disasters increasing
- Effect of natural disasters to critical infrastructure
- Mass evacuation during hurricanes

AGGIES DO

INFORMS Annual Meeting 2020

3

North Carolina Agricultural and Technical State University

CATM

Motivation

Hurricane Florence and Dorian in North Carolina

- Evacuation orders in southeastern North Carolina
- Government agencies response to the incoming hurricane
- Critical preparation plan for mass movement of people

AGGIES DO

INFORMS Annual Meeting 2020

4

North Carolina Agricultural and Technical State University

Research Objectives

- To analyze the hourly traffic flow data during hurricane evacuations.
- To discover association of sensors to predict the hourly traffic during hurricane evacuations.

AGGIES DO

INFORMS Annual Meeting 2020

5

North Carolina Agricultural and Technical State University

Previous Studies

Study/Methodology	Optimization	Simulation	Temporospatial	Empirical
Liu et. al, 2006	√	√		
Wolshon, 2008				√
Wolshon & McArdle, 2009			√	
Archibald and McNeil, 2012			√	
Bish & Sherali, 2013	√			
Sun et al, 2017	√			

AGGIES DO

INFORMS Annual Meeting 2020

6

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

CATM

Data

Source of the data

- North Carolina Department of Transportation
- Traffic Survey Group

AGGIES DO

INFORMS Annual Meeting 2020

7

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

CATM

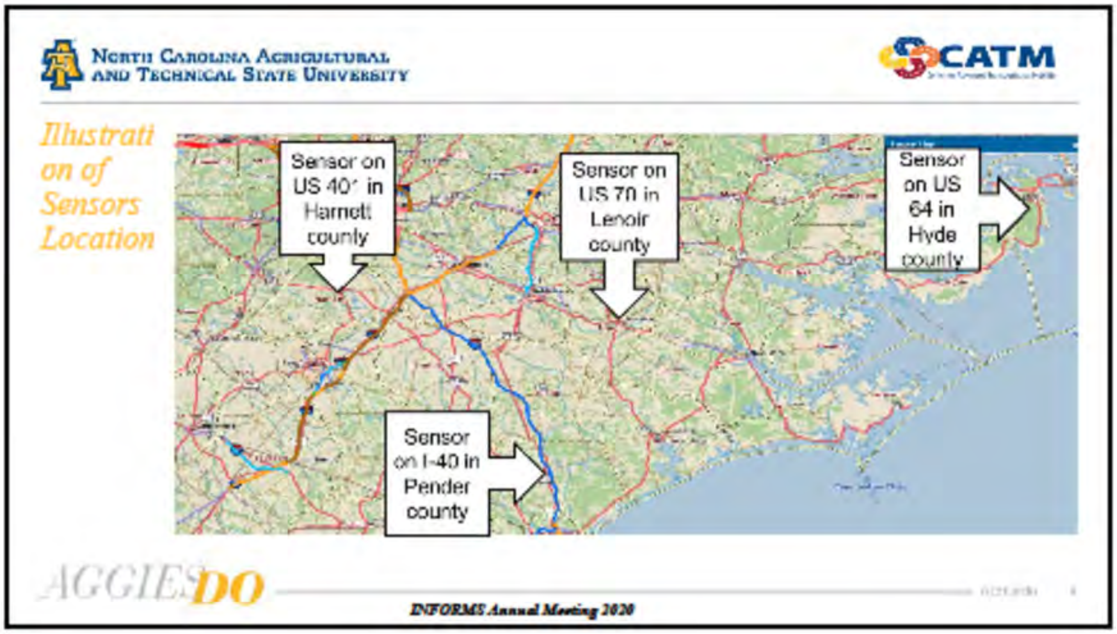
Description of Data

- Traffic volume data in North Carolina during a hurricane evacuation
- Time period: 9/5/2018 - 9/20/2018
- Counties (Data): 42 in NC
- 1 or more sensors for each county in NC
- Each sensor: Sensor Location County, Route, lane direction

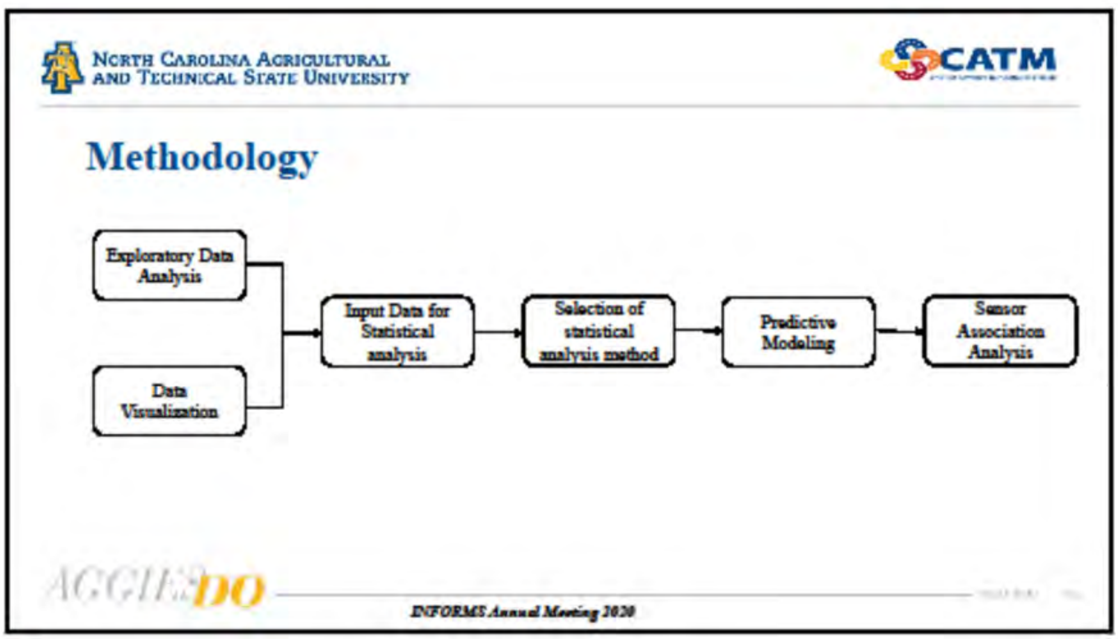
AGGIES DO

INFORMS Annual Meeting 2020

8


North Carolina Agricultural and Technical State University
CATM
Illustration of Sensors Location
Sensor on US 401 in Harnett county
Sensor on US 70 in Lenoir county
Sensor on US 64 in Hyde county
Sensor on I-40 in Pender county
AGGIES DO
INFORMS Annual Meeting 2020

9


North Carolina Agricultural and Technical State University
CATM
Methodology
Exploratory Data Analysis
Data Visualization
Input Data for Statistical analysis
Selection of statistical analysis method
Predictive Modeling
Sensor Association Analysis
AGGIES DO
INFORMS Annual Meeting 2020

10

North Carolina Agricultural and Technical State University

Method

Linear regression

- Prediction of hourly traffic volume at each sensor location
  - Dependent variable (DV) = Hourly traffic volume
  - Independent variables (IV)
    - Traffic volume at site before 1hr, 2hr, 3hr, 4hr
    - Traffic volume at other sensor site before 1hr, 2hr, 3hr, 4hr

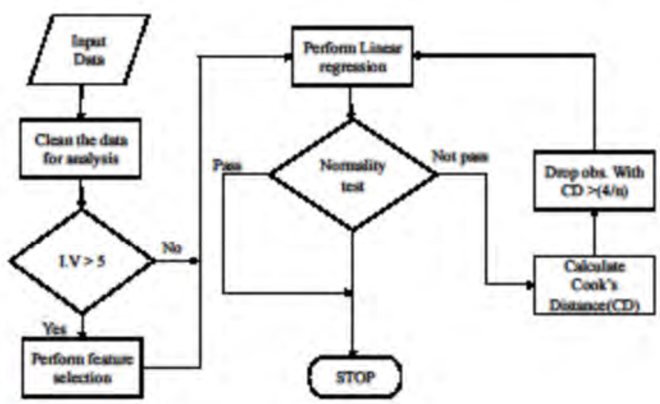
AGGIES DO

INFORMS Annual Meeting 2020

11

North Carolina Agricultural and Technical State University

Procedure for statistical analysis



AGGIES DO

INFORMS Annual Meeting 2020

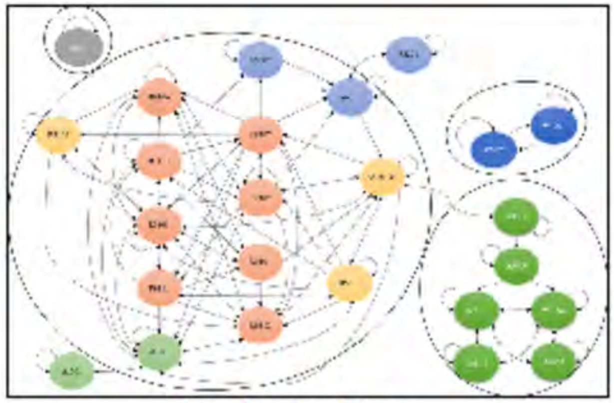
12

SM1

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

Results

Sensor	County	Sensor	County
A2501	Cumberland	A6301	Nash
A4201	Harnett	A6302	Nash
R9101	Wake	R3201	Edgecombe
R9102	Wake	A9501	Wayne
R9103	Wake	A3003	Duplin
R9106	Wake	A7101	Pender
R9107	Wake	W7002	Pender
R9111	Wake	A6401	New Hanover
R9112	Wake	W2301	Columbus
R9113	Wake	A2702	Dare
R5001	Johnston	W4701	Hyde
A5001D4	Johnston	A9001	Vance
R3103	Durham		



Sensor Association Diagram

AGGIES DO

INFORMS Annual Meeting 2020

13

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

Results continue…

Sensor	County	Sensor	County
A2501	Cumberland	A6301	Nash
A4201	Harnett	A6302	Nash
R9101	Wake	R3201	Edgecombe
R9102	Wake	A9501	Wayne
R9103	Wake	A3003	Duplin
R9106	Wake	A7101	Pender
R9107	Wake	W7002	Pender
R9111	Wake	A6401	New Hanover
R9112	Wake	W2301	Columbus
R9113	Wake	A2702	Dare
R5001	Johnston	W4701	Hyde
A5001D4	Johnston		
R3103	Durham		

Image drawn on open source website:diymaps.net/nc

AGGIES DO

INFORMS Annual Meeting 2020

14

North Carolina Agricultural and Technical State University

Conclusions

- Developed a prediction model for hourly volume at each sensor location in NC.
- Identified sensors associations based on hourly traffic volumes.

Limitations

- Need more traffic volume evacuation data.
- Need to investigate data visualization method for sensors association analysis.

AGGIES DO

INFORMS Annual Meeting 2020

15

North Carolina Agricultural and Technical State University

Thank you !/ Questions

AGGIES DO

INFORMS Annual Meeting 2020

16

North Carolina Agricultural and Technical State University

SIMULATION MODELING OF HURRICANE EVACUATIONS IN EASTERN NORTH CAROLINA

Xiuli Qu, Mahmud Parvez, Younho Seong
North Carolina A&T State University

CATM
Center for Advanced Transportation Mobility

AGGIES DO

1

North Carolina Agricultural and Technical State University

CATM

Outline

- Introduction
- Research Objective
- Problem Description
- Simulation Model
- Case Study
- Conclusions

AGGIES DO

2

2

North Carolina Agricultural and Technical State University

CATM

Introduction

Background

- More major hurricanes affecting the United States in recent years
  - Harvey (2017), Irma (2017), Florence (2018), Michael (2018), Dorian (2019), Laura (2020), Zeta (2020) and Ida (2021)
- Significant disruptions and damages
  - Caused many casualties
  - Damaged thousands of houses
  - Damaged or disrupted critical infrastructure systems
  - Caused mass evacuations

AGGIES DO

3

3

North Carolina Agricultural and Technical State University

CATM

Introduction

Motivation

- Issues occurred during the recent hurricane evacuations
  - Traffic congestion
  - Fuel shortage
- Challenges of managing hurricane evacuations
  - Effective traffic control strategies to reduce congestion
  - Diverse evacuation behavior
  - Supply logistics
- Better traffic control and supply management needed for mass evacuations

AGGIES DO

4

4

North Carolina Agricultural and Technical State University

Introduction

Related Work

- Focuses of the related studies
  - Proposing effective supply and demand management strategies to avoid congestion and enable timely evacuation
  - Traffic assignment approaches and travel time modeling to represent congestion and traffic flow propagation
  - Evacuation behavior studies estimating evacuation response rates and demand distributions
- Research Gap: Need considering evacuation behavior when developing evacuation traffic control strategies

AGGIES DO 5

5

North Carolina Agricultural and Technical State University

Research Objectives

- Research Objectives
  - To estimate the evacuation traffic volume and pattern
  - To support hurricane evacuation management
- Research Questions
  - How does the percentage of families choosing shelter-in-place affect evacuation traffic and the average evacuation travel time?
  - How can optimized individual evacuation plans affect evacuation traffic and individuals' evacuation travel time?

AGGIES DO 6

6

North Carolina Agricultural and Technical State University

Problem Description

Hurricane Evacuations in North Carolina

- Mandatory or voluntary evacuation orders to the potentially affected counties two or three days before the forecasted landfall
- The government agencies provide evacuation guides, recommend evacuation routes, and deploy more emergency response resources.
- Usually, the government does not provide public transportation services for hurricane evacuation.
- Most NC residents in the affected region choose to evacuate from the region. However, some residents choose staying home.

AGGIES DO

7

7

North Carolina Agricultural and Technical State University

Problem Description

Evacuation Zone in Eastern North Carolina

AGGIES DO

8

8

North Carolina Agricultural and Technical State University

Problem Description

Assumptions

- A three-day hurricane evacuation period
- The percentage of road capacity for evacuation traffic is constant on each day, but increases from one day to the next.
- A family evacuates together by one vehicle or stays home together.

AGGIES DO 9

9

North Carolina Agricultural and Technical State University

Simulation Model

MATSim

- Open-source agent-based transport simulation (MATSim) framework
- Three modules in the MATSim-based simulation model
  - Network generation module
  - Population and departure generation module
  - Scenario generation module

MATSim
Multi-Agent Transport Simulation

AGGIES DO 10

10

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

CATM

Simulation Model

MATSim Framework

Network Generation
1. Download a road map
2. Choose the region
3. Select roads to be included
4. Export the map file

Network File →

Population and Departure
1. Identify the size and distribution of the affected population
2. Estimate the distribution of departure times
3. Add the functions to generate random agent departures

Departure Time and Population →

Scenario Generation
1. Load the network file
2. Specify the evacuation area
3. Choose a traffic type
4. Specify a sample size
5. Choose a departure time distribution
6. Specify the population size and location
7. Create the scenario input files

Scenario Input Files →

Simulation
1. Set the number of iterations
2. Run the model to simulate evacuation traffic volume, travel time, and road utilization

AGGIES DO

11

11

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

CATM

Case Study

Hurricane Florence in North Carolina

- Evacuation orders were issued to the 16 NC counties three days before landfall.
- During Hurricane Florence, most NC families in the affected region chose to evacuate before landfall.
- The NC government recommended evacuation routes and provided evacuation guide.

AGGIES DO

12

North Carolina Agricultural and Technical State University

CATM

Case Study

Road Network and Population Distribution in the Study Area

AGGIES DO

13

13

North Carolina Agricultural and Technical State University

CATM

Case Study

Two Scenarios

		Scenario 1	Scenario 2
Percentage of families choosing shelter-in-place		5%	10%
Departure and available road capacity	48–72 hours before landfall	8% of families and 10% road capacity	
	24–48 hours before landfall	20% of families and 28% road capacity	
	Within 24 hours before landfall	67% families and 90% road capacity	62% families and 90% road capacity
Departure time distribution	95% evacuees depart during the daytime (6AM – 6PM) 5% evacuees depart during the nighttime (6PM – 6AM) Uniform distributions with two departure rates for the daytime and nighttime, respectively		

AGGIES DO

14

14

North Carolina Agricultural and Technical State University

CATM

Model Validation

- Hourly traffic data in eastern North Carolina during Hurricane Florence were provided by the NCDOT traffic survey group.
- Only one sensor located in Wayne County collected hourly traffic data within 24-72 hours before the landfall.
- The observed and simulated daily evacuation traffic volumes at this location are used to validate our hurricane evacuation simulation model.

	Observed Daily Evacuation Traffic	Simulated Daily Evacuation Traffic		
		Average	Standard Error	95% Interval
48–72 hours before landfall	234	232	17	[199.68, 265.32]
24–48 hours before landfall	348	357	11	[335.44, 378.56]

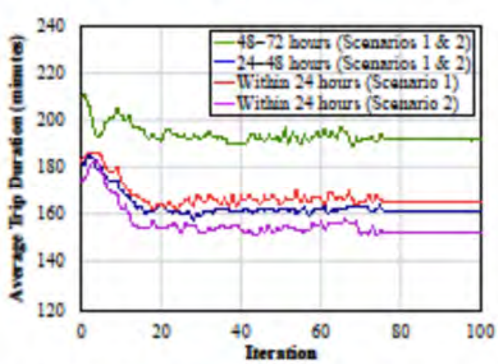
AGGIES DO 15

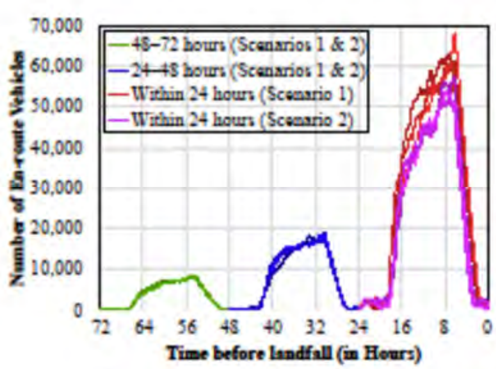
15

North Carolina Agricultural and Technical State University

CATM

Case Study Results





AGGIES DO 16

16

North Carolina Agricultural and Technical State University

Conclusions

- Developed an agent-based hurricane evacuation simulation model that captures the evacuation route selection by individuals
- The model has been populated using the highway transportation system in the eastern NC evacuation zone.
- The model has been validated using the evacuation scenario in NC during Hurricane Florence.
- The simulation model could be used to evaluate traffic volumes under different evacuation scenarios.

AGGIES DO 17

17

North Carolina Agricultural and Technical State University

Questions?

AGGIES DO 18

18