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Methodology for Quantifying Resiliency of Transportation Systems

Hannah Rose Russell

METHODOLOGY FOR QUANTIFYING RESILIENCY OF TRANSPORTATION SYSTEMS

By

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ABSTRACT

The National Science Foundation's definition of resiliency is "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (National Science Foundation, 2016). While this definition is informative and useful, it lacks a quantitative reference. There is a need for a method of quantifying resilience to better plan and prepare for system wide disruptions. The research effort described herein provides a quantifiable measures of system resiliency, consistent with NSF's definition. Fundamentally, a system disruption can be partitioned into five distinctive states: the stable pre-event state, the absorption state, the disrupted state, the recovered state, and stable recovered state. The proposed method identifies these states by measuring system output and quantifies each component on a value scale between zero and one. The resiliency measure then unifies these metrics to provide an overall assessment of resiliency, which accounts for the system's ability to absorb, recover, and adapt. This approach to quantifying resiliency is applicable to any real-world or simulated system with measureable outputs. This paper first documents the development of the resiliency quantification method and then applies the method toward four complex, real world, transportation systems undergoing disruptions. These case studies consisted of six maritime port, three airports, two localized refueling systems, and the Colorado Department of Transportation's cyber network. Each system had a measurable drop in functionality due to a disruption. In general the results of this research showed that the proposed method of quantifying resiliency can be utilized for any transportation system.

1.0 INTRODUCTION

The need to enhance resiliency within the transportation systems and their management capabilities is vital toward providing safe, reliable mobility. Traditionally, civil infrastructure as included design limits that anticipating the reality of continually changing conditions. When these design limits are reached, the resulting disruption can and often does have a significant impact on the operations. Disruptions to the operations of transportation systems have generally been tolerated by the public as routine. Flight cancelation, delayed shipments, lane closure, power outages are tolerated as everyday occurrences to be expected with the movement of people and goods. Global climate change and an increase tendency toward urbanization are likely to increase the rate disruptions within the transportation system.

The meaning and definition of resilience is often represented differently depending on the context and field, to which it is applied. The systems engineering and cyber security company MITRE corporation has developed a definition of resiliency as "the persistence under uncertainty of a system's mission-oriented performant in the face of some set of disturbances that are likely to occur given some specified timeframe." (Musman & Agbolo-Amison, 2014). This definition was developed after looking at existing resiliency definitions produced by researchers like Gilbert who defines resiliency as : "the ability to provide and maintain an acceptable level of service in the face of faults and challenges to normal operations" (Gilbert. 2010), and Holling who defines resiliency as "the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist" (Holling, 1993). The United States Army Corps of Engineers defines resiliency as "the ability to anticipate, prepare for and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions (Executive Order 13563)" (USASCE, 2016). This definition shadows from the definition developed by the National Science Foundation: "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events. The essential features of resiliency are the ability to absorb disturbances, or avoid disruptions, and "bounce back" and respond. The core element of resiliency is "bouncing back," which in this context is taken to mean the recovery of levels of service by the infrastructure after a disturbance." (NSF, 2016). For the purpose of this research paper, the NSF definition of resiliency is explored for the application to system operations. The NSF definition includes desirable characteristics that are unaccounted for in the previously stated definitions.

The ability of a system to absorb, adapt, and recover after a disaster is critical to the success of the system. Absorption is the process of a system reducing the effect of a shock by incorporating and withstanding it. This is seen in the drop-in functionality of a system due to a disruptive event. Adaptation is the process of adjusting to new conditions for better functionality. In order for recovery to occur, adaptation must first happen. Recovery is a return to a normal state, as defined before the loss in functionality.

Resilient infrastructure is providing the means to deliver the essential goods and supplies needed to safely and quickly recover from a storm, attack, or other major disruption. There is an evident need to better understand the relationship between system performance, disruptions, and resiliency on both a local and regional level. Quantitative methods and tools, stemming from engineering science and vulnerability studies, provide quick assessments of "resilience" at broad spatial scales, but do not dip below the surface into local scale, place-based, community resilience. Qualitative methods, on the other hand, help answer research questions that cannot be addressed with numerical data and investigate questions of attitude, perception, and social interaction." (Dhanak, et. al., 2019).

Topics concerning resiliency have increased over the years to parallel the increasing range of hazards faced by developing technology and global climate change. AECOM claims that with the increasing number of threats, "infrastructure owners, managers and operators need to understand today's challenges, anticipate the future, collaborate across businesses and borders, and prioritize spending to optimize the benefits." (Sawislak et. al., 2019). The American Society of Civil Engineer's 2017 Infrastructure Report Card highlights the importance of resiliency and provides physical examples. One example is how the San Francisco Airport is "leading the way in the effort to make our nation's infrastructure more prepared for a natural disaster" with the introduction of a new air traffic control tower capable of withstanding a 7.5 magnitude earthquake (Moylan, 2017).

A quantification of resiliency allows systems to analyze current resiliency, track future improvements, and model possible scenarios. Currently, there are multiple methods of quantifying resiliency, all with their own definition for quantification. A common method used is the scorecard method. The scorecard is a way for stakeholders to assess their resilience using predetermined questions designed to target indicator frameworks. The Department of Homeland Security has developed the Plan Integration for Resilience Scorecard method to reduce the country's vulnerabilities to hazards (Homeland Security, 2017).

A similar method of resiliency quantification is the resilience matrix created by the US Army Corps of Engineers. They utilize a 16 cell decision making matrix based on the Network Centric Warfare doctrine of the military. This matrix produce a quantification of "poor", "moderate" or "good" resiliency. They also utilize a second method of quantification called the Baseline

Resilience Indicator for Communities (BRIC). This method is a composite matrix that calculates a resiliency index value based on up to six sub-indexes (Rosati et. al., 2015). Utilizing a resilience range of “poor”, “moderate”, “good” or “low”, “medium”, “high” is a common output for resilience quantification. Most inputs for this method require stakeholder feedback for a variety of multiple-choice questions.

A third method of resiliency quantification utilizes stakeholder feedback to output delays and queues in operations. This technique was created for assessing seaports by Kamal Achuthan (2011), but has the potential for use across all transportation systems. The Methodology for Assessing Resilience for Seaports (MARS) models the wet and dry side of port operations before outputting delay and queue time. Stakeholders must assess the results and determine if the times are satisfactory for their seaport (Moylan, 2017).

Transportation Infrastructure and Vulnerability

Maritime ports are vital to a nation’s infrastructure and economy. In 2014, seaports contributed to 26 percent of the United States’ $17.4 trillion economy. Ports help to deliver essential goods including food and gasoline throughout a country. Ports employ 23.1 million people and contribute $1.1 trillion to personal wages and local consumption (American Association of Port Authorities, 2015). In the United States, there are 29 ports on the West Coast and 16 on the East Coast (Welshans, 2015). Ten metropolitan ports across the country account for 60 percent of international goods arriving into the country (Tomer & Kane, 2015).

Ports are vulnerable to disruptive events, natural or otherwise. In the last 26 years, sea levels have risen 2.6 inches (NOAA, 2008). With rising sea levels, major hurricanes (category three or higher) in the Atlantic have increased 74 percent (NOAA, 2015). With maritime ports located within close proximity to large bodies of water, storm surge and changing currents and tides has a major effect. This increase in natural disruptions, has made the need for resilient marine transportation systems even more vital. In addition to the economic impact of a disruption to a port, the environmental effects that could occur within the waters also threaten the ecosystem. Furthermore, as elements of an interconnected system of channels and waterways, ports play a critical role in supply-chain.

Hurricanes, oil spills, and labor disputes are all examples of events that can cause a major disruption to a port. Hurricane Sandy in October 2012, closed the Port of New York/New Jersey for over a week due to flooding, loss of power, and damages to the port that prevented immediate reopening. It was estimated by the Port Authority of New York and New Jersey (PANYNJ) that the port closure cost $170 million (Smythe, 2013). Between the time of the partial reopening of the port (three days after landfall) and the time the port returned to full operation (eight days after landfall), dwell times of vessels at the Port of New York/New Jersey climbed as high as 50 hours (Wolshon, Parr, Farhadi, & Mitchell, 2018). The overall impact of a disruption on a port is a function of vulnerability of the port and the severity of the disruption. The resiliency of ports and inland waterways is critical for maintaining the flow of essential goods throughout the United States and is critical to national security and defense readiness.

Airports play a key role in the transportation infrastructure of our nation. They connect cities and global economies. In 2017, the Airport Council announced the total economic output of U.S. commercial airports exceeded $1.4 trillion dollars. The 493 commercial airports in the United States also support more than 11.5 million jobs as of 2017. These economic powerhouses continue to strengthen as the economy improves and technological advances are made (Scavuzzi, 2018).

Vulnerability is a documented trait of airports. Disruptive events natural or otherwise can collapse the functionality of an airport. Since 1851, only eighteen hurricane seasons have passed without a known storm impacting the state of Florida. All 168 other years, Florida has experienced at least one tropical or subtropical cyclone. With airport operations relying on compatible weather, these major disruptions have led to an increasing importance for resilient systems.

Hurricanes, snowstorms, and security threats are all examples of events that can cause a major disruption to an airport. Hurricane Irma made landfall in the Florida Keys as a category 4 hurricane. With 130MPH winds and significant damage, Key West International Airport was closed for ten days due to Hurricane Irma. With the airport closed, the recovery of the local community was impacted negatively. The overall impact of a disruption on an airport is a function of the vulnerability of the airport and the severity of the disruption the airport is facing. A highly resilient airport is critical to success of the nation's economy and transportation system (NOAA, 2016).

The ability of the citizens of the US to purchase fuel is critical to the nation's transportation system and economy. Gasoline is the main fuel used in transportation in the U.S. According to the U.S. Energy Information Administration, in 2018, Americans used about 143 billion gallons of motor gasoline and 186 million gallons of aviation gasoline (EIA, 2019).

Disruptive events can negatively impact the refueling system of gasoline stations in the U.S. Flooding, hurricanes, and government instability are examples of events that cause an increase in fuel purchases. In these situations, the normal supply and demand of fuel becomes unbalanced, and refueling stations may run low. In the case of a mandatory evacuation due to a natural disaster, consumers fill up their fuel tanks at once, throwing off the balance of the normal supply and demand. As fueling stations run low on gasoline, chaos can occur, causing greater safety concerns.

During Hurricane Irma, high-volume evacuations and refueling disruptions led to widespread fuel shortages days before the hurricane made landfall. These shortages created panic as evacuees became stranded on the side of the road with no fuel, exasperating traffic congestion. With the climate changing and natural disruptions increasing, the need for resilient refueling stations has become more vital. The safety and transportation facilities of our nation depend it.

Cybersecurity is a growing field as technology advances. Communication, entertainment, and transportation are all fields that rely on technology. However, this technology can be accessed without authorization and private information stolen. Physical infrastructure like traffic signals and self-driving vehicles can also be accessed by those intending to inflict harm on others. Cybersecurity is the art of protecting this technology and information.

According to Forbes, private sector companies are projected to spend over $1 trillion on digital security globally through 2021. Currently, Bank of America spends around $500 million a year on cyber security. Agencies responsible for protecting our physical infrastructure on a local, state, and federal level have a limited budget for cybersecurity given how critical the nation's infrastructure is to our society functioning (Tonar & Talton, 2018).

Any system with technology is at risk for a cyber-attack. In 2018, the Colorado DOT experienced a cyber-attack by a threat actor using malware. This attack led to the governor of Colorado declaring a state of emergency. This disruption to the Colorado DOT effected their ability to operate effectively and cost the state millions of dollars. Cybersecurity is critical to the national security and economy of our country.

Goals and Objectives

The goal of this research is to develop a method of quantifying resiliency for a wide range of transportation systems that is intuitive, intrinsic, and parallels the NSF definition. Using plots of system performance over time, this research identifies five discrete states of a system disruption: the stable pre-event state, the absorption state, the adaptive state, the recovery state, and the stable recovered state. In this paper, formulations are presented which quantify the adaption, absorption, and recovery. The proposed approach brings together these discrete states to provide an overall measure of operational resiliency. The resiliency assessment is demonstrated in this paper for four unique critical infrastructure applications: seaports (local and regional), airports, gasoline consumption, and cyber security. The application of the resiliency index can lead to more informed decision making for emergency managers and public officials. Ideally, the index will be used to evaluate, objectively, the operational resiliency of systems in response to policy, protective action decisions, and infrastructure improvements. The resiliency index allows for the evaluation of various hazards, timescales, and regions. Community and transportation planners may also find this tool useful to demonstrate the benefits of investment on resiliency, using a quantifiable metrics.

2.0 LITERATURE REVIEW

Prior research is available that demonstrates the significance of a high resiliency and lessons learned from other disruptive events that can be applied in the future to achieve a better resiliency. A few of these studies are presented in the following sections in further detail. Studies are also presented on different ways to quantify resiliency, quantify port performance, assess port resiliency, and utilize data collected from Automatic Identification Systems (AIS) technology.

3.1.0 Importance of High Resiliency

As an integral aspect of modern existence, electricity is one of the most significant scientific discoveries. "In 2013, the energy sector reaches such a level of significance that it was declared to be uniquely critical by the Presidential Policy Directive (PPD-21)." (Chovancikova & Dvorak, 2019). Currently, electricity plays a major role in rail transportation. The resilience of the electricity system is critical to success of rail transport. According to Chovancikova and Dvorak (2019), without electricity, almost all technological equipment on the railway would fail. This study on resilience quantification would assist with the success of rail transportation by providing electrical systems with a numerical value to represent their current resilience and areas for improvement.

Thousands of different entities own and operate the electrical power system. This diversity prevents large blackouts due to a singular failure. Operators of these systems strive to assure safe and reliable service, but power outages are unpreventable with our current technology and power system. The book *Enhancing the Resilience of the Nation's Electricity System* (2017), claims that the electrical power system's reliability can be improved but never perfected. This book focuses on "identifying, developing, and implementing strategies to increase the power system's resilience”. This study on resilience quantification also seeks to improve system resilience but the improvement is based on awareness of their current resilience value and areas of improvement.

Autonomous vehicles are on the rise, and with their emergence arises new security risks. As autonomous vehicles communicate with their environment to operate safely, a cyber-attack has the possibility of hijacking the vehicles communication system and using the vehicle as a weapon. A study by Subke and Moshref, (2019) looks at the vulnerability of communication devices within the autonomous vehicle and ways to improve the resilience of the remote diagnostic communication.

The desire for increased efficiency has driven cities to adopt advanced Intelligent Transportation Systems (ITS). With these emerging technologies, potential threats are arising. A study by Ganin and others was conducted in 2019 to illustrate the current resilience to ITS. The authors modeled disruptions in 10 urban areas and analyzed the worst case scenarios. These disruptions were cyber-attacks on Intelligent Transportation Systems. The study found that a locked traffic signal caused more disruption than a fully disabled signal (Ganin et. al., 2019). Quantifying the resiliency of the transportation network during a modeled disruption would have further developed this study on the analysis of resilience in Intelligent Transportation Systems.

In this study, the ability to recover rapidly from a disruptive event produces a high level of resiliency. This is important when an airport may need to be used “as the staging area for an entire city’s relief efforts”, as seen in Jeff Price’s article Ivan the Terrible: Lessons in Disaster. The Pensacola Regional Airport suffered a direct hit from hurricane Ivan but was able to immediately reopen and provide relief to the city. This is a prime example of the importance of a high resiliency

(Price, 2005). Another study by Smith, Waggoner, Sandra, and Hall (2007), discusses how airports are “essential and irresistible assets in major disaster responses”, however this is limited by the length of time it takes for an airport to reopen. A high resiliency allows an airport to transform into a command post, shelter, or temporary hospital in the face of disaster. This study also focuses on the impact sound emergency management may have on the resiliency of an airport. Sean Boderick (2005), agrees that “airports are the lifeblood of the relief efforts and need to be reopened quickly” as to provide shelter to responders. Another reason a high level of resiliency is important is to lessen monetary loss. Sean Hunter (2007), discusses loss of operations Louis Armstrong New Orleans International Airport faced after being closed two weeks from the effect of Hurricane Katrina. In January 2007, daily departures represented only 64% of the daily departures before Hurricane Katrina. Another article on the effect of Hurricane Katrina discusses the impact on New Orleans Lakefront Airport. This article by Robert Fluhr (2007), looks into how the loss of operations caused the closer of their air traffic control tower. If New Orleans Lakefront Airport had a high level of resiliency, this could have been avoided.

3.2.0 Lessons Learned from Historical Disruptions

Infrastructure is essential to quality of life. A study by Hallegatte, Rentschler, and Rozenberg (2019), looks at the ability of infrastructure to meet users’ needs during and after a major disruption. Millions of people face the consequences of unreliable electricity grids, inadequate water and sanitation systems, and overloaded transportation networks, all of which is magnified after a natural disaster. The study by Hallegatte and others identifies five obstacles that prevent resilient infrastructure and recommendations to overcome the obstacles. This study on quantifying resiliency can benefit from the research done by Hallegate and others. The obstacles that prevent resilient infrastructure and their solutions can benefit those who know their resilience value and need suggestions for improvement methods (Hallegatte, et. al., 2019).

As the path of a hurricane is forecasted, a wave of fuel shortages follow. Evacuees fill up, planning a long journey away from home and non-evacuees begin to horde fuel to keep their generators running. Fuel shortages discourage safe evacuations and cause chaos. A study by the Center for Advanced Transportation Mobility proposes a computational model to predict fuel shortages due to future hurricanes. The prediction of where fuel shortages occur will provide insight into the best method of refueling for a resilient transportation network. The lessons learned from past hurricanes and this predictive model can be used to enable effective hurricane evacuations in the future and increase the resilience of the transportation network (Multiscale model, 2019).

To increase the level of resiliency at an airport, data from previous disruptive events should be analyzed. A study by Jeff Price (2005), discusses eight lessons learned from Pensacola Regional Airport's experience with Hurricane Ivan. These lessons in preparation can be applied to any airport about to experience a known disruption. Sean Brokerick (2005), also wrote an article on lessons learned from airports that have experienced a hurricane, however he includes lessons learned from response teams and lessons applicable to general emergency planning as well. His study focuses on multiple airports affected by hurricane Katrina and he suggests ranking recovery tasks in order of importance to achieve the highest level of resiliency. A study that addresses a different set of lessons learned is Navigating Storms by John Heimlich (2005). He discusses how hurricanes can impact the price of jet fuel. When "every penny increase in the price of a gallon of jet fuel drives an additional $190 million in annual fuel costs", it is an important topic to consider (Heimlich, 2005). After Hurricane Katrina, the price of jet fuel rose 49 cents per gallon, creating a loss of revenue for airports trying to recover from a state of devastation. After this event the Air

Transport Association was formed to keep the increase of price in jet fuel from jumping rapidly. Looking back on data from previous disruptive events, allows airports to learn how to adapt in times of devastation and return to normal operation as quickly as possible.

3.3.0 Quantifying Resiliency

In the United Kingdom, 95% of supplies come by sea, including over one third of the UK's food supply, making continuous port operations a necessity for the sustainability of supply chains, economy, and port business. The resilience of UK ports relies on multiple, interdependent stakeholders. Kamal Achuthan (2011), has created a Methodology for Assessing Resilience of Seaports (MARS). Assessing the resilience of seaports is necessary for stakeholders to improve the resilience of ports by assessing and developing contingency plans. MARS is capable of modeling both wet-side and dry-side operations before, during, and after a disaster. It is based on existing data already collected for port operations management. The user must input downtimes or port resources affected and tolerable limits for the complete port system and individual stakeholders. MARS will model the delays and queues in operations to determine the resilience instead of the dwell times as in this study. Assessing the delays and queues allows the user to alter downtime inputs and until recovery time objectives can be met.

The Ports Resiliency Index (PRI) was developed by Morris and Sempier (2016), using the Delphi Method for ports along the Gulf of Mexico. The PRI measures the resilience of Port organizations to costal hazards by asking eight sections of multiple choice questions. A range of resilience can be determined for each section based on the percentage of questions answered "yes" compared to the total number of questions. The range of resilience is decided by the project team (i.e., 0-49% = low; 50-75% = medium; 76-100% = high) (Morris & Sempier 2016). The eight sections that make up the PRI are Planning Documents for Hazards and Threats, Hazard Assessment:

Infrastructure and Assets, Insurance and Risk Management, Continuity of Operations Planning for Infrastructure and Facilities, Internal Port Authority Communications, Tenant and External Stakeholder Communications, Emergency Operations Location (Physical or Virtual), and Critical Records and Finance. The method of quantifying resiliency in this study does not require port stakeholders to answer multiple choice questions.

According to Morris (2016), a Resilience Index is an indicator of a Port organization's ability to reach and maintain an acceptable level of functioning and structure after a disaster. The Ports Resiliency Index (PRI) is a self-assessment tool for determining if Ports and the regional marine transportation sector are prepared to maintain operations during and after disasters. This assessment is to be completed with a group of internal and external Port stakeholders. The PRI is capable of identifying strengths and weaknesses in management and operations, assessing the overall resilience of the Ports industry, and identifying action items the industry should work towards to address system vulnerabilities and maintain long-term viability. It is recommended that the PRI be revisited every 1-2 years. The method in which the PRI was developed consisted of a checklist of possible indicators of resilience for ports taken from the American Association of Port Authorities 2006 Emergency Best Practices Manual, the NOAA Port Resilience Planning Tool, and academic sources. Leaders in the ports and marine transportation industry were also asked to identify measures of resilience. These indicators were written in the form of 'yes' or 'no' questions and grouped into broad categories. The Port Resiliency Index is determined using a percentage system. The Resilience Index is identified as LOW, MEDIUM, or HIGH in different categories. A high Resilience Index indicates a Port is well prepared for a disaster and will likely reopen with few difficulties. The method of quantifying resiliency in this study does not require port stakeholders to answer yes or no questions and the determined resilience of the system is given as a numerical value.

The community self-assessment Resilience Index by Seimpier et al. (2010), provides community leaders a simple method of predicting if their community will reach and maintain an acceptable level of functioning after a disaster. This assessment does not claim to replace a detailed study. When this self-assessment is completed, a Resilience Index will be assigned to determine how long it may take a community to provide basic services and reoccupy homes and businesses after a disaster. These indexes are defined as LOW, MEDIUM, or HIGH. The method of quantifying resiliency presented in this study provides the resilience of the system as a numerical value, unlike the community self-assessment Resilience Index by Seimpier et al.

Seaports and their intermodal connectors support the global supply chain and provide regional economic activity. According to Wakeman, Miller, and Python. (2015), climate change and the disruption of major weather events bring a need for enhanced costal resilience. They define disaster resilience "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events," and that "enhanced resilience allows better anticipation of disasters and better planning to reduce disaster losses – rather than waiting for an event to occur and paying for it afterward" (Cutter et al., 2013). The objective of this research is to create a standardized framework for resilience in transportation systems that integrates physical infrastructure and social systems. This was done by gaining information from stakeholder interviews and workshops to create flow charts that show links between social and infrastructural assets that provide rapid recovery on the coast after major events. The method of quantifying resiliency presented in this study determines a numerical value for resilience that is determined by functionality and not infrastructure.

The Department of Homeland Security along with its partners, has developed a scorecard method for quantifying resiliency using spatial evaluation. The goal of this scorecard method is to help communities identify conflicting policies in respect to disaster protocol for different departments in the community. Physical and social vulnerability areas should be mapped by each department and compared to reveal vulnerability hotspots. Each disaster plan is scored and the community in whole receives a score for resilience. This method utilizes spatial mapping to generate a resilience value while the method of quantifying resiliency presented in this paper requires the functionality for a system as an input (Department of Homeland Security, 2017).

The United States Army Corps of Engineers has created a three tier approach for quantifying resiliency. They assessed multiple quantification methods already in use, and modified them to fit their needs. Their resilience matrix consists of 16 cells that cover the preparation, absorption, recovery, and adaptation of a system within physical, information, cognitive, and social domains. A percentage value is then assigned to each cell and the rating of “poor”, “moderate”, or “good”. This method of quantification differs from the resiliency quantification method in this paper as the method by the United States Army Corps of Engineers does not output a numerical resiliency index value for the system and the inputs are based off stakeholder feedback and not historical data (Rosatui, Touzinsky, & Jeff Lillycrop, 2015).

Moreover, a study dealing with the quantification of resilience titled “Stochastic measures of resilience and their application to container terminals”, was authored by Raghav Pant, Kash Barker, Jose Emmanuel Ramirez-Marque, Claudio M. Rocco (2014). This study incorporates aspects of stochasticity and uncertainty in terms such as time to total system restoration and time to full system service resilience in a model. The resiliency decision making framework created includes commodity flows at a port, full or partial terminal closures due to disruptive events and restoration activities and was applied in a case study at the port of Catoosa in Oklahoma (Pant, et.al, 2014).

3.4.0 Quantifying Port Performance

The performance of maritime ports is often measured with indicators such as container throughput and facility productivity. A quantitative measure of port performance is of great importance for models of port operations. Chen et al. (2016), proposes to derive port performance indicators from vessel GPS traces and maritime open data. Port performance indicators include ship traffic, container throughput, berth utilization, and terminal productivity. These indicators are directly related to vessel counts and the amount of containers handled. The authors propose the container-handling events at terminals are the basis of a quantified port performance measurement. Strengths and weaknesses of different terminals are compared to benefit terminal productivity, linear schedule optimization, and regional economic development planning. The methodology for this study consists of large-scale, real-world GPS traces of containerships at major container ports. Variation of data from ports throughout the world, from different times of year, and from various maritime open data sources validate the study. The authors found that the proposed framework can accurately estimate port performance indicators and compare port performance rankings and regional port performance rankings. The resiliency quantification method presented in this study can also be used to determine port performance rankings, but it would be done using a numerical value scale for resilience.

Efficient cargo transfers are critical to port performance. There are many diverse ways to measure port performance and efficiency, Ducruet, Itoh, and Merk (2014), proposes a method that is based on turnaround time. This study hypothesis that turnaround time efficiency of individual ports may exhibit certain commonalities functionally and/or regionally outside of individual situations. An overview of time efficiency in world container ports is analyzed for 1996, 2006, and 2011 to identify possible determinants of time efficiency, such as the volume of traffic and size of vessels. In the case study on maritime ports utilizing the resiliency quantification method in this study, dwell time is used to determine the functionality of the port, similar to the turnaround time in this study. The difference in the port performance quantification is that the study by Ducruet and others also incorporates vessel size in the turnaround time.

The capacity utilization of a seaport can be found using well-known standard queuing models following the methodology proposed by Layaa and Dullaert. (2014). The authors of this study used the seaport of Dar es Salaam (Tanzania) as a case study. Historical data on Dar es Salaam terminal performance for the general cargo and the container terminal has been analyzed to validate the model. Using standard queuing models, this study found that the Dar es Salaam terminal capacity was underutilized and vessels were subjected to lengthy queues. While a standard queuing model can be used to quickly evaluate seaport terminal capacity, actual ship arrivals and service time distributions require further analysis.

3.5.0 Port Resiliency Assessment

Adam Rose and Shy-Yi Liao (2005) address regional resilience towards disasters in their paper "Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions". They utilize the computable general equilibrium modeling approach in order to estimate the regional economic impacts of earthquakes and other disasters that can cause supply chain disruptions. Some of the main functions of this model included operational definitions of individual and regional resilience, identification of production function parameters and development of the algorithms for recalibrating production functions to data.

In addition, Mo Mansouri, Roshanak Nilchiani and Alsi Mostashari (2010) conducted a research project titled “A Policy Making Framework for Resilient Port Infrastructure Systems”. In their work they developed a Risk Management-based Decision Analysis framework, with the goal of forming a systematic process for making strategic and investment decisions in case of disruptions. The disruption cases considered ranged from natural disasters, to organizational, technological and human factors. Their approach can help to identify common elements of uncertainty in port systems, evaluate the costs incurred with various potential failures and with investing in resilience strategies.

In their article titled, “Resilience Framework for Ports and Other Intermodal Components,” Rahul Nair, Hakob Avetisyan and Elise Miller-Hooks (2011) discuss ports and intermodal freight systems, highlighting the dangers that hinder cargo transportation and the infrastructure’s vulnerability to disasters. They quantify resilience as the post disruption fraction of demand that can be satisfied while using specific available resources and managing to maintain a prescribed level of service. Additionally, they employ their concept on a system level and propose a generic framework for its application in intermodal facilities. In another article, Elise Miller-Hooks, along with Xiaodong Zhang and Reza Faturechi (Miller-Hooks and Faturechi, 2012) conducted another research study related to resilience named “Measuring and Maximizing Resilience of Freight Transportation Networks”. Their model, apart from measuring resilience levels of a freight network, includes optimal setting of actions and allocation of budget between preparedness and recovery activities under level-of-service constraints.

The National Center for Risk and Economic Analysis of Terrorism Events at the University of Southern California spearheaded a project titled “PortSec: Port Security Risk and Resource Management System” (Orosz, 2011). Its objective was to create a system for risk assessment and security resource allocation for various dangers that hinder seaport operations. This decision matrix is used by the port authorities to manage and balance the increasing safety restrictions. This matrix allows the Port Authorities to maximize business throughput and minimize environmental impacts. The project has two main uses, strategic and tactical. Strategic usage includes the creation of tools for evaluation of the cost-benefit by adding/modifying new port counter-measures. On the other hand, the tactical usage of the tool provides up-to-date risk assessment for both identified areas of interest and for the overall port complex.

The Center for Transportation & Logistics at the Massachusetts Institute of Technology (MIT) conducted a multi-year Port Resilience project (Rice and Trepte, 2013). The goal of the study was to estimate the capacity required to absorb various failures of United States ports. The project included a port capacity analysis, port failure mode analysis and a detailed port resilience survey. In addition, they developed a platform called MIT Port Mapper, which is designed to identify U.S. ports that can potentially absorb cargo in the event of a port disruption. The user chooses the state he wishes to examine and either all or a portion of the state's ports. In addition, the platform is used for gathering information on the type of materials handled in each port (e.g. radioactive, containers); the data in the platform was obtained from the Army Corps of Engineers.

Moreover, the Americas Relief Team (2013) in collaboration with FedEx conducted a project titled "Port Resiliency Program" Its objective was the preparation of airports and seaports in the Caribbean and Latin America to be more resilient in the face of natural disasters by applying lessons learned in Hurricane Katrina and the Haiti earthquake. Their approach for achieving their goal comprised of three main steps: Initial self-assessment by the airport or seaport; planning of a workshop in Miami to identify gaps and training needs in sea and air port operations; and a site visit to present targeted training and a tabletop exercise to assess the preparedness of the airport or seaport (Port Resiliency Program, n.d.).

A study conducted by Tiffany C. Smythe (2013), from the Center for Maritime Policy and Strategy of the U.S. Coast Guard Academy, titled “Assessing the Impacts of Hurricane Sandy on the Port of New York and New Jersey’s Maritime Responders and Response Infrastructure,” focused on Hurricane Sandy. The goal of the study was to identify “lessons learned” from this hurricane, in order to educate the maritime community in the necessary actions required to mitigate impact during future storm events. The methodology used for achieving the goal included three main steps: meetings with the U.S. Coast Guard, data collection via participation in meetings and semi-structured interviews with key informants, and qualitative data analysis of the interview content. In addition, the research aimed to lay the groundwork for larger-scale and longer-term studies related to coastal storms and port resilience planning.

Other qualitative analyses of port disruptions due to hurricanes have been undertaken to study stakeholder perceptions (Becker, Matson, Fischer, & Mastrandrea, 2015). This article proposed a storm impact typology for two ports (Gulfport, Mississippi and Providence, Rhode Island) to include direct damages, indirect costs, and intangible consequences. The authors found that formal planning did not address many stakeholder concerns, particularly the impacts of intangible consequences that are borne by a large number of stakeholders and society at large.

In addition, an important area of research in the field of port resilience deals with the identification of the costs associated with port disruptions. Adam Rose and Dan Wei (2013), in their paper called “Estimating the Economic Consequences of a Port Shutdown: The Special Role of Resilience” address this matter. They developed a demand and supply-driven methodology that takes into account imports, exports and the major types of resilience in terms of alternative options. The study was successful in developing a tool to estimate the total economic consequences of a seaport disruption. After applying their approach to a 90-day disruption at the seaports of Beaumont and Port Arthur, Texas, they concluded that a carefully thought out resilience plan can reduce the impacts of disruption by as much as 70%.

Studies regarding port resilience have also been conducted outside the U.S. An example is a paper from Andrew Grainger and Kamal Achuthan (2014) from the University of Nottingham, as part of a collaborative project with the United Kingdom Department of Transport, titled "Port Resilience: a Primer". The study focused on the importance of U.K. ports, various vulnerability issues often encountered in them, preparedness methods followed to address those problems and various actions that can be taken in order to improve port resilience. Some of these actions include the development and adoption of strict planning and business continuity standards, development of simulation tools that can help understand and predict specific events taking place and identification of incentive mechanisms to ensure stakeholder interests towards resilience.

Hui Shan Loh and Vinh Van Thai (2014) in their paper "Managing Port-Related Supply Chain Disruptions: A Conceptual Paper" focused on the management side of port resiliency. They developed a management model that addresses a full set of operational risks from a holistic perspective, and in connection with various supply chain disruptions. Therefore, their model identifies the necessary actions taken from ports in order to minimize port-related supply chain disruptions. The proposed approach incorporates the theories of risk, quality and business continuity management in order to make decisions in the institutional bearings, management policies and operations actions related to port disruptions.

The National Cooperative Freight Research Program of the Transportation Research Board developed a large project called "Making U.S. Ports Resilient as Part of Extended Intermodal Supply Chains" (Southworth, Hayes, McLeod, & Strauss-Wieder, 2014). The main project tasks first included a thorough literature review on past disruption events that affected port operations, emphasizing the actions taken to tackle the problem and limit the extent of the disruption. Next, interviews with port operations, truck, rail, and ocean vessel carriers were conducted in order to understand their opinions on current levels of port resiliency, as well as on what are the best means of enhancing resiliency and speeding recovery should a disruption occur. Later, two detailed case studies of port disruptions were developed, the impacts of the superstorm Sandy's on the major East Coast ports and the extended lock closures along the Columbia River System in the Pacific Northwest. Last, the team developed guidelines suitable for public-sector decision makers who might become involved in a disruption recovery event.

An interesting project was conducted by the Stevens Institute of Technology, and funded from University Transportation Research Center, Region II, with the title "Port Resilience: Overcoming Threats to Maritime Infrastructure and Operations from Climate Change". The study states that the growing concerns about climate change and severe weather events occurring has transformed the area of port and coastal resilience into an important component in operations planning. The principal objective of the project is the creation of a standardized framework for the improvement of resilience in ports and transportation systems, via the integration of physical infrastructure and social systems. Stakeholder interviews, and workshops were organized that improved social awareness and identified the most important problems encountered while dealing with disruptions. Some of the solutions identified was the implementation of strict design standards, the organization of the transport systems as a whole, in terms of the entire supply chain, and to look beyond local operations (Wakeman, et.al., 2015). Last, the project suggested a coordinated organizational scheme at the state and regional level that can assist in the interaction towards the landside operations and water side logistics teams throughout the whole disruption cycle.

Another project with significant value to the problem addressed in our study was conducted from the Centre for Transport Studies of the University College London (Achuthan et al., 2015), titled “Resilience of the Food Supply to Port Flooding on East Coast”. The study argues that since the UK imports more than 40% of its food and drink supplies, with most of it arriving by sea, it is of utmost importance for port systems to be able and adopt good resilience plans. The methodology followed in the project consisted of engagement with stakeholders, modelling and analysis of the UK ports and shipping import functions, and the development of disruption scenarios using simulation. Some of the key findings extracted from the project were the degree of the disruption at a port would vary according to the food type moved and the shipment method, and that rerouting RoRo and container vessels to other available ports can potentially reduce the impacts of the event to almost half.

Furthermore, the Gulf of Mexico Alliance (Morris, 2016) conducted a study named “Ports Resilience Index: Three Case Studies in the Gulf of Mexico”. The objective of the project is the production of a simple and easily implementable regional tool that port and marine transportation authorities can use to evaluate and assess their level of resilience, as well as predict their ability to achieve an acceptable level of service during and after major weather events. The Ports Resilience Index is constructed using the Delphi Method, commonly used for quantifying variables of uncertainty and reaching a statistical consensus. The case studies considered were the Port of

Corpus Christi in Texas, the Port of Pascagoula in Mississippi and the Port of Lake Charles in Louisiana.

A research paper from Justice et al. (2016), named “US Container Port Resilience in a Complex and Dynamic World” addressed the problem of how container ports in the U.S. can potentially be affected by various negative events and how they can implement resilience practices to counteract the issues. The authors emphasized the importance of resilience as a way of dealing with uncertainties, while also mentioning that due to these potential changes, the ‘business as usual’ approach adopted by most organizations may not be able to guarantee successful port operations. Last, they state that in order to manage and encompass resilience, innovative and creative methods are required.

Hong Chen, Kevin Cullinane and Nan Liu (2017) also dealt with the subject of measuring resilience in transportation networks, in their paper titled “Developing a Model for Measuring the Resilience of a Port-Hinterland Container Transportation Network”. In their study, after developing their own definition of resilience in transportation networks and port operations, they developed a model to quantify resilience while incorporating links, nodes, cost, time and port capacity from the perspective of shippers. They considered a single seaport in their model and applied their methodology to the Gothenburg port and part of its hinterland.

Hyungmin Cho and Heekyung Park (2017), co-authored a paper titled “Constructing Resilience Model of Port Infrastructure Based on System Dynamics”, creating another study that focused on building resilience models of ports. In their work, they state that since port infrastructure and operations are complex processes and difficult to analyze all their components, a systemic approach can prove efficient. Their system dynamics model incorporates the cargo process as its performance level and identifies the elements corresponding to various resilience attributes.

Additionally, the model includes factors such as changes in cargo volumes and financial states, and with the application of different disruption scenarios, is used as a method of comparing the resilience levels of port infrastructure.

A relevant work that focused on the impacts of hurricanes in port operations was conducted by Touzinsky et al. (2018), titled “Using Empirical Data to Quantify Port Resilience: Hurricane Matthew and the Southeastern Seaboard”. In their study they used Automatic Identification System based vessel arrival data on three case study ports hit by hurricane Matthew, Charleston, Savannah and Jacksonville. Their goal was to calculate cumulative dwell times and net vessel counts in order to simulate and quantify the behavior of the system during all the main stages of the hurricane. These stages included pre-storm, preparedness, resistance, recovery and post-storm. In each stage, they used Bayesian analysis for understanding the system performance variations over the whole hurricane incident time.

3.6.0 Utilization of Automatic Identification Systems (AIS) data

Automatic Identification System technology can provide commercial vessel trajectory data that is valuable for research. Zhao and Altan (2018), presents an algorithm that can be used to compress this data from its large, inefficient, initial form. The improved Douglas-Peucker algorithm takes vessel trajectory data and makes it easier to store, query, and process. A case study of AIS data gathered over the duration of a month in the Chinese Zhou Shan Islands proves that the Douglas Peucker algorithm can effectively compress ship trajectory information. In the maritime port case study utilizing the proposed method of quantifying resiliency in this study, AIS data is analyzed but this method of compressing data is not used.

Vessels in congested waterways risk collision. The spatial distribution of vessels in not commonly available as a detailed map. Using Automatic Identification System technology, Altan and Otay (2018), found a solution to distribute vessels in congested waterways to avoid collision. In the maritime port case study utilizing the proposed method of quantifying resiliency in this study, AIS data is analyzed but it is not for the purpose of collision prevention.

Automatic Identification System receivers collect vessel movement information that can be used to classify vessel motion patterns. A study by Chen et al. (2018), presents a method to aid in automatic vessel motion pattern classification in inland waterways. The first step is to use the Least-squares Cubic Spline Curves Approximation technique, followed by a traditional classification model based on Lp-norm sparse representation, and the Matching Pursuit-Fletcher Reeves method. The model created was validated in this study by two AIS datasets from the Yangtze River. Following the previously stated methodology, the proposed model was found to effectively classify vessel motion patterns in inland waterways. In the maritime port case study utilizing the proposed method of quantifying resiliency in this study, AIS data is analyzed but vessel classification is included in the data purchase. Separating the vessels by classification is part of the methodology to determine the resilience of ports based on the functionality of dwell time.

Data from Automatic Identification System technology is critical in collision avoidance, risk evaluation, and navigation behavior study. However, raw AIS data contains outliers and error that can result in wrong conclusions. Zhang Meng, Xiao, and Fu (2018), proposes a three step process to produce a valid multi-regime vessel trajectory reconstruction model. The first step is outlier removal, followed by ship navigational state estimation, and vessel trajectory fitting for different navigation states, namely hoteling, maneuvering, and normal-speed sailing. This proposed model was validated with a large AIS dataset containing movements of more than 500 ships in Singapore Port. The created model was then compared with three other popular trajectory reconstruction models based on the same data set. The authors found that their proposed model performed significantly better than the popular linear regression model, polynomial regression model, and weighted regression model. In the maritime port case study utilizing the proposed method of quantifying resiliency in this study, AIS data is analyzed and outliers are removed but vessels need not be fitted for different navigational states and trajectories.

4.0 METHODOLOGY

This study proposes a method for quantifying resiliency and demonstrates its applicability with four case studies. The first case study analyzes the resiliency of six maritime ports on the East Coast during the disruption of Hurricane Matthew in 2016. The second case study analyzes the resiliency of three Florida airports during Hurricane Irma. The third case study looks at fuel shortages during Hurricane Irma and analyzes the resilience of the refueling system. The final case study analyzes the resilience of the Colorado Department of Transportation during the February 2018 cyber-attack.

Broadly, this analysis consists of two primary tasks to determine the resilience for each case study. The first primary step is to create time-dependent resiliency plots for each system. The second task is determine the resilience value for each system based on the time-dependent resiliency plots and the values found for the systems absorption, disruption, and recovery states. The following sections will explain each task in further detail.

4.1.0 Generic Time-Dependent Resiliency Plots

To calculate a resilience value, time-dependent resiliency plots must be created. These plots are line graphs that show the functionality of a transportation system with time. It is important for the plot to show a stable operating state before the disruption, the disruptions, and a return to the operating state before the event took place. An informative, time-dependent resiliency plot will follow the pattern of no slope, negative slope, no slope, positive slope, and finally no slope.

4.1.1 Calculating the Resiliency Value for Transportation Systems

NSF's definition of resiliency calls for a means of measuring the system's ability to absorb, adapt, and recover (NSF, 2016). This provides insight into how resiliency can be quantified. Figure 1(a) shows generic time-dependent resiliency plot for an increasing service system (the dependent variable increase as service increases) undergoing a disruptive event. Figure 1(b) provides an example of a decreasing service system (the dependent variable decreases with as service increases) experiencing a disruption (Henry & Ramirez-Marquez, 2012). Let function $f(t)$ represent a direct measure of system output at any time t. System S will undergo five distinctive states. Prior to event e ($t < t_e$), the system is operating in Stable Pre-Event State. After event e, output decreases as the system absorbs the impact of the disruption. During this period, when performance is decreasing, the system is in the Absorption State, $t_e < t \leq t_a$. Eventually, the system will stabilize as the effect of the disruption reaches its maximum impact on performance. While system performance is no longer decreasing, system operates in the Disrupted State as output is still reduced from the pre-event conditions $f(t_a) \cong f(t_{a+1}) \neq f(t_{e-1})$. The system will remain in this Disrupted State until a recovery action is taken at $t = t_d$. The system begins to recover as performance increases during the Recovery State, $f(t_{d+1}) > f(t_d)$. This recovery continues until the system reaches a Stable Post-Recovered State at $t = t_R$.

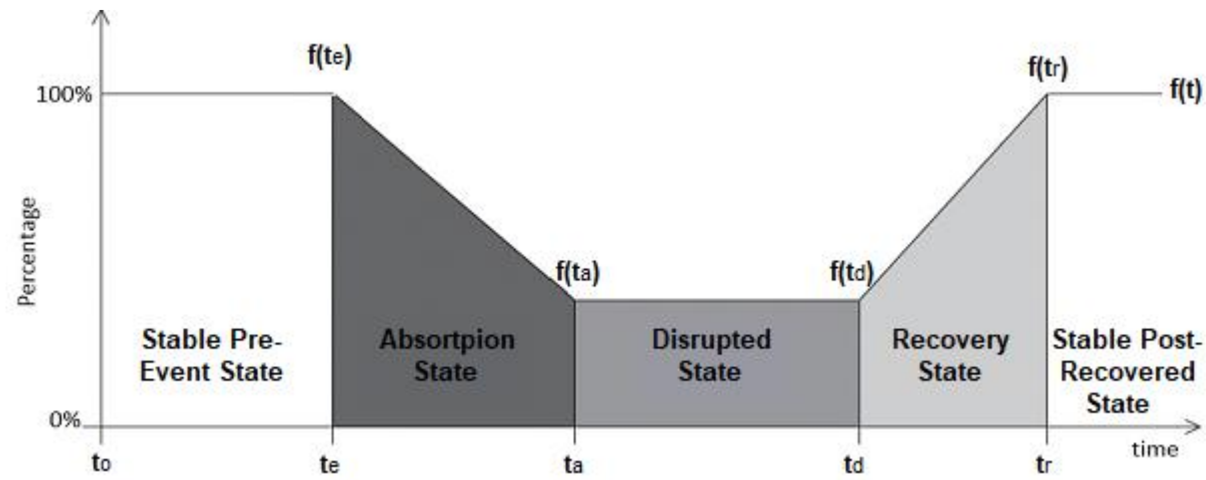

Figure 1: Time-dependent resiliency plot of an increasing service system

(Henry & Ramirez-Marquez, 2012)

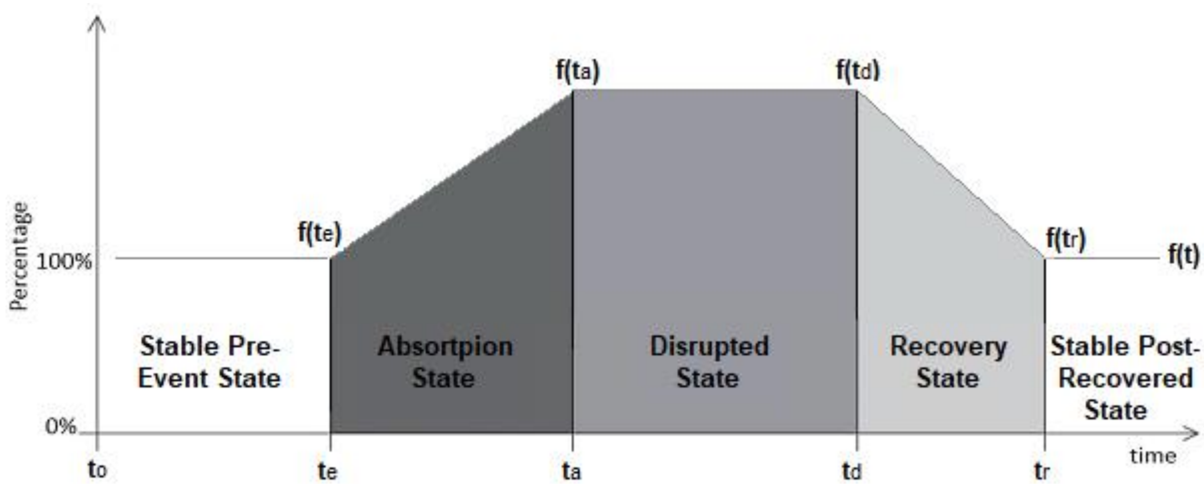

Figure 2: Time-dependent resiliency plot of a decreasing service system

(Henry & Ramirez-Marquez, 2012)

The system functionality between t_e and t_a can be used as a direct measure of absorption. In particular, the angle created between in the functionality plot for $f(t_{e)} < f(t) \leq f(t_a)$. *Figure 3* shows this angle as $\theta_{\overline{E}}$ and is calculated in equation 1. As formulated, $\theta_{\overline{E}}$ has a maximum value of 90 degrees ($\frac{\pi}{2}$ radians) and a minimum value of zero degrees (zero radians). Therefore, the angle

$\theta_{\overline{E}}$ can be normalized as a value between 1 and zero by dividing Equation 1 by 90 degrees ($\frac{\pi}{2}$ radians). This results in the function taking a value closer to one when the loss in functionality is greatest and a value closer to zero when the functionality loss is the lowest. By subtracting this function from one, this is reversed, resulting in values closer to one representing a more gradual loss in functionality and a better ability to absorb the impact of the disruption. Equation 2 formulates the system's absorption as R_A.

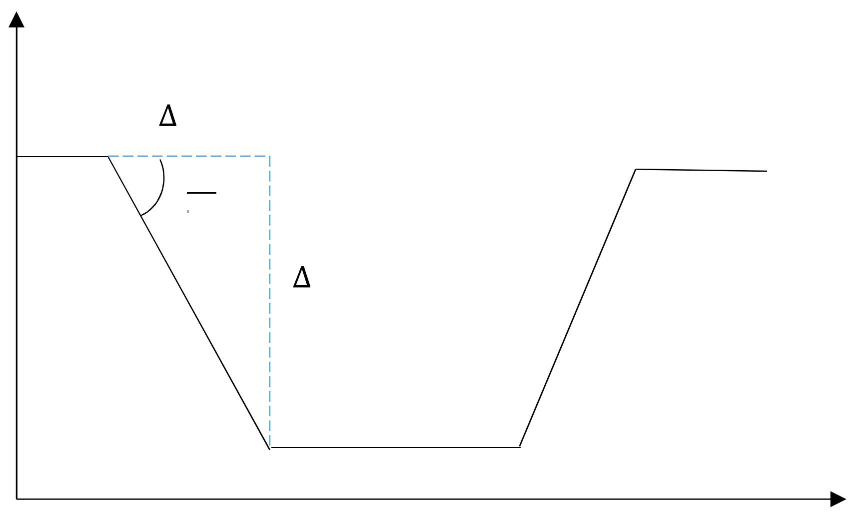

Figure 3: Absorption State Diagram

$$\tan^{-1}(\theta_{\overline{A}}) = \frac{\Delta Y}{\Delta t} \qquad \text{Equation 1}$$

$$R_A = 1 - \frac{2}{\pi}\left|t\ ^{-1}\left(\frac{f(t_a)-f(t_e)}{t_a-t_e}\right)\right| \qquad \text{Equation 2}$$

The disrupted state spans the period between the absorption state and the recovery state ($t_a < t < t_d$. Ideally, the disrupted state is as short as possible. The length of the disrupted state is calculated as $t_d - t_a$. This value can be normalized as the ratio of time disrupted and the total time of the disruptive event. *Figure 4* shows the disrupted state diagram, labeling these two periods. Equation 3 defines R_D as the systems resiliency during the disrupted state. In the formulation, the ratio of time within the disruptive state to the overall duration of the event, is subtracted from one. This allows the formulation to take a value of one when $t_a = t_d$. This is the ideal situation because it suggests recovery begins immediately following the absorption state (i.e. there is no measureable disrupted state). Longer periods of disruption result in a disrupted state resiliency value closer to zero.

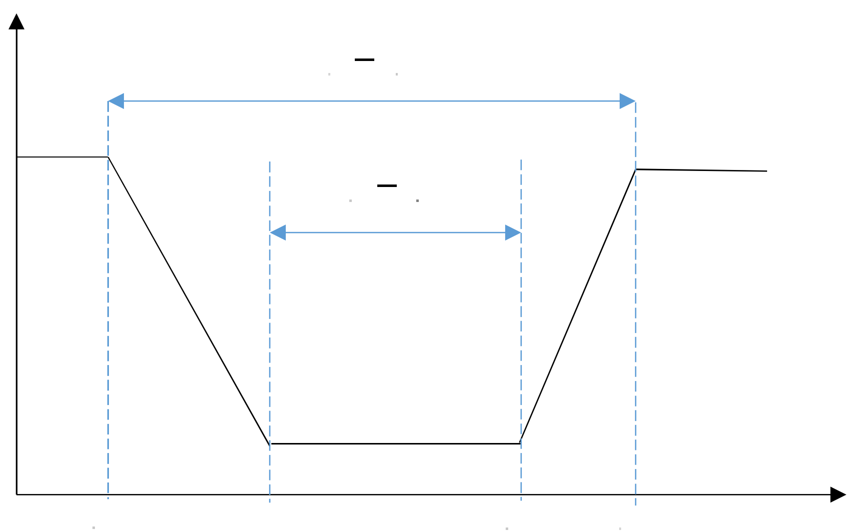

Figure 4: Disrupted State Diagram

$$R_D = 1 - \frac{t_e - t_a}{t_r - t_e} \qquad \text{Equation 3}$$

The recovery state begins only after a recovery action has been taken and the system begins to increase in functionality. Similar, to the absorption state, the recovery state can be quantified as a function of the angle generated by the functionality curve as the system transitions between the disrupted state and the stable recovered state. This angle is defined as $\theta_{\overline{D}}$ in Equation 1 and shown in the recovery state diagram (*Figure 5*). Again, the angle must be normalized by dividing the function by 90 degrees ($\frac{\pi}{2}$ radians). Equation 5 provides the formulation for the resiliency of the recovery state. Values closer to one, represent a more rapid transition to the stable recovered state whereas lower values are indicative of a more gradual system response (Parr, 2019).

$$\theta_{\overline{D}} = \tan^{-1}\left(\frac{\Delta Y}{\Delta t}\right) \qquad \text{Equation 4}$$

$$R_R = \frac{2}{\pi}\left|\tan^{-1}\left(\frac{\mathrm{f}(\mathrm{t_r})-\mathrm{f}(\mathrm{t_d})}{\mathrm{t_r}-\mathrm{t_e}}\right)\right| \qquad \text{Equation 5}$$

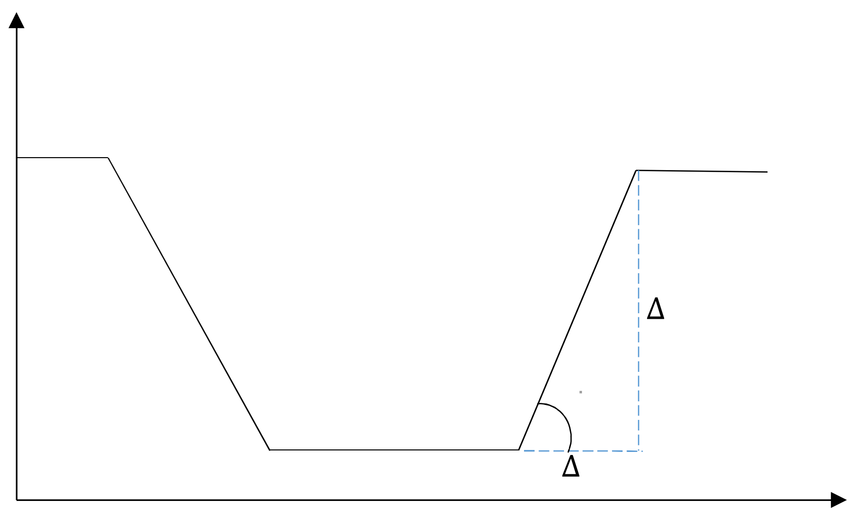

Figure 5: Recovery State Diagram

The NSF defines a system’s resiliency as a function of its ability to absorb, adapt, and recover. This inherently suggests that a system unable to absorb, adapt, or recover is decidedly, not resilient. Therefore, a quantification for resiliency needs to reflect these three characteristics. Equation 6 provides such a formulation for system resiliency that is in line with NSF’s definition and fundamental to any generic system with measureable output.

$$R = R_A * R_D * R_R \qquad \text{Equation 6}$$

These equations yield a resiliency metric that can be applied to any transportation system. User imputed values allow this methodology to be adjusted to fit different measures of functionality. Each state is critical to the overall resilience of the system. One poor value will negatively impact the resiliency metric.

5.0 RESULTS

The following chapter documents the application of the resiliency metric on four complex, real world, transportation systems undergoing disruptions. Each section opens with a general description of the transportation infrastructure and the data source used in the analysis. This is followed by general description of the disruptive event and the detailed time-dependent resiliency plots. Each section then concludes by providing the absorption, adaption, recovery, and resilience for each transportation system, as well as summary of significant findings and conclusions.

4.2.0 Regional Port Resiliency

This section applies the resiliency metric methodology to six different ports that were hit by Hurricane Matthew in 2016. Each of these ports are vital to the Southeastern United States' economy and their resiliency is paramount. They all individually contribute, although in different ways, to this transportation network. Outlined below are the specifics of each port, along with their contributions to the economy of the Southeastern United States.

Port Miami

The Port of Miami is located on the East Coast of South Florida in Miami-Dade County. It is a significant conduit for international trade as it is the closest U.S. container port to the Panama Canal. This port has seven container ports, nine cruise terminals, 13 ship -to-shore cranes, and on dock intermodal freight rail. Port of Miami's trade region comprises of Latin America, the Caribbean, Europe, the Middle East, India, and Africa. The port is home to 22 Cruise lines and 55 innovative ships. In 2018, the capacity of twenty-foot equivalent units of containerized cargo was estimated to be 1.1 million. Port of Miami continues to expand to accommodate the growing economy (Miami Dade, n.d.).

Port Everglades

Port Everglades is located in Fort Lauderdale on the East Coast of Florida. This port is home to more than 20 shipping lines a 43-acre near-dock Intermodal Container Transfer Facility (ICTF), and 10 cruise lines. Nine cranes allow Port Everglades to move products from Central America, the Caribbean, South America, and Europe. It is South Florida's main seaport for receiving petroleum products. The ICTF operated by Florida East Coast Railway (FECR) has reduced congestion on roads and harmful air emissions. In Fiscal Year 2017, Port Everglades was considered the 10th busiest container port in the nation, moving more than 6.6 million tons of containerized cargo (Port Everglades, n.d.).

Port of Jacksonville (JAXPORT)

JAXPORT is located on the East Coast of North Florida. It is a 1,500-acre, international trade seaport, uniquely equipped to handle temperature controlled freight. JAXPORT owns and maintains six terminals, two of which are intermodal rail terminals. Carnival Cruise Line operates out of the lone cruise terminal (JAXPORT, 2019).

Port of Palm Beach

The Port of Palm Beach is located on the East Coast of Florida, 80 miles north of Miami and 135 miles south of Port Canaveral. The port directly and indirectly employs approximately 2,400 people and contributes $260 million in business revenue. While only consisting of 156 acres of land, the Port of Palm Beach handles diesel fuel, molasses, liquid asphalt, and other bulk commodities. The majority of exported cargo travels to the island nations of the Caribbean. The Florida East Coast Railway services the port with pier-side box, hopper, and intermodal cars operating 24 hours a day. (Port of Palm Beach, n.d.).

Port of Savannah

The Port of Savannah is on the coast of South Georgia and is owned and operated by the Georgia Ports Authority. The Port of Savannah is made up of the Garden City Terminal and an Ocean Terminal. Both are modern, deep-water terminals. The Garden City Terminal is North America's busiest single-terminal container facility as of Fiscal Year 2018. The Ocean Terminal is a 200 acre facility that processes a wide variety of cargo including but not limited to wood products, steel, and automobiles. In 2018, the capacity of twenty-foot equivalent units of containerized cargo handled was 4.2 million (Georgia Ports, n.d.).

Port of Charleston

The Port of Charleston is owned by South Carolina Ports and is located on the East Coast of South Carolina. The port boasts 19 cranes, 9 berths, and 6 container terminals, two of which are intermodal. A 500 ton barge crane and a 52 foot channel will be completed in 2021. The major trading partners with Port Charleston include North Europe, Northeast Asia, India, Southeast Asia, and South America. In 2018, the port handled almost 2.3 million twenty-foot equivalent units of containerized cargo (Port Charleston, n.d.).

Hurricane Matthew was a Category 5 storm on the Saffir-Simpson Hurricane Wind Scale. It first made landfall in Haiti on October 4th, 2016. After traveling past Haiti, Matthew made landfall in eastern Cuba, western Grand Bahama Island, and South Carolina. Hurricane Matthew was also predicted to make landfall in Florida, but remained about 30 nautical miles offshore until making landfall in South Carolina. With a max wind speed of 167 mph and a maximum measured storm surge of 13 feet, Matthew caused over 14 billion dollars of damage and 585 direct fatalities (National Hurricane Center, 2017). Hurricane Matthew traveled down the east coast of Florida October 7th, 2016, as a category-3 storm on the Saffir-Simpson scale. This hurricane impacted functionality at Port Everglades, Port of Charleston, Port of Jacksonville, PortMiami, Port of Palm Beach, and Port of Savannah, among others. The effect of this hurricane is measured in terms of the resiliency of each port based on dwell time and vessel arrivals.

To determine the resiliency metric of Port Everglades, Port of Charleston, Port of Jacksonville, Port of Miami, Port of Palm Beach, and Port of Savannah, time-dependent resiliency plots were created with data purchased from maritimedata.com. The Maritime Transportation Security act of 2002 mandates all commercial vessels to carry Automatic Identification System (AIS) technology. Transponders on ships broadcast location information to other ships through a very high frequency (VHF) radio spectrum. Receivers on land record the data and archive it. This data can be purchased from a commercial vendor and used for data analysis. The headings of the data purchased for this study included the PORT_NAME, UNLOCODE, TIMESTAMP, DATE, MOVE TYPE, MMSI, VESSEL SUMMARY TYPE, VESSEL TYPE, LENGTH, WIDTH, DWT, GRT, PASSENGERS, CRUDE_CAPACITY, LIQUID_OIL, LIQUID_GAS, CARGO_HANDLING, DRAUGHT ACTUAL, DRAUGHT MAX, NEXT PORT, and NEXT PORT ARRIVAL TIMESTAMP. This allowed arrivals and departures to be matched with their corresponding vessel for the calculations of dwell times. For the purpose of this study, the data purchased included all vessel activity from January 1st, 2016 to December 31st, 2016. This time period was selected because of the dates Hurricane Matthew disrupted Port Everglades, Port of Charleston, Port of Jacksonville, Port of Miami, Port of Palm Beach, and Port of Savannah.

The first method of determining the resiliency metrics was to analyze the number of daily arrivals. The number of vessels arriving at the port each day indicate the functionality of the port. In Figure 6, the x-axis shows the date and the y-axis provides the number of containerized cargo vessels arriving. The day Hurricane Matthew made landfall in Florida is also indicated on the figure. As Hurricane Matthew approached the United States, the East Coast prepared for any possible landfall location before the hurricane ultimately came ashore in South Carolina. The dates corresponding to the event (t_E), the end of the absorption state (t_A), the end of the disruptive state (t_U), and the end of the recovery state (t_R), are also provided as they are utilized in the methodology of determining the resiliency value. The dates on the figure are for the region, however, as the individual ports differed in absorption, disruption, and recovery time. Some ports felt the impact of the storm earlier or later based on proximity to the hurricane and were disrupted for different periods of time. Ports further to the south, were generally, less disrupted than ports to the north. However, each of the study ports showed a measurable impact from the storm.

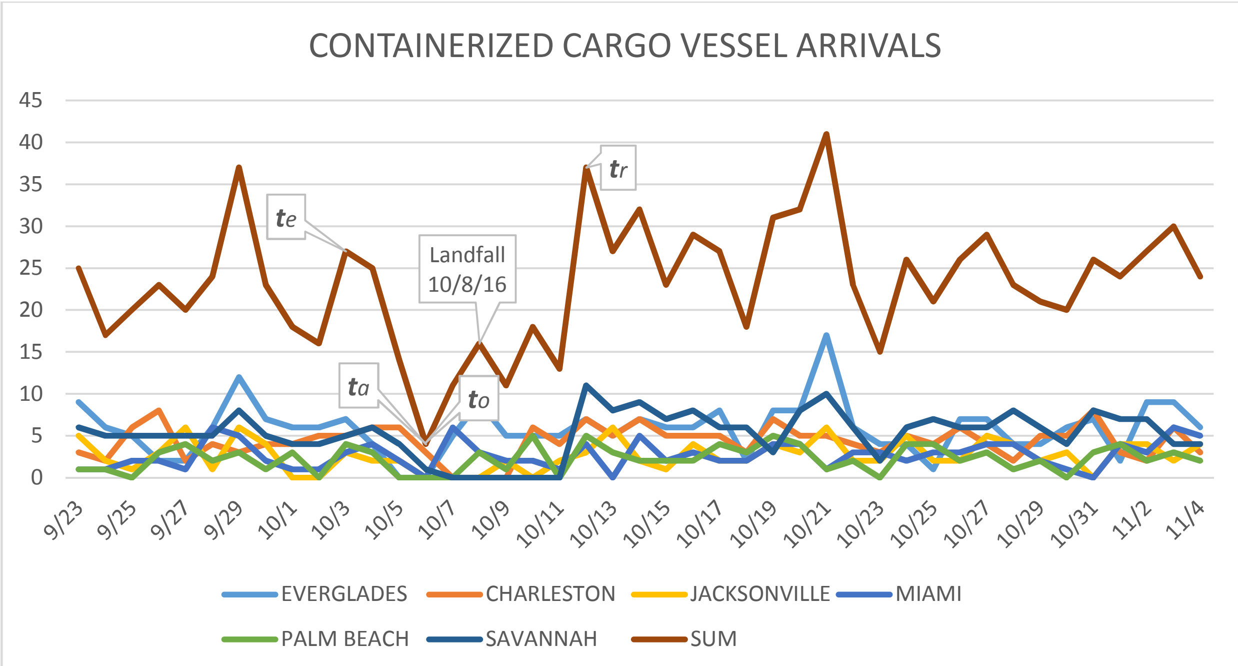

Figure 6: Containerized Cargo Vessel Daily Arrivals

Table 1 shows the resiliency results calculated for each port and the region as a whole. In general, closures issued by managers significantly hindered each of the port's ability to absorb the impact of the storm. The average absorption was only 0.243, with the regional absorption calculated at 0.161. The Port of Jacksonville showed the strongest absorption at 0.5 whereas the Port of West Palm Beach was the weakest at 0.126. The poor performance of the absorption was expected because closures tend to bring a sudden halt to operations. With no vessels arriving, a rapid drop in vessel arrivals was expected. In general, many of the ports in the study reopened relatively quickly, following the passage of the storm resulting in high disruption state values. This was expected, as many of the ports did not suffer significant damage and were able to resume receiving containerized cargo vessels. Recovery was also relatively high, with an average port recovery value of 0.859 and a regional recovery value of 0.900. This suggest that not only were the ports able to reopen quickly after the storm, they were accommodating as many vessels, or in some cases even more vessels, than prior to the storms passing. Overall, the resiliency of each port was limited by its ability to absorb the impact of the event. The regional resiliency was 0.145 with the Port of Jacksonville having the largest resiliency value of 0.211. This was unexpected because of Jacksonville's proximity to landfall. Ports W. Palm Beach and Charleston showed the lowest resiliency values of 0.110. Charleston's resiliency was limited by its ability to adapt (i.e. end the disrupted state). This was likely because Charleston was closest to landfall, possibly suffering infrastructure damage (Parr et.al., 2019).

Table 1: Containerized Cargo Vessel Arrivals Resiliency Results

PORT OF CALL	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
MIAMI	0.156	1.000	0.874	0.136
EVERGLADES	0.177	0.800	0.861	0.122
W. PALM BEACH	0.126	1.000	0.874	0.110
JACKSONVILLE	0.500	0.600	0.705	0.211
SAVANNAH	0.295	0.500	0.942	0.139
CHARLESTON	0.205	0.600	0.895	0.110
AVERAGE	0.243	0.75	0.859	0.138
REGIONAL	0.161	1.000	0.90	0.145

The second method of determining the resiliency metric of Port Everglades, Port of Charleston, Port of Jacksonville, Port of Miami, Port of Palm Beach, and Port of Savannah was to analyze the average, daily, dwell times for the study ports and the region using the time-dependent resiliency plot in Figure 7. The x-axis provides the date and the primary y-axis shows the average daily dwell times for the six study ports. The secondary y-axis shows the average daily dwell time for the region, as a whole. Hurricane Matthew began impacting regional dwell times on October 4, 2016. This was evident in a sharp spike in average daily dwell times. Diminished dwell times continued until landfall, corresponding with port closures. However, as the ports reopened, dwell times began their accent to normalcy, signifying a brief disrupted state on a regional level. By October 11, 2016 regional dwell times generally returned to their pre-storm levels (Parr, et.at., 2019).

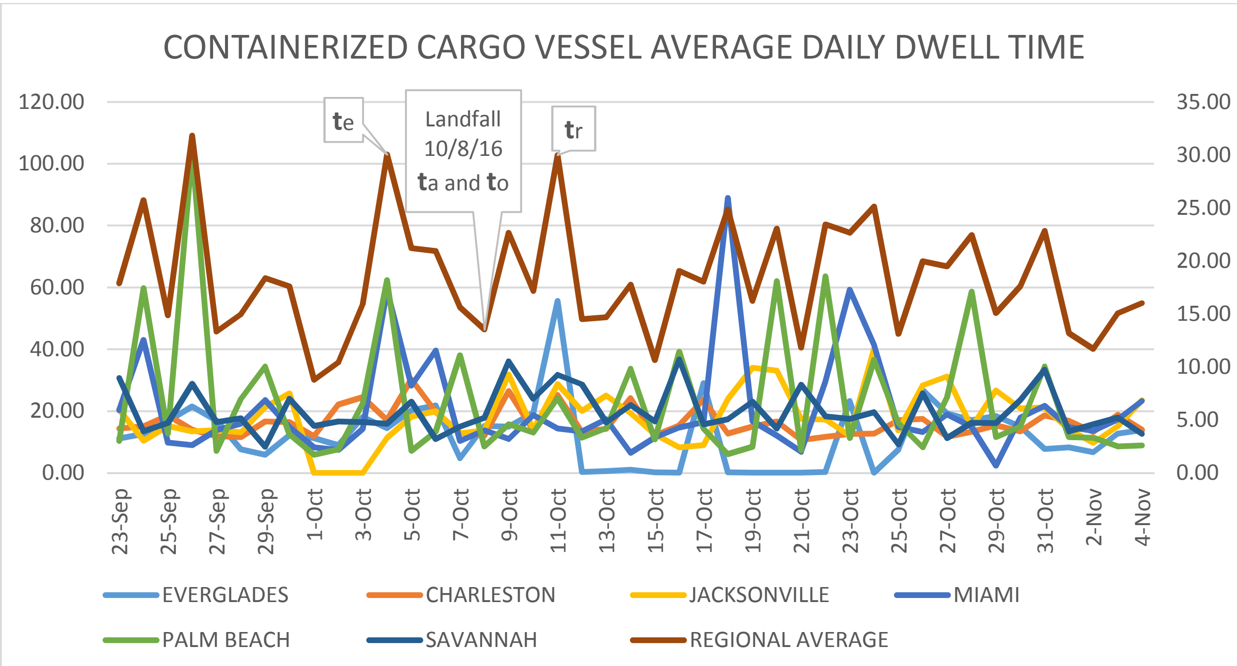

Figure 7: Containerized Cargo Vessel Average Daily Dwell Times

Table 2 provides the resiliency results for containerized cargo vessel average daily dwell times. In general, the study ports struggled to absorb the impact of the storm and subsequent closures. However regionally, the absorption value was significantly higher than five of the six study ports. The Port of West Palm Beach was the only individual port able to absorb the impact of the disruptive event at a higher level than the region as a whole. The disruptive state at individual ports was in general, longer for average daily dwell times and for vessel arrivals. This may suggest that while ports may be able to receive vessels, their ability to handle cargo may still be inhibited. Interestingly, the regional dwell time showed no disruptive state, i.e. recovery coincided with the end of the absorption state. This was likely because while ports to the south were impacted by the storm first, they reopened sooner initiating a recovery while northern ports were still in the disrupted state. The resiliency at individual ports was generally lower for average daily dwell times when compared to vessel arrivals. However, the regional resiliencies were much closer in magnitude (Parr, et.at., 2019).

Table 2: Containerized Cargo Vessel Average Daily Dwell Time Resiliency Results

PORT OF CALL	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
MIAMI	0.058	0.250	0.994	0.014
EVERGLADES	0.049	0.750	0.935	0.034
W. PALM BEACH	0.283	1.000	0.931	0.264
JACKSONVILLE	0.038	0.400	0.965	0.015
SAVANNAH	0.032	0.286	0.969	0.009
CHARLESTON	0.050	0.667	0.921	0.030
AVERAGE	0.085	0.559	0.953	0.061
REGIONAL	0.151	1.000	0.885	0.134

4.3.0 Florida Airport Resilience

The resiliency metric methodology is applied to three Florida airports impacted by Hurricane Irma in this chapter. Each airport felt an impact from Hurricane Irma, but the intensity varied. Outlined below is the methodology and results found for the resiliency metric of Miami International Airport (MIA), Orlando International Airport (MCO), and Tampa International Airport (TPA), due to the disruption of Hurricane Irma.

Miami International Airport

Miami International Airport (MIA) is a primary airport in South Florida. They have 28 based aircraft and average 1139 operations per day as of December 2018. General aviation makes up 4% of their operations, while commercial operations make up 86%. MIA experienced Hurricane Irma as a Category 3 hurricane and was closed for three days due to the disruption (KMIA, n.d.).

Orlando International Airport

Orlando International Airport (MCO) is a primary airport in Central Florida. They have 32 based aircraft and average 973 operations per day as of December 2018. General aviation makes up 4% of their operations, while commercial operations make up 91%. MCO experienced Hurricane Irma as a Category 3 hurricane and the disruption caused the airport to close for two days (KMCO, n.d.).

Tampa International Airport

Tampa International Airport (TPA) is a primary airport on the west coast of Florida. They have 68 based aircraft and average 581 operations per day as of May 2019. General aviation makes up 12% of their operations, while commercial operations make up 81%. TPA experienced Hurricane Irma as a Category 3 hurricane and the disruption caused the airport to have a loss of over 97% of daily operations for two days (KTPA, n.d.).

Operations data was obtained for Miami International Airport (MIA), Orlando International Airport (MCO), and Tampa International Airport (TPA) from the FAA. This data was freely downloaded through the Operations Network OPSNET. OPSNET is the official source of National Airspace System's (NAS) air traffic operations data. For the purpose of this study, data extracted from the website was for the month of September from 2013-2017, for all three airports. The number of total operations by the day of the week for the month of September was found for all five years at each airport. By comparing the operations data for every Wednesday for example, the average number of operations that occur on a Wednesday at LAL from 2013-2016 can be compared to the number of operations that took place on Wednesday during the week of the hurricane in 2017. The reason the data was separated by day of the week and not a whole week is because before and after a storm, residents of the area evacuate and then return. If the evacuation and return occurred in the same week, the increase of number of operations for these events would overshadow the lack of operations on the day Hurricane Irma passed over the airport and the days of distress afterwards.

Hurricane Irma started as a tropical storm west of the Cape Verde Islands in the morning of August 30th, 2017. Within 30 hours, Irma became a Category 3 storm on the Saffir-Simpson Hurricane Wind Scale with winds reaching 115 MPH. This rapidly growing intensity is unusual. On September 5th, 2017, Hurricane Irma became a rare Category 5 hurricane and stayed a Category 5 for three days. With winds of 185 MPH, Irma became the strongest hurricane ever observed in the open Atlantic Ocean. Hurricane Irma made landfall in the Florida Keys on September 10th, 2017, as a Category 4 storm. Irma traveled up the west coast of Florida, but at 425 miles wide, devastating winds were felt throughout the state (National Hurricane Center, 2017). Hurricane Irma caused damage and loss of revenue at many airports throughout the state of Florida. The quicker an airport can be restored to working order, the higher the level of resiliency. This corresponds to quicker relief efforts to the local community and less money lost in passenger revenues.

Figure 8 shows the time-dependent resiliency figure for Orlando International Airport, Tampa International Airport, and Miami International Airport. The airports are all in a stable, preexisting state before Hurricane Irma. As the hurricane moves closer, MIA's operations dwindle. Tampa International Airport experiences an increase in operations as evacuations occur. TPA differs from MIA and MCO with more than double the percentage of general aviation operations. General aviation operations are made by private aircraft with no set passenger schedule, allowing them to evacuate and return when convenient. General aviation aircraft are smaller than commercial aircraft, and do not create as much wake turbulence when departing, allowing more aircraft to utilize the runway in a set amount of time. Tampa International Airport also has 68 based aircraft, while MIA and MCO have less than 35. Miami International airport is the furthest south, causing operations to decline earlier than TIA or MCO. All three airports spend at least two days in the disrupted state with zero operations. On September 12th, 2017, all three airports begin to recover from Hurricane Irma. Orlando International Airport bounces back the quickest while Miami International Airport faces a low number of operations for five more days. All three airports are able to return to a stable operating state within a week of Hurricane Irma making landfall.

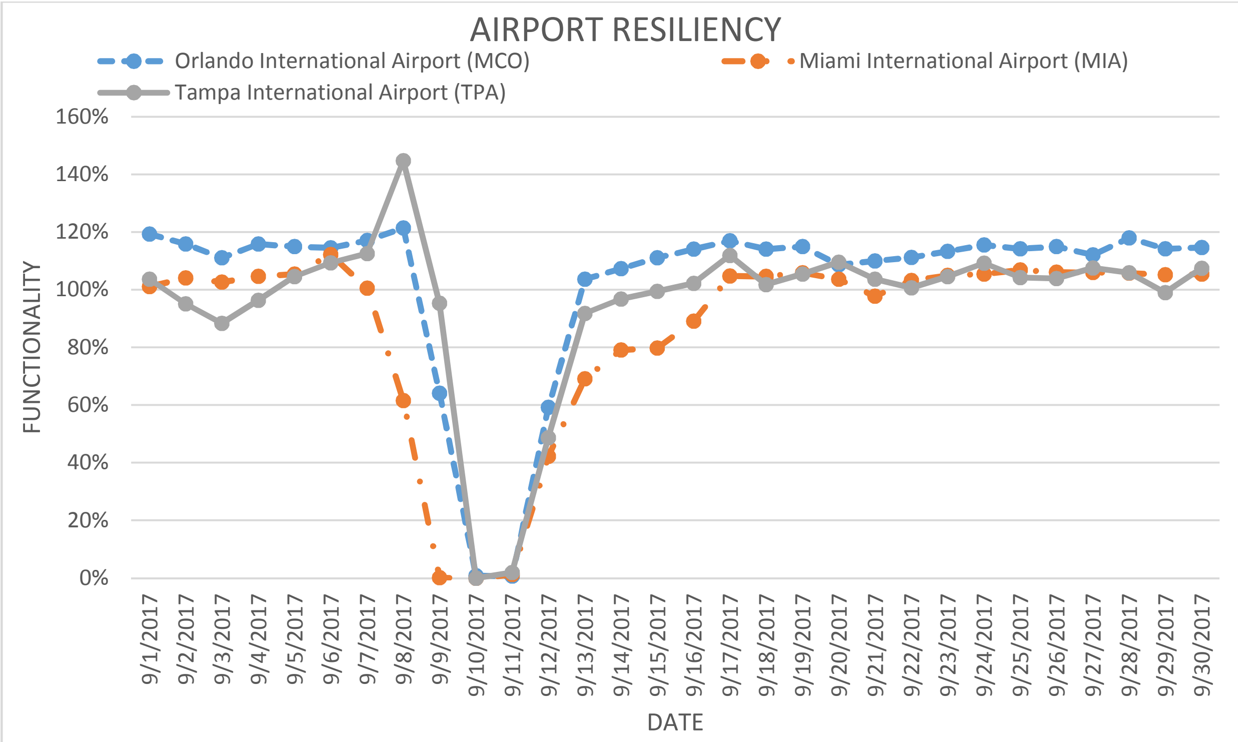

Figure 8: Operations data for MCO, MIA, and TPA

Table 3 shows that Tama International Airport had the highest resilience value. All three airports had a similar pattern in their operations during Hurricane Irma, but the deciding factor in the highest resilience value was Tampa International Airport's preparation. There is a spike in operations just days before the airport closes as evacuees exit the area. These operations allow TPA to absorb the impact of the hurricane better than MCO or MIA. The increase in operations also allows TPA to have a higher disruption value, which compares the time that TPA spent with no operations to the time TPA spent experiencing any impact in operations from Hurricane Irma. Because the Hurricane impacted TPA's operations for seven days, but only closed the airport for two days, TPA's disruption value is higher than MCO who was impacted for only six days, but closed for two days and Miami who was impacted for eleven days, but closed for a total of three days.

Table 3: Resilience values for MCO, MIA, and TIA during Hurricane Irma

AIRPORT	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
ORLANDO (MCO)	0.0119	0.8	0.9878	0.0094
TAMPA (TPA)	0.0169	0.8333	0.9862	0.0139
MIAMI (MIA)	0.0126	0.8	0.9637	0.0097

4.5.0 Fuel Shortages during Hurricane Irma

Fuel shortages are a common occurrence with hurricane evacuations. This chapter applies the resiliency metric methodology to the refueling system in Naples and Tampa, Florida during Hurricane Irma. Outlined below is information on Naples and Tampa, Florida, Hurricane Irma, and the resiliency metric for both cities.

Fuel shortage data was obtained through Gasbuddy and documented in Islam (2019). Gasbuddy is website and mobile app that provides an online database designed to help motorists find the lowest gas prices and best gas stations, among other things. During Hurricane Irma, the website posted live updates on fuel availability and station outages. Gasbuddy provides the hourly percentage of gas stations without fuel for a region. For this research on quantifying resiliency, the data was adapted to show the percentage of gas stations with fuel in Naples and Tampa, Florida.

As Hurricane Irma moved towards Florida, fuel stations faced shortages days before landfall. Hurricane Irma became a threatening Category 5 hurricane before making landfall and the predicted path of the hurricane shifted frequently, causing nearly the entire state of Florida to feel threatened. The ensuing evacuations resulted in regions of localized fuel shortages. As a result, the State of Florida released strategic fuel reserves to alleviate some areas. This corresponds to a relatively high level of resiliency for the refueling system in the region.

Figure 9 displays the data obtained as a time-dependent resiliency plot. Days before Hurricane Irma arrived, gas stations began to run out of fuel. On September 6th, 2017, four days before the hurricane made landfall in Florida, only 70% of gas stations had fuel. The functionality dropped quickly as less than 40% of gas stations had fuel in the state of Florida. Gas stations in the Naples area slowly refueled as time passed.

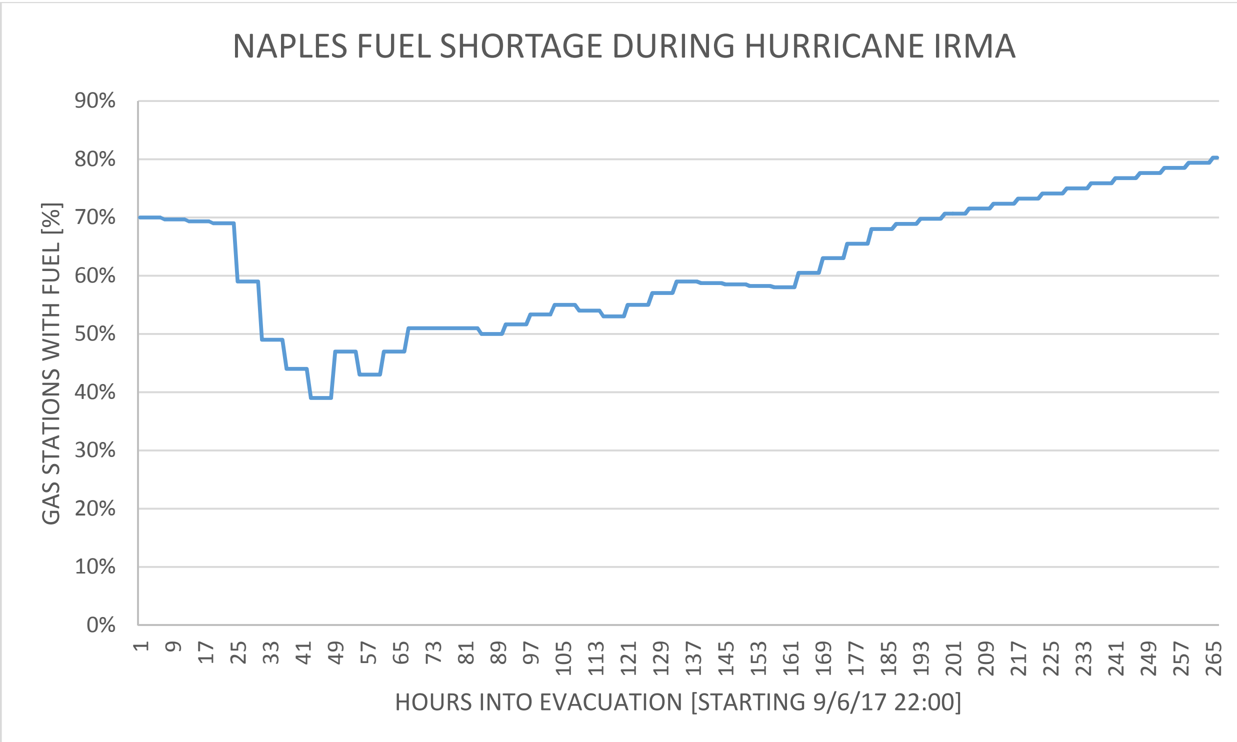

Figure 9: Percentage of gas stations without fuel in the Naples area.

Figure 10 displays data for the Tampa area. Less than 80% of gas stations had fuel in the state of Florida four days before Hurricane Irma made landfall in Florida. Gas stations in Tampa took longer to fun out of fuel than those in Naples. This is necessary for a high resilience value. The recovery of Tampa was drawn out over multiple days. For a high resilience value, the recovery state must happen quickly.

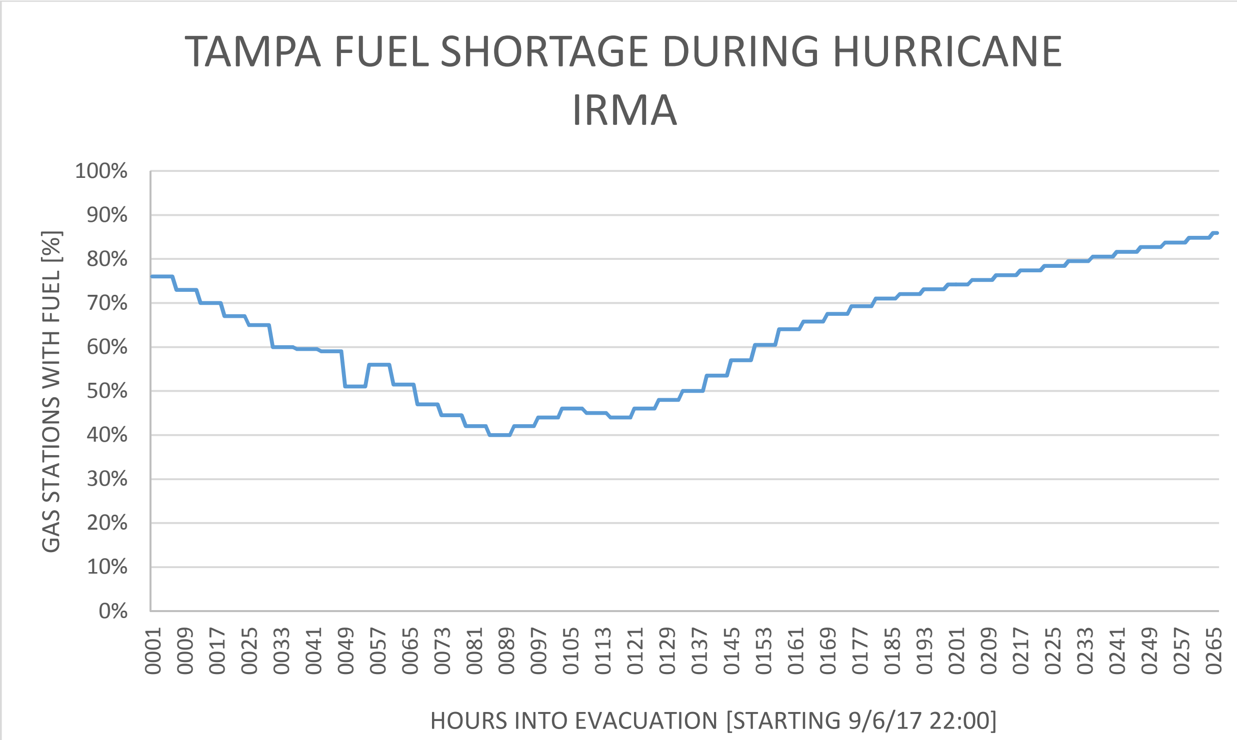

Figure 10: Percentage of gas stations without fuel in the Tampa area.

The table below shows the resiliency metrics for the Tampa are and Naples area as a result of Hurricane Irma. Table 4 shows that the Tampa area had the highest resilience value. The main difference in the plots was the absorption state of Tampa compared to Naples. Tampa slowly decreased in gas stations without fuel over four days while Naples dropped over a period of less than 24 hours.

These findings may be a result of the different evacuation patterns Tampa and Naples, Florida faced. The path of Hurricane Irma was variable. Landfall was a high probability in South Florida, but initial projects had Hurricane Irma traveling up the east coast of Florida. The Tampa region did not begin to evacuate until substantially until 48 hours before Hurricane Irma made landfall (Acevedo, 2019).

Table 4: Resilience values for Naples and Tampa

CITY	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
NAPLES	0.3594	0.9702	0.1308	0.0456
TAMPA	0.7308	0.8317	0.2156	0.1311

4.6.0 Cyberattack on the Colorado Department of Transportation (CDOT)

The resiliency metric methodology can also be applied to the disruption caused by a cyberattack on the Colorado DOT. Outlined below is the specifics of the attack and the CDOT's resiliency metric for this event. Mr. Johnny Olson of the Colorado DOT provided functionality data for the DOT before, during, and after the time of this security attack in his study *Colorado DOT: Dealing with Ransomware Incident*. An after-action report was also released on July 17th, 2018 by the state, validating the data obtained from Johnny Olson (Colorado Division, 2018).

The Colorado Department of Transportation (CDOT) was part of a statewide emergency on March 1st, 2018, after a threat actor gained access to their database. The threat actor gained access to CDOT's database on February 18th, 2018, and installed SamSam ransomware malware. On February 21st, 2018, the security breach was discovered when the malware became active and took over 150 servers and 2000 workstations. By February 28th, the malware was believed to be contained until new activity occurred that night by the attacker. This led the DOT to contact the Governor and request help from the Colorado National Guard. At this point, the Governor declared a statewide emergency. With assistance from the National Guard, FBI, and Department of Homeland Security, among others, the attack was blocked and the affected servers and workstations re-imaged. A four phase plan was developed to remove the threat and prevent future attacks (Colorado Division, 2018).

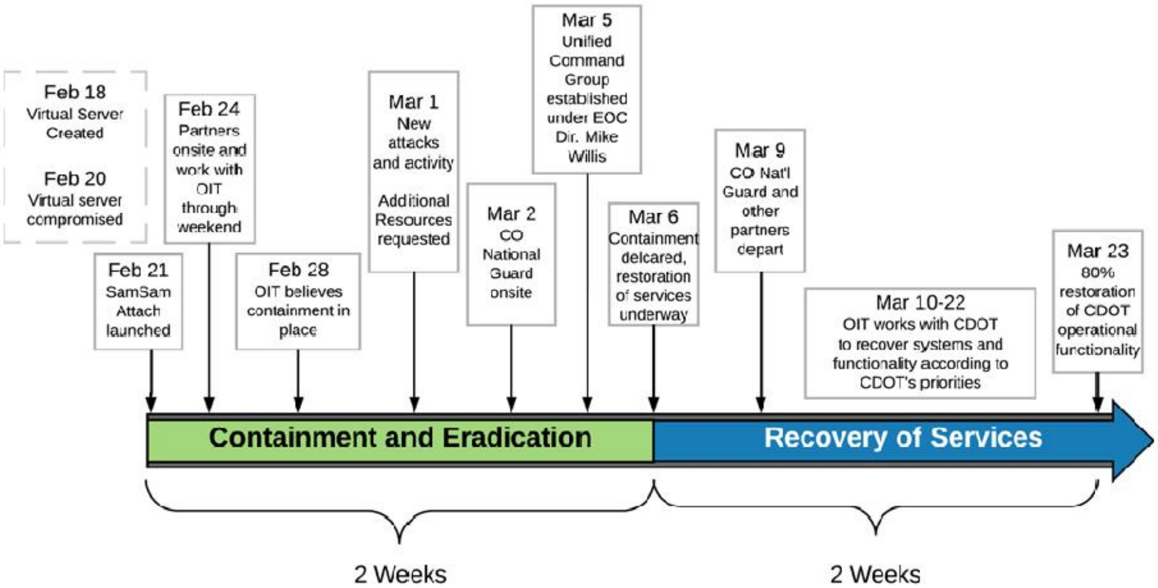

Figure 11: Timeline of cyber-attack on Colorado Department of Transportation.

Figure *12* displays the data obtained as a time-dependent resiliency plot. Before the cyber-attack, the Colorado DOT operated at 100% functionality. Because the cyber-attack was sudden and aggressive, the operational functionality dropped to 0% in 24 hours. This is a poor absorption state. With such a quick drop in functionality, catastrophic failure of the system is possible. After five days, functionality begins to increase with the assistance from the National Guard, FBI, and Department of Homeland Security, among others. The recovery stage of this cyber-attack lasts months. For a high resilience value, the recovery state must happen quickly.

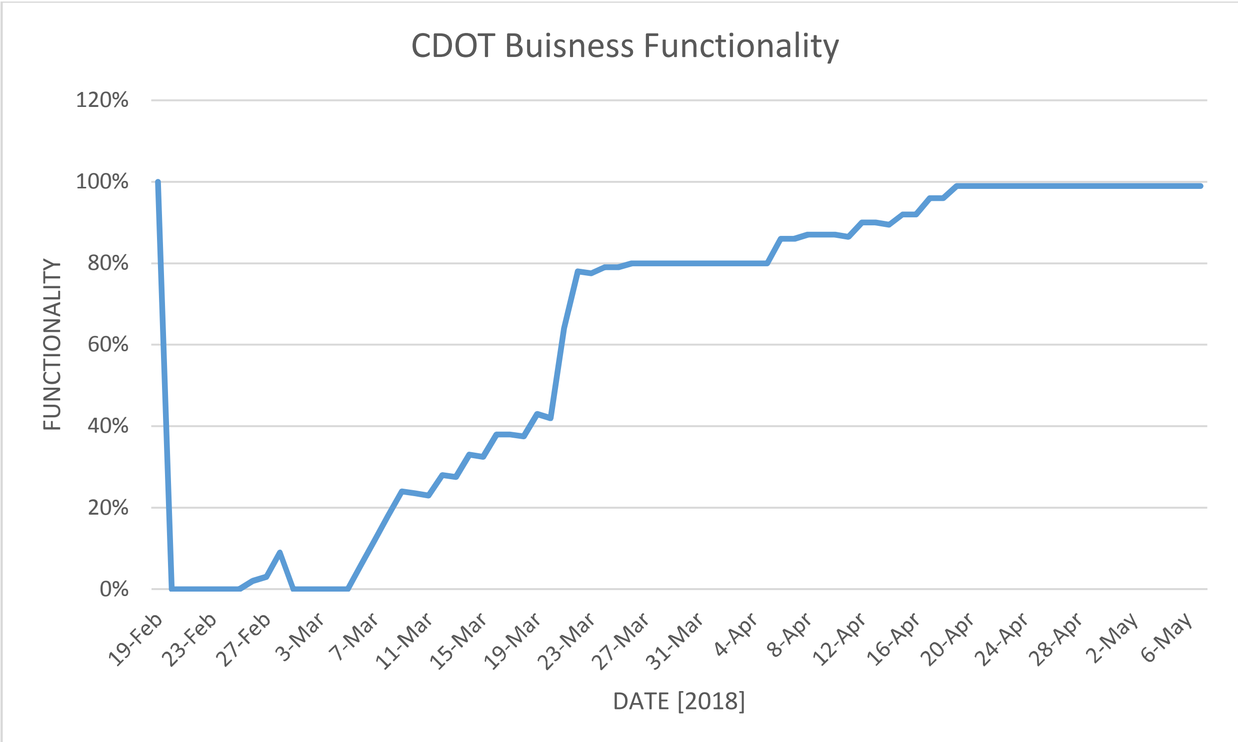

Figure 12: Functionality of the Colorado DOT during and after a cyber-attack

Using the time-dependent resiliency plot for the functionality of the Colorado DOT, a resilience value can be calculated. Table 5 displays the values calculated for the absorption, disruption, and recovery states and the total resilience value. These values allow the Colorado DOT to see where there is room for improvement in their score. Their recovery value could be better for example, with the implementation of an improved Cyber Incident Response Plan as discussed in the after-action report. The absorption value is quite low for this event. This is because the functionality of the Colorado DOT went from 100% to 0% overnight. Unplanned, major disruptions often cause a sharp drop in functionality. It is best to be prepared for any scenario to avoid sharp drops in functionality.

Table 5: Resilience value for the Colorado DOT based on the 2018 cyber-attack

ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
0.00637	0.77966	0.7284	0.00362

6.0.0 CONCLUSION

This research presented a methodology for quantifying resiliency of transportation systems. Using the methodology developed in this research, any transportation system can determine their resilience to a disruptive event and determine where growth is needed to increase resilience. The resilience of a system during one disruptive event can be compared to the resilience of a separate disruptive event on the same system or an identical disruptive event affecting a separate transportation system. This methodology can also be adapted to predict the resilience of a transportation system to a future disruptive event through modeling approaches.

In general, the results of this research showed that the resiliency metric can be utilized for various transportation systems. The resiliency metric methodology was applied to available data on maritime ports and their operations during Hurricane Matthew, including arrivals and dwell times of vessels, to analyze consequences of the disruptive event. The metric provides opportunities for exploring the consequences of alternative decisions in responding to a hurricane event. The general framework for the metric has been established, and a customized analysis has been conducted for each of the six ports considered: Port of Miami, Port Everglades, Port of Palm Beach, Port of Jacksonville, Port of Savannah, and Port of Charleston. Baseline operations at the six ports were compared to operations during Hurricane Matthew to determine the resilience metric for each port. These results show that the length of the absorption, disruption, and recovery states are critical to the resilience of the port.

Data from three airports was analyzed using the resiliency metric methodology. Miami International Airport, Tampa International Airport, and Orlando International Airport were disrupted by Hurricane Irma in 2017. The resiliency metric provides the opportunity to learn from Hurricane Irma and how to better prepare for future hurricanes. Average operations at each airport were compared to operations during the month of September in 2017, to determine the resilience metric for each airport. While the path of Hurricane Irma constantly shifted, the results show that the airport with the most preparation had the highest resilience.

During Hurricane Irma, many regions experienced localized fuel shortages. The resiliency metric methodology was applied to the refueling system in Naples and Tampa, Florida. This metric provides an opportunity for the failure of the fueling systems to be analyzed in the absorption, disruption, and recovery states. Data from Gasbuddy provided functionality for the refueling regions based on the number of gas stations without fuel. These results showed that Naples, FL had a steep drop in functionality during the absorption state, yielding a lower resiliency metric than Tampa, Florida. Tampa, FL refueling stations took longer to run dry possibly due to the forecasted path of the hurricane.

The resiliency metric was also applied to a cyberattack the Colorado DOT experienced in 2018. The metric shows the sharp drop in functionality that occurred overnight. Because this attack was sudden and unprepared for specifically, the results were drastic. Such a low absorption value yielded a low resiliency metric. This analysis is beneficial to many government agencies, lacking cybersecurity funding.

The proposed methodology of the resiliency metric signifies a vast improvement over the general resiliency quantification methods using indices like “high”, “medium”, and “low”. The limitations of this quantification method fall in the comparison of natural disruptions. The resilience values of two systems facing the same disruption have comparison limitations due to different inputs unaccounted for. For example, the comparison of the resilience of two airports during Hurricane Irma must be taken at face value, when the intensity of the hurricane was variable at the two airport locations. The resiliency metric can also be used to predict the resilience of a transportation system to a future disruptive event, however there are limitations in this aspect as well. The accuracy of the prediction is limited by the existing historical data of past disruptions on the system that is used in the proposed model.

Based on the findings of this research, it is expected that a numerical quantification of resilience could be developed for discrete systems other than those relating to transportation. Future researchers will be able to build upon this work by developing a method of determining the robustness of a system and accounting for additional inputs. An area of particular significance in this methodology is the ability to determine a numeric value for each state of absorption, disruption, and recovery. For example, this allows the low absorption value for Orlando International Airport due to Hurricane Irma to be analyzed. Their sharp drop in functionality in two days can be improved upon in the future by the knowledge of the past. The resiliency metric is an improvement to the current resiliency quantification of vague categories. This research presents a sought-after approach to quantifying resiliency by addressing the quantification shortcoming.

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