MULTI-SCALE MODELS FOR TRANSPORTATION SYSTEMS UNDER EMERGENCY

FINAL REPORT

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16. Abstract

In recent years natural disasters have caused significant disruptions to transportation systems, which had to cascade negative impacts on humanitarian operations, related infrastructure, and associated industries in the affected areas. How to prepare for and respond to transportation system disruptions is a complex decision incorporating a variety of factors, from system use to system preparation. To address these challenges, the project team has developed optimization models for flight rescheduling and road restoration after a natural disaster and integrated the models as a decision-making tool. The data of North Carolina emergency response activities, air flights, and road closures during Hurricane Matthew were used to test the models and tool. The testing results show that the integrated tool can quickly find optimal sets and sequences for road restoration and flight schedules recovery at an affected airport and 50 counties. The tool can also visualize the damaged connections between counties, airports and resource centers, and the road restoration schedule and flight schedules recovery plan. The optimization models and decision-making tool developed in this project can support deploying effective restoration and recovery of transportation systems during an emergency event, which can improve the mobility of people and disaster relief under emergency.

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EXECUTIVE SUMMARY

Over the past decade, the frequency and intensity of natural disasters have increased, causing significant disruptions to transportation systems. The disruptions to transportation systems directly affect humanitarian activities during a disaster and may cause cascading impacts on other infrastructures and associated industries. Therefore, quick restoration and recovery of transportation systems play an important role in humanitarian operations and community recovery. However, how to prepare for and respond to transportation system disruptions is a complex decision incorporating a variety of factors, from system use to system preparation.

In our CATM project, we searched and reviewed papers published from 2007-2017 that focus on air and road transportation system management and decision-making during disaster preparedness and response phases. From the published papers and government reports, we identified and classified emergency response actions and/or policies in air and road transportation systems. During a natural disaster, major emergency response activities in air transportation systems are flight cancellation and rescheduling, crew rescheduling, and airport asset relocation and protection. Major response activities in road transportation systems are highway contra-flow control and barricade for evacuation and humanitarian relief delivery, closure of transportation assets such as bridges, and restoration of blocked or damaged roads.

To support some of these emergency response activities, we developed optimization models to address a flight rescheduling problem during a severe weather disruption and network optimization models for road restoration problems after a hurricane. These optimization models were integrated as a decision-making tool to support the restoration of air and road transportation systems after a natural disaster such as a hurricane. Meanwhile, we collected the data of North Carolina (NC) emergency response activities, air flights, and road closures during Hurricane Matthew. Using Hurricane Matthew data, we conducted a vulnerability analysis of the southeastern NC highways to a hurricane. Hurricane Matthew data collected were also used to test the optimization models and the decision-making tool developed in this project. The testing results showed that it took less than 5 minutes for the integrated decision-making tool to find optimal sets and sequences of road restoration and flight schedules recovery at the airport and 50 counties of North Carolina affected by

Hurricane Matthew. The integrated tool can also support decision making of transportation system restoration by visualizing the damaged connections between counties, airports and humanitarian resource centers, and the road restoration schedule and flight schedules recovery plan.

The optimization models and decision-making tools developed in this project will improve the effectiveness and efficiency of response activities in local and regional transportation systems during a natural disaster, such as a hurricane. Deploying effective response activities can improve the mobility of people and disaster relief during and after a natural disaster. The results of this project have been published as three peer-reviewed conference papers and presented as posters and oral presentations at national professional conferences and regional transportation conferences and symposiums. One more paper has been submitted to the 2020 TRB Annual Meeting. In addition, three graduate students (including two African American students and one female student) and two undergraduate students (including one African American student and one female student) have been involved in this CATM project. The participation of these students can contribute to the diversity of US transportation workforce in the future.

DESCRIPTION OF PROBLEM

Natural disasters, such as hurricanes, winter storms, and floods, usually cause significant disruptions to transportation systems. These disruptions directly affect humanitarian activities during a disaster and may cause cascading impacts on other infrastructures and associated industries. During Hurricane Matthew, for example, more than 600 roads in North Carolina (NC) were closed due to severe flooding caused by the hurricane, and some of them were closed for more than ten days [1]. The closures of southeastern NC roads caused delays and embargoes on cargo movements in the southeastern North Carolina, and complicated emergency relief delivery in the affected areas [2]. Similar effects were experienced in Texas and Louisiana due to Hurricane Harvey, and in Florida, Georgia and South Carolina due to Hurricane Irma [3]. For example, highways I-45, I-10, I-69 & I-610 were halted in Texas and Louisiana due to Hurricane Harvey, causing loss of billions of dollars [4]. Therefore, quick restoration and recovery of transportation systems play an important role in humanitarian operations and community recovery.

How to prepare for and respond to a disruption in transportation systems is a complex and challenging decision incorporating a variety of factors, from system use to system preparation. To address the emergency response challenges in transportation systems, in this CATM project, we aimed to (1) develop decision-making models for emergency response activities in different transportation modes, and (2) to integrate these models as a decision-making tool to support response activities in multi-mode transportation systems during an emergency event. The research questions of our CATM project are:

- What are the possible emergency-response actions/policies in different transportation modes?
- How can optimization models support decision making when planning for and responding to disruptions in transportation systems?
- How can emergency response optimization models for different transportation modes be integrated into a decision-making tool to support emergency response activities in multi-mode transportation systems?

These research questions were investigated at two interdependent scales – at the local scale of individual transportation modes (e.g., air transportation and road transportation) and at a network level.

METHODOLOGY AND RESULTS

In this CATM project, we conducted five studies addressing the restoration problems in air or road transportation systems after a natural disaster. Before we conducted these studies, we searched for papers published from 2007-2017 that focus on disaster management and decision making of air and road transportation systems during disaster preparedness and response phases. We found and reviewed about 50 relevant papers for road transportation and about 40 relevant papers for air transportation. From the published papers and government reports, we identified and classified emergency response actions and policies in air and road transportation systems. Based on our literature review, we also identified the research gap in disaster management and decision making of air and road transportation systems during disaster preparedness and response phases. To bridge the research gap, we defined and conducted the five studies in this project. The methodology and results of these studies are described in detail in the following subsections.

Study 1 – Vulnerability Assessment of the Southeastern NC Highway Transportation System to a Hurricane

On average, a major hurricane affects North Carolina once in two years [5] and causes significant disruptions to NC transportation systems. During Hurricane Matthew, for example, more than 600 roads in North Carolina were closed due to severe flooding caused by associated storm surge and heavy rain [1]. The closures of southeastern NC roads caused delays and embargoes on cargo movements in southeastern North Carolina, and complicated emergency relief delivery in the affected area [2]. Therefore, it is imperative to assess the vulnerability of a transportation system to natural hazards in preparing for an emergency response to the hazards and mitigating their negative impacts. However, to our best knowledge, no study or project has assessed the vulnerability of the NC highway transportation system to hurricanes or tropical storms. To bridge this gap, in this study, we used the FHWA's vulnerability assessment framework [6] as a guide to assess the vulnerability of the southeastern NC highway transportation system to a hurricane.

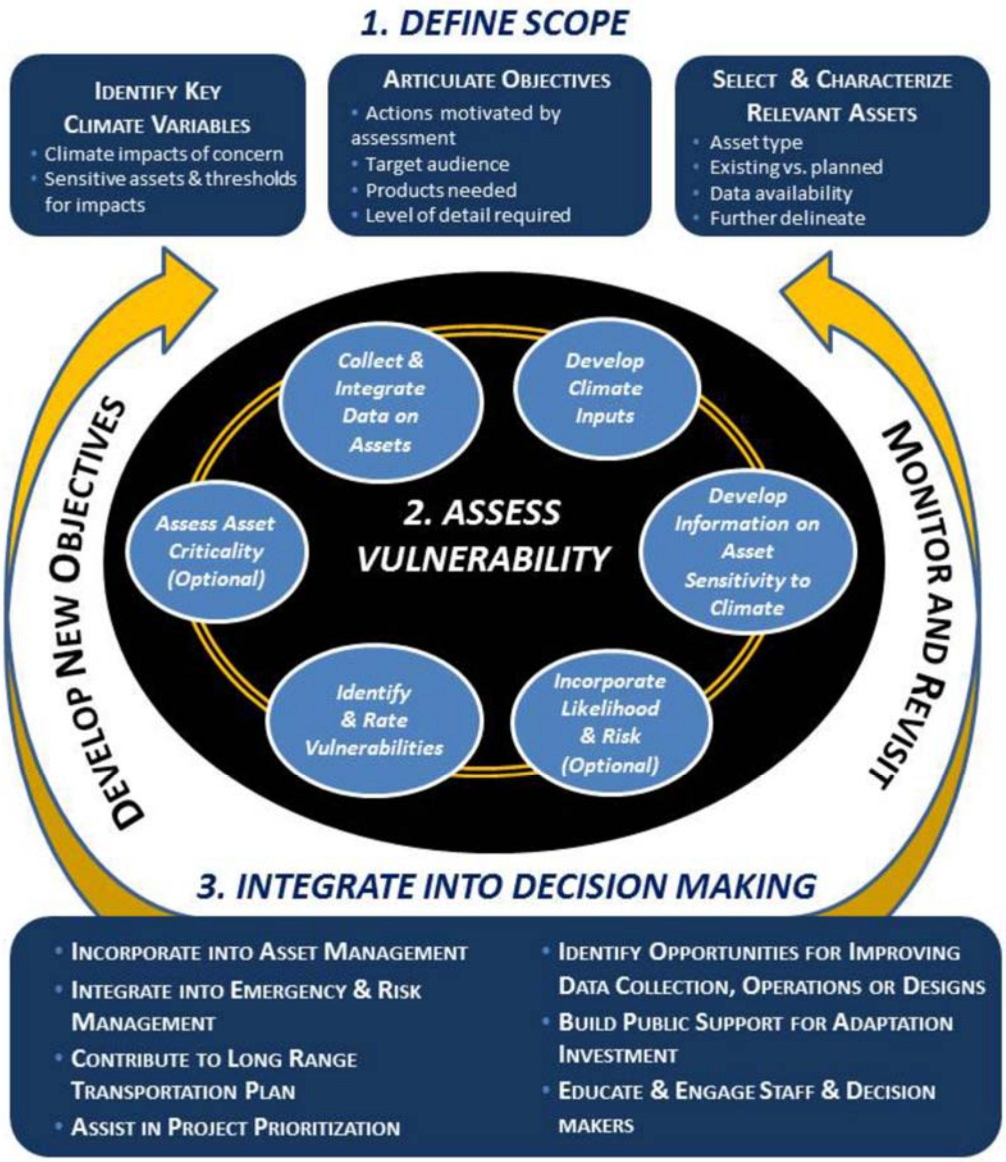


Figure 1: FHWA’s Climate Change and Extreme Weather Vulnerability Assessment Framework [6]

Figure 1 illustrates the FHWA’s vulnerability assessment framework used in the study. The framework was proposed by the USDOT Federal Highway Administration (FHWA) in 2012 for assessing transportation system vulnerability to climate change and extreme weather events [6]. The FHWA’s framework consists of three steps: (1) defining the scope of a project, (2) assessing vulnerability, and (3) integrating vulnerability into decision making.

For Step 1 of the FHWA's framework, we selected the assets used to assess the vulnerability of the southeastern NC transportation system and defined the metrics to evaluate the vulnerability of the selected assets to a hurricane. The southeastern NC highways that were closed due to Hurricane Matthew were selected as the assets of the transportation system of interest because of the importance of highways in a transportation system. Figure 2 shows the two interstate highways and the 15 US highways that were closed due to damages or flooding caused by Hurricane Matthew. Six metrics were chosen to assess the vulnerability of the selected assets to a hurricane. The six metrics measure the exposure, sensitivity and adoptive capacity of the selected assets to two major characteristics of a hurricane (wind speed and precipitation). For wind, the exposure metric is observed peak wind speed at relevant southeastern NC locations during Hurricane Matthew, and the sensitivity metric is past experience with wind. For precipitation, the exposure metrics used in the study are observed peak flood level and observed total rainfall at relevant southeastern NC locations during Hurricane Matthew, and the sensitivity metric is past experience with flood level for Hurricane Matthew. The annual average daily traffic (AADT) is used as a metric for adaptive capacity. Table 1 provides the rationales of the six metrics selected for exposure, sensitivity, and adaptive capacity.

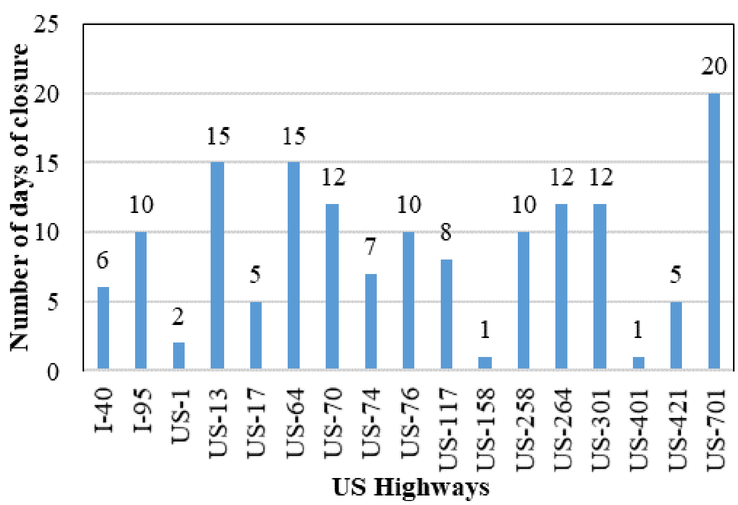


Figure 2: Number of Closure Days of NC Highways during Hurricane Matthew

Table 1: Vulnerability Metrics and Corresponding Data Sources

	Description and Rationale	Data Sources
Exposure Metrics		
Observed peak wind speed	Observed peak wind speeds at a location can provide a proxy for how likely an asset at the location was exposed to wind.	NOAA storm data for North Carolina
Observed peak flood level	Observed peak flood level at a location can provide the proxy for how likely an asset at the location was exposed to a flood caused by precipitation.	USGS Flood Event Viewer
Observed total rainfall	Observed total rainfall at a location can provide the proxy for how likely an asset at the location was exposed to precipitation.	NOAA storm data for North Carolina
Sensitivity Metrics		
Past experience with wind	Past experience with wind speed for a specific event. This data implies that the assets which are affected by this level of wind speed are more likely vulnerable.	NC Department of Safety's WebEOC database
Past experience with flood level	Past experience with flood level for a specific event. This data indicated that the assets which are affected by this level of flood level are more likely vulnerable.	
Adaptive Capacity Metrics		
Average annual daily traffic (AADT)	AADT is the volume of vehicle traffic of a road for a year divided by 365 days. Roadways with higher traffic volumes would affect more drivers/traffic and cause a greater disruption if damaged.	NCDOT GIS

For Step 2 of the FHWA's framework, the data needed for the vulnerability assessment was collected from multiple sources and then used to analyze the vulnerability using the USDOT vulnerability assessment scoring tool (VAST) [7]. By searching for potential sources, we found data for our vulnerability study from the USGS Flood Event Viewer, NOAA storm data for North Carolina, North Carolina Department of Transportation (NCDOT) Geographical Information System (GIS) analysis and North Carolina Department of Safety WebEOC database. Table 1 lists the data sources for each vulnerability metric. For each southeastern NC highway studied, the observed values of peak wind speed and total rainfall during Hurricane Matthew were retrieved from NOAA storm data for North Carolina, and the observed values of peak flood level were obtained using the USGS Flood Event Viewer. NC Department of Transportation provides the average annual daily traffic (AADT) for NC highways, which is the metric for adaptive capacity.

The collected data were first converted to vulnerability scores for individual assets using the VAST. The VAST is an Excel-based tool to calculate metric-based vulnerability scores in terms of the three vulnerability components (exposure, sensitivity, and adaptive capacity). The VAST vulnerability scores range from 1 to 4, 1 representing low vulnerability and 4 representing high vulnerability. Based on the scoring scales given for each metric, the VAST first converts observed values for an asset to its metric-level vulnerability scores and then calculates weighted averages of metric-level vulnerability scores to obtain the component-level vulnerability scores of the asset. Finally, the tool calculates the overall vulnerability score of an asset by averaging its three component-level vulnerability scores. Table 2 summarizes the scoring scales used to convert observed data to metric-level vulnerability scores. The scoring scales for the exposure and adaptive capacity metrics are the default values in the VAST, which are determined by equally dividing the overall range of all values for a metric. The sensitivity scoring scale for past experience with wind is determined based on National Hurricane Center's Saffir-Simpson Hurricane wind scale [8], and the sensitivity scoring scale for flood level is chosen based on the analysis of flood level and damage reports for Hurricane Matthew from WebEOC database [1]. In the study, we chose equal weights to calculate the component-level and overall vulnerability scores.

Table 2: Scoring Scales Used for the Exposure, Sensitivity and Adaptive Capacity Metrics

Vulnerability score	Exposure			Sensitivity		Adaptive capacity (AADT)
	Peak wind speed (mph)	Peak flood level (ft)	Total rainfall (inch)	Wind past experience (mph)	Flood level past experience (ft)	
1	45 – 50.5	16.6 – 27.18	10 – 12	39 -73	2 – 10	300 – 12225
2	50.5 – 56	27.18 – 37.75	12 – 14	73 – 95	10 – 18	12225 – 24150
3	56 – 61.5	37.5 – 48.33	14 – 16	95 – 110	18 – 26	24150 – 36075
4	61.5 – 67	48.33 – 58.9	16 – 18	110 – 200	26 – 60	36075 – 48000

Figure 3 shows the vulnerability scores of all highways selected. A highway with higher vulnerability score is more vulnerable to a hurricane. The figure shows the variation in exposure, sensitivity and adaptive vulnerability scores which are caused by the varying exposure levels to wind and precipitation, and different traffic volumes. The comparison of the exposure vulnerability scores and the closure days of the selected highways reveals that the number of closure days is positively correlated with the exposure vulnerability scores. The result also shows highways with higher traffic volume, such as I-95, I-40, US-64, and

US-701, usually have high overall vulnerability scores because damages or disruptions of a highway with high traffic volume affect more commuters and business operations, and result in a higher adaptive capacity vulnerability scores.

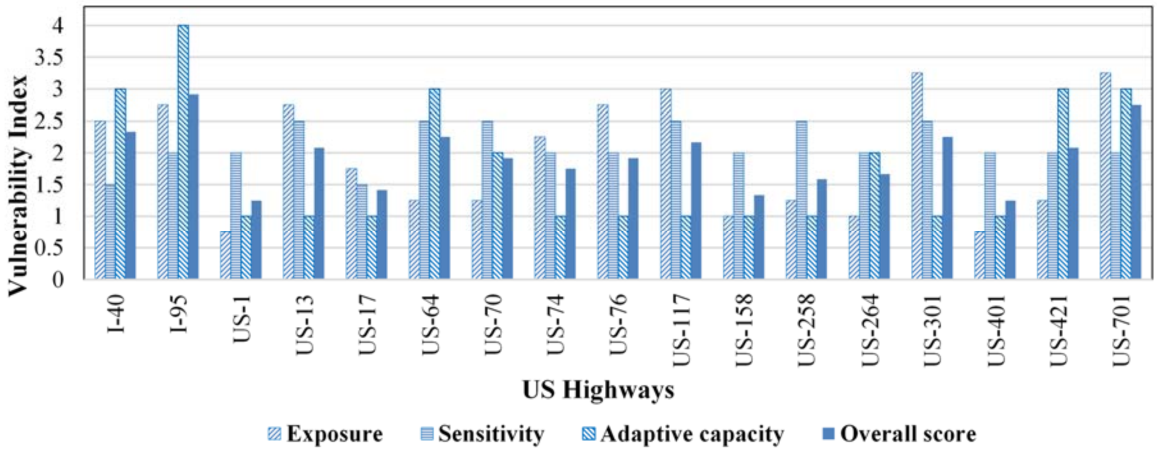


Figure 3: Vulnerability Scores for the Southeastern NC Highways [9]

Study 2 – Decision Making for Road Network Restoration after a Natural Disaster

Natural disasters, such as hurricanes and floods, usually damage or block roads and hence disrupt road transportation networks. Road network disruptions impede accessibility to disaster victims, medical facilities, and supply locations during the first few days after a disaster, and affect commuters' travel and the transportation industry during the road recovery period. Due to the importance of road restoration after natural disasters, many studies in the literature have addressed the road restoration problems after natural disasters [10-30]. Most of these studies focus on road restoration scheduling in the short term (the first few days) or a long term (the recovery period) after a disaster [11-30]. However, to our best knowledge, no study has addressed the road restoration problem in both short term and long term. To bridge this gap, this study addresses the road restoration problems, including resource allocation and restoration scheduling, in both the short term and the long term after a natural disaster such as hurricane. The objectives of this study are (1) to develop an integrated decision-making approach for road restoration in the short and long terms after a natural disaster, (2) to examine which road segments in the eastern NC transportation system are more critical for short term or long term road restoration after a hurricane, and (3) to investigate what factors may affect optimal road restoration schedules.

In this study, we proposed an integrated decision-making approach, in which the short term road restoration (STRR) and long term road recovery (LTRR) problems are solved hierarchically. Figure 4 illustrates the optimization models used in the approach and the input and output for each model. For the STRR problem, a minimum spanning tree (MST) model is built to identify the critical roads to be restored to reconnect the road network with minimum restoration time. Then the maximum flow and resource allocation (MFRA) model is formulated to allocate the available resource to the critical roads identified by the MST model in order to maximize the accessibility to disaster victims. For the detail of the MFRA model, we refer to our recent publication [31]. For the LTRR problem, the critical roads have been restored, and the road network is connected. Thus, the connected network is given to the multi-period resource allocation (MPRA) model. The MPRA model allocates the available resource to recover all the damaged roads in the network with objective of minimizing the affected annual average daily traffic (AADT). The detail of the MPRA model is included in Appendix A.

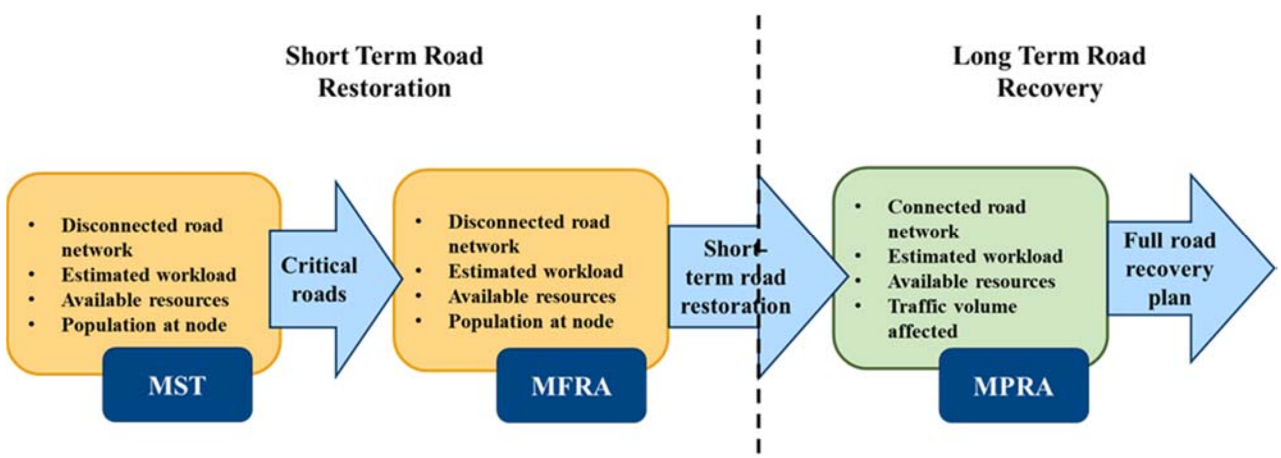


Figure 4: An Integrated Decision-Making Approach for Road Restoration and Recovery after a Natural Disaster

We tested the proposed integrated decision-making approach on the eastern North Carolina road transportation network affected by Hurricane Matthew. Figure 5 shows the eastern North Carolina road transportation network, in which the nodes denote the counties, and the edges represent the roadways linking counties. This road network consists of 50 nodes and 118 links. In the network, solid lines represent undamaged links, whereas dash lines represent damaged links during Hurricane Matthew. In our study, a damaged link between two nodes is defined as the link with capacity that cannot meet the need of humanitarian logistics after a disaster. In addition, the nodes with red and black circles are unreachable and reachable, respectively, from resource nodes. In our study, we considered a single resource node, i.e., node 46, and the other nodes as demand nodes. The node 46 is assigned as resource node since North Carolina state emergency operations center is located at this node.

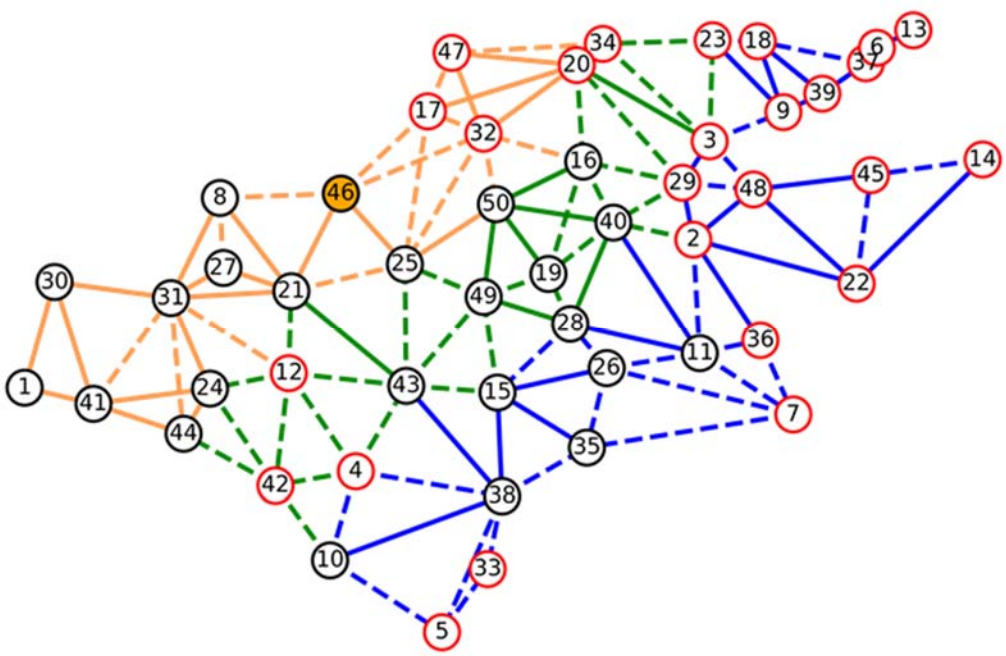


Figure 5: Eastern North Carolina Road Transportation Network

In our study, we tested the proposed decision-making approach in the scenarios representing even and uneven distributions of damage. The even distribution of damage represents the flood damage scenarios caused by heavy rain during a hurricane. On the other hand, the uneven distribution of damage represents the damage variation ranging from high for the coastal region to low for the inland region, which is usually caused by high-speed wind of a hurricane. The regions of edges depend on the distance of edges from the coast. In this study, edges within 60 miles from the coast are considered as coastal edges, edges between 61 to 120 miles from the coast as middle edges, and edges above 120 miles from the coast as inland edges. Figure 5 illustrates the three regions with different colors: blue for coastal edges, green for middle edges and orange for inland edges.

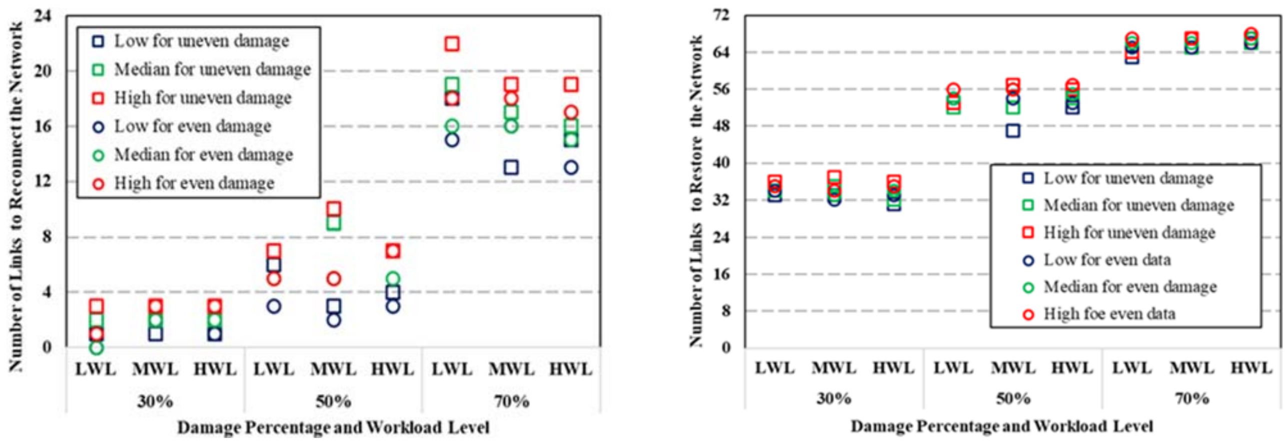
Nine scenarios are designed for the even and uneven damage distributions, respectively, by combining three levels of road damage percentage and three levels of road restoration workload distribution. A constant daily road restoration capacity of 1664 (unit×hours) is assumed for all scenarios in the numerical study, which is estimated based on 208 contractor crews available for road restoration at North Carolina mentioned in FMEA's hurricane Florence report [32].

For the nine scenarios of even damage distribution, the three levels of road damage percentage are 30%, 50% and 70%, which approximately correspond to the percentages of damaged roads by hurricane Irene (2011), Hurricane Matthew (2016) and Hurricane Florence (2018), respectively. For the restoration workload distribution, we estimated the middle-level workload (MWL) based on the daily restoration capacity and the damage scenario of hurricane Matthew, in which about 50% of the edges (67 out of 118 edges) were damaged and it took 25 days to restore those damaged edges. For the scenarios of middle-level workload, restoration workload of each damaged edge is assumed being normally distributed with mean of 620 (unit×hours) and standard deviation of 50. We increase and decrease the mean value for middle-level workload by 20% to get the higher-level workload (HWL) and lower-level workload (LWL), respectively. The standard deviation for workload distribution is also increased or decreased correspondingly.

For the nine scenarios of uneven damage distribution, one level of road damage percentage consists of three road damage percentages for the three regions (coastal, middle and inland) of roads. The three levels of road damage percentage for the even damage scenarios are assigned for middle edges. The levels of road damage percentage for coastal edges and inland edges increase and decrease by 10%, respectively. Thus, the three levels of road damage percentage for the uneven damage scenarios are (20%, 30%, 40%), (40%, 50%, 60%) and (60%, 70%, 80%). In these scenarios, coastal edges are assigned the highest damage percentage as the roads in the coastal region are exposed to more severe wind. The damage percentage for inland edges decreases due to the decrease in its wind speed after a hurricane landfall. For the same reason, the mean values of the restoration workload distributions increase by 20% for coastal edges and decrease by 20% for inland edges.

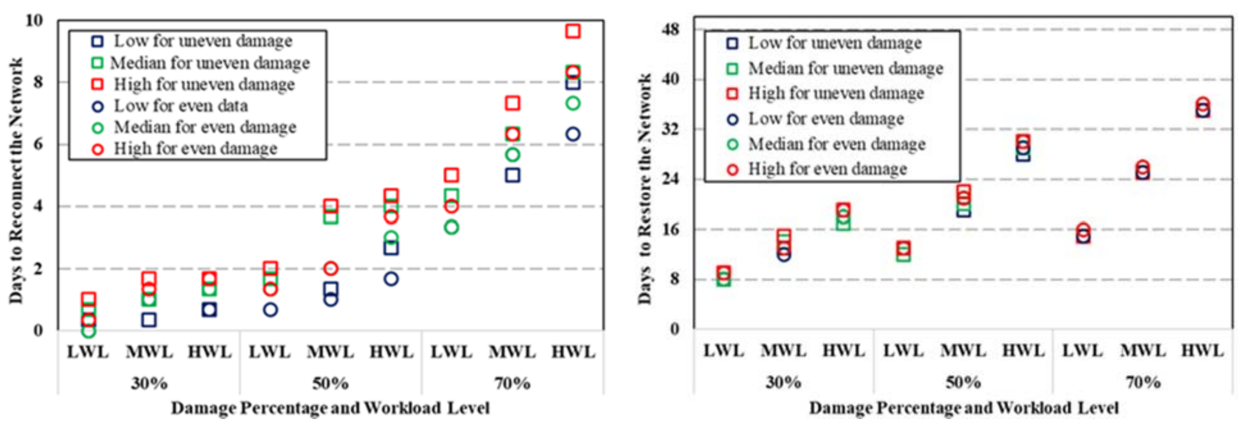
In our study, three cases were randomly generated for each scenario based on the road damage percentage and the road restoration workload distribution of the scenario, and then were solved using the integrated decision-making approach proposed. Figure 6 represents the numbers of damaged links to be restored for the uneven and even damage scenarios. Figure 6(a) shows the numbers of damaged links to be restored to connect all the demand node, i.e., restoring the connectivity of the network. Figure 6(b) illustrates the number of remaining damaged links to restore the entire network in the long term recovery period. The results indicate that in both short term restoration and long term recovery periods, the number of damaged links required to repair depends only on the percentage of roads damaged, but neither on-road damage distribution nor on restoration workload level. Further, it is cleared from the results that if the damage percentage is high to the road network, more links must be restored to reconnect the entire road network. Therefore, to reconnect the entire network for humanitarian operations, emergency management services have sought help from the other agencies or states. Furthermore, agencies need to preposition the restoration resources strategically to aid the restoration activities immediately after the disaster.

Figure 7 represents the days required to connect the network and restore all damaged links for the uneven and even damage scenarios. Figure 7(a) shows the days required to connect the network as early as possible to aid humanitarian activities in the short term restoration period. Figure 7(b) illustrates the days required to restore the entire network in the long term recovery period. In both the short term and the long term, we assume that enough restoration resource and time for road restoration operations. In both the terms, the figure shows that the road restoration days required for all scenarios depends on the road damage percentage and restoration workload level. Importantly, the results indicate that the damage distribution does not affect the time of restoration. Therefore, emergency management services need to decide the restoration activities irrespective of the nature of the damage distribution. In other words, regardless of the damage caused by wind gust or flood due to a hurricane, the best network recovery schedule depends on the amount of damaged road and damage severity caused by the disaster.



(a) Short Term Road Restoration (b) Long Term Road Recovery

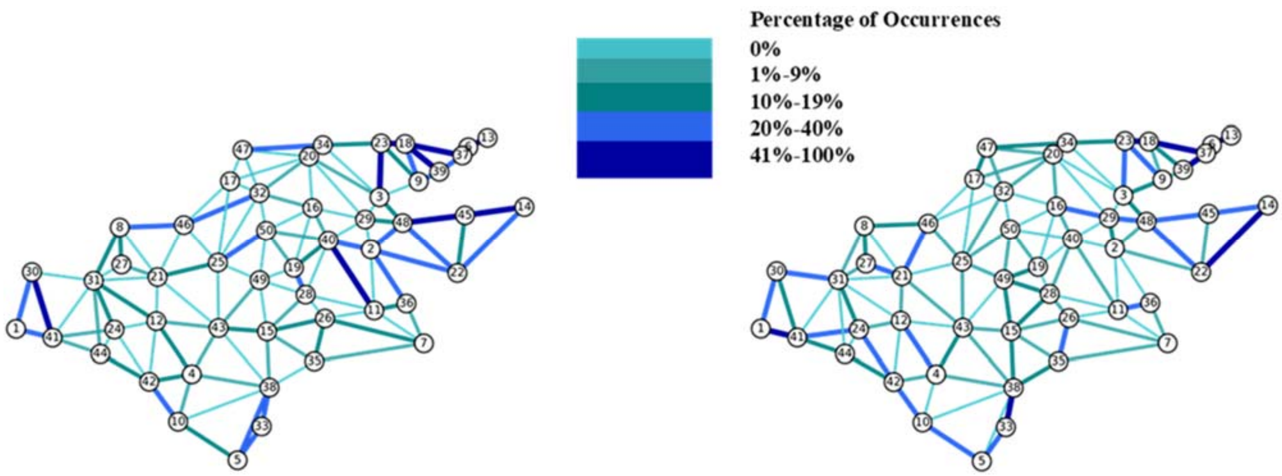
Figure 6: Number of Links Required to Reconnect and Restore the Damaged Network



(a) Short Term Road Restoration (b) Long Term Road Recovery

Figure 7: Days Required to Reconnect and Restore the Damaged Network

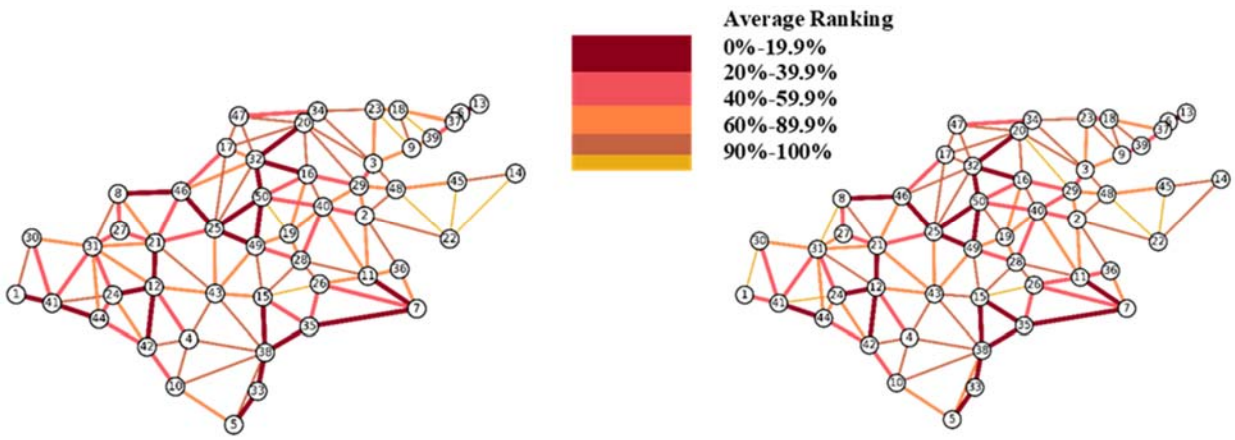
Figure 8 represents the percentage of each edge's occurrences in short term road restoration (STRR) schedules for both uneven and even damage distribution scenarios. The result shows that for both types of scenarios, the restoration schedule includes a similar group of edges in the STRR schedule. This indicates that some group of edges in the road network, e.g., edges (6,13) and (6,37), are essential due to the topology of the network. In other words, the edges (6,13) and (6,37) whenever damage, they must be scheduled to restore in the short term road restoration period to reconnect the road network. Further, these results provide the strategic location for prepositioning restoration resources close to the important edges depicted in Figure 8.



(a) For the Uneven Damage Scenarios (b) For the Even Damage Scenarios

Figure 8: Percentage of Edge Occurrences in short term road restoration schedules

Figures 9(a) and 9(b) represent the average ranking of edges in long term road recovery schedules for both uneven and even damage distribution scenarios, respectively. The results show that the average ranking of edges does not affect by the damage distribution. Also, the rank of the edges in the network is related to the traffic volume in terms of annual average daily traffic (AADT) and the restoration workload. In other words, edges with high rank are scheduled to restore early in order to minimize the affected traffic. Further, the results depict that edges with high rank are distributed evenly throughout the network. This indicates that for long term road recovery, the restoration resource can be located at the center to minimize the distance from all the edges.



(a) For the Uneven Damage Scenarios (b) For the Even Damage Scenarios

Figure 9: Average Ranking in Percentage of Edges in the Uneven and Even Damage Scenarios

In summary, we developed the three optimization models for an integrated decision-making approach that addresses the problems of short term road restoration and long term road recovery after a natural disaster. The approach and optimization models have been tested in the 18 road damage scenarios, which were designed by considering even or uneven damage distribution, road damage percentage and restoration workload. The findings revealed that the number of links required to reconnect and restore the damaged network depends only on the road damage percentage, while the time to reconnect and restore the damaged network depends on the road damage percentage and restoration workload levels. Using the integrated approach proposed in this study, one could estimate the amount of aggregate restoration resource required for a damaged road network after a natural disaster. The output from the model could support decision making related to road restoration during a disaster. The results of this study have been submitted to the 2020 TRB Annual Meeting for presentation and publication.

Study 3 – Visualizing the Impact of a Severe Weather Disruption to an Air Transportation Network

Air Transportation is most commonly controlled and monitored by a sophisticated, coordinated route management system known as a hub and spoke network model [33]. Passengers start at a hub (departure airport) and are transported along the spoke to a destination airport (arrival airport). A representation of the hub and spoke network at an airport hub is shown in Figure 10.

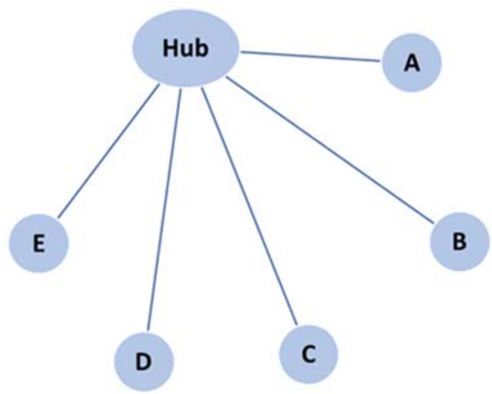


Figure 10: Representation of Hub and Spoke Network

The restoration of airline operations during a severe weather disruption involves the analysis and interpretation of large volumes of flight and weather data. Large datasets, or Big Data, are structured or unstructured datasets that are too large or complex to be analyzed by traditional data-processing applications. In Air Transportation, these large datasets typically contain pertinent airline and flight information based on time intervals [34].

The principal goal of the visualizations analysis is to introduce a decision support tool to interpret and collate large volumes (Big Data) of time-dependent flight and weather data. The visualizations serve as a comprehensive interface for airline stakeholders to assist them with collating, viewing and comprehending the Big Data. Flight and weather data from Hurricane Matthew 2016 are used to generate the visualizations.

There are many prior research studies dedicated to visualizing Big Data. A literature review of the state-of-the-art articles related to Big Data for airline flights and weather conditions were performed. The articles were classified based on the type of Big Data visualized in the article, the details of the data, the methodology used to create the image, the intended audience to interpret and receive the visualizations, and the decisions that audience must address. Table 3 summarizes the classification of the Big Data visualized in the related articles.

Table 3: Classification of Big Data Visualized in the Related Literature

Type of Big Data Visualized	Data Details	Methodology	Intended Audience	Audience Decisions
Airlines (35%)	Real-time, time-dependent flight and weather data	Statistical analysis using programming software	Pilots, air traffic controllers, airline stakeholders	Airline recovery
Hurricanes (35%)	Time-dependent weather data	Statistical analysis using programming software	Pilots, air traffic controllers, airline stakeholders, NASA	Airline recovery
General Big Data (17%)	Time-dependent network data	Statistical analysis using programming software	Scientists, engineers	Disruption management
Severe Weather (13%)	Time-dependent weather data	Statistical analysis using programming software	Scientists, engineers	Airline recovery

The research uses two types of Big Data datasets, flight and weather data, obtained from four sources, The Official Aviation Guide (OAG), Weather Underground, the US Department of Transportation's Bureau of Transportation Statistics National Aviation System (BTS NAS) and Iowa State University's Environmental Mesonet. The data covers the timeframe from September 1, 2016, through October 31, 2016. It includes the landfall period (September 28, 2016 through October 9, 2016) for the severe weather disruption, Hurricane Matthew.

To inform the decisions that Air Transportation officials are faced with, we visualize specific flight and weather variables. The flight variables are a day, time and carrier for the scheduled flights and the number of cancellations. The time-dependent weather variables are visibility levels, wind speed and hurricane landfall path. The visualizations are interpreted for traffic flow (flow-in and flow-out), capacity constraints and connectivity to the hub to influence decisions regarding airline recovery following a severe weather disruption.

Figure 11 shows the total flow of all airline carriers arriving and departing DCA, MCO, ORF and RDU between September 1, 2016 and October 31, 2016. The left side of Figure 7 illustrates the total traffic flow out of the hub and the right side of the figure displays the total traffic flow into the hub. These airport hubs are chosen because they are coastal airports, (MCO and ORF), and in-land airports, (DCA and RDU), that are in the path of Hurricane Matthew 2016. The effects of Hurricane Mathew are most significant at MCO which is visible by the noticeable break in the graph (shown in the circle), indicating that there were no outgoing or incoming flights during October 6-7, 2016. MCO closed on October 6-7, 2016 as Hurricane Matthew made landfall on the Florida coastline. Flights resumed on October 8, 2016 indicating there was at least a 24-hour delay for MCO to return to their pre-hurricane traffic levels and travelers were delayed for at least 24-hours.

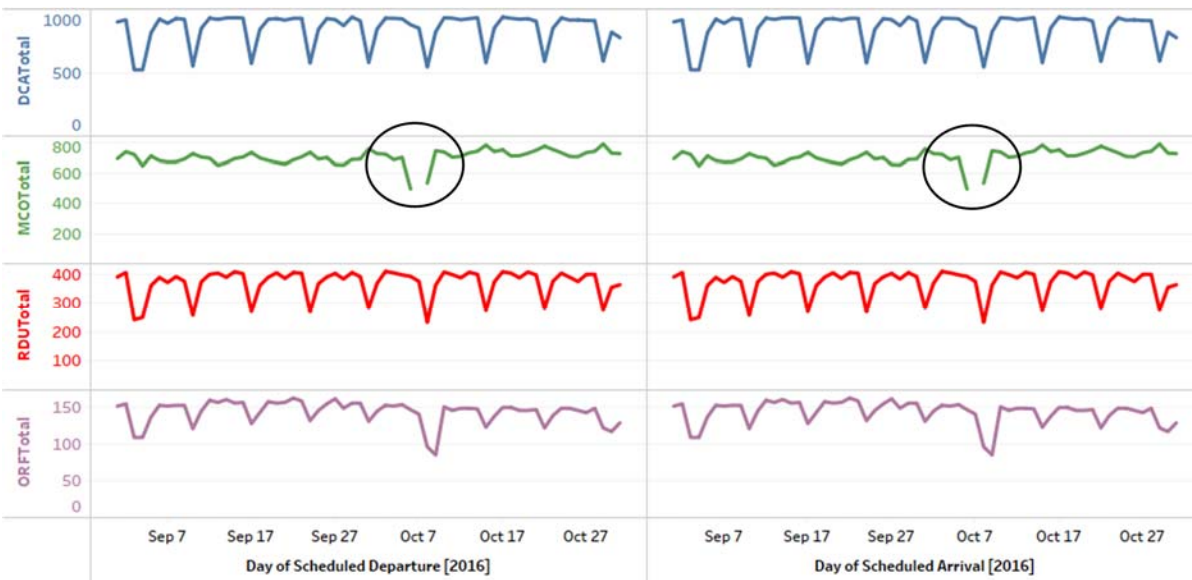


Figure 11: Total Traffic Flow at DCA, MCO, ORF and RDU

Figure 12 also shows a comparison of the percent of arrivals at inland (DCA and RDU) and coastal (MCO and ORF) airport hubs. The graphs of the inland hubs show flights arrived on October 7, 2016. These airports may not have received the full potency of the hurricane weather conditions and could continue to allow flights to arrive. When Hurricane Matthew reached North Carolina (RDU), it was a Category 1 Hurricane that decreased in intensity to a Post Tropical Cyclone by the time it reached Washington DC (DCA). Although the weather conditions are strong, the inland hubs are able to maintain operations.

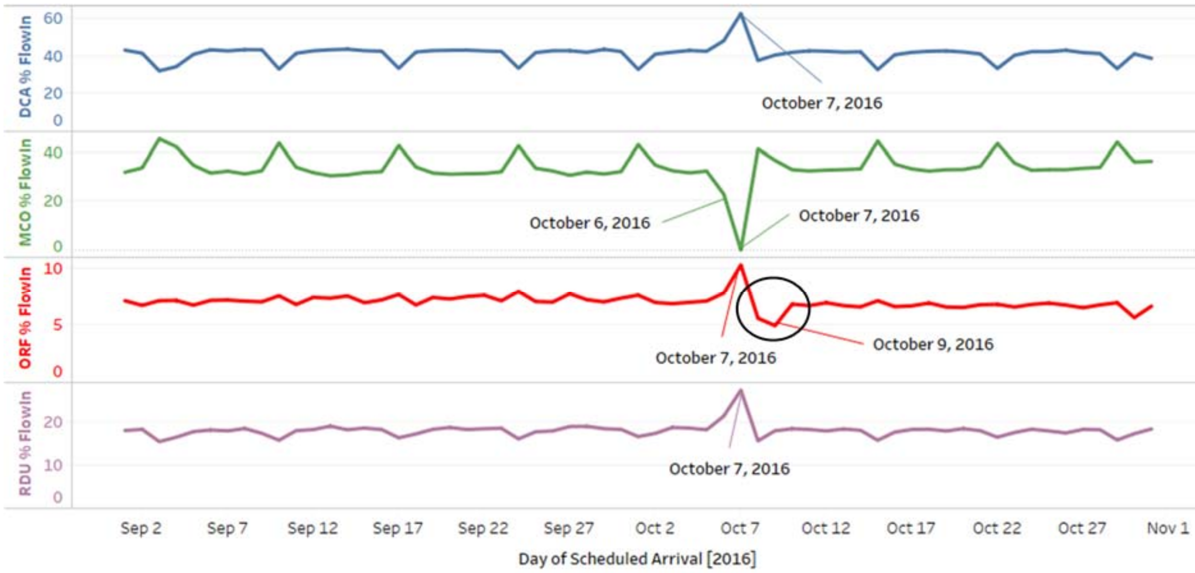


Figure 12: Traffic Flow In to DCA, MCO, ORF and RDU

Figure 13 shows the cancelled flights scheduled to arrive at DCA, MCO, ORF and RDU during the period of study. There are negligible or zero cancelled arrivals at the four airport hubs during September 2016, indicating that there are no capacity constraints or flight route connectivity issues to consider. However, October 2016 shows a high concentration of cancellations between October 6-9, 2016.

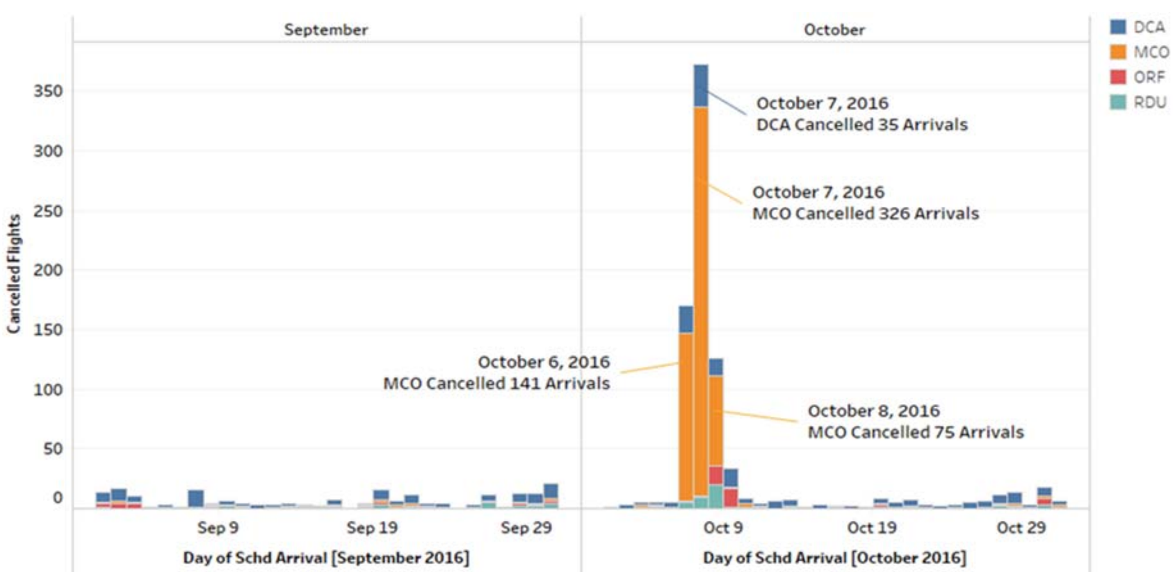


Figure 13: Cancelled Arrivals (Flow In) [35]

The visualizations show that organizing the data to display the traffic flow at a hub and cancellations in the airport network, provides an enhanced understanding of the data, improves the understanding and clarity of the data and assists with recovery decisions to manage capacity constraints and traffic flow following a severe weather event. The visualizations and results are corroborated by interviews with Air transportation officials tasked with decision-making for recovery operations following a severe weather event. The Air transportation officials concur that our analysis is relevant to decision-making and consistent with current practices.

Study 4 – A Deterministic Optimization Model of Flight Schedules Recovery

When unexpected disruptions to normal operations occur, Air transportation officials are faced with what is commonly known as the airline recovery problem [36]. The airline recovery problem is essentially the process of determining how to respond to an unexpected interruption to service or operations. Decision-makers must develop recovery actions for five basic components of air traffic management: Airport Operations, Aircraft Dispositioning, Flight Schedules, Crew Assignment and Passenger Itineraries [37].

The objective of this research is to develop an optimization model for the recovery of Flight Schedules following a severe weather disruption. We conduct a state of the airline network assessment and define a discretized recovery window. We develop a mixed integer linear programming (MILP) model that generates new flight schedules, minimizes delays and circumvents a severe weather event caused by a hurricane.

The literature review is conducted comprehensively, for all components of the airline recovery problem, then filtered specifically for Flight Schedules recovery. The literature is categorized by the component of the airline recovery problem studied in the article. The related literature involving the recovery of Flight Schedules is analyzed by type of disruption, author's approach to the problem, type of data used in the analysis and how the results will be used. Table 4 diagrams the classification of the Flight Schedules recovery in the related literature and highlights the focus of our research, shown in red.

Table 4: Classification of Flight Schedules Recovery Literature

	Disruption			Approach			Data		Results For		
Author	Severe Weather	Capacity Constraints	Combined Disrupts	Case Study	Simulation	Optimization	Theoretical	Actual	Planning	Recovery	Both
Abdelghany, 2008			X			X	X			X	
Abdi, 2008			X	X				X			X
Castro, 2010			X		X		X		X		
Churchill, 2010			X	X			X		X		
Eggenberg, 2010			X			X		X		X	
Filar, 2007			X			X	X		X		
Hu, 2017	X					X		X		X	
Janic, 2015			X			X		X			X
Jozefowiez, 2012			X			X		X		X	
Marla, 2017			X			X		X	X		
McCrea, 2008	X					X		X			X
Sun, 2011		X				X	X			X	
Tu, 2008			X			X		X			X
Zhang, 2008	X					X	X			X	
Zhang, 2017	X					X		X		X	
Glass, Davis, Qu 2019	**X**					**X**		**X**		**X**	

This study extends the work of Study 3 and examines the impact of a severe weather event, i.e. hurricane, on flight schedules at a US hub airport. We consider a daily operational approach for the airline recovery problem by establishing a 24-hour recovery horizon and 30-minute, discretized time slots for flight rescheduling. A state of the network assessment is conducted to determine whether the flight route between the hub and destination airport is safe to travel. We develop a deterministic mixed integer linear programming (MILP) optimization model to generate new flight schedules and minimize delays. The new flight schedules are generated in 30-minute intervals using first-in-first-out (FIFO) flight schedule assignment. The model is tested with time-dependent data. The deterministic MILP optimization model is shown below.

Sets

F = set of flights, $f \in F$

R = set of routes, $r \in R$

T = set of time slots, $t \in T$; td = dummy slot, $td \in T$; $T = t \cup td$

Parameters

$$r_{ft} = \begin{cases} 1 \text{ if route for flight } f \text{ is safe to travel in time slot } t \\ 0 \quad\quad\quad\quad\quad\quad\quad\quad \text{otherwise} \end{cases} \quad (1)$$

os_f = original slot in which flight f is scheduled (2)

pd_f = prior delay time for flight f (3)

Decision Variables

$$y_{ft} = \begin{cases} 1 \text{ if flight } f \text{ is assigned to time slot } t \\ 0 \qquad\qquad \text{otherwise} \end{cases} \quad (4)$$

Objective

$$\min \sum_{f \in F} \sum_{t \in T} 30 * (t - os_f) * y_{ft} + pd_f \quad (5)$$

s.t.

$$\sum_{f \in F} y_{ft} \leq 1 \qquad \forall\, t \in T \quad (6)$$

$$y_{ft} \leq r_{ft} \qquad \forall\, f \in F \quad (7)$$

$$\sum_{t \in T} y_{ft} = 1 \qquad \forall\, f \in F \quad (8)$$

$$y_{ft} \in [0,1] \qquad \forall\, f \in F, \forall\, t \in T \quad (9)$$

The set of flights, *F*, contains the flight information for 4 airport hubs for the period of study. The flight information used in this study is scheduled departure date, carrier name, flight number, departure airport, number of flight cancellations and number of seats on the carrier. The set of flight routes, *R*, contains the state of the network assessment which identifies when the route, r_{ft}, for a flight *f* is safe to travel in a time slot *t*. The set of time slots, *T*, contains the 30-minute intervals in which a flight can be scheduled. There are 34 time slots, *t*, in which a flight can be rescheduled. Slot number 35, *td*, is a dummy slot used when a flight cannot be rescheduled within the 24-hour recovery horizon.

Equation (1) is the binary condition for whether the route for flight *f* is safe to travel in time slot *t* and is represented by r_{ft}. If Equation (1) equals 0, new flight schedules cannot be developed because the flight route for flight *f* is not safe to travel at time *t*. The original time slot, os_f, in which flight *f* is scheduled is shown in Equation (2). The prior delay time, pd_f, for a flight *f* is shown in Equation (3). In the first iteration of the model the prior delay, pd_f, is 0. However, if the first run generates schedules in slot number 35, the prior delay, pd_f, is the prior calculated delay time for that flight *f* and is added to the subsequent iteration of the model. The decision variable, y_{ft}, shown in Equation (4), is a binary condition for whether a flight *f* is assigned to time slot *t*. If Equation (4) equals 0, new flight schedules cannot be defined.

The objective function (5) determines the total delay time across all rescheduled flights given that the time slots are in 30-minute intervals. The constraints of the model are defined in Equations (6 – 8). Constraints (6) ensure at most one flight *f* is scheduled in a time slot *t*. Constraints (7) ensure that a flight is scheduled to a route that is safe to travel. Constraints (8) enforce that a flight is scheduled to one time slot. It should be noted that we include a dummy time slot for all flight routes that is always safe for travel. This ensures that all flights will either be rescheduled during the current time-window, or rescheduled in the next time-window. The candidate flights selected for the next time-window are the set of flights scheduled in the dummy time slot. Constraints (9) represent the binary conditions on the decision variable.

The model is developed to generate new flight schedules in 30-minute intervals for cancelled flights due to a severe weather event. It is coded using Python programming language and tested in a testing scenario. This scenario assumes one airline carrier (American Airlines), one-day schedules for three cancelled flights and uses flight data generated based on the recurring daily schedules of American Airlines carriers. The data contains the carrier number, proposed departure day and time, the number of seats on the aircraft and the original time slot of the scheduled departure. Actual weather data for two days in October 2016 are used to assess whether the route is safe to travel. The route is safe to travel when the visibility level is greater than 5-miles and the windspeed is less than 33 knots. Our initial results show that the model can schedule some cancelled flights to time slots during which the routes are safe to travel, and the remaining flights will be postponed to the next time-window (i.e., next day).

Study 5 – Integrated Decision Making for the Restoration of Air and Road Transportation Systems after a Natural Disaster

Quick restoration and recovery of transportation systems play an important role in humanitarian operations and community recovery after a natural disaster. To support the restoration of transportation systems, we created a visual decision-making tool for the restoration of air and road transportation systems after a natural disaster and tested it in a case study using the impact data of Hurricane Matthew in North Carolina. Figure 14 illustrates the recovery process of air and road transportation operations after a natural disaster and the role of the proposed visual decision-making tool in the recovery process. To facilitate effective decision making during a natural disaster, the decision-making tool proposed for multimodal transportation system restoration integrates the flight rescheduling models and the short-term highway restoration models developed in this CATM project.

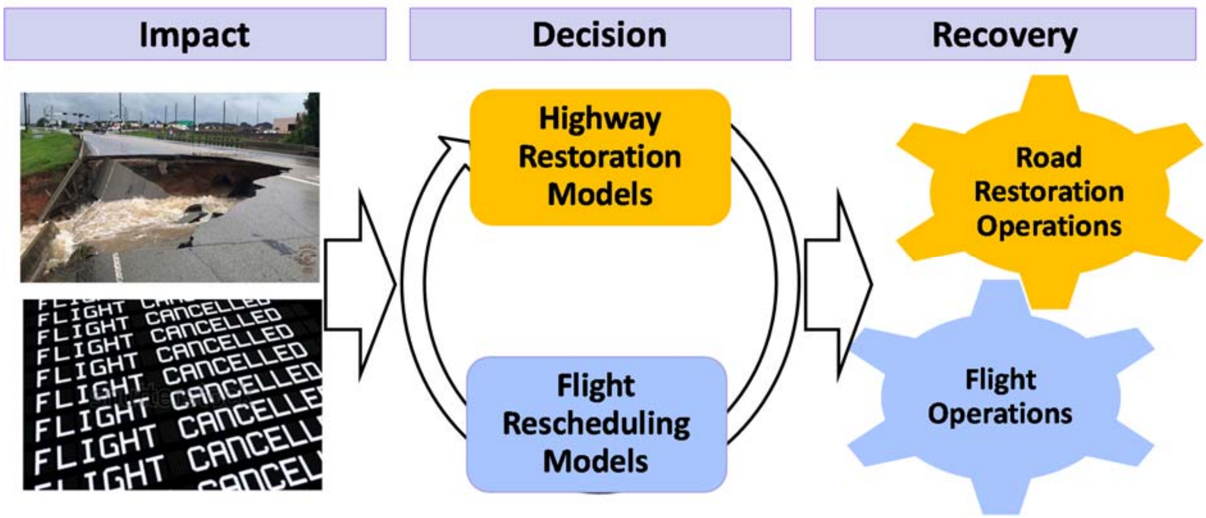


Figure 14: Recovery Process of Air and Road Transportation Operations after a Natural Disaster

The disruption of natural disasters to air transportation is mainly due to flights cancellation, and the disruption to road transportation is because of damaged or blocked roadways. In the decision-making tool, first, the flight rescheduling models summarize the numbers of passengers in the canceled flights who need to travel from each county to the airport and send the information to the short-term highway restoration models. After receiving this information, the highways restoration models take road restoration workload, available restoration resource, the population distribution in the affected area, and the numbers of airline passengers affected an input to generate an optimal set of damaged or blocked roads to be restored within the first three days and the sequence of restoring the selected roads. Based on the optimal road restoration schedule, the short-term highways restoration models summarize the accessibility from each county to the airport and send the information to the flight rescheduling models. This is the initial iteration of the decision-making tool. After the initial iteration, the flight rescheduling models and the highway restoration models are iteratively solved until optimal solutions for flight rescheduling and road restoration converge. In each iteration, the flight rescheduling models reschedule the canceled flights by considering the airport condition for flights and the accessibility from each county to the airport. Then based on an optimal new schedule of canceled flights, the flight rescheduling models summarize the numbers of airline passengers who need to travel by road from each county to the airport on each day, and then send the information to the highway restoration models. Based on the updated need of airline passengers, the highway restoration models update the optimal road restoration sequence, and then send to the flight rescheduling models the updated accessibility from each county to the airport.

In our case study, we tested the decision-making tool for transportation system restoration using the impact data of Hurricane Matthew in North Carolina (NC), including the data of NC emergency response activities and road closures during Hurricane Matthew from WebEOC database [1], flights cancellation during Hurricane Matthew from OAG

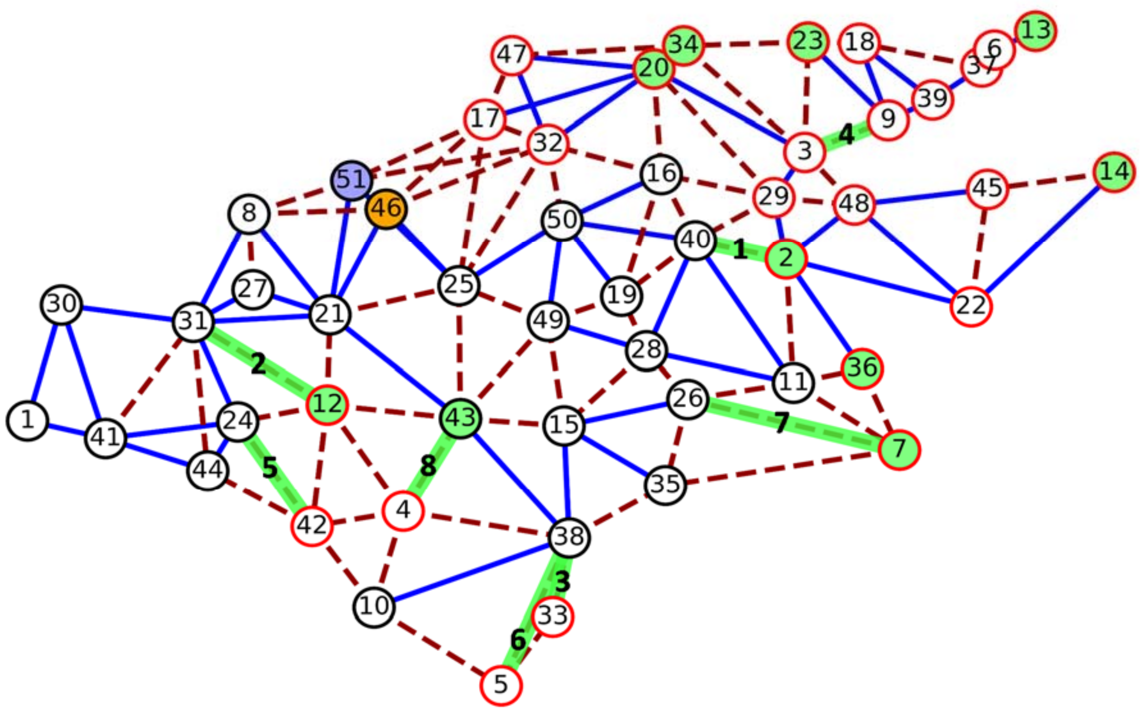


Figure 15: Road Restoration Sequence in the Eastern North Carolina
for the Hurricane Matthew Scenario

Table 5: Index, Name, and Population of the Counties Affected by Hurricane Matthew

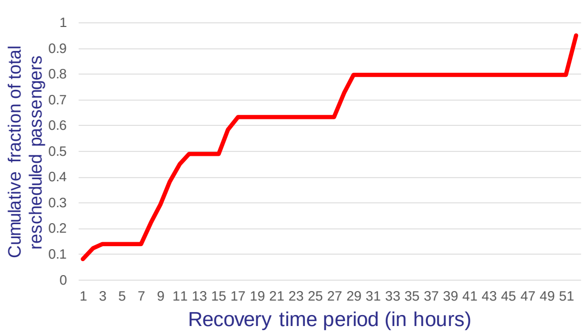
Node Index	County Name	Population	Node Index	County Name	Population
1	Anson	25,275	27	Lee	49,040
2	Beaufort	44,958	28	Lenoir	59,648
3	Bertie	19,773	29	Martin	25,593
4	Bladen	32,278	30	Montgomery	26,822
5	Brunswick	73,143	31	Moore	74,769
6	Camden	6,885	32	Nash	87,420
7	Carteret	59,383	33	New Hanover	160,307
8	Chatham	49,329	34	Northampton	22,086
9	Chowan	14,526	35	Onslow	150,355
10	Columbus	54,749	36	Pamlico	12,934
11	Craven	91,436	37	Pasquotank	34,897
12	Cumberland	302,963	38	Pender	41,082
13	Currituck	18,190	39	Perquimans	11,368
14	Dare	29,967	40	Pitt	133,798
15	Duplin	49,063	41	Richmond	46,564
16	Edgecombe	55,606	42	Robeson	123,339
17	Franklin	47,260	43	Sampson	60,161
18	Gates	10,516	44	Scotland	35,998
19	Greene	18,974	45	Tyrrell	4,149
20	Halifax	57,370	46	Wake	627,846
21	Harnett	91,025	47	Warren	19,972
22	Hertford	22,601	48	Washington	13,723
23	Hoke	33,646	49	Wayne	113,329
24	Hyde	5,826	50	Wilson	73,814
25	Johnston	121,965	51	RDU Airport	1,000
26	Jones	10,381			

Aviation worldwide Ltd [38], and the NC county population from US census data 2010 [39]. Figure 15 shows the eastern NC road transportation network affected by Hurricane Matthew, in which the nodes denote the counties, and the edges represent the roadways linking counties. This road network consists of 51 nodes and 118 links. Node 51 represents the airport in the affected area, and node 46 indicates the location of road restoration resource. The nodes with green background indicate the counties from which some airline passengers need to travel by road to the airport. In the network, solid lines represent undamaged links, whereas dash lines represent damaged links during Hurricane Matthew. Table 5 displays the population of the 50 NC counties affected by Hurricane Matthew.

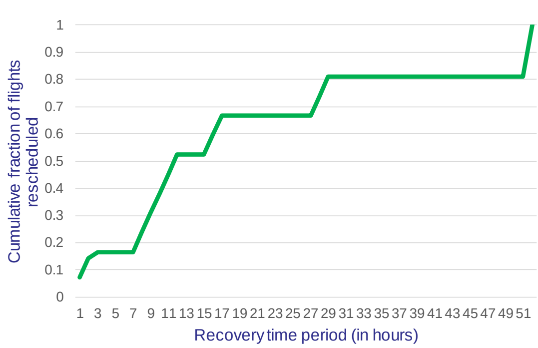
Figure 15 also shows the optimal road restoration schedule to reconnect the 50 counties and the airport. The set of damaged links to be restored is highlighted in green in the graph, and the numbers associated with each highlighted link indicate the restoration sequence of these roads. Corresponding to the road restoration schedule, Table 6 shows the recovery time by which airline passengers can travel by road from a county to the airport. Figure 16 shows the flight rescheduling results. This figure reveals that more than 65% passengers and flights can be rescheduled within 24 hours, and all canceled flights can be rescheduled within about 48 hours.

Table 6: Passengers and Restoration Time for the Path from Counties to the Airport

Node Index	County Name	Number of Passengers from the County to the Airport	Restoration time (in Hours)
43	Sampson	428	0
2	Beaufort	120	8
14	Dare	206	8
20	Halifax	556	8
34	Northampton	174	8
36	Pamlico	112	8
12	Cumberland	1947	16
13	Currituck	127	28
23	Hoke	240	28
7	Carteret	636	52



(a) Passengers Rescheduled



(b) Flights Rescheduled

Figure 16: Percentages of Passengers and Flights Rescheduled after the Hurricane

In the decision-making tool for multimodal transportation system restoration was implemented using Python. The computational time of decision making for road restoration and flight schedules recovery in the case study was within 5 minutes. This tool can also visualize the damaged connections between counties, counties disconnected from airports and regional coordinate centers, and the road restoration schedule and flight schedules recovery.

FINDINGS, CONCLUSIONS, RECOMMENDATIONS

In our CATM project, we (1) assessed the vulnerability of the southeastern NC highways to a hurricane using the impact data of Hurricane Matthew; (2) investigated the patterns of flight cancellations and delays caused by a severe weather disruption using visualization; (3) developed and tested a decision-making approach for road restoration in the short and long terms after a natural disaster; (4) developed an optimization model for flight schedules recovery after a severe weather disruptions; (5) integrated the flight rescheduling models and the short-term highway restoration models to create a decision-making tool for multimodal transportation system restoration after a natural disaster, and tested the decision-making tool in a case study. Our vulnerability analysis results revealed the positive correlation between exposure vulnerability scores and the closure days of southeastern NC highways during Hurricane Matthew and also showed that the highways with higher traffic volume are more vulnerable.

Our visualization study has demonstrated that the Tableau software successfully visualized the flight and weather activity during the period of study, and it can be used to develop a dashboard that shows the real-time impact of severe weather disruption. Our results have shown that visualizations can be used to forecast and predict airport flow, flight cancellations and departure delays and that the total traffics before, during and after a hurricane disruption can provide insights and trends to help decision-makers manage the flight schedules recovery problem.

The optimization models, approaches and tools developed in this project can support decision making for the restoration of air and road transportation systems after a natural disaster. These models, approaches or tools can estimate the amount of aggregate restoration resource required for a damaged road network after a natural disaster, identify an optimal set and order of damaged or blocked roads to quickly reconnect critical locations, generate an optimal plan to recover a damaged road network, and optimize the new schedules of cancelled flights. The outputs of these models or tools could improve the effectiveness and efficiency of response activities in local and regional transportation systems during a natural disaster. Deploying effective response activities can improve the mobility of people and disaster relief during and after a natural disaster.

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APPENDIX A: Multi-Period Resource Allocation (MPRA) Model

In the study of the road network restoration after a natural disaster, we address the short term road restoration and long term road recovery problems after a natural disaster. In the short term road restoration problem, the critical roads are identified and their restoration sequence is decided to reconnect the damaged road network within the shortest time. In the long term road recovery (LTRR) problem, the critical roads have been restored and the road network is connected. The remaining damaged road must be restored with minimal impact in daily traffic flow. Thus, the objective of the LTRR problem is to minimize the impact of road recovery activities on daily traffic. In this study, road reconstruction is not considered in the LTRR problem. Only road restoration activities such as road repair and debris clearance are considered in the LTRR problem. That means that no new edge can be added to the graph.

The LTRR problem is defined on a weighted undirected graph $G = (V, E)$ representing the damaged road network. In the graph, nodes (V) represent critical locations, and edges (E) denote damaged and undamaged links among critical locations. Each edge is associated with two weights: restoration workload and annual average daily traffic (AADT). The restoration workload weight of a damaged edge represents the aggregated workload, in units of repair/clearance team times time, required to restore the damaged edge (i.e., corresponding main damaged road). The restoration workload weights of all undamaged edges equal 0.

For the LTRR problem, the road recovery period is divided into multiple time intervals. In this study, the LTRR problem is formulated as a MILP model, called the MPRA model, that allocates available aggregated restoration resource to the unrestored edges of the graph over the road recovery period. The objective of the MPRA problem is minimizing the affected AADT associated with edge, i.e., affected traffic volume on the road, as early as possible. From the disaster management respective, road usability can be measured by the total time, and the amount of vehicle traverse the edge. Thus, the LTRR problem is formulated as:

$$\text{Minimize} \quad \sum_{\forall t} \sum_{\forall (i,j) \in E_D^{II}} v_{ij} (1 - \gamma_{i,j}^t) \tag{10}$$

$$\text{Subjected to} \quad \gamma_{ij}^t \geq \gamma_{ij}^{t-1} \quad \forall (i,j) \in E_D^{II}, \; t \in T \tag{11}$$

$$Y_{i,j}^{t-1} + y_{i,j}^{t} = Y_{i,j}^{t} \qquad \forall (i,j) \in E_D^{II}, \quad t \in T \tag{12}$$

$$w_{i,j} - Y_{i,j}^{t} \leq \left(1 - \gamma_{i,j}^{t}\right) w_{i,j}, \qquad \forall (i,j) \in E_D^{II},\ t \in T \tag{13}$$

$$w_{i,j} - Y_{i,j}^{t} \geq 1 - \gamma_{i,j}^{t}, \qquad \forall (i,j) \in E_D^{II}, t \in T \tag{14}$$

$$\sum_{(i,j)\in E_D^{II}} y_{i,j}^{t} \leq r_t, \ \ \forall t \in T \tag{15}$$

$$Y_{i,j}^{t}, y_{i,j}^{t} \geq 0, \qquad \forall (i,j) \in E_D^{II}, t \in T \tag{16}$$

$$\gamma_{ij}^{t} \ \in \{0,1\} \qquad \forall (i,j) \in E_D^{II},\ t \in T \tag{17}$$

Table 7: Notation for the MPRA Model

Sets	
E	Set of edges of the network
E_D^{II}	Set of damaged edges in the recovery period
V	Set of nodes of the network
T	Set of time intervals of the recovery period
Indices	
i and j	Indices for nodes
t	Index for time intervals
Parameters	
r_t	The aggregate amount of restoration resources in time interval t
w_{ij}	Amount of workload for a damaged edge, i.e., restoration resources needed to fully restore edge
v_{ij}	Affected AADT on the edge(i, j)
Decision Variables	
y_{ij}^{t}	Amount of restoration resources allocated to the edge (i, j) in time interval t
Y_{ij}^{t}	The total amount of restoration resources allocated to the edge (i, j) by the end of time interval t
γ_{ij}^{t}	$=\begin{cases} 1, & \text{if edge } (i,j) \text{ is fully restored at the end of time interval } t \\ 0, & \text{otherwise} \end{cases}$

Table 7 displays the notation for the sets, indices, parameters, and decision variables used in the MPRA models. In the MPRA model, the objective function (10) minimizes the total affected AADT, i.e., the total number of vehicles that could traverse the damaged edges over the time intervals. Constraints (11) ensure that any restored edge can be traversed once it is restored. Constraints (12) track the cumulative amounts of restoration resource allocated to each damaged edge by the end of each time interval. Constraints (13) and (14) determine whether enough restoration resource has been allocated to each damaged edge to restore it by the end of each time interval. Constraints (15) ensure that the total amount of restoration resource allocated does not exceed the total available resource in each time interval. Constraints (16) and (17) are non-negativity and binary restrictions for decision variables.

APPENDIX B: Codes for Air Rescheduling and Road Restoration Models

B.1 MST.py

```
"""
Created on Wed Jan 16 10:33:38 2019
@author: Sachin Mhatre
"""

# A Python program for Prim's Minimum Spanning Tree (MST) algorithm.
# The program is for adjacency matrix representation of the graph

import sys # Library for INT_MAX
import numpy as np

class Graph():

    def __init__(self, vertices):
        self.V = vertices
        self.graph = [[-1 for column in range(vertices)]
                      for row in range(vertices)]

    # A utility function to print the constructed MST stored in parent[]
    def printMST(self, parent):
        print ("Edge \tWeight")
        for i in range(1,self.V):
            print (parent[i],"-",i,"\t",self.graph[i][ parent[i] ])

    # A utility function to find the vertex with
    # minimum distance value, from the set of vertices
    # not yet included in shortest path tree
    def minKey(self, key, mstSet):

        # Initilaize min value
        min = sys.maxsize

        for v in range(self.V):
            if key[v] < min and mstSet[v] == False:
                min = key[v]
                min_index = v
```

```
        return min_index

    # Function to construct and print MST for a graph
    # represented using adjacency matrix representation
    def primMST(self):

        #Key values used to pick minimum weight edge in cut
        key = [sys.maxsize] * self.V
        parent = [None] * self.V # Array to store constructed MST
        # Make key 0 so that this vertex is picked as first vertex
        key[0] = 0
        mstSet = [False] * self.V

        parent[0] = -1 # First node is always the root of

        for cout in range(self.V):
            # Pick the minimum distance vertex from
            # the set of vertices not yet processed.
            # u is always equal to src in first iteration
            u = self.minKey(key, mstSet)

            # Put the minimum distance vertex in
            # the shortest path tree
            mstSet[u] = True

            # Update dist value of the adjacent vertices
            # of the picked vertex only if the current
            # distance is greater than new distance and
            # the vertex in not in the shotest path tree
            for v in range(self.V):
                # graph[u][v] is non zero only for adjacent vertices of m
                # mstSet[v] is false for vertices not yet included in MST
                # Update the key only if graph[u][v] is smaller than key[v]
                if self.graph[u][v] >= 0 and mstSet[v] == False and key[v] > self.graph[u][v]:
                        key[v] = self.graph[u][v]
                        parent[v] = u
```

```
        self.printMST(parent)
        return parent

def STRREdges (numNodes, edgeFileName):
        allEdges = np.genfromtxt(edgeFileName, dtype='int', delimiter=',')
        edgeList = allEdges.tolist()

        g = Graph(numNodes)
        for edge in edgeList:
             g.graph[edge[0]-1][edge[1]-1]=edge[3]
             g.graph[edge[1]-1][edge[0]-1]= edge[3]

        mst = g.primMST()
        for i in range(1,g.V):
            if g.graph[i][mst[i]] > 0:
                for j in range(0,len(edgeList)):
                    if (i==(edgeList[j][0]-1) and mst[i]==(edgeList[j][1]-1)) or
                            (i==(edgeList[j][1]-1) and mst[i]==(edgeList[j][0]-1)):
                        edgeList[j][2] = 1
                        break

        return edgeList
```

B.2 STRR.py

```
"""
Created on Sun Aug 25 18:41:40 2019
@author: Sachin Mhatre
"""

from docplex.mp.model import Model
from docplex.mp.context import Context

'''
#Function to solve the STRR model
Function of STRR (SourceNodes, DemandNodes, NodeWeights, Edgelist,
         DmgEdge, TimePeriods,AffectedPopulation, EdgeWorkload,
         AirportNode = 51, TimeIntervals = 4,ResCapacity = 200)
```

```
Parameters
   SourceNodes - List of source node indices (Positive integers)
   DemandNodes - List of demand node indices (Positive integers)
   NodeWeight - Dictionary of node indices, names and weights (population)
   Edgelist – List of undamaged edges and damaged edges to restore
   Dmg Edge – List of damaged edges to be restored
   TimePeriods – List of time periods indices (positive integers starting 1)
   AffectedPopulation – Population associated with each pair of source and demand
                              nodes in each time Period
   ResCapacity – Constant restoration resources available
   AirportNode – Node index for the airport
   EdgeWorkload – List of workload to restore each edge
   TimeInterval - Number of hours for each interval

Returns
   listRestorationSequence
   dictRoadResSequence
   dictResTime_County
   dictResAllocation
'''
def STRR (SourceNodes, DemandNodes, NodeWeights, Edgelist, DmgEdge,
        TimePeriods,AffectedPopulation, EdgeWorkload,
        AirportNode = 51, TimeIntervals = 4,ResCapacity = 200):

   mq= Model(name="STRR")

#Decision variables
#flow from i to j
   f = {(e[0],e[1],t) : mq.continuous_var(name = "f_e{0}_{1}_t{2}".format(e[0],e[1],t))
               for e in Edgelist for t in TimePeriods}
   for e in Edgelist:
      for t in TimePeriods:
         f[(e[1],e[0],t)] = mq.continuous_var(name = "f_e{0}_{1}_t{2}".format(e[1],e[0],t))

#path from demand to source node
   z = {(d,s,t) : mq.binary_var(name = "z_d{0}_s{1}_t{2}".format(d,s,t))
   for s in SourceNodes for d in DemandNodes for t in TimePeriods}
```

```
#gamma in the model
   g = {(e,t) : mq.binary_var(name = "g_dmgedge{0}_{1}_t{2}".format(e[0],e[1],t))
   for e in DmgEdge for t in TimePeriods}

# Y cumulative resource allocated
   YC = {(e,t) : mq.continuous_var(name =
"YC_dmgedge{0}_{1}_t{2}".format(e[0],e[1],t))
   for e in DmgEdge for t in TimePeriods}

# small y in model
   y = {(e,t) : mq.continuous_var(name = "y_dmgedge{0}_{1}_t{2}".format(e[0],e[1],t))
   for e in DmgEdge  for t in TimePeriods}

#objective function
   mq.maximize(mq.sum(AffectedPopulation.get((d,s,t),0)* z[d,s,t] for d in
                    DemandNodes for s in SourceNodes for t in TimePeriods))

#Constraints to guarantee no flow on any damaged edge
   for e in DmgEdge:
     for t in TimePeriods:
        mq.add_constraint(100*g[e,t] >= f[e[0],e[1],t])
        mq.add_constraint(100*g[e,t] >= f[e[1],e[0],t])

        if t > 1:
           mq.add_constraint(g[e,t] >= g[e,t-1])

#Constraints to detect any path from each resource node to each demand node
#Flow balance constraints for each source node
   for s in SourceNodes:
      DNodes = set()
      for e in Edgelist:
         if e[0] == s:
            DNodes = DNodes.union({e[1]})
         if e[1] == s:
            DNodes = DNodes.union({e[0]})
      for t in TimePeriods:
          mq.add_constraint(mq.sum(z[d,s,t] for d in DemandNodes)
         + mq.sum(f[k,s,t] for k in DNodes) == mq.sum (f[s,l,t] for l in DNodes))
```

```
#Flow balance constraints for demand node
    for d in DemandNodes:
        DNodes = set()
        for e in Edgelist:
            if e[0] == d:
                DNodes = DNodes.union({e[1]})
            if e[1] == d:
                DNodes = DNodes.union({e[0]})
        for t in TimePeriods:
            mq.add_constraint(mq.sum(f[k,d,t] for k in DNodes )
        == mq.sum(z[d,s,t] for s in SourceNodes) + mq.sum(f[d,l,t] for l in DNodes))

#workload
    for e in DmgEdge:
        for t in TimePeriods:
            # w1
            mq.add_constraint(YC[e,t] >= EdgeWorkload.get(e,0) * g[e,t])
            # w2
            mq.add_constraint(EdgeWorkload.get(e,0) - YC[e,t] >= 1 - g[e,t])
            #Clearance Cumulative
            if t == 1:
                mq.add_constraint(YC[e,t] == y[e,t])
            else:
                mq.add_constraint(YC[e,t] == YC[e,t-1] + y[e,t])

    for t in TimePeriods:
        mq.add_constraint(mq.sum(y[e,t] for e in DmgEdge) <= ResCapacity)

# Connectivity at the last time period

    for d in DemandNodes:
        for s in SourceNodes:
            t = TimePeriods[-1]
            mq.add_constraint(z[d,s,t] == 1 )

# Constraints of z(t) >= z(t-1)
    for d in DemandNodes:
```

```
        for s in SourceNodes:
            for t in TimePeriods:
                if t == 1:
                    continue
                else:
                    mq.add_constraint(z[d,s,t] >= z[d,s,t-1] )

#solution
    sol = mq.solve()
    if sol is None:
        print('Not enough resource for road restoration in the given period')
        return None

# Solution Export
# Road restoration sequence based on gamma in the model
    dictRoadResSequence = {}
    listRestorationSequence = []
# Resource allocation (smalll y in model)
    dictResAllocation = {}
    for e in DmgEdge:
        for t in TimePeriods:
            nameRoad = "g_dmgedge{0}_{1}_t{2}".format(e[0],e[1],t)
            var = int(mq.get_var_by_name(nameRoad).solution_value)
            if (var > 0) and (dictRoadResSequence.get(e) == None):
                dictRoadResSequence[e] = t
                listRestorationSequence.append([t,e])

            nameResource = "y_dmgedge{0}_{1}_t{2}".format(e[0],e[1],t)
            var = round(mq.get_var_by_name(nameResource).solution_value)
            if var > 0:
                dictResAllocation[(e,t)] = var

    listRestorationSequence.sort()


    dictResSchedule_County = {}
    dictResTime_County = {}
    s = AirportNode
```

```
    for d in DemandNodes:
        for key, value in NodeWeights.items():
            if int(key[0]) == d:
                d_name = key[1]
                break

        for t in TimePeriods:
                name = "z_d{0}_s{1}_t{2}".format(d,s,t)
                var = int(mq.get_var_by_name(name).solution_value)
                dictResSchedule_County[(key[0],t)] = var

                if (t == 1):
                    if (var == 1):
                        ResTime = 0
                        preVar = 1
                    else:
                        preVar = 0
                else:
                    if (preVar != var):
                        ResTime = t*int(TimeIntervals)
                        preVar = var

        dictResTime_County[d_name] = ResTime

    return listRestorationSequence, dictRoadResSequence, dictResTime_County,
          dictResAllocation

#Function for InitSTRR
def initSTRR (TimePeriods, SourceNodes, DemandNodes, edgeList,
          CountynPopulation,dictPop_CountytoAirport):
    Edgelist = []
    EdgeMST = []
    EdgeWorkload ={}

    for edge in edgeList:
        EdgeWorkload[(edge[0],edge[1])] = edge[3]
        if edge[2]<2:
            Edgelist.append((edge[0],edge[1]))
```

```
        if edge[2]==1:
            EdgeMST.append((edge[0],edge[1]))

    AffectedPopulation = {}

    for key, value in CountynPopulation.items():
        for key1, value1 in dictPop_CountytoAirport.items():
            for t in TimePeriods:
                AffectedPopulation[(int(key[0]),46,t)] = int(value)
                if key1 == key[1]:
                    AffectedPopulation[(int(key[0]),51,t)] = int(value1)


# Call the STRR function
    initSol = STRR(SourceNodes, DemandNodes, CountynPopulation, Edgelist,
                EdgeMST, TimePeriods, AffectedPopulation, EdgeWorkload)

    return initSol


def iterSTRR(TimePeriods, SourceNodes, DemandNodes, edgeList,
            CountynPopulation, dictDailyPop_CountytoAirport,settings):
    Edgelist = []
    EdgeMST = []
    EdgeWorkload ={}

    for edge in edgeList:
        EdgeWorkload[(edge[0],edge[1])] = edge[3]
        if edge[2]<2:
            Edgelist.append((edge[0],edge[1]))
        if edge[2]==1:
            EdgeMST.append((edge[0],edge[1]))

    AffectedPopulation = {}
    numIntervals = int(settings['numTimePeriods']/settings['numDays'])

    for key, value in AffectedPopulation.items():
        for t in TimePeriods:
```

```
            AffectedPopulation[(int(key[0]),46,t)] = int(settings['weightRCC']*value)

        for key1, value1 in dictDailyPop_CountytoAirport.items():
            if key1[0] == key[1]:
                for t in range(numIntervals):
                    t1 = (key1[1]-1)*numIntervals+t+1
                    AffectedPopulation[(int(key[0]),51,t1)] =
                                                int(settings['weightAirport']*value1)

    #call STRR
    iterSol = STRR(SourceNodes, DemandNodes, CountynPopulation,
                Edgelist,EdgeMST, TimePeriods,AffectedPopulation,EdgeWorkload)

    return iterSol
```

B.3 AIR.py

```
"""
Created on Mon Aug  5 15:16:46 2019
@author: lbdavis
"""

from gurobipy import *
import numpy as np
import pandas as pd

#read route availability from inputfile
#RoutePass = pd.read_excel("inputfile.xlsx",index=0)
RoutePass = pd.read_excel("R3.xlsx",sheet_name="Routes", index_col=0)

#Define input parameters

[Numflights,Numslots] = RoutePass.shape
OriginalSched = [13,14,17]
#OriginalSched =
pd.read_excel("R3.xlsx",index=0,sheet_name="Original",usecols=[1])
#OriginalSched.values.tolist()
SlotOriginal = np.zeros(Numflights)
```

```
#define original schedule for flights
for (index,val) in enumerate(OriginalSched):
   SlotOriginal[index] = val-1
print(SlotOriginal)

#create new model
m = Model("mip1")

#define variables
y=m.addVars(Numflights,Numslots,vtype=GRB.BINARY,name="y")

m.update()
#define constraints
#define constraints (1)

for tidx in range(0,Numslots):
   expr1 = LinExpr()
   for fidx in range(0,Numflights):
      expr1 += y[fidx,tidx]
   m.addConstr(expr1,GRB.LESS_EQUAL,1)
m.update()
#define constraints(2)
for fidx in range(0,Numflights):
   expr2 = LinExpr()
   for tidx in range(0,Numslots):
      expr2 += RoutePass.iloc[fidx,tidx]*y[fidx,tidx]
   m.addConstr(expr2==1)

#define constraints (3)
for fidx in range(0,Numflights):
   for tidx in range(0,Numslots):
      if tidx <= OriginalSched[fidx]:
         m.addConstr(y[fidx,tidx]==0)

#define objective
obj = 0
for fidx in range(0,Numflights):
```

```
    for tidx in range(0,Numslots):
        obj += 30*(tidx-SlotOriginal[fidx])*y[fidx,tidx]

m.setObjective(obj,GRB.MINIMIZE)
m.update()
m.optimize()
m.write("file.lp")

#get results
print('Objective function value:',m.objVal)
#print variable values
for v in m.getVars():
    print(v.varname, v.x)
```

B.4 FlightAssign.mod

```
set Flights;
set Counties;

#parameters
param Capacity{Flights}; #capacity for each flight
param SamplePopulation{Counties}; #population of potential flyers in each county
#param M; # upper bound on people assigned to flight
#param M2; # lower bound on people assigned to flight

#decision variables
var x{Counties,Flights} integer ; # number of people from county assigned to a flight
var z{Counties,Flights} binary;  #1 if people from county c assigned to a flight, 0
otherwise
var totalsched >=0;

#objective function
minimize objfun:  #maximize assignments
        sum{c in Counties, f in Flights} z[c,f];

#constraints

#Do not assign more people from a county than is possible
```

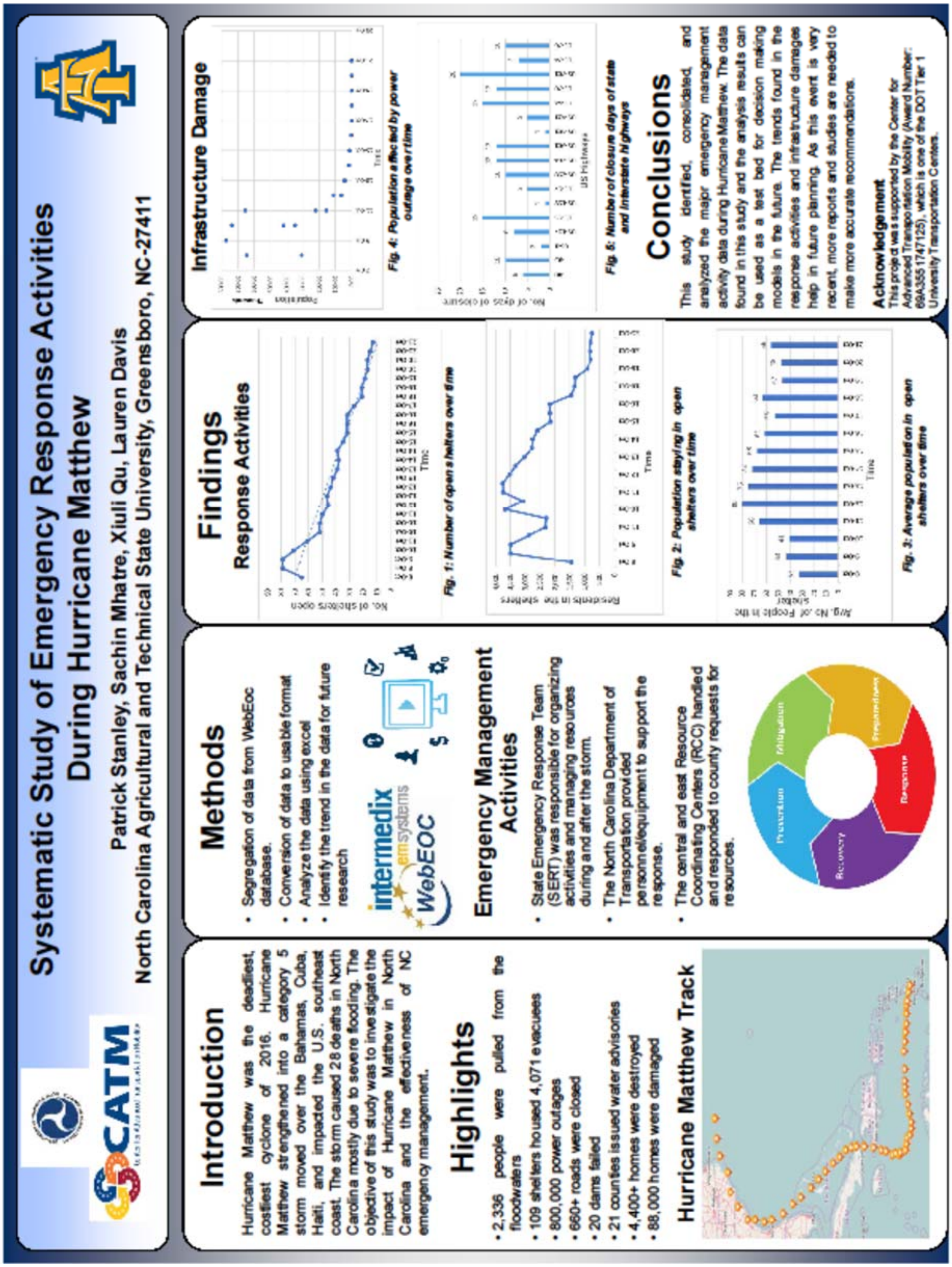
```
subject to CountyCapacity {c in Counties}:
        sum{f in Flights} x[c,f] <= SamplePopulation[c];

#Do not assign more people to flight than there is seat capacity on the flight
subject to FlightCapacity {f in Flights}:
        sum{c in Counties} x[c,f] <= Capacity[f];

#At least 50 % of capacity on the flight is used
subject to minFlightCapacity {f in Flights}:
        sum{c in Counties} x[c,f] >= 0.5*Capacity[f];

#Determine upper bound on population assigned to flight
        subject to boundUpper {c in Counties, f in Flights}:
        x[c,f] <= 209*z[c,f];

#Determine upper bound on population assigned to flight
        subject to CountyAssignmentub {c in Counties, f in Flights}:
        x[c,f] >= 2*z[c,f];

#ensure flight has diversity
subject to FlightDiversity {f in Flights}:
sum{c in Counties}z[c,f] >= 3;

#calculate total passengers scheduled
subject to totalpassengers:
        sum{c in Counties, f in Flights} x[c,f] = totalsched;
```

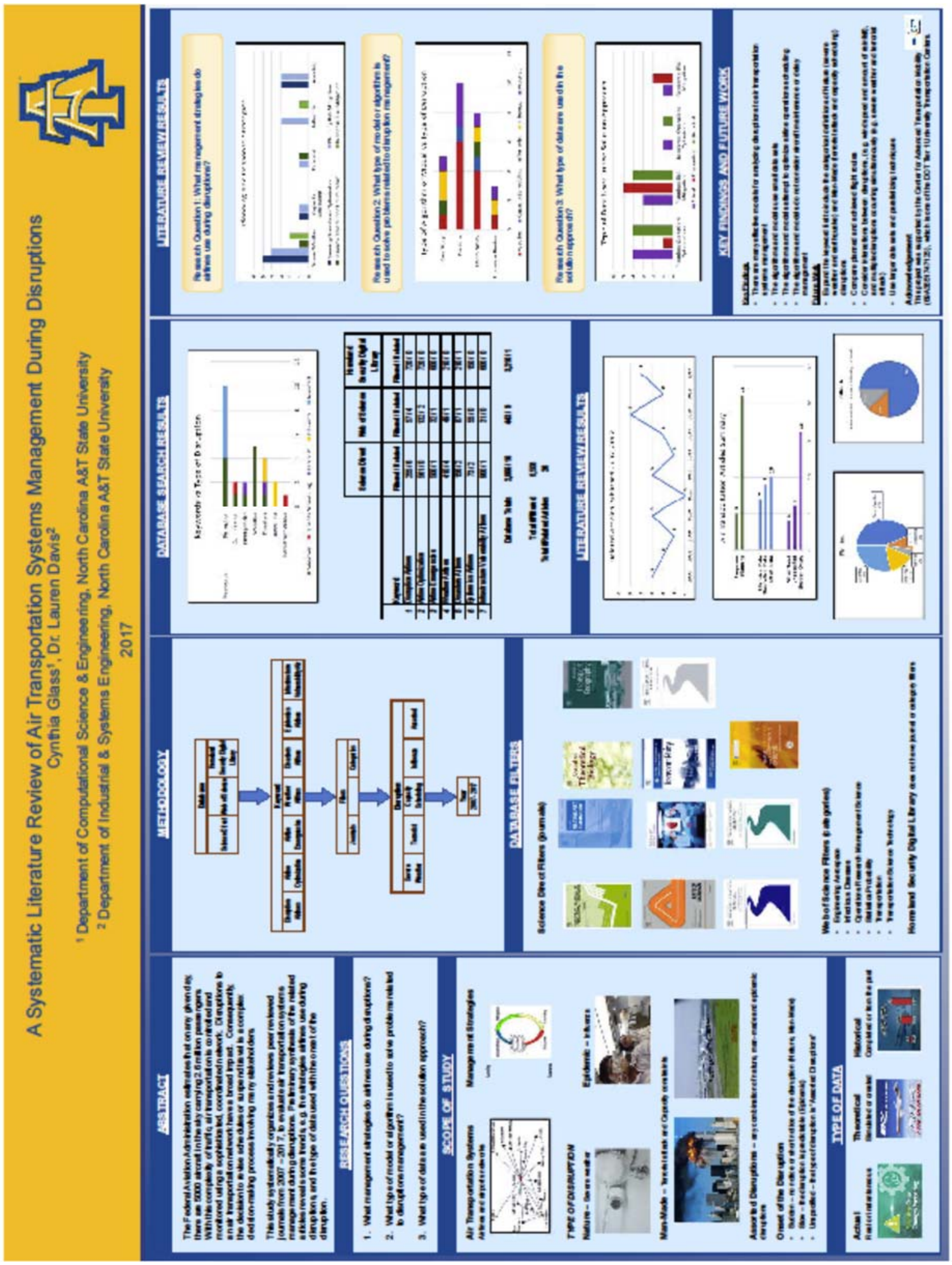
B.5 FlightAssign.mod

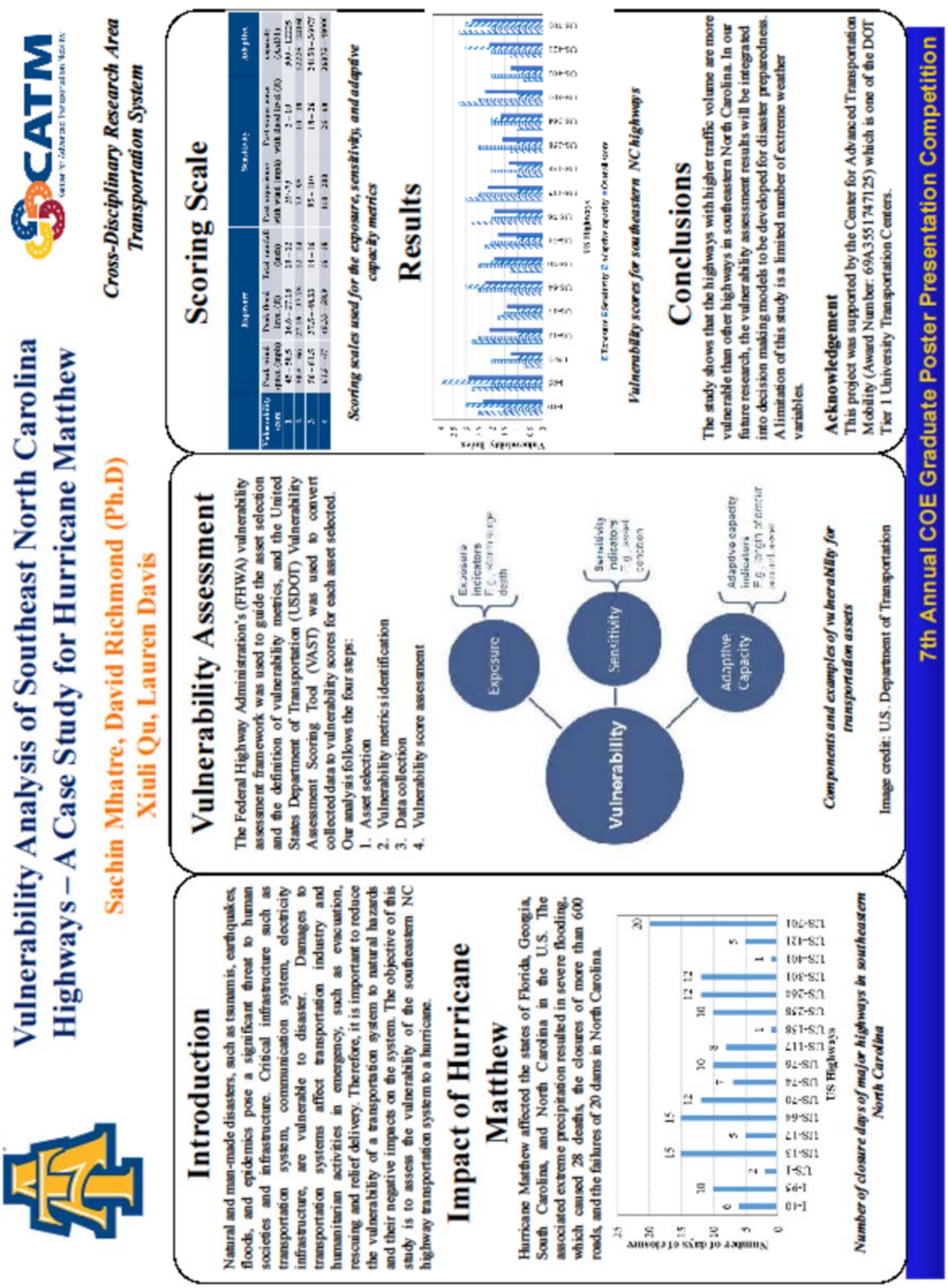
```
#set declaration
set Flights;                    # set of flights
set Counties;                   #set of counties

#parameter declaration
param T >=0;                            #time horizon or number of Slots
param N;                                # number of gates
param pop{Counties,Flights}; # number of people from county C scheduled for flight
f
```

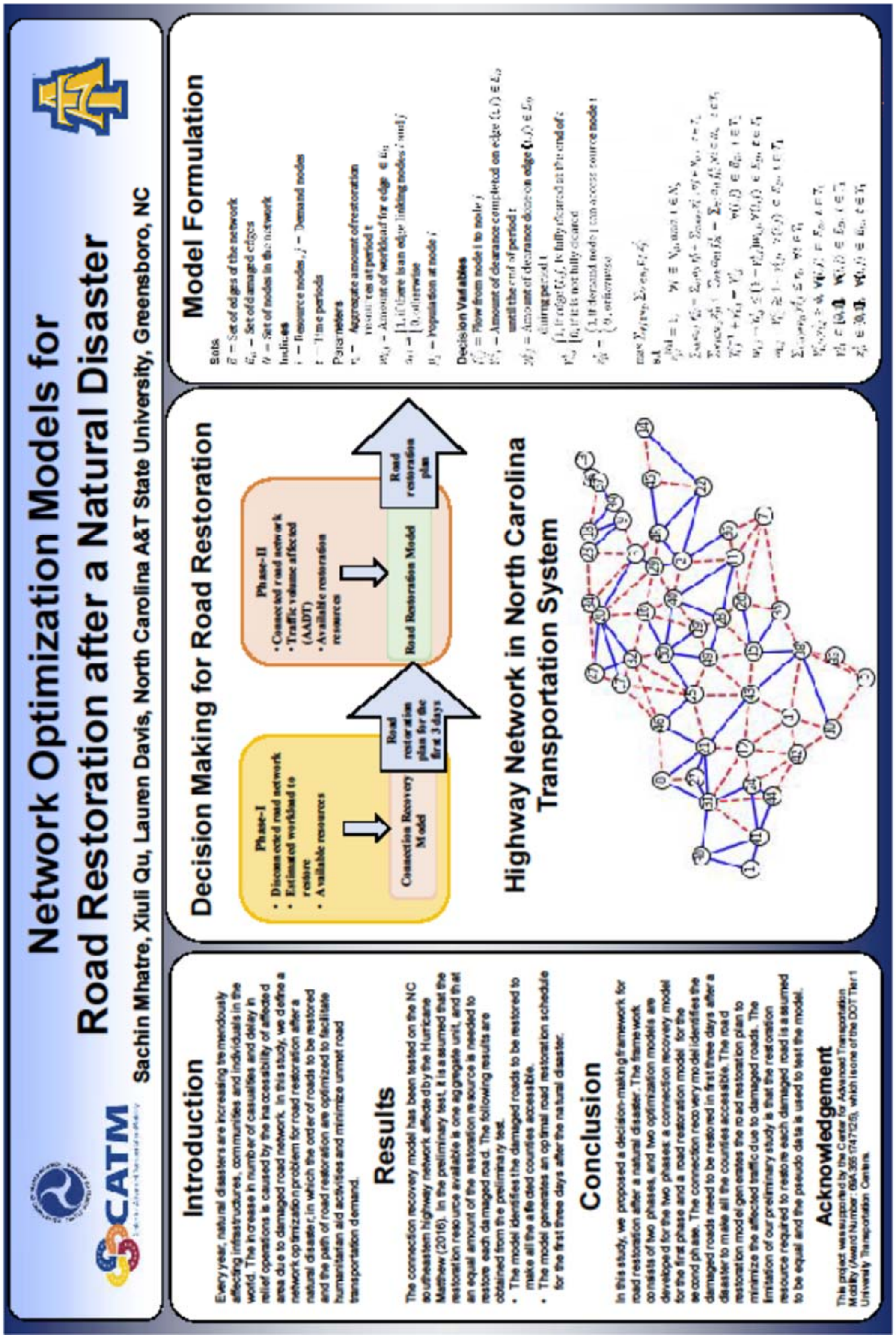
```
param r{Counties,1..T}; #road passability constraints

#variable declaration
var y{Flights, 1..T} binary;  # assignment of flights to slots
var numpass{Flights,1..T} >=0;
var numflyers{1..T} >=0;

#model declaration
minimize delaytime:
        sum{f in Flights, t in 1..T} t*y[f,t];

subject to maxflightassigned {t in 1..T-1}:
        sum{f in Flights} y[f,t] <= N;

subject to requiredassign {f in Flights}:
        sum{t in 1..T} y[f,t] = 1;

subject to roadpassability {f in Flights, t in 1..T}:
        sum {c in Counties}pop[c,f]*r[c,t] >= y[f,t]*0.5*sum{c in Counties}pop[c,f];

subject to numpasscons {t in 1..T, f in Flights}:
        sum{c in Counties}pop[c,f]*r[c,t] = numpass[f,t];
subject to numgood {t in 1..T}:
        sum{f in Flights}numpass[f,t]*y[f,t] = numflyers[t];
```

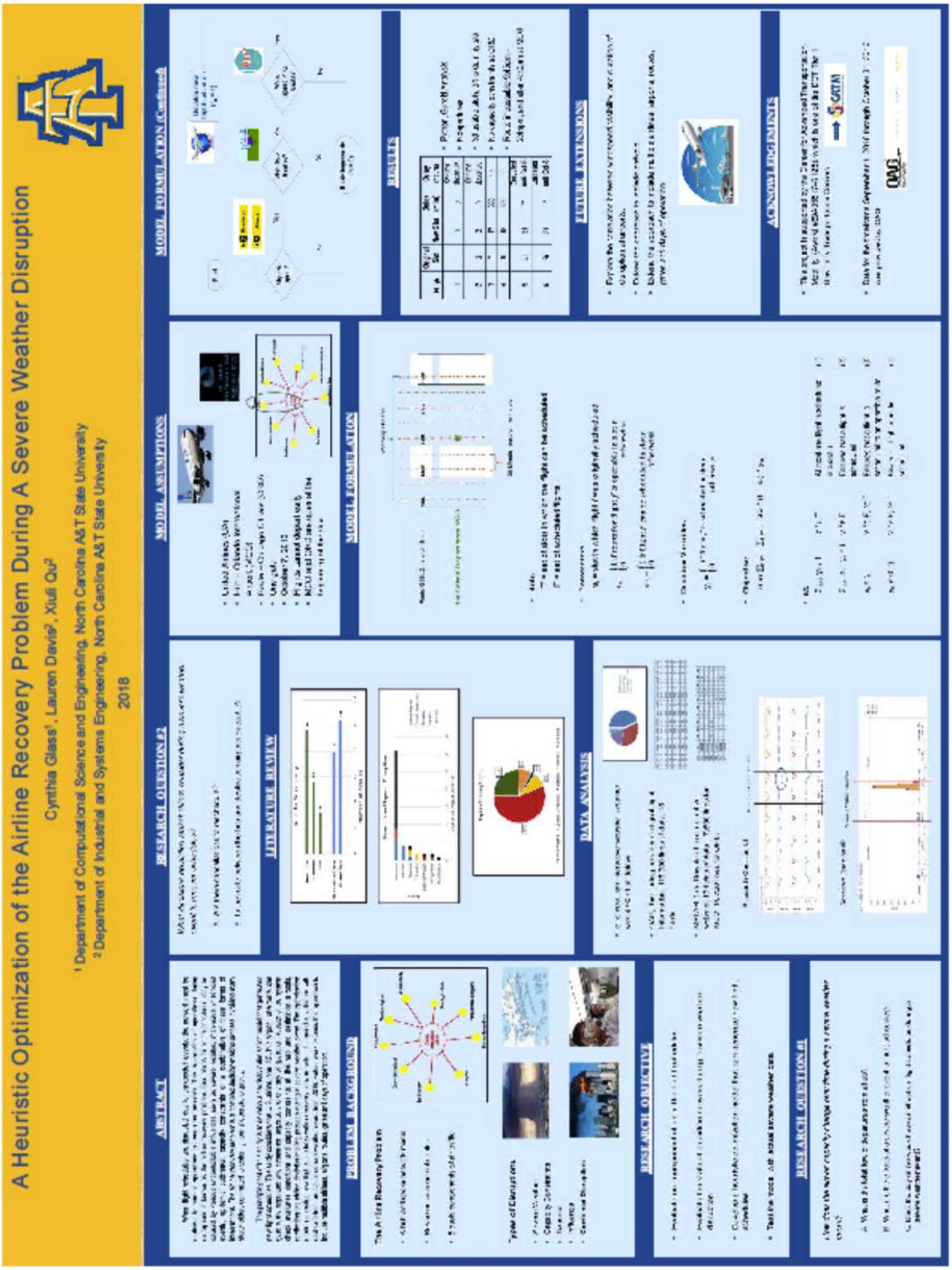
APPENDIX B: Posters and Presentation Slides

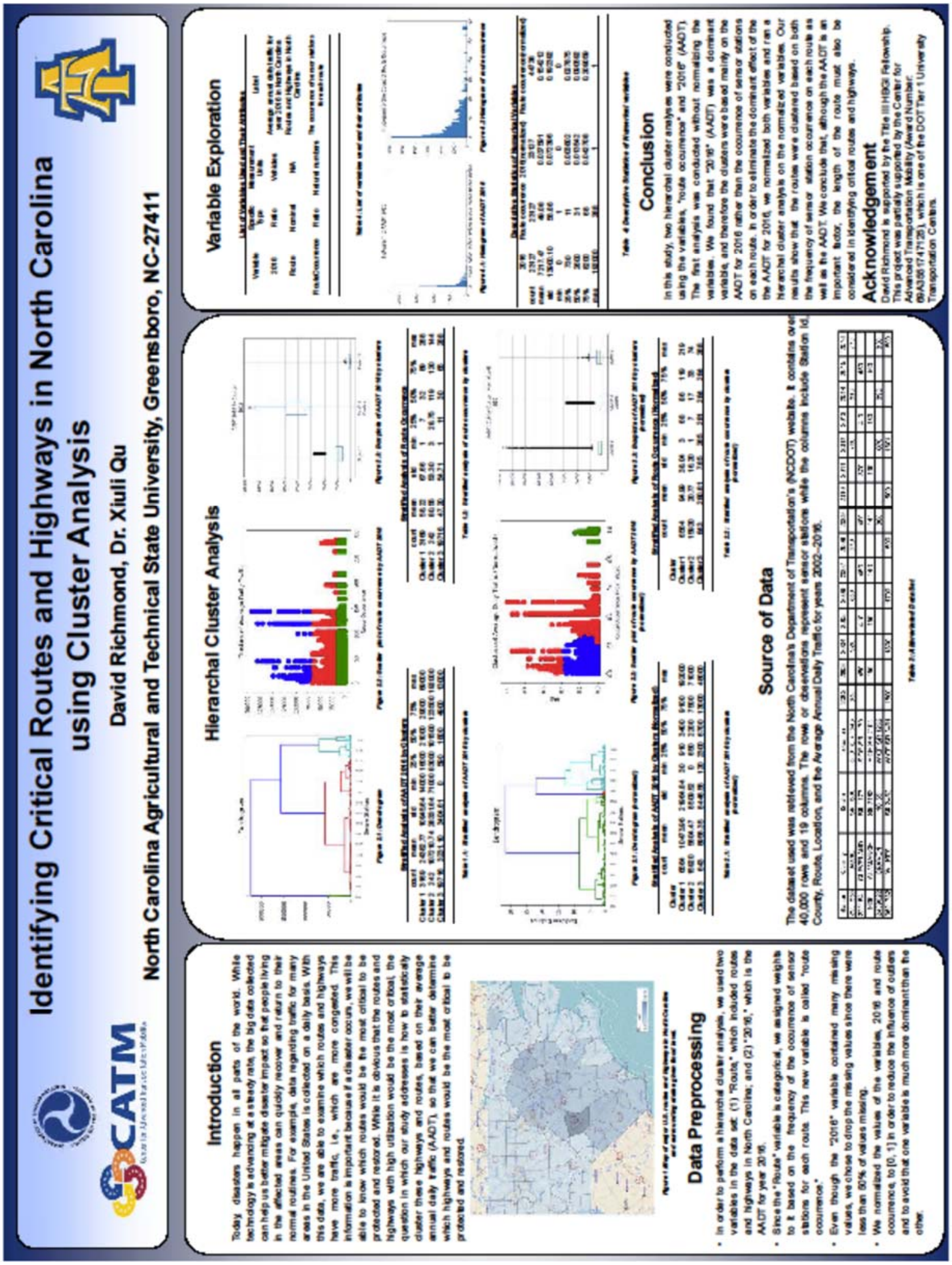



A Systematic Literature Review of Air Transportation Systems Management During Disruptions
Cynthia Glass[1], Dr. Lauren Davis[2]
[1] Department of Computational Science & Engineering, North Carolina A&T State University
[2] Department of Industrial & Systems Engineering, North Carolina A&T State University
2017
ABSTRACT
RESEARCH QUESTIONS
SCOPE OF STUDY
TYPE OF DATA
METHODOLOGY
DATABASE FILTERS
DATABASE SEARCH RESULTS
LITERATURE REVIEW RESULTS
KEY FINDINGS AND FUTURE WORK


Vulnerability Analysis of Southeast North Carolina Highways – A Case Study for Hurricane Matthew
Sachin Mhatre, David Richmond (Ph.D)
Xiuli Qu, Lauren Davis
CATM
Cross-Disciplinary Research Area
Transportation System
Introduction
Natural and man-made disasters, such as tsunamis, earthquakes, floods, and epidemics pose a significant threat to human societies and infrastructure. Critical infrastructure such as transportation system, communication system, electricity infrastructure, are vulnerable to disaster. Damages to transportation systems affect transportation industry and humanitarian activities in emergency, such as evacuation, rescuing and relief delivery. Therefore, it is important to reduce the vulnerability of a transportation system to natural hazards and their negative impacts on the system. The objective of this study is to assess the vulnerability of the southeastern NC highway transportation system to a hurricane.
Impact of Hurricane Matthew
Hurricane Matthew affected the states of Florida, Georgia, South Carolina, and North Carolina in the U.S. The associated extreme precipitation resulted in severe flooding, which caused 28 deaths, the closures of more than 600 roads, and the failures of 20 dams in North Carolina.
Number of days of closure
US Highways
I-40
I-95
US-1
US-13
US-17
US-64
US-70
US-74
US-76
US-117
US-158
US-258
US-264
US-301
US-401
US-421
US-701
Number of closure days of major highways in southeastern North Carolina
Vulnerability Assessment
The Federal Highway Administration's (FHWA) vulnerability assessment framework was used to guide the asset selection and the definition of vulnerability metrics, and the United States Department of Transportation (USDOT) Vulnerability Assessment Scoring Tool (VAST) was used to convert collected data to vulnerability scores for each asset selected.
Our analysis follows the four steps:
1. Asset selection
2. Vulnerability metrics identification
3. Data collection
4. Vulnerability score assessment
Vulnerability
Exposure
Sensitivity
Adaptive Capacity
Exposure indicators
Sensitivity indicators
Adaptive capacity indicators
Components and examples of vulnerability for transportation assets
Image credit: U.S. Department of Transportation
Scoring Scale
Exposure
Sensitivity
Adaptive
Scoring scales used for the exposure, sensitivity, and adaptive capacity metrics
Results
US Highways
Vulnerability scores for southeastern NC highways
Conclusions
The study shows that the highways with higher traffic volume are more vulnerable than other highways in southeastern North Carolina. In our future research, the vulnerability assessment results will be integrated into decision making models to be developed for disaster preparedness. A limitation of this study is a limited number of extreme weather variables.
Acknowledgement
This project was supported by the Center for Advanced Transportation Mobility (Award Number: 69A3551747125) which is one of the DOT Tier 1 University Transportation Centers.
7th Annual COE Graduate Poster Presentation Competition


Network Optimization Models for
Road Restoration after a Natural Disaster
CATM
Sachin Mhatre, Xiuli Qu, Lauren Davis, North Carolina A&T State University, Greensboro, NC
Introduction
Every year, natural disasters are increasing tremendously affecting infrastructures, communities and individuals in the world. The increase in number of casualties and delay in relief operations is caused by the inaccessibility of affected area due to damaged road network. In this study, we define a network optimization problem for road restoration after a natural disaster, in which the order of roads to be restored and the path of road restoration are optimized to facilitate humanitarian aid activities and minimize unmet road transportation demand.
Results
The connection recovery model has been tested on the NC southeastern highway network affected by the Hurricane Matthew (2016). In the preliminary test, it is assumed that the restoration resource available is one aggregate unit, and that an equal amount of the restoration resource is needed to restore each damaged road. The following results are obtained from the preliminary test.
• The model identifies the damaged roads to be restored to make all the affected counties accessible.
• The model generates an optimal road restoration schedule for the first three days after the natural disaster.
Conclusion
In this study, we proposed a decision-making framework for road restoration after a natural disaster. The framework consists of two phases, and two optimization models are developed for the two phases: a connection recovery model for the first phase and a road restoration model for the second phase. The connection recovery model identifies the damaged roads need to be restored in first three days after a disaster to make all the counties accessible. The road restoration model generates the road restoration plan to minimize the affected traffic due to damaged roads. The limitation of our preliminary study is that the restoration resource required to restore each damaged road is assumed to be equal and the pseudo data is used to test the model.
Acknowledgement
This project was supported by the Center for Advanced Transportation Mobility (Award Number: 69A3551747125), which is one of the DOT Tier 1 University Transportation Centers.
Decision Making for Road Restoration
Phase-I
• Disconnected road network
• Estimated workload to restore
• Available resources
Connection Recovery Model
Road restoration plan for the first 3 days
Phase-II
• Connected road network
• Traffic volume affected (AADT)
• Available restoration resources
Road Restoration Model
Road restoration plan
Highway Network in North Carolina Transportation System
Model Formulation
Sets
Indices
Parameters
Decision Variables


A Heuristic Optimization of the Airline Recovery Problem During A Severe Weather Disruption
Cynthia Glass¹, Lauren Davis², Xiuli Qu²
¹ Department of Computational Science and Engineering, North Carolina A&T State University
² Department of Industrial and Systems Engineering, North Carolina A&T State University
2018
ABSTRACT
PROBLEM BACKGROUND
RESEARCH OBJECTIVE
RESEARCH QUESTION #1
RESEARCH QUESTION #2
LITERATURE REVIEW
DATA ANALYSIS
MODEL ASSUMPTIONS
MODEL FORMULATION
MODEL FORMULATION (Continued)
RESULTS
FUTURE EXTENSIONS
ACKNOWLEDGEMENTS



Identifying Critical Routes and Highways in North Carolina using Cluster Analysis
David Richmond, Dr. Xiuli Qu
North Carolina Agricultural and Technical State University, Greensboro, NC-27411
CATM
Introduction
Today, disasters happen in all parts of the world. While technology is advancing at a steady rate, the big data collected can help us better mitigate disaster impact so that people living in the affected areas can quickly recover and return to their normal routines. For example, data regarding traffic for many areas in the United States is collected on a daily basis. With this data, we are able to examine which routes and highways have more traffic, i.e., which are more congested. This information is important because if a disaster occurs, we will be able to know which routes would be the most critical to be protected and restored. While it is obvious that the routes and highways with high utilization would be the most critical, the question in which our study addresses is how to statistically cluster these highways and routes, based on their average annual daily traffic (AADT), so that we can better determine which highways and routes would be the most critical to be protected and restored.
Data Preprocessing
In order to perform a hierarchal cluster analysis, we used two variables in the data set: (1) "Route," which included routes and highways in North Carolina; and (2) "2016," which is the AADT for year 2016.
Since the "Route" variable is categorical, we assigned weights to it based on the frequency of the occurrence of sensor stations for each route. This new variable is called "route occurrence."
Even though the "2016" variable contained many missing values, we chose to drop the missing values since there were less than 60% of values missing.
We normalized the values of the variables, 2016 and route occurrence, to [0, 1] in order to reduce the influence of outliers and to avoid that one variable is much more dominant than the other.
Hierarchal Cluster Analysis
Source of Data
The dataset used was retrieved from the North Carolina's Department of Transportation's (NCDOT) website. It contains over 40,000 rows and 19 columns. The rows or observations represent sensor stations while the columns include Station Id, County, Route, Location, and the Average Annual Daily Traffic for years 2002–2016.
Variable Exploration
Conclusion
In this study, two hierarchal cluster analyses were conducted using the variables, "route occurrence" and "2016" (AADT). The first analysis was conducted without normalizing the variables. We found that "2016" (AADT) was a dominant variable, and therefore the clusters were based mainly on the AADT for 2016 rather than the occurrence of sensor stations on each route. In order to eliminate the dominant effect of the the AADT for 2016, we normalized both variables and ran a hierarchal cluster analysis on the normalized variables. Our results show that the routes were clustered based on both the frequency of sensor station occurrence on each route as well as the AADT. We conclude that, although the AADT is an important factor, the length of the route must also be considered in identifying critical routes and highways.
Acknowledgement
David Richmond is supported by the Title III HBGI Fellowship. This project was partially supported by the Center for Advanced Transportation Mobility (Award Number: 69A3551747125), which is one of the DOT Tier 1 University Transportation Centers.

Study of Evacuation Activities During Hurricane Irma

Theanna Drennon, Sachin Mhatre, Xiuli Qu
North Carolina Agricultural and Technical State University, Greensboro, NC-27411

Introduction

Hurricane Irma was the deadliest, costliest cyclone of 2017. Hurricane Irma strengthened into a category 5 storm moved over Cape Verde, Leeward Island, Greater Antilles, Turks and Caicos Islands, The Bahamas, and impacted the U.S. southeast coast. The storm caused 7 million evacuations throughout the impacted areas due to severe flooding and strong winds. The objective of this study was to investigate the evacuation of Hurricane Irma in the impacted areas and the effectiveness of their evacuation preparation and response activities.

Fig. 1 Track of Hurricane Irma

Fig. 2 Risks of Lives and Property

Impacts of Hurricane Irma

- At 07:59 Eastern time on September 10th Irma hit the United States with a wind gust of 93 mph in Florida.
- From Florida Irma moved throughout GA and SC.
- $13.5 – 19 billion in insured loss due to wind damages.
- At least 134 deaths, 92 in the United States
- Nearly 6.9 Million left without power in Florida, Georgia, North Carolina, South Carolina, and Alabama
- After the hurricane highway A1A was mostly sand, water, and debris.
- Roads off Hollywood Boulevard were flooded.
- Sheridan Street Bridge was closed along with State Road 80 due to transmission lines.
- Property damage was $42.5-$65 billion.

Acknowledgement

This project was supported by the Center for Advanced Transportation Mobility (Award Number: 69A3551747125), which is one of the DOT Tier 1 University Transportation Centers.

Hurricane Irma Evacuation

- Evacuation orders were issued to 39 counties in Florida, 24 mandatory and 15 voluntary ones.
- Nearly 7 million people evacuated their homes.
- Allowed to use the left shoulder as a lane for moving traffic on northbound Interstate 75 from Wildwood
- Suspended tolls on all toll roads in Florida
- Before the storm many gas stations in the Gainesville and Miami-Fort Lauderdale areas were out of fuel.
- Gas was 53 cents higher, making each gallon $2.73.

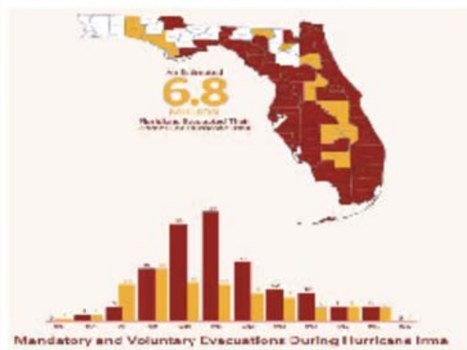


Fig. 3 Evacuation of Florida

Lessons Learned from Evacuation

- Make sure to have an evacuation plan before having to evacuate under mandatory orders, including alternative routes
- Have supplies and gear ready to go instead of trying to gather last minute
- Leave as early as possible
- Residents get nervous and evacuate all at once, causing massive traffic issues.

Fig. 4 Traffic

Lessons Learned from Irma

- Keep battery-operated fans
- Test your generator before each hurricane season
- Allow utility companies to remove or trim trees. This could cause less power outages in the future.
- There needs to be better coordination and centralizing the flow of information within the JAC.
- Provide training and assistance to the people served related to emergency management planning
- Develop a list of emergency coordinating officers
- Deliver more direct assistance and resources to different entities

Fig. 5 Power Outages

References

Fig. 1. http://mobile.wunderground.com/hurricane/atlantic/2017/tropical-storm-irma
Fig. 2: https://www.accuweather.com/en/weather-news/hurricane-irma-to-lash-georgia-to-the-carolinas-with-damaging-winds-flooding-and-severe-weather/70002868
Fig. 3: http://fl-counties.com/sites/default/files/2018-02/Evacuations%20Report.pdf
Fig. 4: http://www.chicagotribune.com/news/nationworld/ct-hurricane-irma-evacuations-traffic-20170907-story.html
Fig. 5: https://patch.com/florida/miami/sthurricane-irma-almost-3-million-predicted-be-without-power-florida-southea

Integrated Decision-Making Model for the Restoration of Air and Road Transportation Systems after a Hurricane

Xiuli Qu, Lauren Davis, Sachin Mhatre, Cynthia Glass

North Carolina Agricultural and Technical State University, Greensboro, NC

Introduction

Natural disasters, such as hurricanes, winter storms and floods, usually cause significant disruptions to transportation systems. These disruptions directly affect humanitarian activities during a disaster and may cause cascading impacts on other infrastructures and associated industries. Therefore, quick restoration and recovery of transportation systems play an important role in humanitarian operations and community recovery.

To support the restoration of transportation systems, our team has developed decision-making models for flight rescheduling and road restoration after a hurricane, and integrated the models to create a visual decision-making tool.

Motivation

Hurricane Matthew caused

- More than 600 roads were closed in NC, and some were closed up to 21 days.
- More than 5,000 flights were cancelled in the US, and some airports closed during October 5 – 9, 2016.

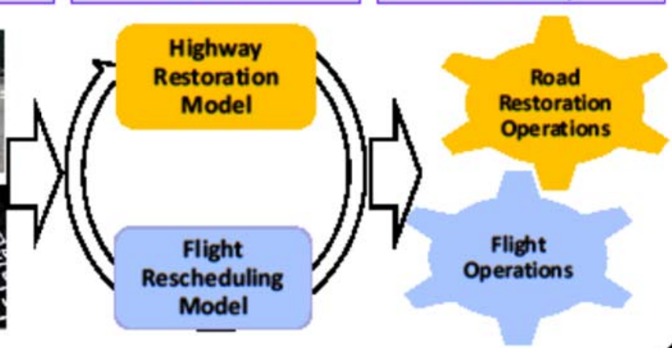
Conclusion

- The computational time of decision making for road restoration and flight schedules recovery for about 50 locations is within 5 minutes.
- The tool visualizes the damaged connections between counties, and counties disconnected from airports and regional coordinate centers.
- The tool also visualizes the road restoration schedule and flight schedules recovery.
- The model and tool were tested using the impact data from Hurricane Matthew (2016) on North Carolina.

Impact

Decision

Recovery

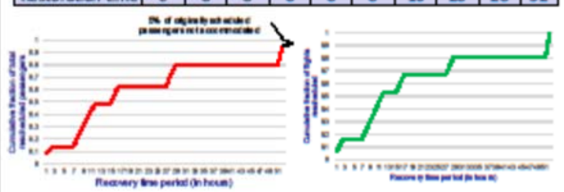


Results

								41	[illegible]
1	Anson	11	Craven	21	Harnett	31	Moore	42	Robeson
2	Beaufort	12	Cumberland	22	Hertford	32	Nash	43	Sampson
3	Bertie	13	Currituck	23	Hoke	33	New Hanover	44	Scotland
4	Bladen	14	Dare	24	Hyde	34	Northampton	45	Tyrrell
5	Brunswick	15	Duplin	25	Johnston	35	Onslow	46	Wake
6	Camden	16	Edgecombe	26	Jones	36	Pamlico	47	Warren
7	Carteret	17	Franklin	27	Lee	37	Pasquotank	48	Washington
8	Chatham	18	Gates	28	Lenoir	38	Pender	49	Wayne
9	Chowan	19	Greene	29	Martin	39	Perquimans	50	Wilson
10	Columbus	20	Halifax	30	Montgomery	40	Pitt	51	RDU

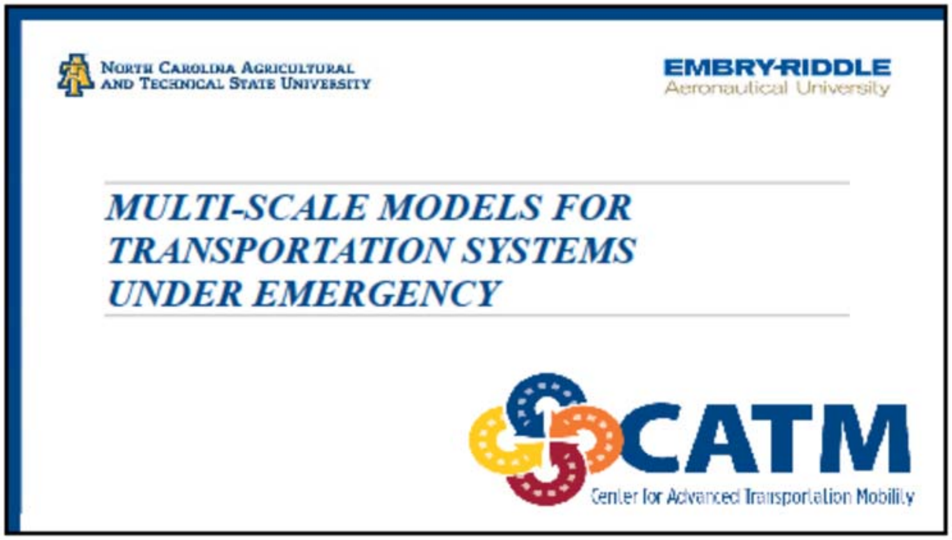
Restoration time for the path from counties to the airport (in hours)

County	43	2	14	20	34	36	12	13	23	7
Restoration time	0	8	8	8	8	8	16	28	28	52



Acknowledgement

This research was 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.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MULTI-SCALE MODELS FOR TRANSPORTATION SYSTEMS UNDER EMERGENCY
CATM
Center for Advanced Transportation Mobility

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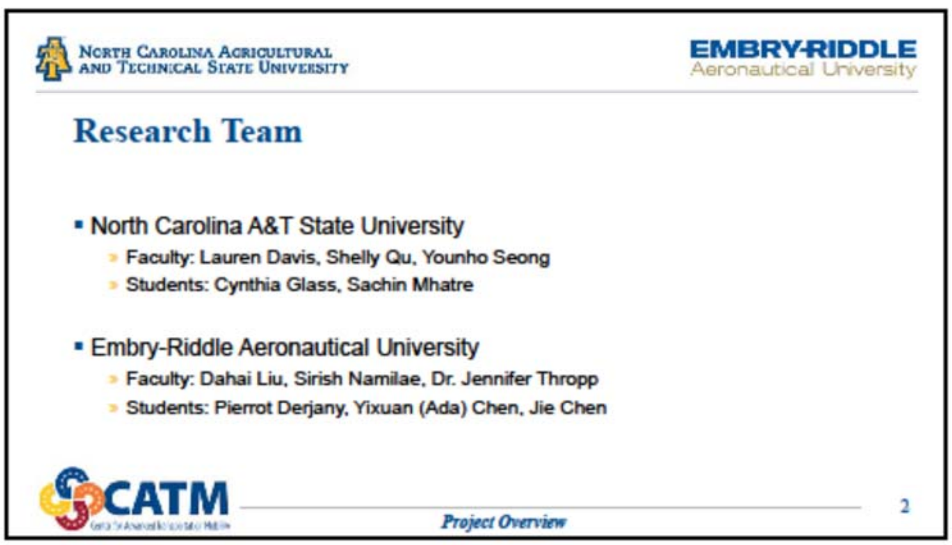
North Carolina Agricultural and Technical State University
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2

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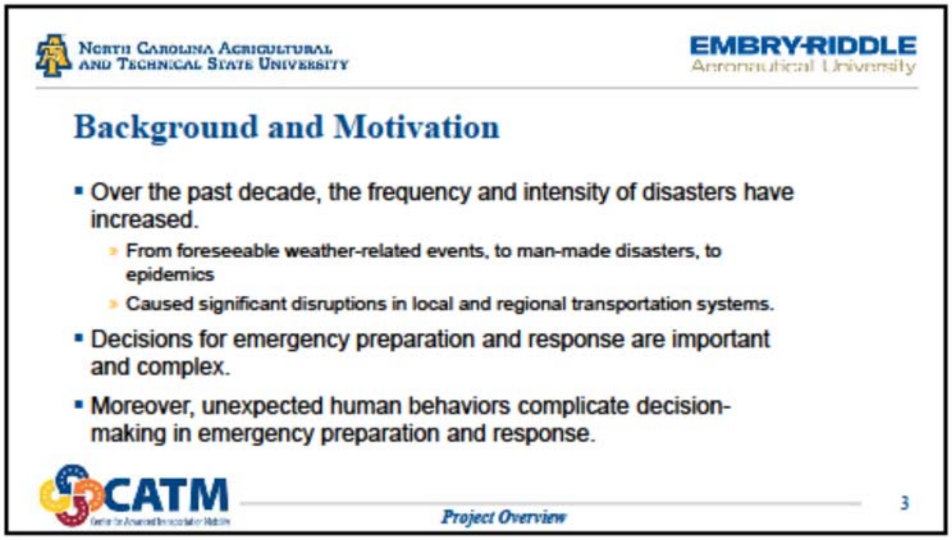
North Carolina Agricultural and Technical State University
EMBRY-RIDDLE Aeronautical University
Background and Motivation
▪ Over the past decade, the frequency and intensity of disasters have increased.
» From foreseeable weather-related events, to man-made disasters, to epidemics
» Caused significant disruptions in local and regional transportation systems.
▪ Decisions for emergency preparation and response are important and complex.
▪ Moreover, unexpected human behaviors complicate decision-making in emergency preparation and response.
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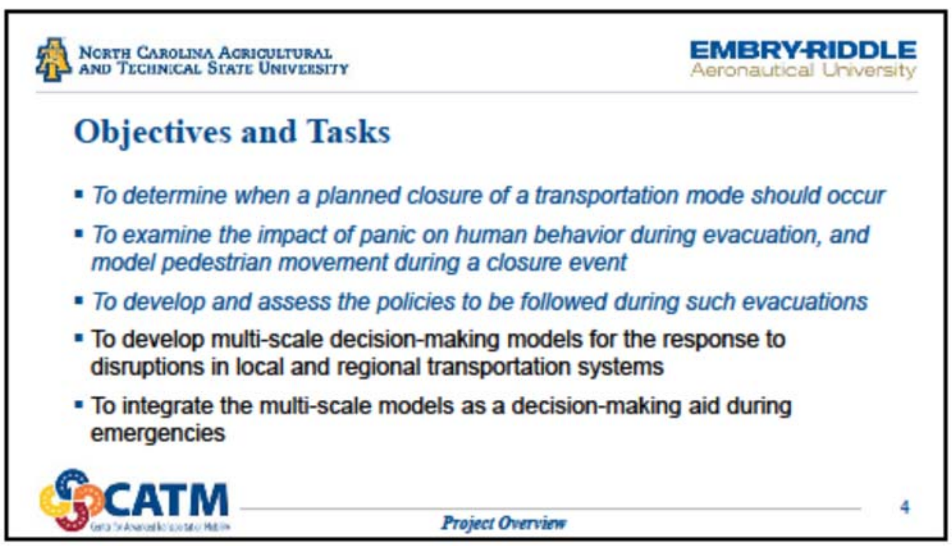
North Carolina Agricultural and Technical State University
EMBRY-RIDDLE Aeronautical University
Objectives and Tasks
▪ To determine when a planned closure of a transportation mode should occur
▪ To examine the impact of panic on human behavior during evacuation, and model pedestrian movement during a closure event
▪ To develop and assess the policies to be followed during such evacuations
▪ To develop multi-scale decision-making models for the response to disruptions in local and regional transportation systems
▪ To integrate the multi-scale models as a decision-making aid during emergencies
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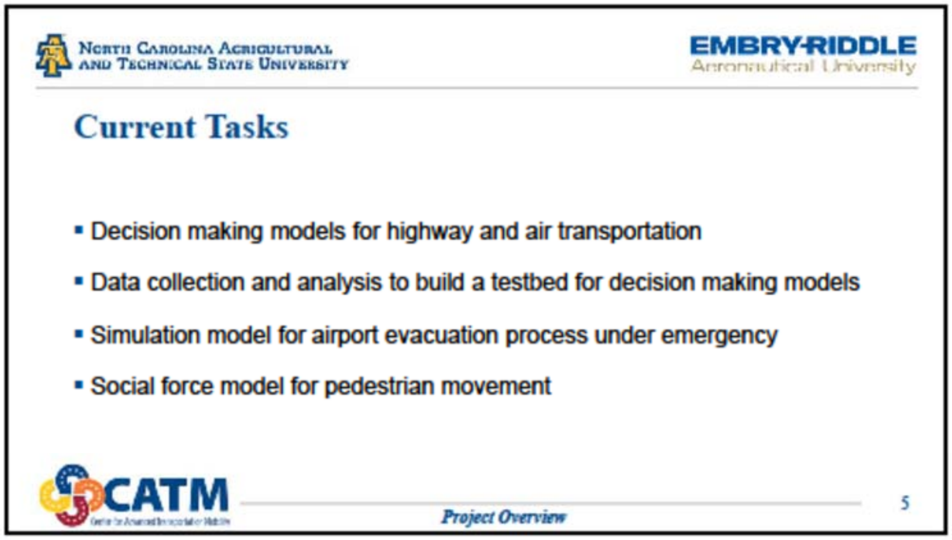
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Current Tasks
▪ Decision making models for highway and air transportation
▪ Data collection and analysis to build a testbed for decision making models
▪ Simulation model for airport evacuation process under emergency
▪ Social force model for pedestrian movement
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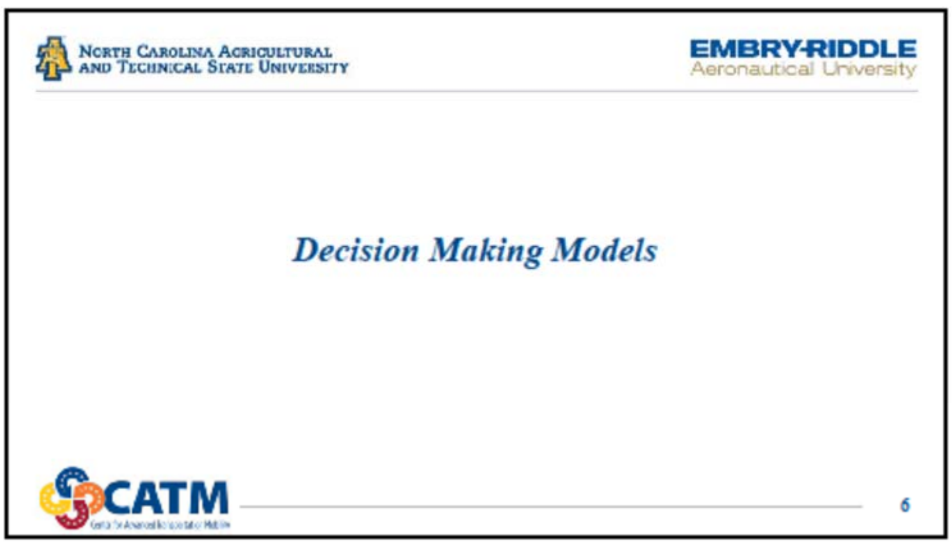
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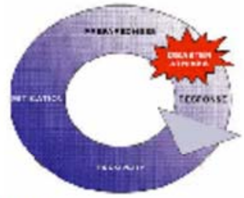
Disaster Operations Management

- Transportation system management during a disaster plays an important role in disaster operations.
  - Disaster operations are a set of activities of performed before, during and after a disaster to prevent loss of human life, reduce economic loss and return to a state of normal operations.
- Disaster management phases
  - Mitigation
  - **Preparedness**
  - **Response**
  - Recovery



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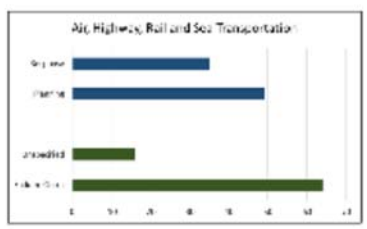
Literature Review

- Scope
  - Disaster types: Sudden onset including natural and man-made disasters
  - Disaster management phases: Preparedness and response
- Databases
  - Web of Science
  - Pre-Quest (ABI-INFORMS),
  - Science Direct
  - Compendex (Engineering Village 2)
  - Transportation Research Record
  - Homeland Security Digital Library
- Results



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Preparedness and Response Activities

- Preparedness Activities
  - Closure of transportation assets, such as airports, tunnels, bridges, and subways
  - Crew rescheduling, and flight cancellation and rescheduling
  - Airport asset relocation and protection
  - Highway contra-flow control and barricade
- Response Activities
  - Repair and restoration of highways and roads
  - Cleaning and reopening of transportation services, such as airlines, subways, bus

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Decision Making Models 9

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Decisions for Preparedness Activities

- What are the best times to start the protection activities for an airport before a hurricane?
- What is the best time to close an airport before a hurricane?
- What is the best policy to control lane access for contra-flows during a hurricane evacuation?

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Decision Making Models 10

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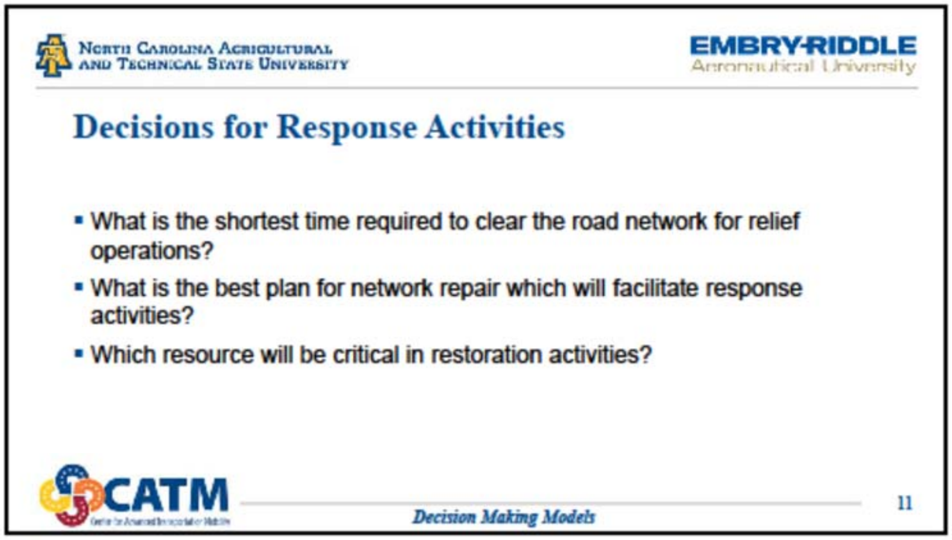
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Decisions for Response Activities
What is the shortest time required to clear the road network for relief operations?
What is the best plan for network repair which will facilitate response activities?
Which resource will be critical in restoration activities?
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Decision Making Models
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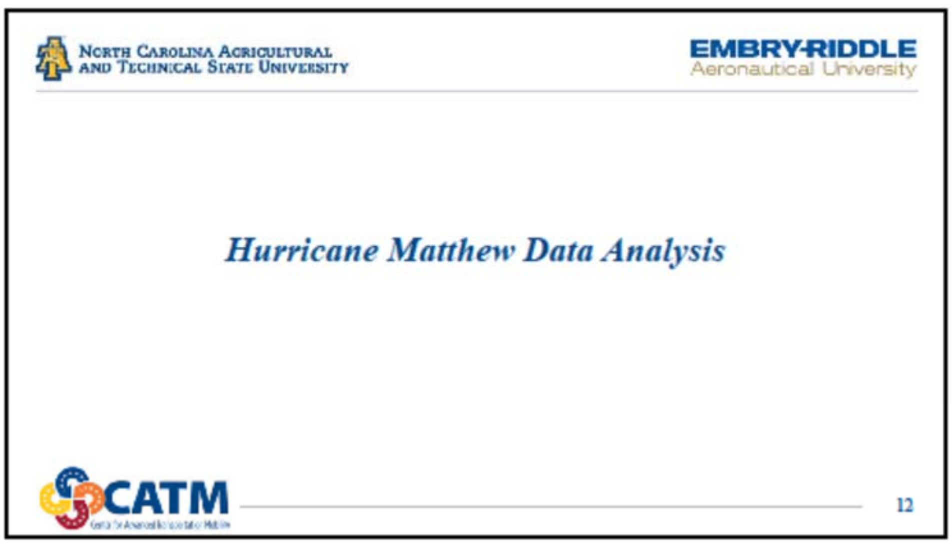
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Hurricane Matthew Data Analysis
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Introduction

- Hurricane Matthew was the deadliest, costliest cyclone of 2016.
- Damages in North Carolina
  - 28 deaths caused by severe flooding, and 2,336 people pulled from the floodwaters
  - 21 counties issued water advisories
  - 660+ roads were closed and 20 dams failed
  - 109 shelters housed 4,071 evacuees
  - 4,400+ homes were destroyed, and 88,000 homes were damaged.
  - 800,000 power outages

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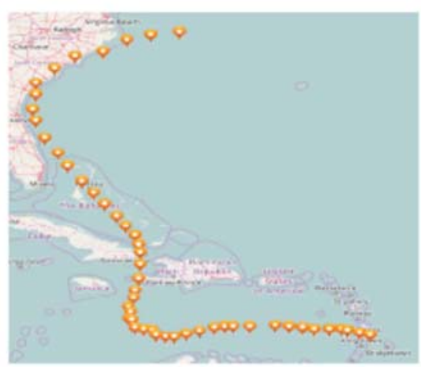
Methods

- Segregation of data from WebEoc database.
- Conversion of data to usable format
- Analyze the data using excel
- Identify the trend in the data for future research



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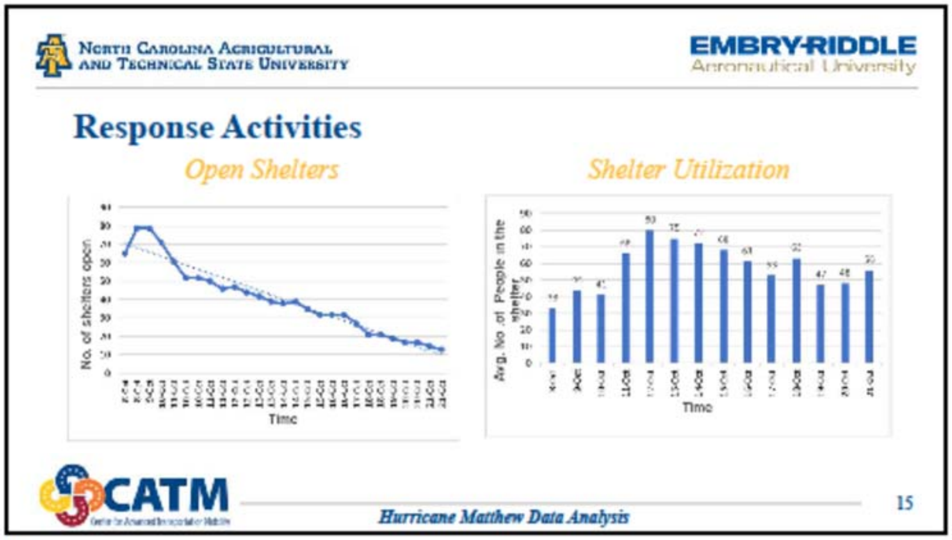
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Response Activities
Open Shelters
No. of shelters open
Time
Shelter Utilization
Avg. No. of People in the shelter
Time
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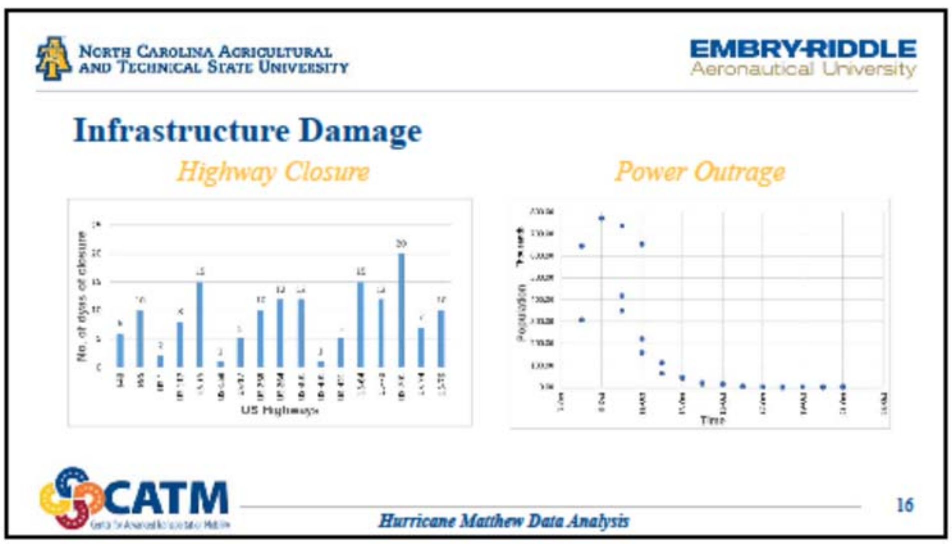
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Infrastructure Damage
Highway Closure
No. of dyas of closure
US Highways
Power Outrage
Population
Time
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Hurricane Matthew Data Analysis
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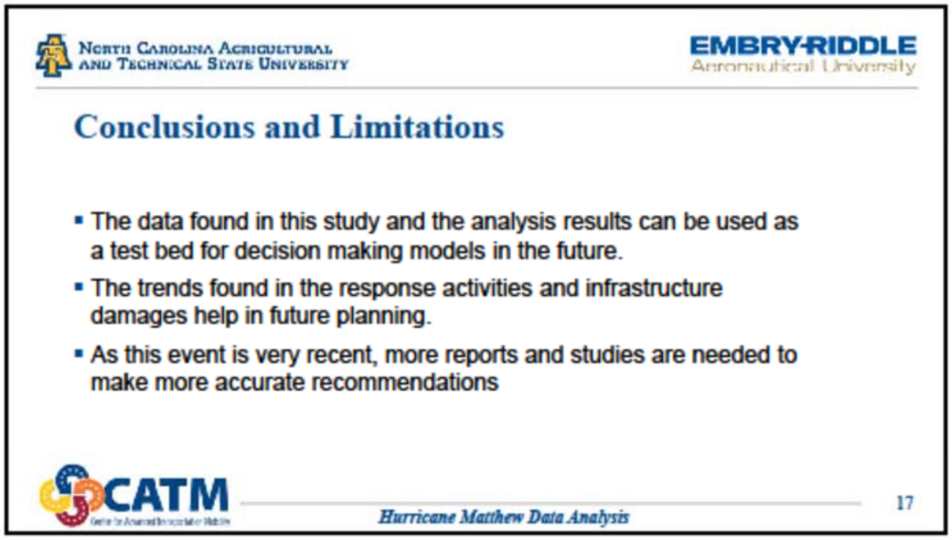
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Conclusions and Limitations
▪ The data found in this study and the analysis results can be used as a test bed for decision making models in the future.
▪ The trends found in the response activities and infrastructure damages help in future planning.
▪ As this event is very recent, more reports and studies are needed to make more accurate recommendations
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Hurricane Matthew Data Analysis
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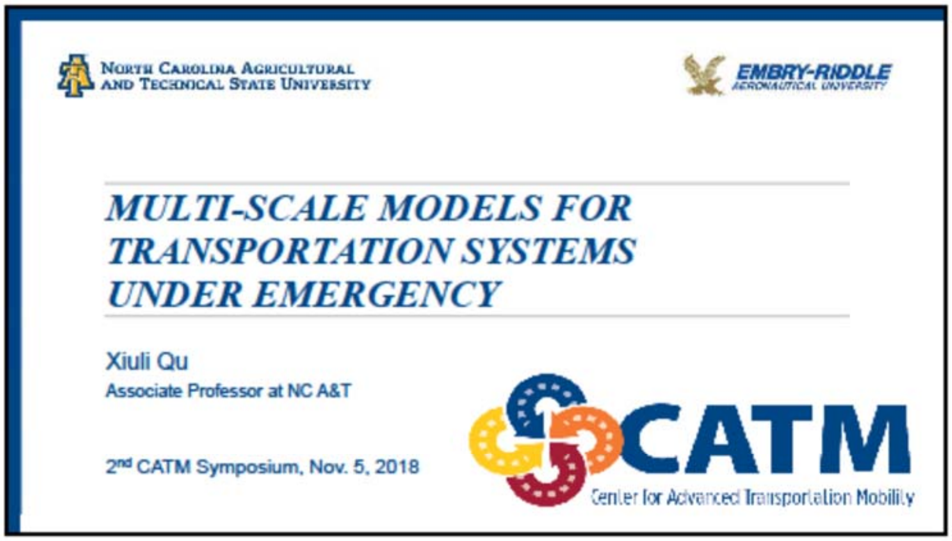
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MULTI-SCALE MODELS FOR TRANSPORTATION SYSTEMS UNDER EMERGENCY
Xiuli Qu
Associate Professor at NC A&T
2nd CATM Symposium, Nov. 5, 2018
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1


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Students: Jie Chen, Yixuan (Ada) Cheng, Pierrot Derjany, Kaiping Li
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Project Overview
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North Carolina Agricultural and Technical State University — Embry-Riddle Aeronautical University

Background and Motivation

- Increased natural disasters in terms of frequency and intensity
  - Recent major hurricanes: ***Matthew (2016)***
    Harvey (2017), ***Irma (2017)***, Maria (2017)
    Florence (2018), ***Michael (2018)***
  - Caused significant disruptions in local and regional transportation systems
- Decisions for emergency preparation and response are important and complex.
- Moreover, unexpected human behaviors complicate decision-making in emergency preparation and response.

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3

North Carolina Agricultural and Technical State University — Embry-Riddle Aeronautical University

Objectives and Tasks

- Thrust 1: Multi-transportation-mode decision-making models for emergency response in local and regional transportation systems
  - Developed multi-scale decision-making models for the response to disruptions in transportation systems
  - To incorporate human panic behavior in decision-making models for emergency response
- Thrust 2: Human behavior during an emergency
- To integrate the multi-scale models as a decision-making aid during emergencies

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Airline Recovery Problem During a Severe Weather Disruption

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5

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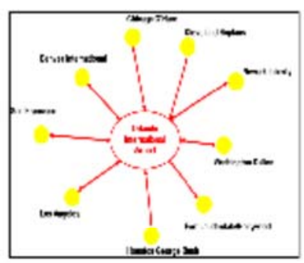
Airline Recovery Problem

- Airline Recovery Problem
  - A hub and spoke network model
  - Revise or suspend schedules
  - 5 basic components of air traffic
- Disruptions: **Severe Weather**, Influenza, Terrorist, Cyber Attacks, etc.



CATM

Airline Recovery Problem

6

6

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Research Objectives and Questions

- Problem Scope: One component of air traffic – Flight schedules
- Objectives
  - Evaluate the state of an airline network during a severe weather disruption
  - Develop a heuristic optimization model that can generate new flight schedules
  - Test the model with actual severe weather data
- Research Questions
  - How does the airport capacity change over time during a severe weather event?
  - How can airlines recover flight schedules affected a severe weather event?

CATM — *Airline Recovery Problem* — 7

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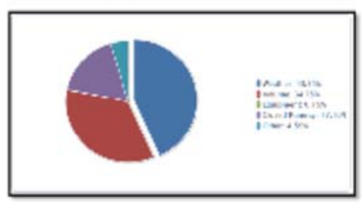
Data Sources

Three Databases

- BTS NAS, an interactive website. Weather was 43% of all delays.
- OAG, the leading provider of digital flight information. 116,000 lines of data, 15 fields.
- METAR Data Download, an interactive website. 19 fields of data. 17,600 lines for MCO, 18,720 lines for ORD.

Causes of National Aviation System Delays
All US Carriers and Airports (September – October 2018)



CATM — *Airline Recovery Problem* — 8

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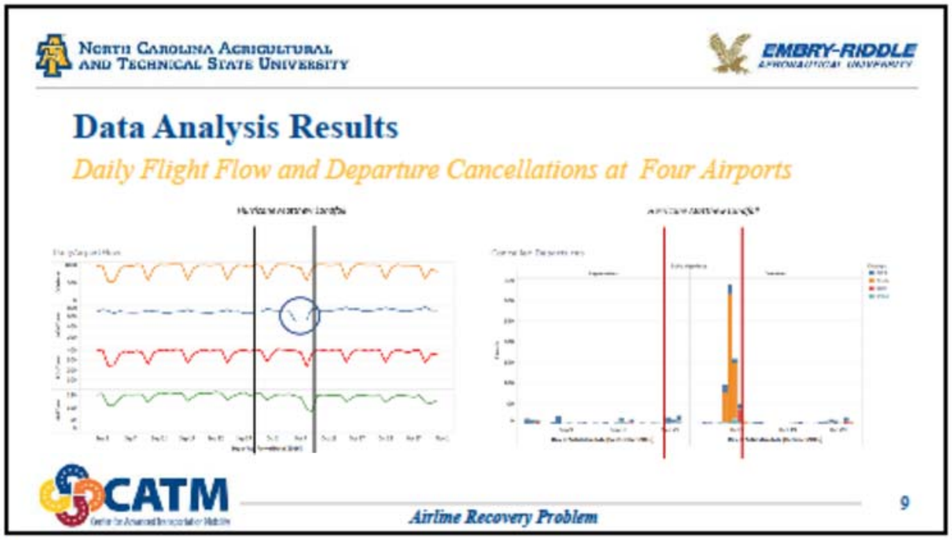
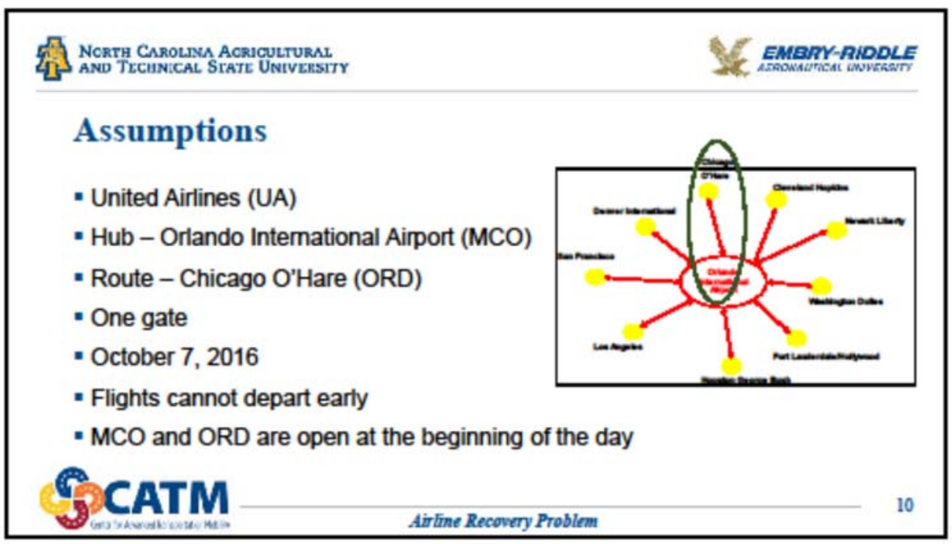
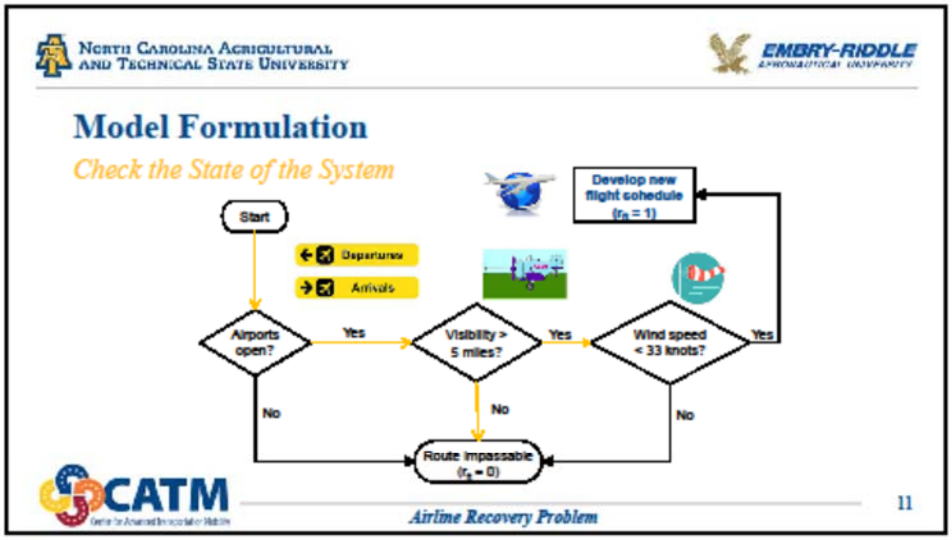

North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Data Analysis Results
Daily Flight Flow and Departure Cancellations at Four Airports
CATM
Airline Recovery Problem
9

9


North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Assumptions
▪ United Airlines (UA)
▪ Hub – Orlando International Airport (MCO)
▪ Route – Chicago O'Hare (ORD)
▪ One gate
▪ October 7, 2016
▪ Flights cannot depart early
▪ MCO and ORD are open at the beginning of the day
Chicago O'Hare
Cleveland Hopkins
Denver International
Newark Liberty
San Francisco
Washington Dulles
Los Angeles
Fort Lauderdale/Hollywood
CATM
Airline Recovery Problem
10

10


North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Model Formulation
Check the State of the System
Start
Departures
Arrivals
Airports open?
Yes
Visibility > 5 miles?
Yes
Wind speed < 33 knots?
Yes
Develop new flight schedule
No
No
No
Route impassable
CATM
Airline Recovery Problem
11

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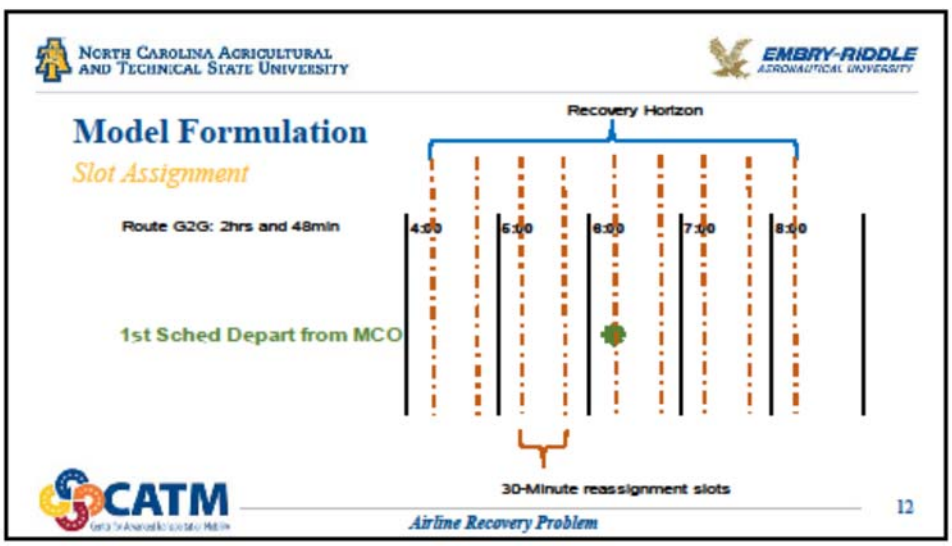
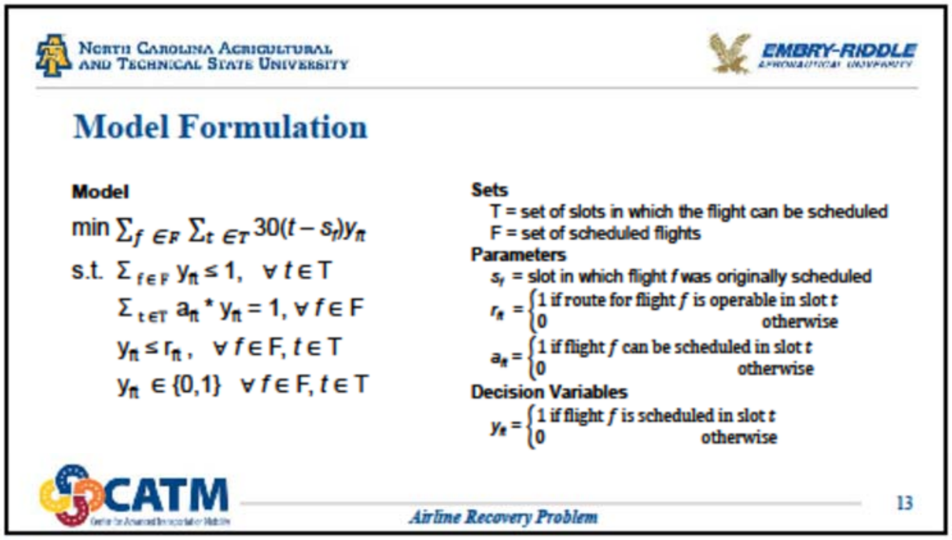

North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Model Formulation
Slot Assignment
Recovery Horizon
Route G2G: 2hrs and 48min
4:00
6:00
6:00
7:00
8:00
1st Sched Depart from MCO
30-Minute reassignment slots
CATM
Airline Recovery Problem
12

12


North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Model Formulation
Model
min ∑f ∈F ∑t ∈T 30(t – sf)yft
s.t. Σ f∈F yft ≤ 1, ∀ t ∈ T
Σ t∈T aft * yft = 1, ∀ f ∈ F
yft ≤ rft , ∀ f ∈ F, t ∈ T
yft ∈ {0,1} ∀ f ∈ F, t ∈ T
Sets
T = set of slots in which the flight can be scheduled
F = set of scheduled flights
Parameters
sf = slot in which flight f was originally scheduled
rft = 1 if route for flight f is operable in slot t; 0 otherwise
aft = 1 if flight f can be scheduled in slot t; 0 otherwise
Decision Variables
yft = 1 if flight f is scheduled in slot t; 0 otherwise
CATM
Airline Recovery Problem
13

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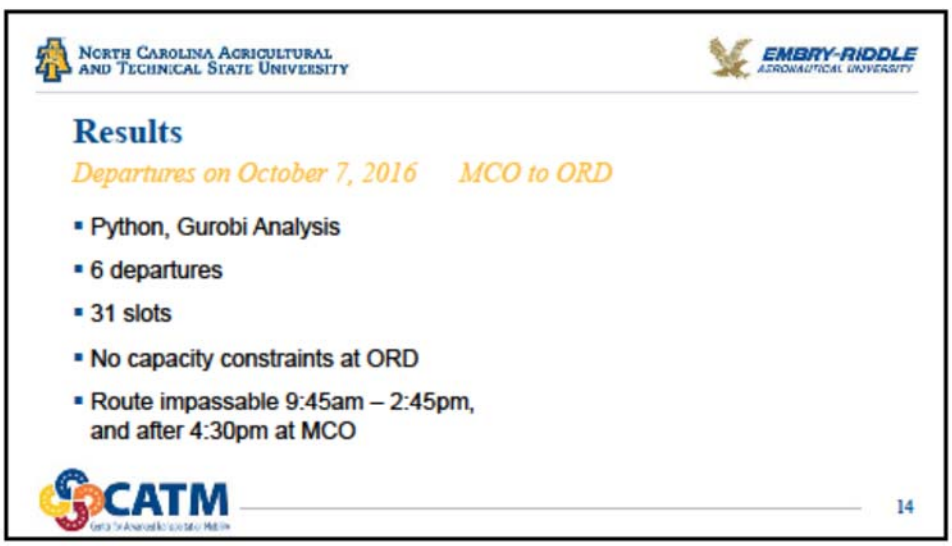
North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Results
Departures on October 7, 2016 MCO to ORD
Python, Gurobi Analysis
6 departures
31 slots
No capacity constraints at ORD
Route impassable 9:45am – 2:45pm, and after 4:30pm at MCO
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Future Extensions

- Explore the correlation between windspeed, visibility, and duration of disruption at airports.
- Extend the approach to include arrivals.
- Extend the approach to include multiple airlines, airports, routes, gates and days of operation.

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Road Restoration After a Natural Disaster

CATM — 16

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Motivation

- Impact of natural disasters, especially hurricane, on transportation system,
- Hurricanes, Tornadoes, Flash flooding
- Hurricane Matthew (2016) in US and NC
  - Closures of more than 600 roads
  - Failures of 200 dams

CATM — Road Restoration — 17

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Problem Statement

- Assumptions
  - Damaged and blocked roads due to a natural disaster
  - Unconnected road network with locations as nodes and roads as edges
  - Resources are stored at some nodes.
  - Affected people stay at demand nodes.
- Research Questions
  - Which set of damaged roads need to be restored so that all nodes are connected?
  - What is the road restoration schedule to restore all damaged roads in the road network?

CATM — Road Restoration — 18

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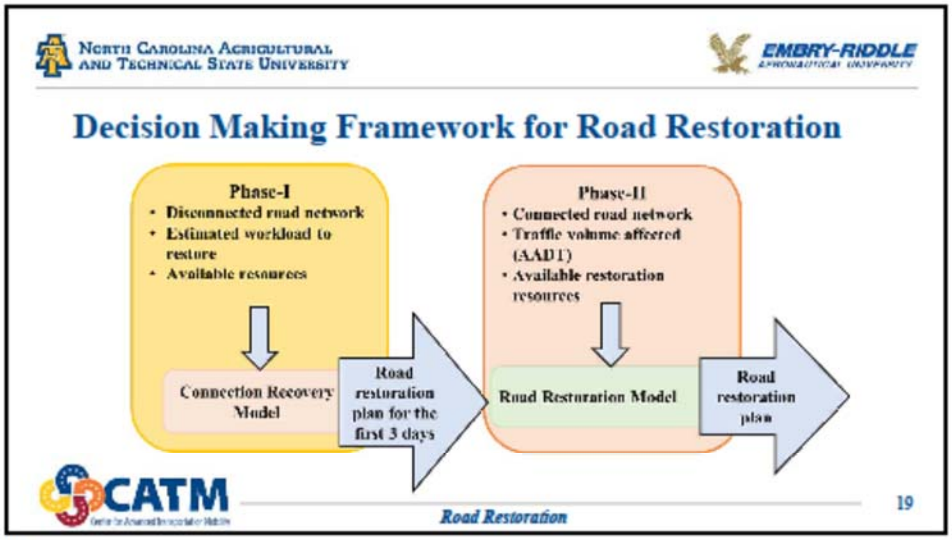
North Carolina Agricultural and Technical State University
Embry-Riddle Aeronautical University
Decision Making Framework for Road Restoration
Phase-I
• Disconnected road network
• Estimated workload to restore
• Available resources
Connection Recovery Model
Road restoration plan for the first 3 days
Phase-II
• Connected road network
• Traffic volume affected (AADT)
• Available restoration resources
Road Restoration Model
Road restoration plan
CATM
Road Restoration
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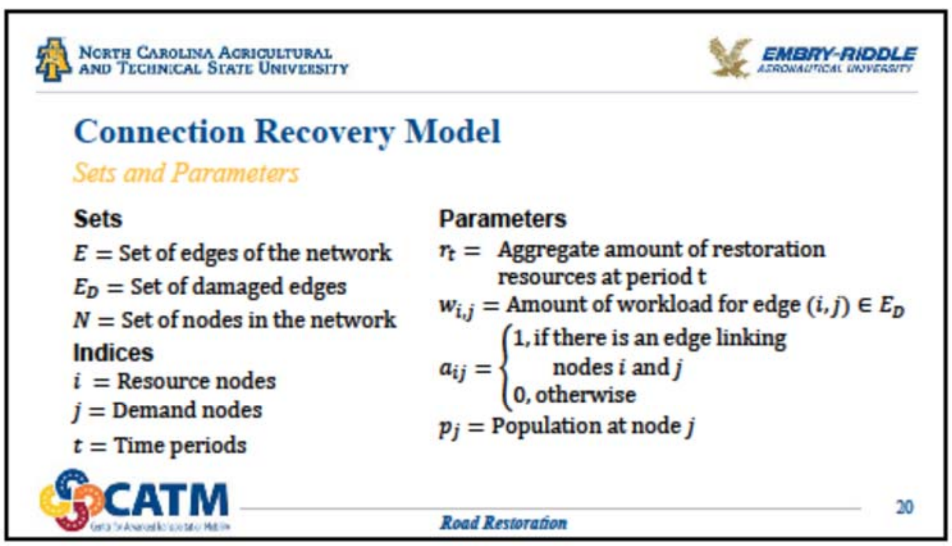
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Connection Recovery Model
Sets and Parameters
Sets
E = Set of edges of the network
E_D = Set of damaged edges
N = Set of nodes in the network
Indices
i = Resource nodes
j = Demand nodes
t = Time periods
Parameters
r_t = Aggregate amount of restoration resources at period t
$w_{i,j}$ = Amount of workload for edge $(i, j) \in E_D$
$a_{ij} = \begin{cases} 1, \text{if there is an edge linking nodes } i \text{ and } j \\ 0, \text{otherwise} \end{cases}$
p_j = Population at node j
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Road Restoration
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Connection Recovery Model

Decision Variables

$f_{i,j}^{t}$ = Flow from node i to node j

$Y_{i,j}^{t}$ = Amount of clearance completed on edge $(i,j) \in E_D$ until the end of period t

$y_{i,j}^{t}$ = Amount of clearance done on edge $(i,j) \in E_D$ duirng period t

$$\gamma_{i,j}^{t} = \begin{cases} 1, \text{ if edge } (i,j) \text{ is fully cleared at the end of } t \\ 0, \text{ if it is not fully cleared} \end{cases}$$

$$z_{ji}^{t} = \begin{cases} 1, \text{ if demand node j can access source node } i \\ 0, \textit{otherwise} \end{cases}$$

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Connection Recovery Model

$$\max \sum_{\forall j \in N_D} \sum_{\forall i \in N_s} p_j z_{ji}^{t}$$

$$\text{s.t. } z_{ji}^{|T_1|} = 1, \quad \forall j \in N_D, \; i \in N_s$$

$$\sum_{\forall k} a_{kj} f_{kj}^{t} = \sum_{\forall l} a_{jl} f_{jl}^{t} + \sum_{\forall i \in N_s} z_{ji}^{t}, \quad \forall j \in N_D, \; t \in T_1$$

$$\sum_{\forall j \in N_D} z_{ji}^{t} + \sum_{\forall k} a_{ki} f_{ki}^{t} = \sum_{\forall l} a_{il} f_{il}^{t}, \quad \forall i \in N_s, \; t \in T_1$$

$$Y_{i,j}^{t-1} + y_{i,j}^{t} = Y_{i,j}^{t}, \quad \forall (i,j) \in E_D, \; t \in T_1$$

$$w_{i,j} - Y_{i,j}^{t} \le (1 - \gamma_{i,j}^{t}) w_{i,j}, \quad \forall (i,j) \in E_D, \; t \in T_1$$

$$w_{i,j} - Y_{i,j}^{t} \ge 1 - \gamma_{i,j}^{t}, \quad \forall (i,j) \in E_D, \; t \in T_1$$

$$\sum_{(i,j) \in E_D} y_{i,j}^{t} \le r_t, \quad \forall t \in T_1$$

$$Y_{i,j}^{t}, y_{i,j}^{t} \ge 0, \quad \forall (i,j) \in E_D, \; t \in T_1$$

$$\gamma_{ij}^{t} \in \{0,1\}, \quad \forall (i,j) \in E_D, \; t \in T_1$$

$$z_{ji}^{t} \in \{0,1\}, \quad \forall j \in N_D, \; i \in N_s t \in T_1$$

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Connection Recovery Model

Testing and Results

- Testing Scenario
  - Highways of southeastern NC
  - Damaged roads by Hurricane Matthew
- Results
  - The model identifies the damaged roads to be restored to make all the affected counties accessible.
  - The model generates an optimal road restoration schedule for the first three days after the natural disaster.

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Road Restoration 23

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Conclusions and Future Work

- Proposed a two-phase decision making framework for road restoration
- Developed and preliminarily test the optimization model for Phase-I.
- To collect road restoration workload data to test the model using the real data.
- To develop an optimization model for Phase-II

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Road Restoration 24

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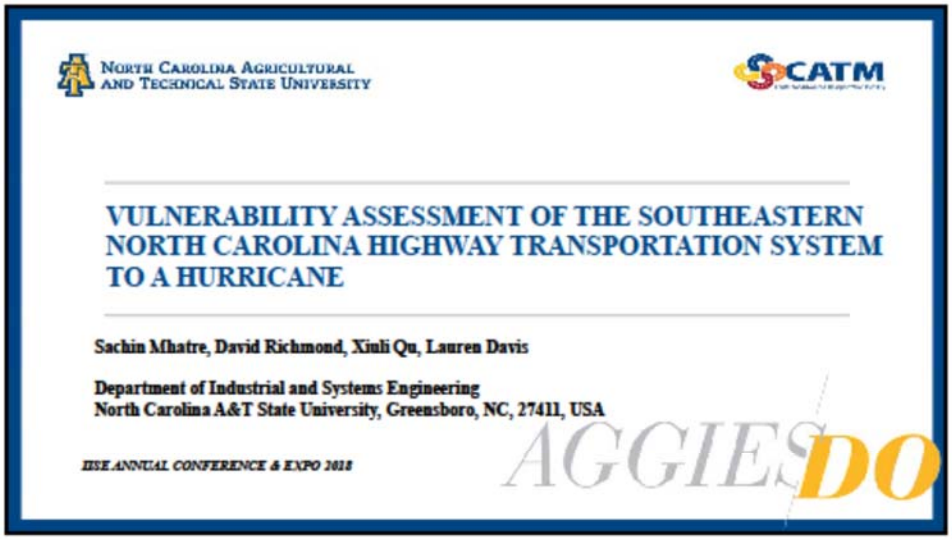
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VULNERABILITY ASSESSMENT OF THE SOUTHEASTERN NORTH CAROLINA HIGHWAY TRANSPORTATION SYSTEM TO A HURRICANE
Sachin Mhatre, David Richmond, Xiuli Qu, Lauren Davis
Department of Industrial and Systems Engineering
North Carolina A&T State University, Greensboro, NC, 27411, USA
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Outline
▪ Introduction
▪ Impacts of Hurricane Matthew
▪ Vulnerability Assessment Method
▪ Results
▪ Conclusions and Limitations
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Introduction

- Impact of natural disasters, especially hurricanes, on transportation systems.
- Hurricane Matthew (2016) Impact
  - US
  - NC

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Hurricane Matthew Impact

On North Carolina

- Caused 28 deaths
- Closures of more than 600 roads
- Failures of 200 dams

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FHWA Vulnerability Assessment Method

- The FHWA's framework consists of three steps:

1) Defining the scope of a project
2) Assessing vulnerability
3) Integrating vulnerability into decision making

Source: The Federal Highway Administration's Climate Change & Extreme Weather Vulnerability Assessment framework

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Vulnerability Assessment Method

1. **Asset Selection:**
   NC highways
2. **Vulnerability Metrics:**
   Exposure
   - Observed peak wind speed
   - Observed peak flood level
   - Observed total rainfall

   Sensitivity
   - Past experience with wind
   - Past experience with flood level

   Adaptive Capacity
   - Average Annual Daily Traffic

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3. Data Sources

	Data source
Exposure Metrics	
Observed peak wind speed	NOAA storm data for North Carolina
Observed peak flood level	USGS Flood Event Viewer
Observed total rainfall	NOAA storm data for North Carolina
Sensitivity Metrics	
Past experience with wind	NC Department of Safety's WebEOC database
Past experience with flood level	
Adaptive Capacity Metrics	
Average annual daily traffic (AADT)	NCDOT GIS

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Vulnerability Assessment Process

Observed values converted into vulnerability score for individual asset

↓

Converts observed values for an asset to its metric-level vulnerability scores

↓

Calculate weighted average of metric-level vulnerability scores to obtain the component-level vulnerability scores of the asset

↓

Overall vulnerability score of an asset by averaging its three component level vulnerability scores

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Scoring Scales for the Exposure, Sensitivity, and Adaptive Capacity Metrics

	Exposure			Sensitivity		Adaptive
Vulnerability score	Peak wind speed (mph)	Peak flood level (ft)	Total rainfall (inch)	Past experience with wind (mph)	Past experience with flood level (ft)	capacity (AADT)
1	45 – 50.5	16.6 – 27.18	10 – 12	39 -73	2 – 10	300 – 12225
2	50.5 – 56	27.18 – 37.75	12 – 14	73 – 95	10 – 18	12225 – 24150
3	56 – 61.5	37.5 – 48.33	14 – 16	95 – 110	18 – 26	24150 – 36075
4	61.5 – 67	48.33 – 58.9	16 – 18	110 – 200	26 – 60	36075 – 48000

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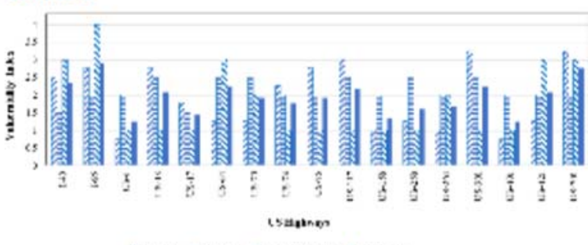
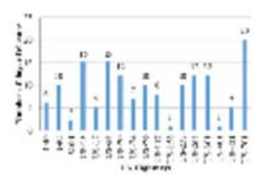
Results





- Variation in vulnerability scores which is caused by the varying exposure levels.
- Closure days is positively correlated with the exposure vulnerability scores.
- Highways with higher traffic volume, usually have high overall vulnerability scores.

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Conclusions

- Our analysis results revealed the variation in the vulnerability scores of the highways studied due to different exposure levels of highways to wind and precipitation.
- Positive correlation between exposure vulnerability scores and the closure days of southeastern NC highways during Hurricane Matthew.
- The study shows that the highways with higher traffic volume are more vulnerable than other highways in southeastern North Carolina.

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Limitations

- A limitation of this study is a limited number of extreme weather variables.
- In our future research, we will consider more climate variables like storm surge, increased sea level, etc.
- Another limitation of this study is using equal weights to combine metric-level vulnerability scores into component-level and overall vulnerability score

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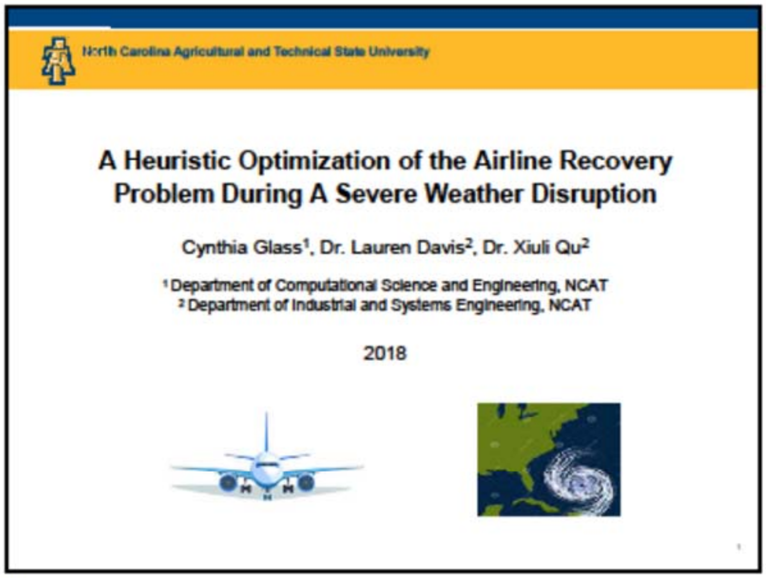
North Carolina Agricultural and Technical State University
A Heuristic Optimization of the Airline Recovery Problem During A Severe Weather Disruption
Cynthia Glass[1], Dr. Lauren Davis[2], Dr. Xiuli Qu[2]
[1] Department of Computational Science and Engineering, NCAT
[2] Department of Industrial and Systems Engineering, NCAT
2018

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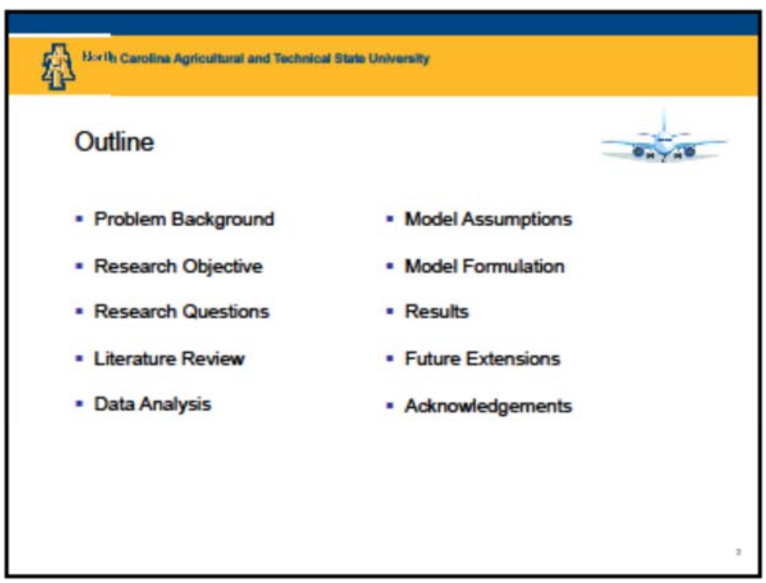
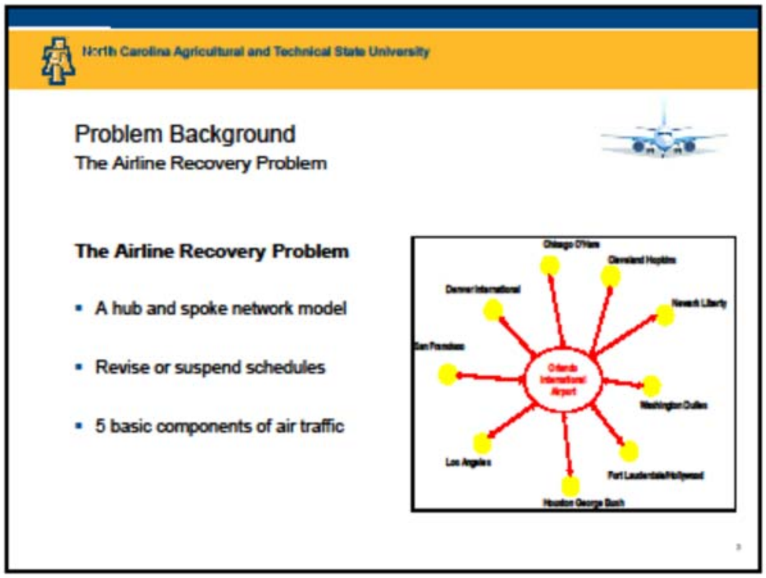

North Carolina Agricultural and Technical State University
Outline
Problem Background
Research Objective
Research Questions
Literature Review
Data Analysis
Model Assumptions
Model Formulation
Results
Future Extensions
Acknowledgements

2


North Carolina Agricultural and Technical State University
Problem Background
The Airline Recovery Problem
The Airline Recovery Problem
▪ A hub and spoke network model
▪ Revise or suspend schedules
▪ 5 basic components of air traffic
Chicago O'Hare
Cleveland Hopkins
Denver International
Newark Liberty
San Francisco
Orlando International Airport
Washington Dulles
Los Angeles
Fort Lauderdale/Hollywood
Houston George Bush

3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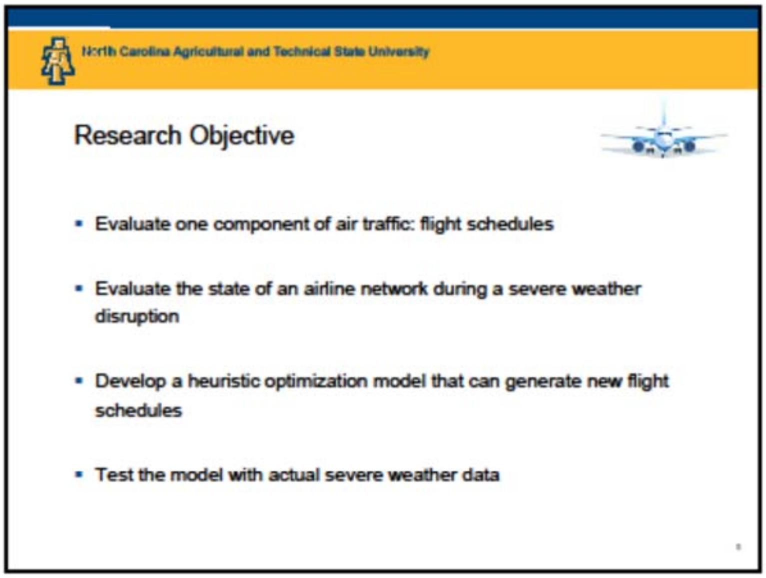
Problem Background
Types of Disruptions
Types of Disruptions
▪ Severe Weather
▪ Capacity Constraints
▪ Terrorist
▪ Influenza
▪ Combined Disruptions

4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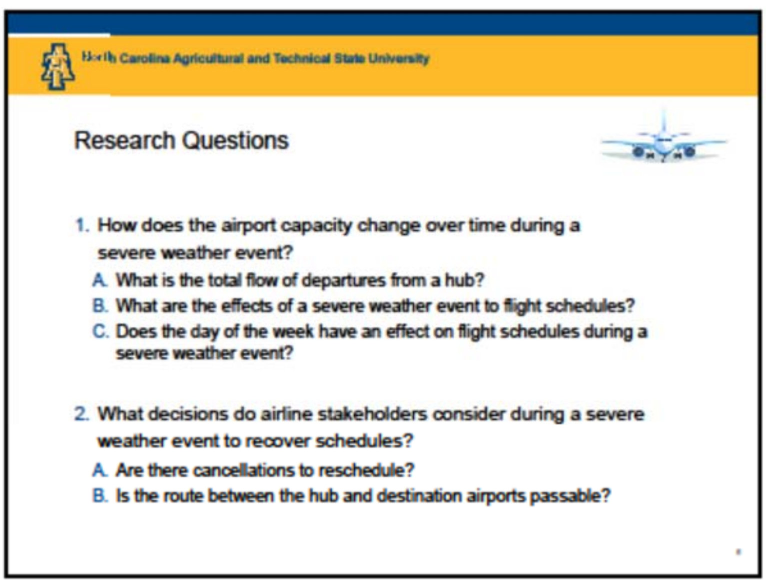
▪ Evaluate one component of air traffic: flight schedules
▪ Evaluate the state of an airline network during a severe weather disruption
▪ Develop a heuristic optimization model that can generate new flight schedules
▪ Test the model with actual severe weather data

5


North Carolina Agricultural and Technical State University
Research Questions
1. How does the airport capacity change over time during a severe weather event?
A. What is the total flow of departures from a hub?
B. What are the effects of a severe weather event to flight schedules?
C. Does the day of the week have an effect on flight schedules during a severe weather event?
2. What decisions do airline stakeholders consider during a severe weather event to recover schedules?
A. Are there cancellations to reschedule?
B. Is the route between the hub and destination airports passable?

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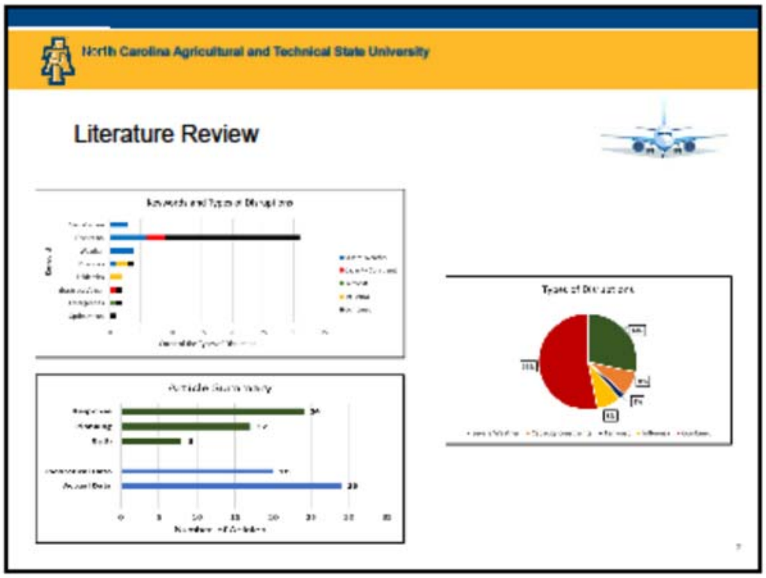
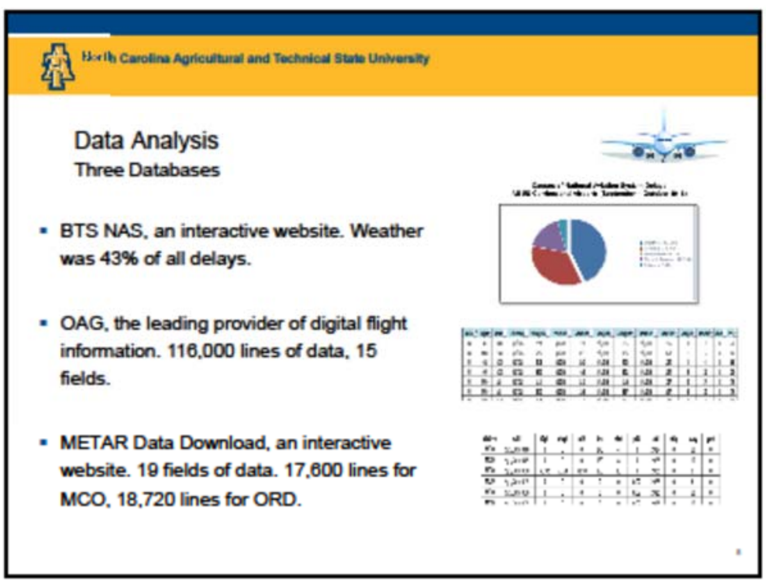

North Carolina Agricultural and Technical State University
Literature Review
Types of Disruptions
Article Summary
Number of Articles

7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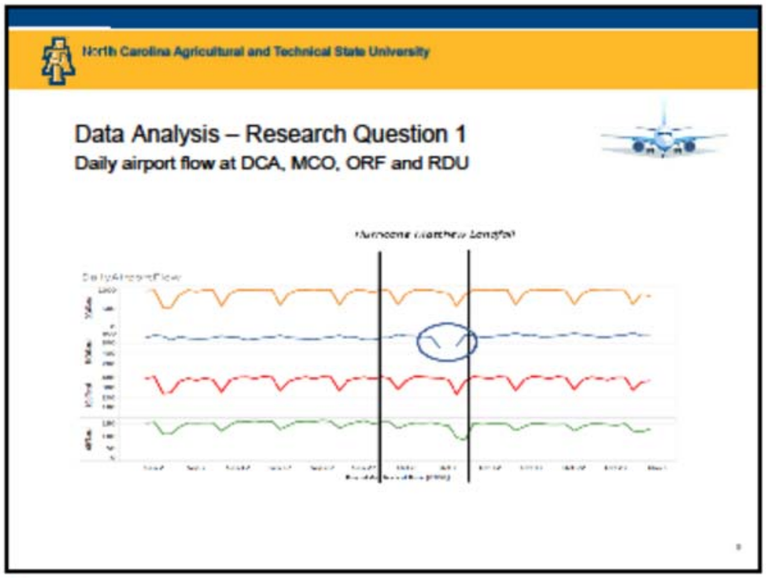
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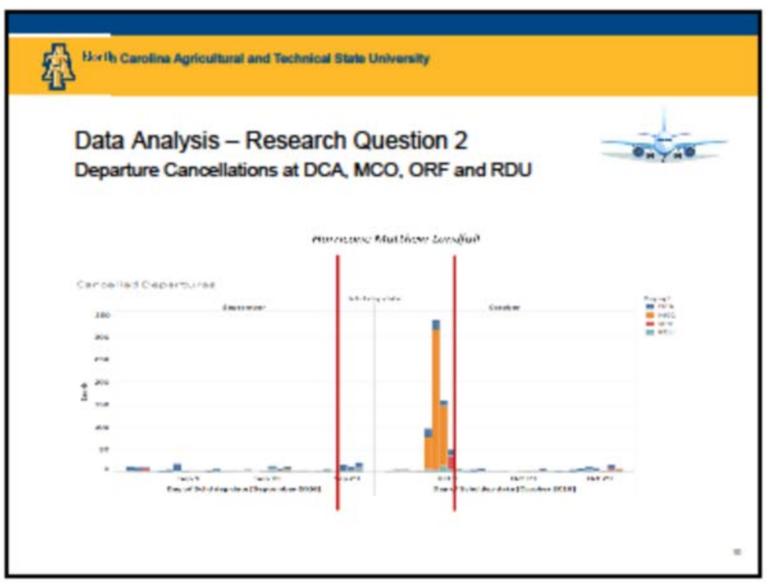
Data Analysis – Research Question 1
Daily airport flow at DCA, MCO, ORF and RDU

9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Data Analysis – Research Question 2
Departure Cancellations at DCA, MCO, ORF and RDU
Hurricane Matthew Landfall
Cancelled Departures

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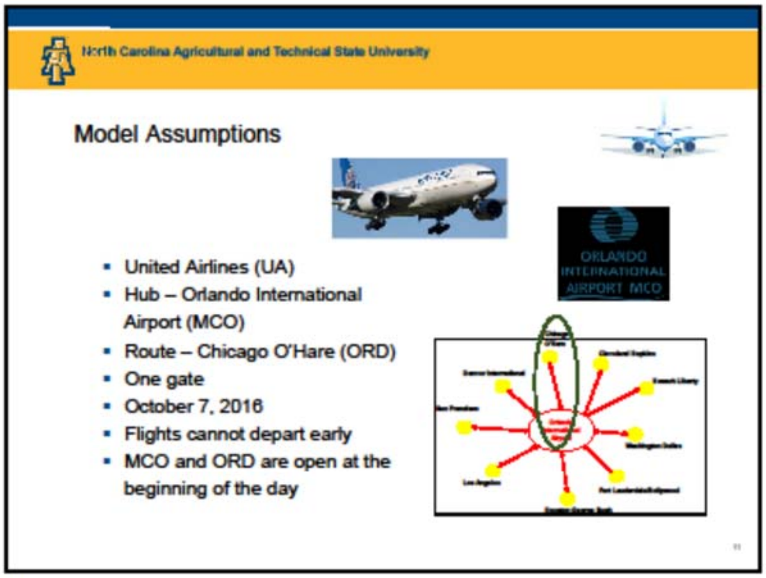
North Carolina Agricultural and Technical State University
Model Assumptions
United Airlines (UA)
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Route – Chicago O'Hare (ORD)
One gate
October 7, 2016
Flights cannot depart early
MCO and ORD are open at the beginning of the day
ORLANDO INTERNATIONAL AIRPORT MCO

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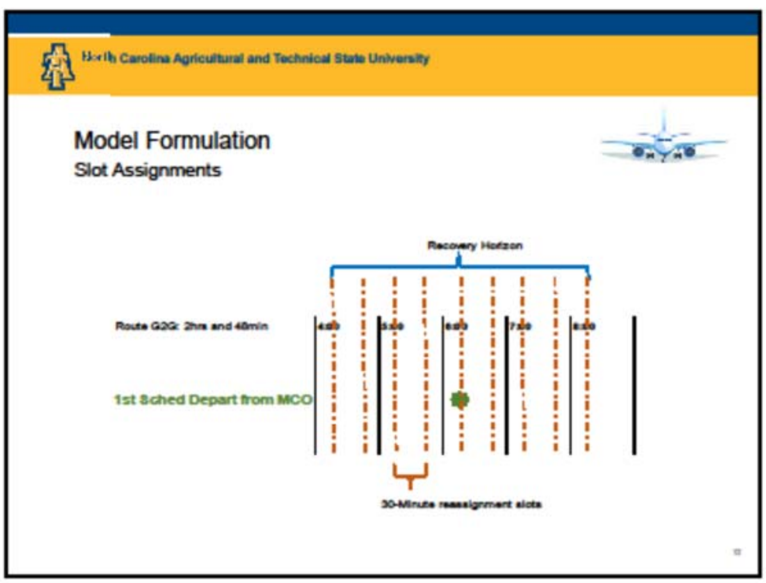
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Model Formulation
Slot Assignments
Recovery Horizon
Route G2G: 2hrs and 48min
1st Sched Depart from MCO
30-Minute reassignment slots

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Model Formulation

- **Sets**
  - T = set of slots in which the flight can be scheduled
  - F = set of scheduled flights
- **Parameters**
  - s_f = slot in which flight *f* was originally scheduled
  - $r_{ft} = \begin{cases} 1 \text{ if route for flight } f \text{ is operable in slot } t \\ 0 \quad \text{otherwise} \end{cases}$
  - $a_{ft} = \begin{cases} 1 \text{ if flight } f \text{ can be scheduled in slot } t \\ 0 \quad \text{otherwise} \end{cases}$
- **Decision Variables**
  - $y_{ft} = \begin{cases} 1 \text{ if flight } f \text{ is scheduled in slot } t \\ 0 \quad \text{otherwise} \end{cases}$
- **Objective**
  - $\min \sum_{f \in F} \sum_{t \in T} 30 * (t - s_f) * y_{ft}$

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Model Formulation

- s.t.

$\sum_{f \in F} y_{ft} \leq 1$	$\forall t \in T$	At most one flight is scheduled in a slot, *t*
$\sum_{t \in T} a_{ft} * y_{ft} = 1$	$\forall f \in F$	Ensures that a flight is scheduled
$y_{ft} \leq r_{ft}$	$\forall f \in F, t \in T$	Ensures that a flight is scheduled to an operable route
$y_{ft} \in \{0,1\}$	$\forall f \in F, t \in T$	Binary – a flight must be scheduled

14

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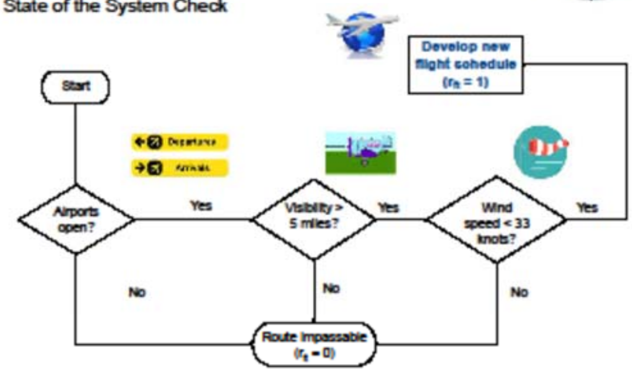
Model Formulation

State of the System Check



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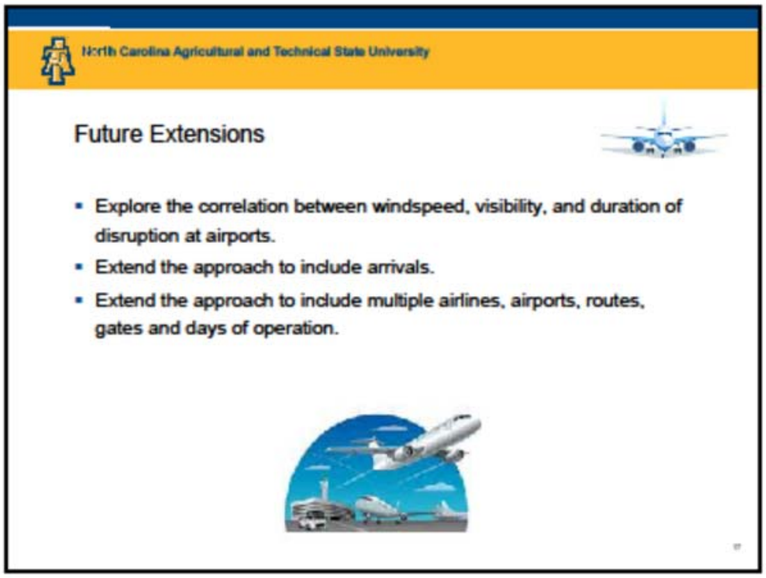
Results

Departures on October 7, 2016: MCO to ORD

Flight	Original Slot	New Slot	Delay (mins)	Delay (hours)
1	1	1	0	On-time departure
2	3	3	0	On-time departure
3	7	7	330	5.5
4	9	18	300	5.0
5	21	31	--	Cancelled until Oct 8
6	26	31	--	Cancelled until Oct 8

- Python, Gurobi Analysis
- 6 departures
- 31 slots
- No capacity constraints at ORD
- Route impassable 9:45am – 2:45pm, and after 4:30pm at MCO

16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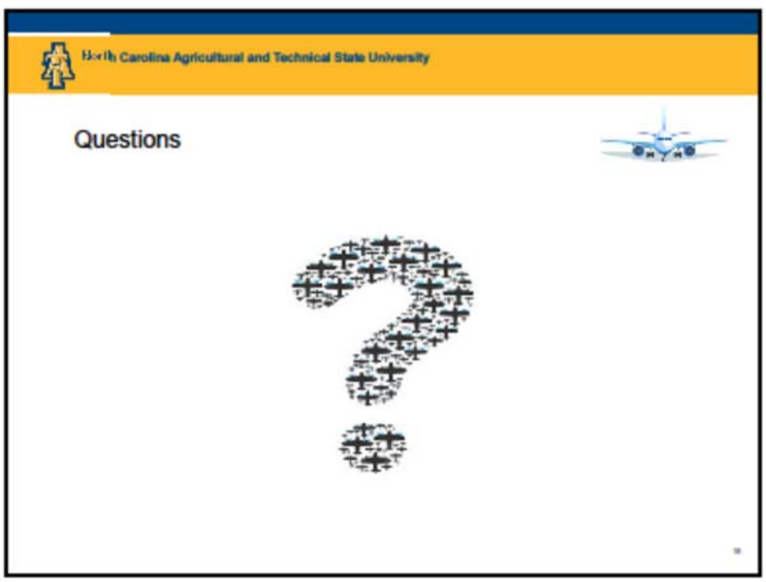
Future Extensions
▪ Explore the correlation between windspeed, visibility, and duration of disruption at airports.
▪ Extend the approach to include arrivals.
▪ Extend the approach to include multiple airlines, airports, routes, gates and days of operation.

17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Questions

18


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Network Optimization Models For Road Restoration After A Natural Disaster
Sachin Mhatre, Xiuli Qu, Lauren Davis
Department of Industrial and Systems Engineering
North Carolina A&T State University, Greensboro, NC
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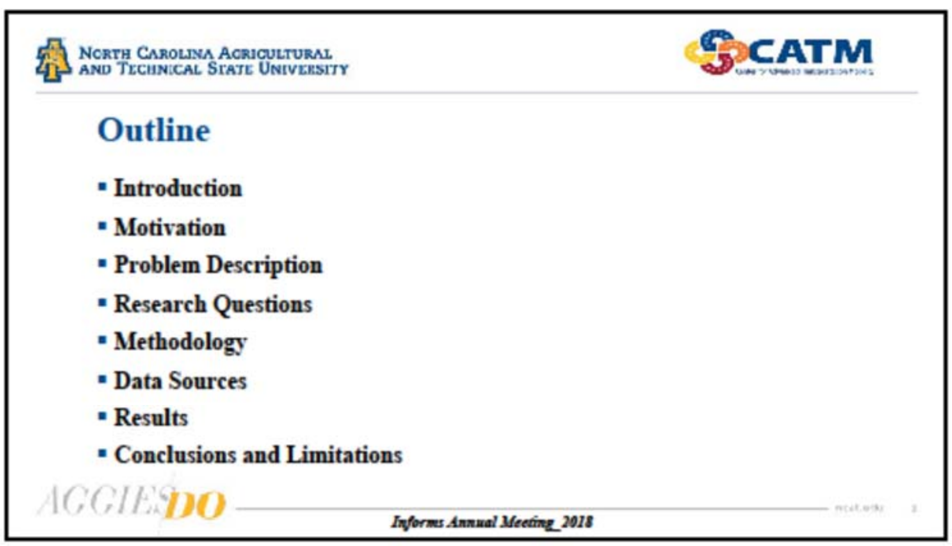
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Outline
▪ Introduction
▪ Motivation
▪ Problem Description
▪ Research Questions
▪ Methodology
▪ Data Sources
▪ Results
▪ Conclusions and Limitations
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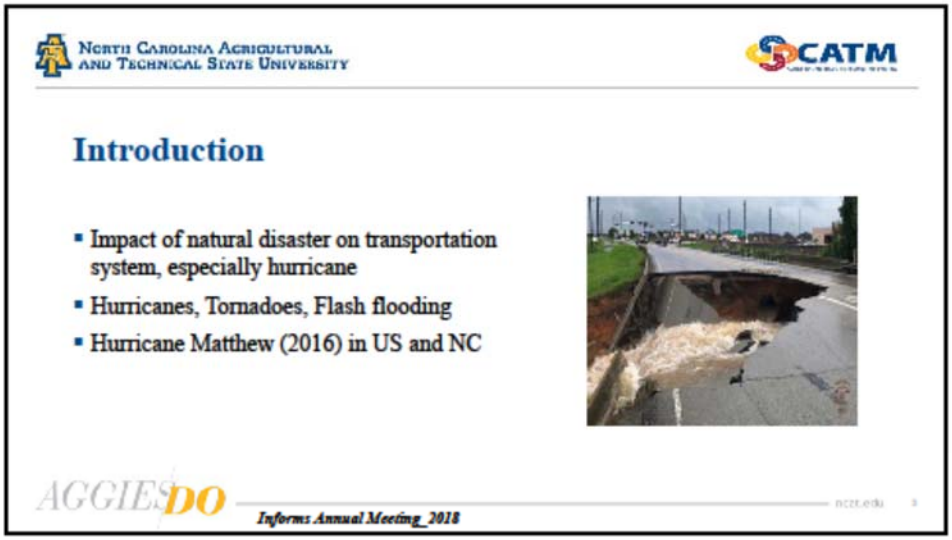
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Introduction
▪ Impact of natural disaster on transportation system, especially hurricane
▪ Hurricanes, Tornadoes, Flash flooding
▪ Hurricane Matthew (2016) in US and NC
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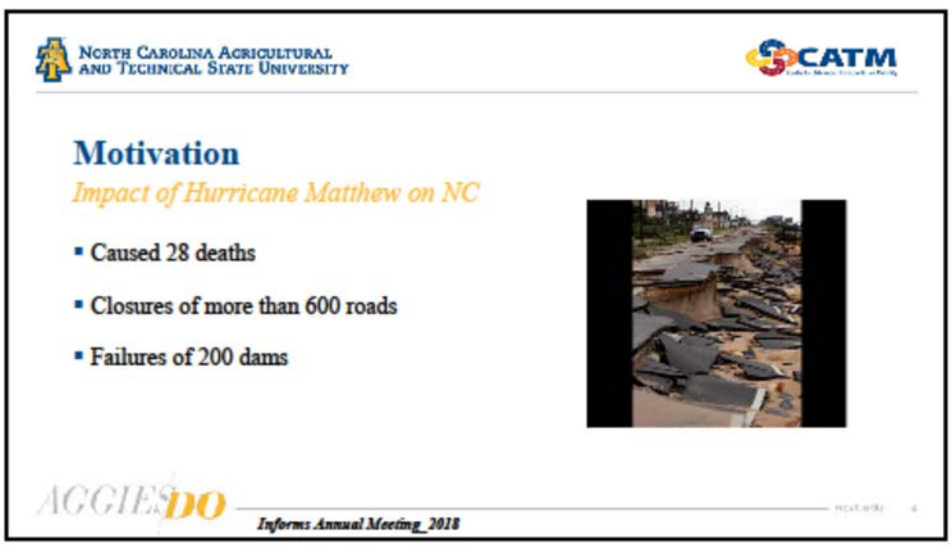
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Motivation
Impact of Hurricane Matthew on NC
▪ Caused 28 deaths
▪ Closures of more than 600 roads
▪ Failures of 200 dams
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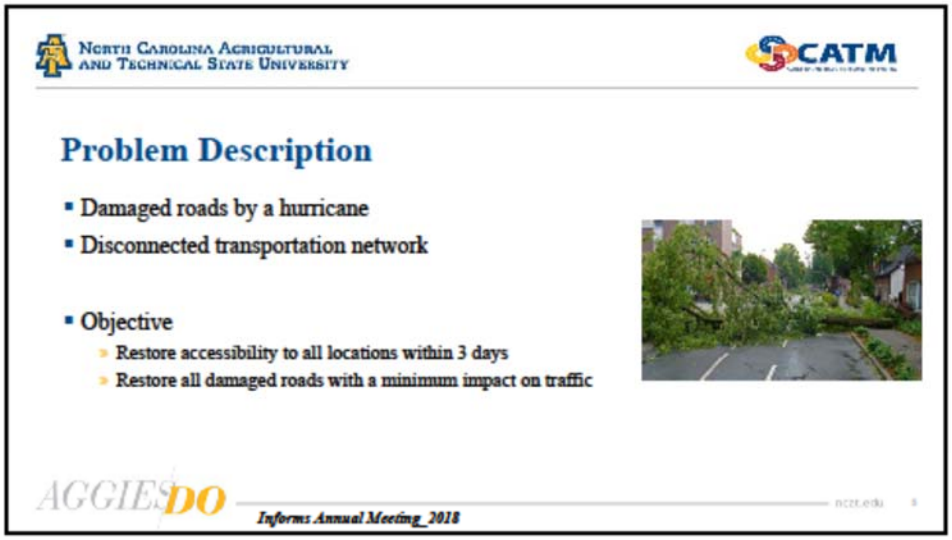
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CATM
Problem Description
▪ Damaged roads by a hurricane
▪ Disconnected transportation network
▪ Objective
» Restore accessibility to all locations within 3 days
» Restore all damaged roads with a minimum impact on traffic
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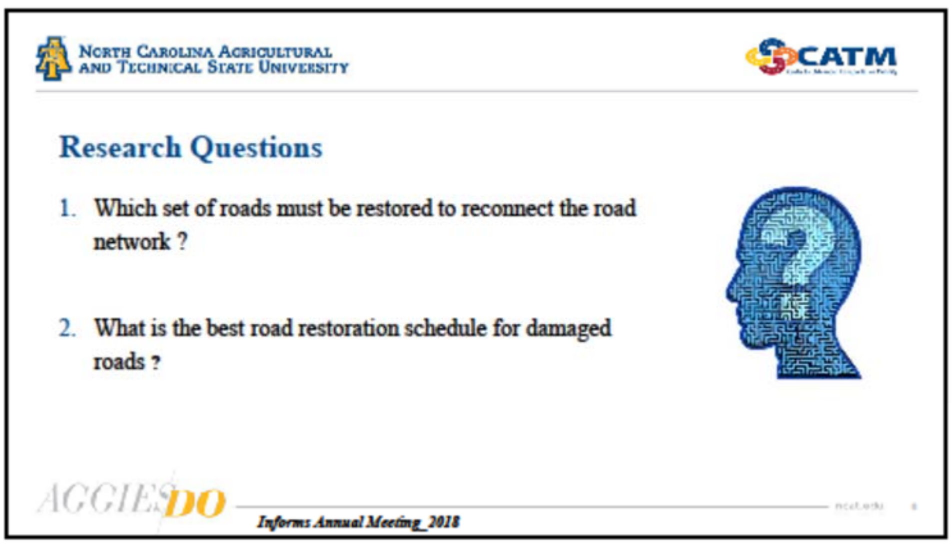
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Research Questions
1. Which set of roads must be restored to reconnect the road network ?
2. What is the best road restoration schedule for damaged roads ?
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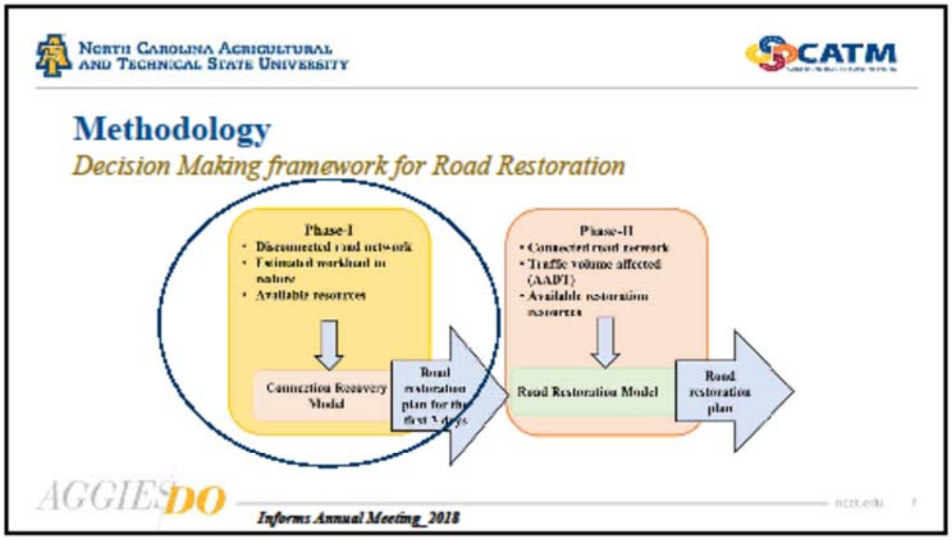

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Methodology
Decision Making framework for Road Restoration
Phase-I
• Disconnected road network
• Estimated workload in nature
• Available resources
Connection Recovery Model
Road restoration plan for the first 3 days
Phase-II
• Connected road network
• Traffic volume affected (AADT)
• Available restoration resources
Road Restoration Model
Road restoration plan
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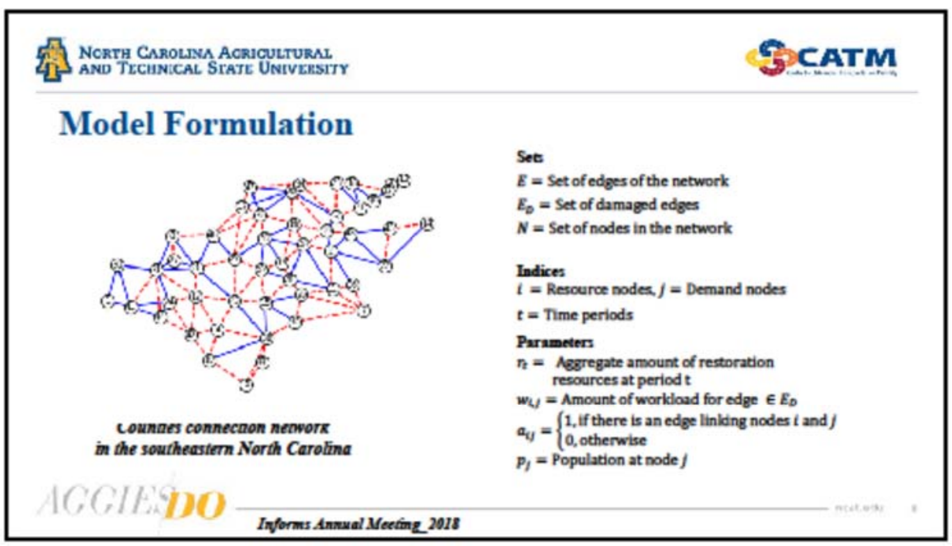

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Model Formulation
Counties connection network in the southeastern North Carolina
Sets
E = Set of edges of the network
E_D = Set of damaged edges
N = Set of nodes in the network
Indices
i = Resource nodes, j = Demand nodes
t = Time periods
Parameters
r_t = Aggregate amount of restoration resources at period t
w_i,j = Amount of workload for edge ∈ E_D
a_ij = {1, if there is an edge linking nodes i and j; 0, otherwise}
p_j = Population at node j
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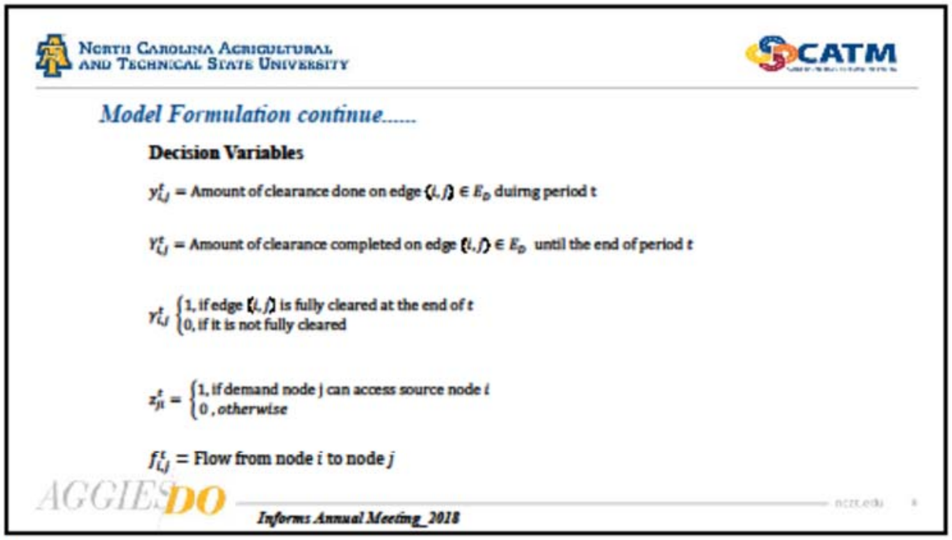
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Model Formulation continue......
Decision Variables
$y_{i,j}^t$ = Amount of clearance done on edge $(i,j) \in E_D$ duirng period t
$Y_{i,j}^t$ = Amount of clearance completed on edge $(i,j) \in E_D$ until the end of period t
$\gamma_{i,j}^t$ $\begin{cases} 1, \text{if edge } (i,j) \text{ is fully cleared at the end of } t \\ 0, \text{if it is not fully cleared} \end{cases}$
$z_{ji}^t = \begin{cases} 1, \text{if demand node j can access source node } i \\ 0, \textit{otherwise} \end{cases}$
$f_{i,j}^t$ = Flow from node i to node j
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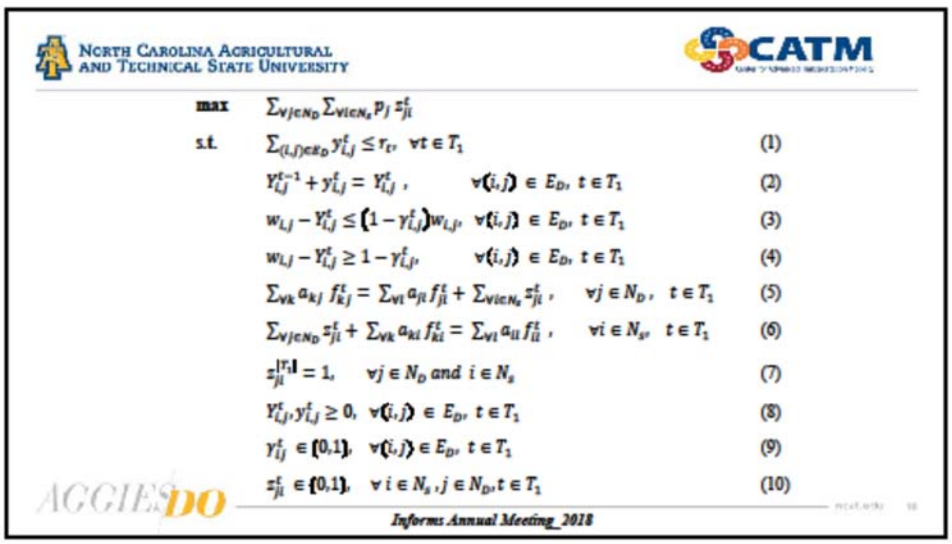
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max $\sum_{\forall j \in N_D} \sum_{\forall i \in N_s} p_j z_{ji}^t$
s.t. $\sum_{(i,j) \in E_D} y_{i,j}^t \leq r_t, \ \forall t \in T_1$ (1)
$Y_{i,j}^{t-1} + y_{i,j}^t = Y_{i,j}^t, \quad \forall (i,j) \in E_D, \ t \in T_1$ (2)
$w_{i,j} - Y_{i,j}^t \leq (1 - \gamma_{i,j}^t) w_{i,j}, \ \forall (i,j) \in E_D, \ t \in T_1$ (3)
$w_{i,j} - Y_{i,j}^t \geq 1 - \gamma_{i,j}^t, \quad \forall (i,j) \in E_D, \ t \in T_1$ (4)
$\sum_{\forall k} a_{kj} f_{kj}^t = \sum_{\forall l} a_{jl} f_{jl}^t + \sum_{\forall i \in N_s} z_{ji}^t, \quad \forall j \in N_D, \ t \in T_1$ (5)
$\sum_{\forall j \in N_D} z_{ji}^t + \sum_{\forall k} a_{ki} f_{ki}^t = \sum_{\forall l} a_{il} f_{il}^t, \quad \forall i \in N_s, \ t \in T_1$ (6)
$z_{ji}^{|T_1|} = 1, \quad \forall j \in N_D \text{ and } i \in N_s$ (7)
$Y_{i,j}^t, y_{i,j}^t \geq 0, \ \forall (i,j) \in E_D, \ t \in T_1$ (8)
$\gamma_{ij}^t \in \{0,1\}, \ \forall (i,j) \in E_D, \ t \in T_1$ (9)
$z_{ji}^t \in \{0,1\}, \ \forall i \in N_s, j \in N_D, t \in T_1$ (10)
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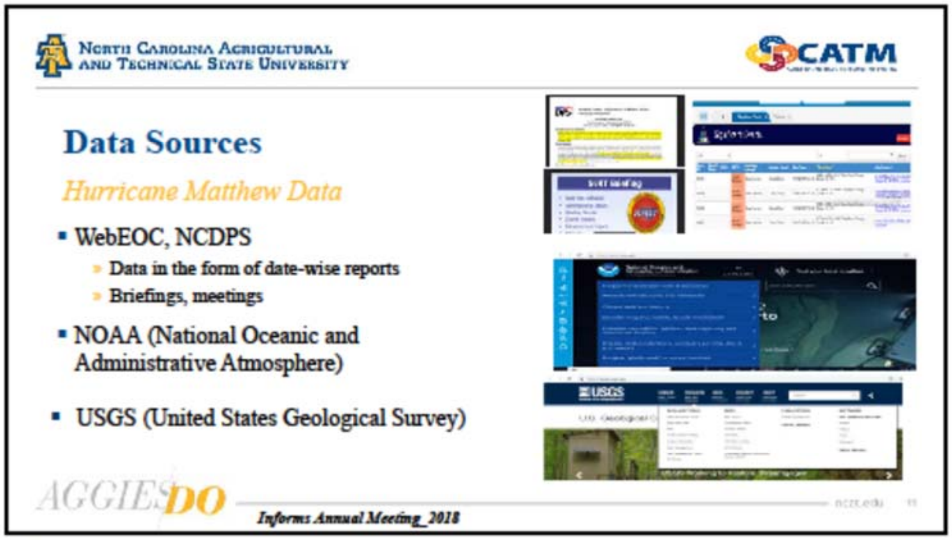
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Data Sources
Hurricane Matthew Data
WebEOC, NCDPS
Data in the form of date-wise reports
Briefings, meetings
NOAA (National Oceanic and Administrative Atmosphere)
USGS (United States Geological Survey)
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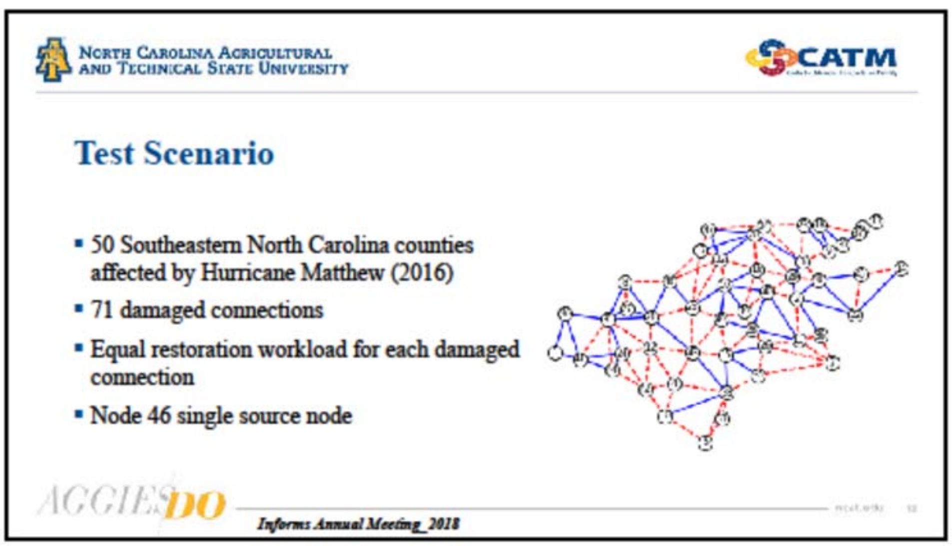
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Test Scenario
50 Southeastern North Carolina counties affected by Hurricane Matthew (2016)
71 damaged connections
Equal restoration workload for each damaged connection
Node 46 single source node
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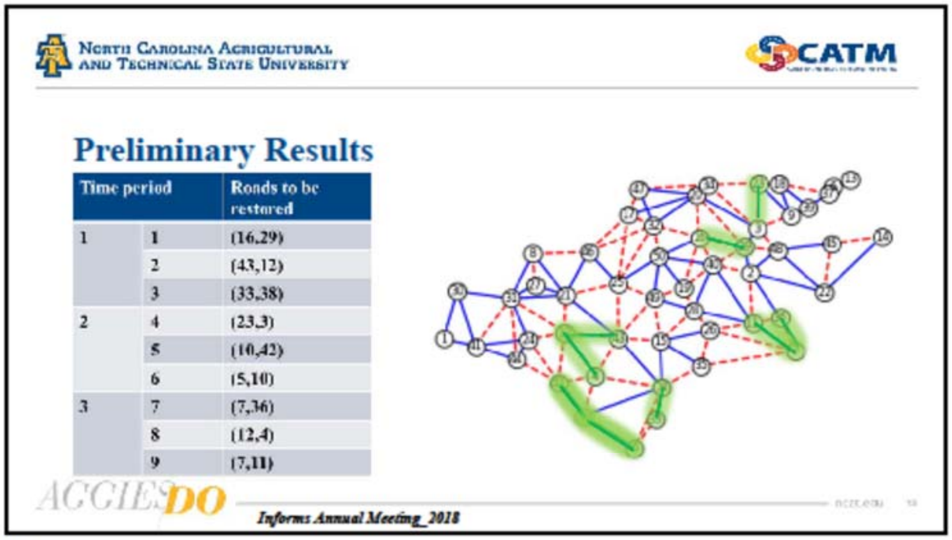

Time period		Roads to be restored
1	1	(16,29)
	2	(43,12)
	3	(33,38)
2	4	(23,3)
	5	(10,42)
	6	(5,10)
3	7	(7,36)
	8	(12,4)
	9	(7,11)

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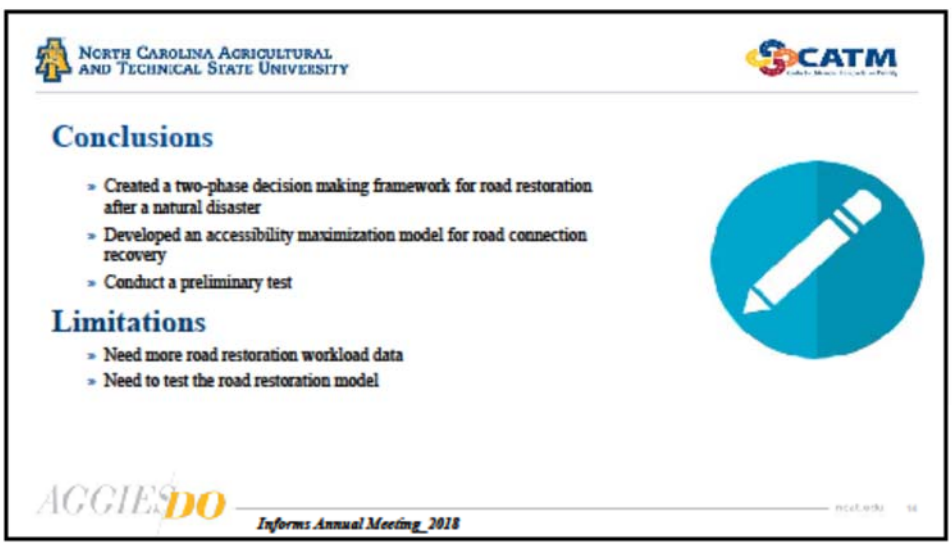

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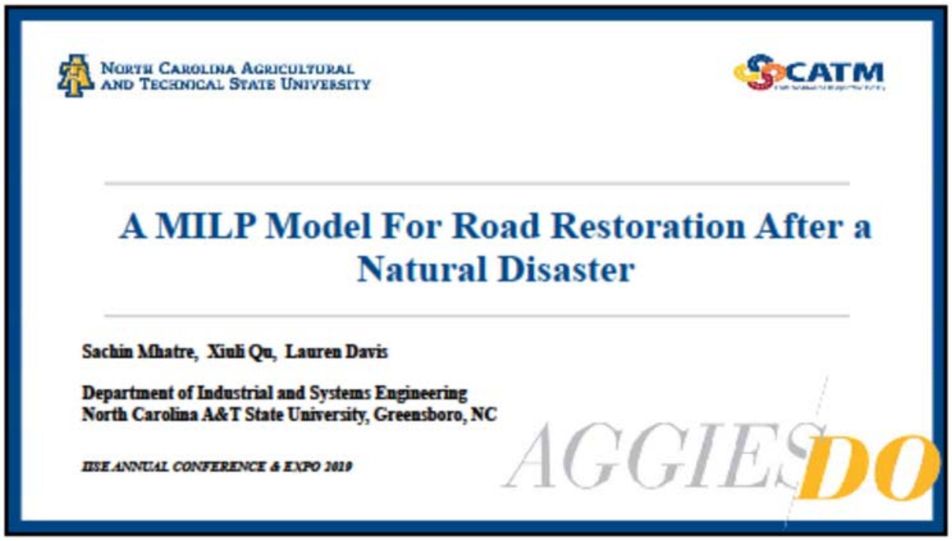
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A MILP Model For Road Restoration After a Natural Disaster
Sachin Mhatre, Xiuli Qu, Lauren Davis
Department of Industrial and Systems Engineering
North Carolina A&T State University, Greensboro, NC
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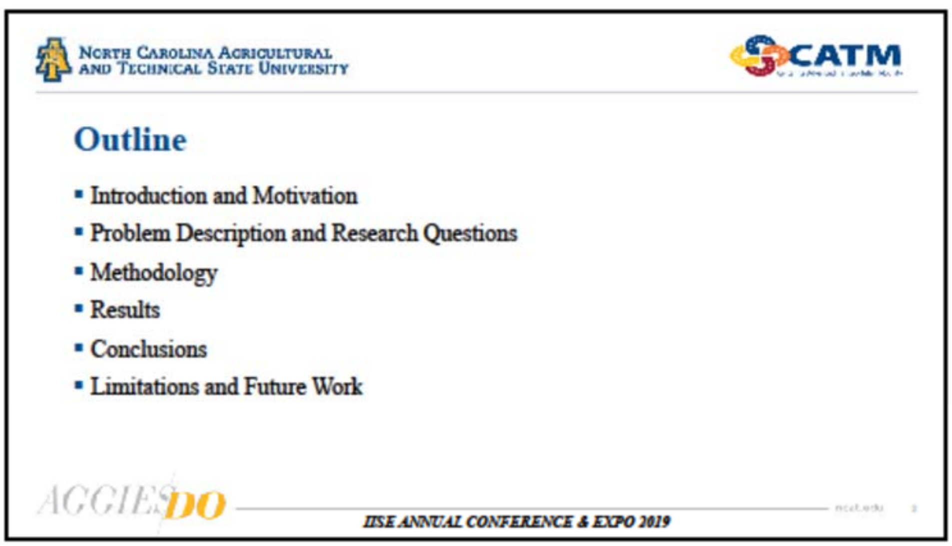
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Outline
▪ Introduction and Motivation
▪ Problem Description and Research Questions
▪ Methodology
▪ Results
▪ Conclusions
▪ Limitations and Future Work
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2

NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

Introduction

Background

- Impact of natural disaster on transportation system, especially hurricane
- Hurricanes, Tornadoes, Flash flooding
- Hurricane Matthew (2016) in US and NC

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NORTH CAROLINA AGRICULTURAL AND TECHNICAL STATE UNIVERSITY

Motivation

Impact of Hurricane Matthew on North Carolina

- Caused 28 deaths
- Closures of more than 600 roads
- Failures of 200 dams

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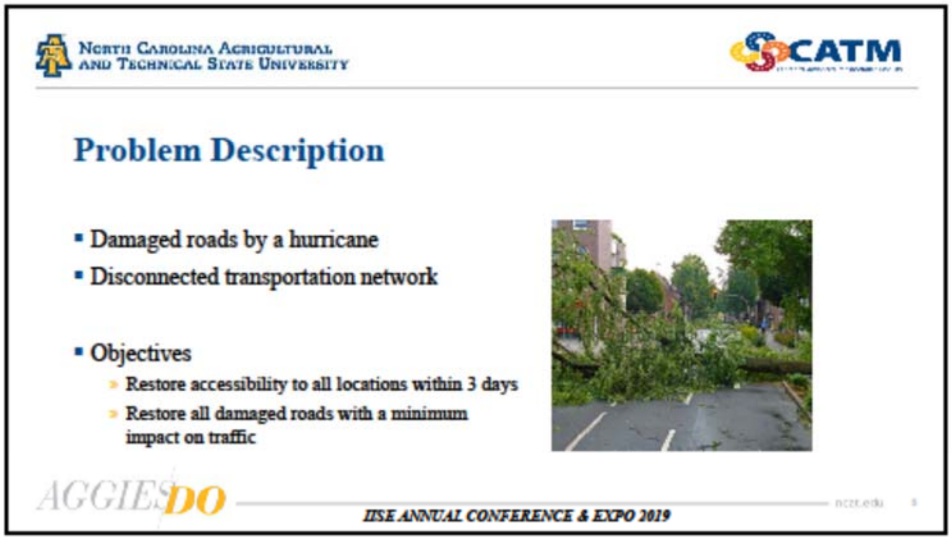
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Problem Description
Damaged roads by a hurricane
Disconnected transportation network
Objectives
Restore accessibility to all locations within 3 days
Restore all damaged roads with a minimum impact on traffic
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Research Questions
1. Which set of roads must be restored to reconnect the road network ?
2. What is the best road restoration schedule for damaged roads ?
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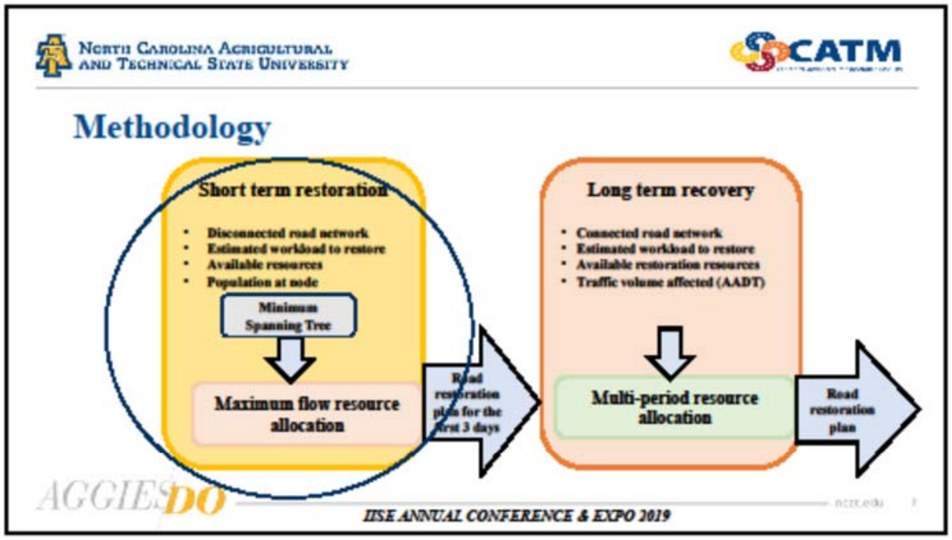
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Methodology
Short term restoration
Disconnected road network
Estimated workload to restore
Available resources
Population at node
Minimum Spanning Tree
Maximum flow resource allocation
Road restoration plan for the first 3 days
Long term recovery
Connected road network
Estimated workload to restore
Available restoration resources
Traffic volume affected (AADT)
Multi-period resource allocation
Road restoration plan
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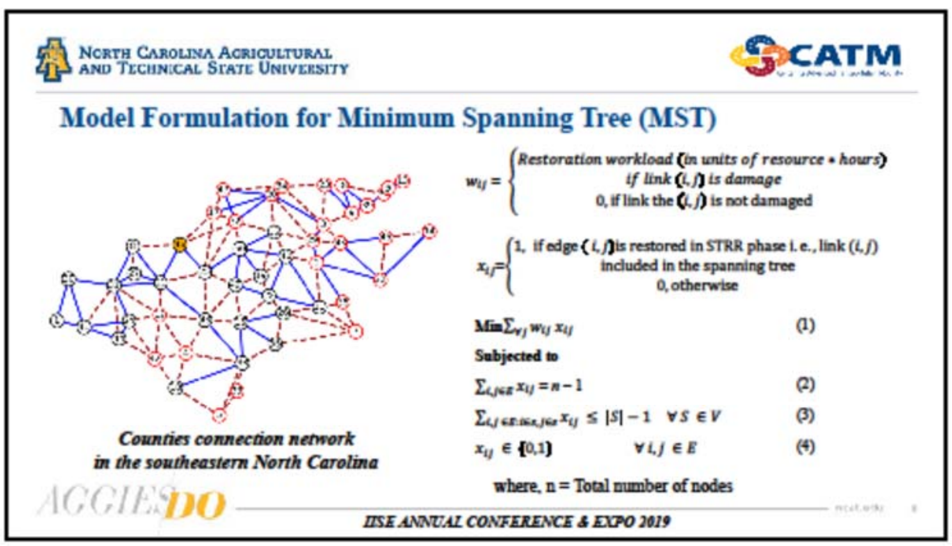
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Model Formulation for Minimum Spanning Tree (MST)
$w_{ij} = \begin{cases} \text{Restoration workload (in units of resource * hours)} \\ \text{if link } (i,j) \text{ is damage} \\ 0, \text{if link the } (i,j) \text{ is not damaged} \end{cases}$
$x_{ij} = \begin{cases} 1, \text{ if edge } (i,j) \text{ is restored in STRR phase i. e., link } (i,j) \\ \text{included in the spanning tree} \\ 0, \text{otherwise} \end{cases}$
$\text{Min} \sum_{\forall j} w_{ij} x_{ij}$ (1)
Subjected to
$\sum_{i,j \in E} x_{ij} = n - 1$ (2)
$\sum_{i,j \in E: i \in s, j \in s} x_{ij} \leq |S| - 1 \quad \forall S \in V$ (3)
$x_{ij} \in \{0,1\} \quad \forall i,j \in E$ (4)
where, n = Total number of nodes
Counties connection network in the southeastern North Carolina
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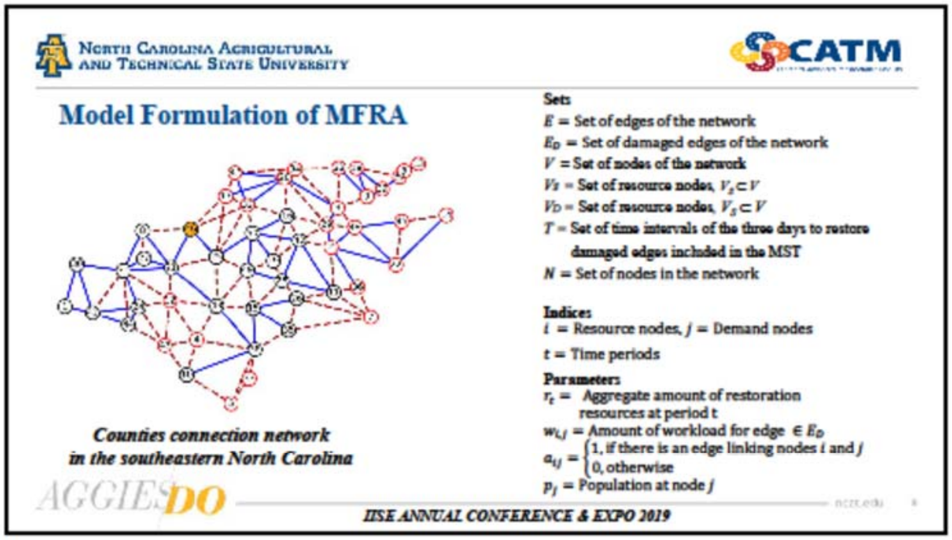
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Model Formulation of MFRA
Sets
E = Set of edges of the network
E_D = Set of damaged edges of the network
V = Set of nodes of the network
V_S = Set of resource nodes, $V_s \subset V$
V_D = Set of resource nodes, $V_s \subset V$
T = Set of time intervals of the three days to restore damaged edges included in the MST
N = Set of nodes in the network
Indices
i = Resource nodes, j = Demand nodes
t = Time periods
Parameters
r_t = Aggregate amount of restoration resources at period t
$w_{i,j}$ = Amount of workload for edge $\in E_D$
$a_{ij} = \begin{cases} 1, \text{if there is an edge linking nodes } i \text{ and } j \\ 0, \text{otherwise} \end{cases}$
p_j = Population at node j
Counties connection network in the southeastern North Carolina
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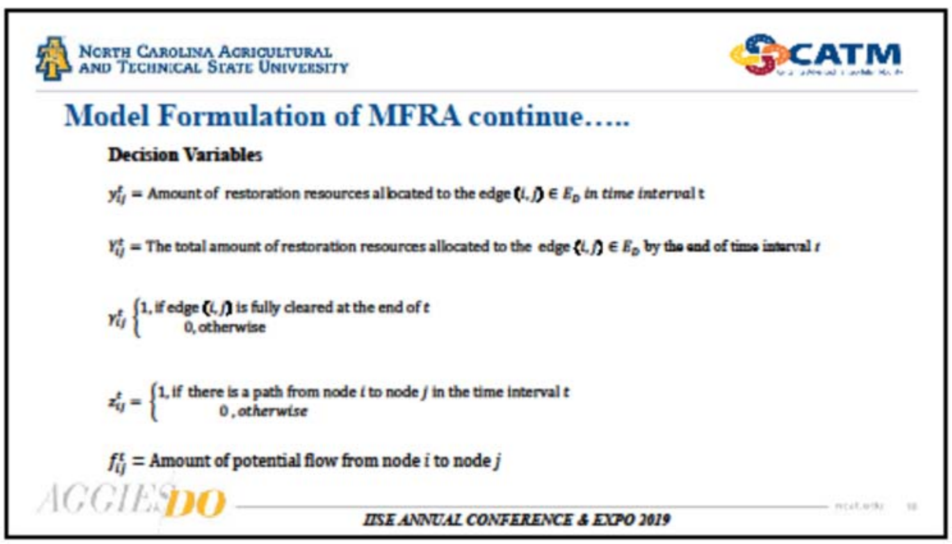
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Model Formulation of MFRA continue…..
Decision Variables
y_{ij}^t = Amount of restoration resources allocated to the edge $(i, j) \in E_D$ in time interval t
Y_{ij}^t = The total amount of restoration resources allocated to the edge $(i, j) \in E_D$ by the end of time interval t
$\gamma_{ij}^t \begin{cases} 1, \text{if edge } (i, j) \text{ is fully cleared at the end of } t \\ 0, \text{otherwise} \end{cases}$
$z_{ij}^t = \begin{cases} 1, \text{if there is a path from node } i \text{ to node } j \text{ in the time interval } t \\ 0, \textit{otherwise} \end{cases}$
f_{ij}^t = Amount of potential flow from node i to node j
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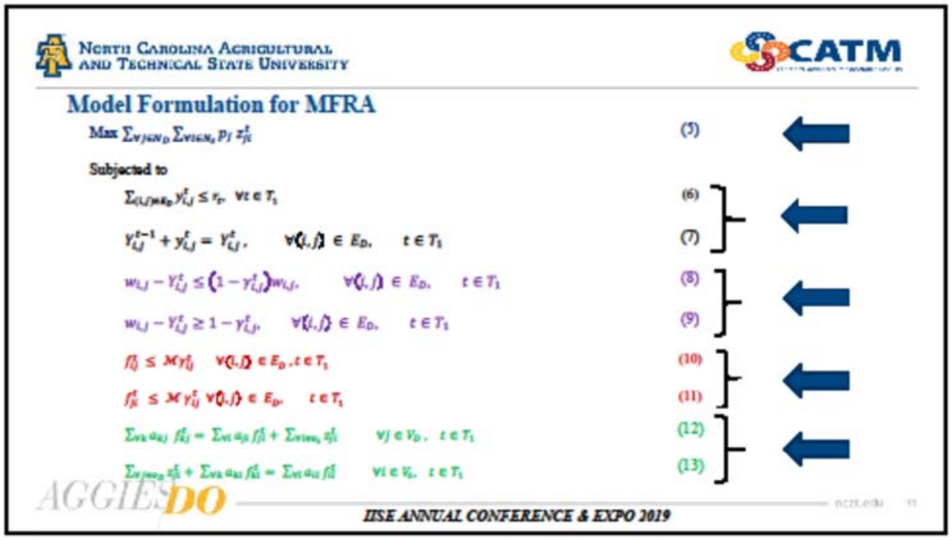
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Model Formulation for MFRA
Max $\sum_{\forall j \in N_D} \sum_{\forall i \in N_s} p_j z_{ji}^t$ (5)
Subjected to
$\sum_{(i,j) \in E_D} y_{i,j}^t \le r_t, \ \forall t \in T_1$ (6)
$Y_{i,j}^{t-1} + y_{i,j}^t = Y_{i,j}^t, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (7)
$w_{i,j} - Y_{i,j}^t \le (1 - \gamma_{i,j}^t) w_{i,j}, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (8)
$w_{i,j} - Y_{i,j}^t \ge 1 - \gamma_{i,j}^t, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (9)
$f_{ij}^t \le M \gamma_{ij}^t \quad \forall (i,j) \in E_D, t \in T_1$ (10)
$f_{ji}^t \le M \gamma_{ij}^t \ \forall (i,j) \in E_D, \quad t \in T_1$ (11)
$\sum_{\forall k} a_{kj} f_{kj}^t = \sum_{\forall i} a_{ji} f_{ji}^t + \sum_{\forall i \in V_s} z_{ji}^t \quad \forall j \in V_D, \ t \in T_1$ (12)
$\sum_{\forall j \in V_D} z_{ji}^t + \sum_{\forall k} a_{ki} f_{ki}^t = \sum_{\forall l} a_{il} f_{il}^t \quad \forall i \in V_s, \ t \in T_1$ (13)
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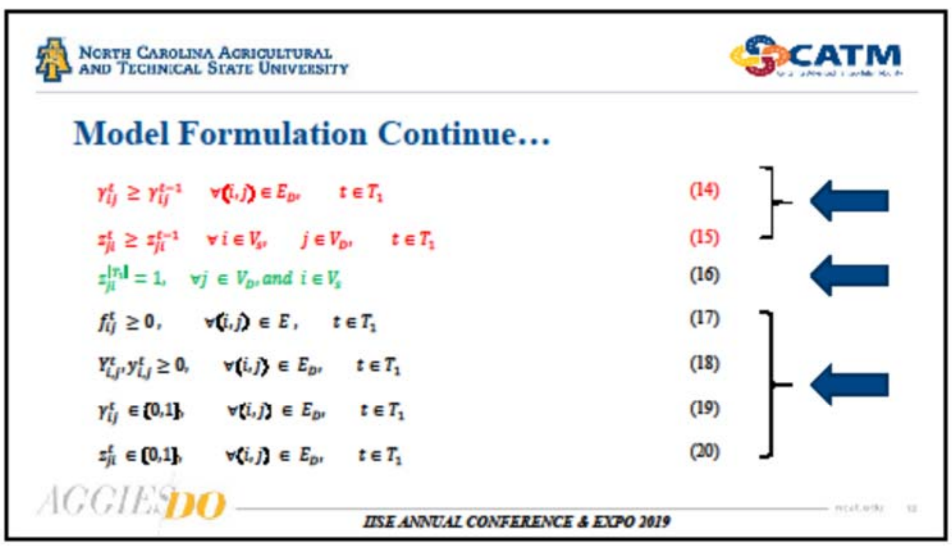
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Model Formulation Continue…
$\gamma_{ij}^t \ge \gamma_{ij}^{t-1} \quad \forall (i,j) \in E_D, \quad t \in T_1$ (14)
$z_{ji}^t \ge z_{ji}^{t-1} \quad \forall i \in V_s, \quad j \in V_D, \quad t \in T_1$ (15)
$z_{ji}^{|T_1|} = 1, \quad \forall j \in V_D, and \ i \in V_s$ (16)
$f_{ij}^t \ge 0, \quad \forall (i,j) \in E, \quad t \in T_1$ (17)
$Y_{i,j}^t, y_{i,j}^t \ge 0, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (18)
$\gamma_{ij}^t \in \{0,1\}, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (19)
$z_{ji}^t \in \{0,1\}, \quad \forall (i,j) \in E_D, \quad t \in T_1$ (20)
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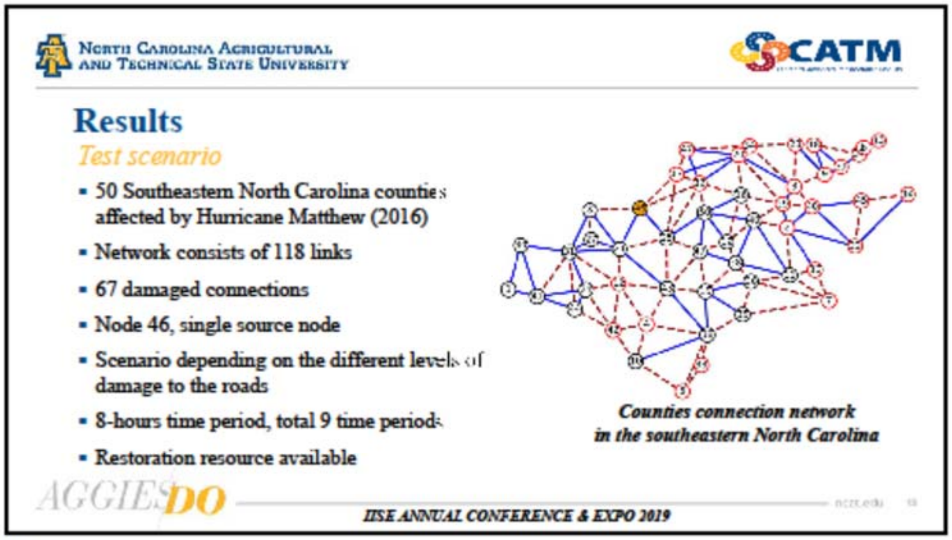
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Results
Test scenario
▪ 50 Southeastern North Carolina counties affected by Hurricane Matthew (2016)
▪ Network consists of 118 links
▪ 67 damaged connections
▪ Node 46, single source node
▪ Scenario depending on the different levels of damage to the roads
▪ 8-hours time period, total 9 time periods
▪ Restoration resource available
Counties connection network in the southeastern North Carolina
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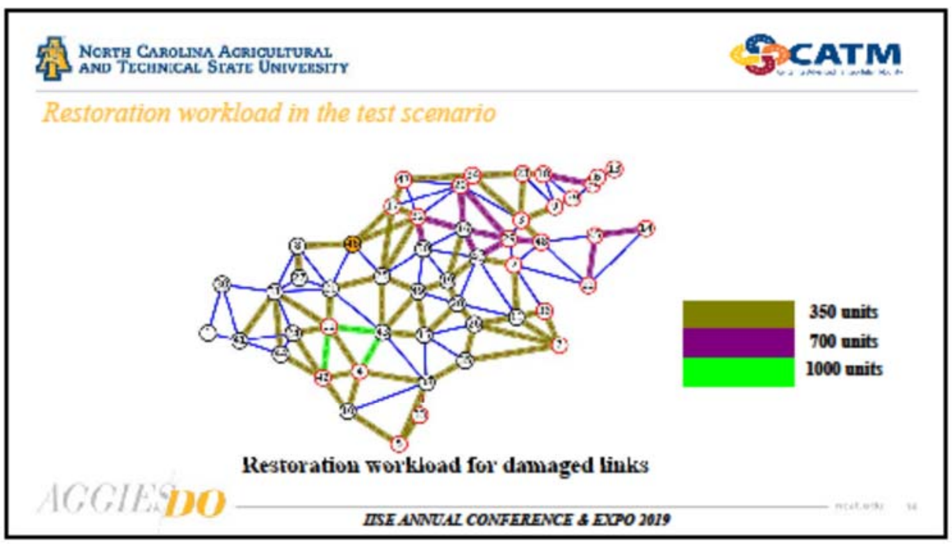
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Restoration workload in the test scenario
350 units
700 units
1000 units
Restoration workload for damaged links
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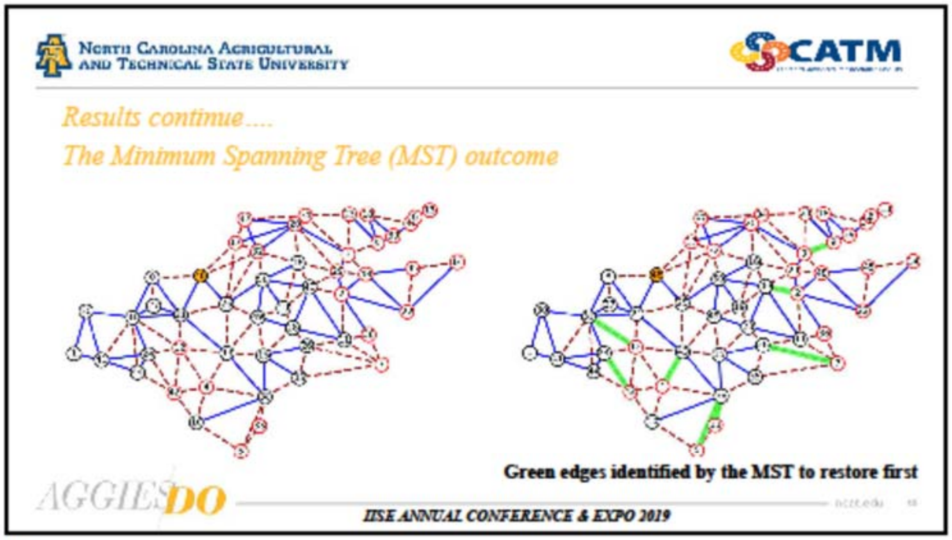

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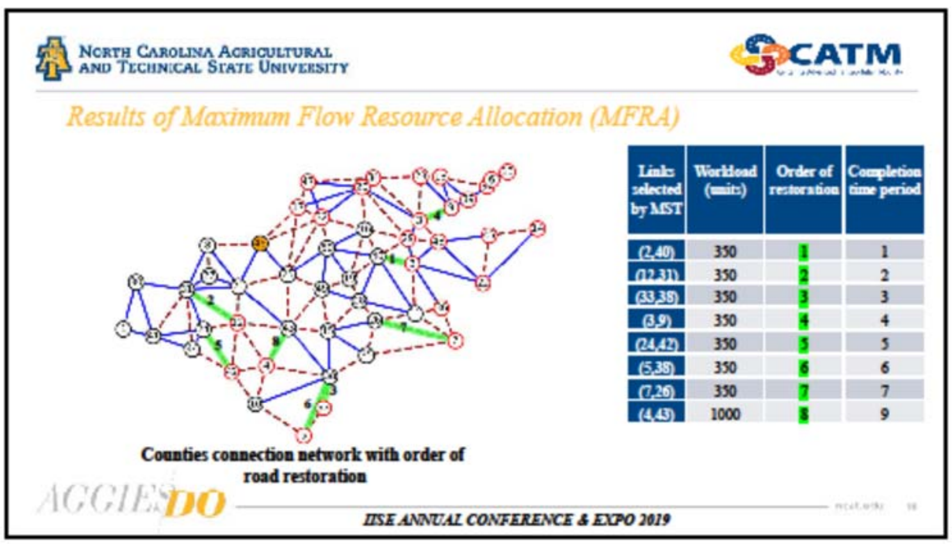
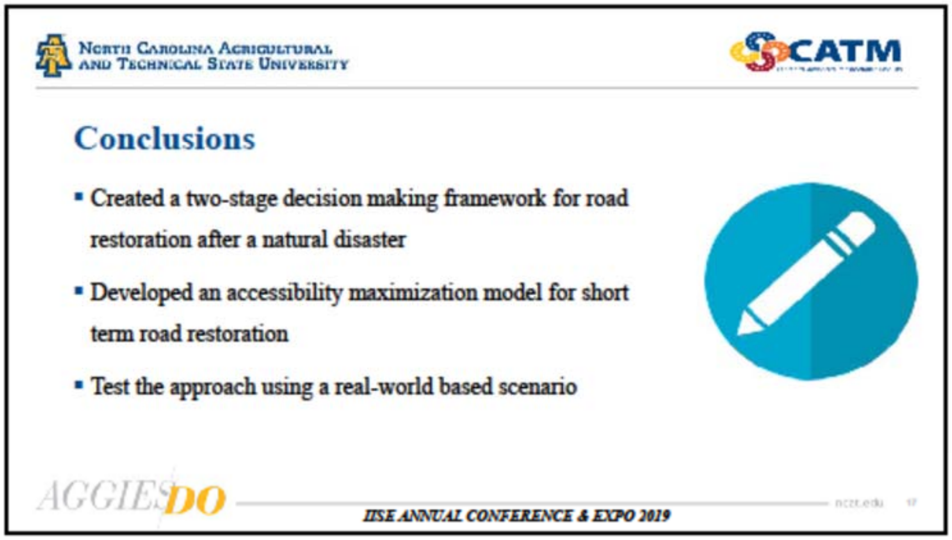


Links selected by MST	Workload (units)	Order of restoration	Completion time period
(2,40)	350	1	1
(12,31)	350	2	2
(33,38)	350	3	3
(3,9)	350	4	4
(24,42)	350	5	5
(5,38)	350	6	6
(7,26)	350	7	7
(4,43)	1000	8	9

16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Conclusions
▪ Created a two-stage decision making framework for road restoration after a natural disaster
▪ Developed an accessibility maximization model for short term road restoration
▪ Test the approach using a real-world based scenario
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North Carolina Agricultural and Technical State University
CATM
Limitations and Future Work
▪ Need more road restoration workload data
▪ Need to test the long-term road restoration model
▪ Design and conduct a comprehensive experiment to test the approach and provide insights for emergency administrative
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