2016

Quantitative Analysis of Marine Transportation Systems Resiliency

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QUANTITATIVE ANALYSIS OF MARINE TRANSPORTATION SYSTEMS RESILIENCY

A Thesis
Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Science in Civil Engineering

in

The Department of Civil and Environmental Engineering

by
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August 2016
ACKNOWLEDGEMENTS

The author acknowledges that the NAIS data upon which this work is based was obtained from the U.S. Coast Guard by researchers at the U.S. Army Engineer Research and Development Center (ERDC) and processed using software developed jointly by the Coastal Inlets Research Program and the Navigation Systems Research Program. The author gratefully acknowledges the Gulf Coast Center for Evacuation and Transportation Resiliency; a United States Department of Transportation sponsored University Transportation Center at Louisiana State University, and a member of the University of Arkansas’s Maritime Research and Education Center (MarTREC). The author also recognizes the support of Mr. Steve Nerheim of the Houston-Galveston Vessel Traffic Service (VTS) who was instrumental in compiling and explaining the channel closure data used in this study. The author also thanks for his valuable contributions. However, any opinions, findings, conclusions, and recommendations presented in this study are those of the authors and do not necessarily reflect the views of the sponsors.
TABLE OF CONTENTS

ACKNOWLEDGEMENTS .............................................................................................................. ii

ABSTRACT ................................................................................................................................ v

CHAPTER 1. INTRODUCTION .................................................................................................... 1
  1.1 Research Motivation ......................................................................................................... 3
  1.2 Research Approach .......................................................................................................... 4

CHAPTER 2. LITERATURE REVIEW ......................................................................................... 5
  2.1 Marine Transportation System Network (MTSN) .......................................................... 6
  2.2 Potential Threats, Risks and Disruptions to MTS ............................................................. 7
  2.3 Definition of Resiliency .................................................................................................... 8
  2.4 Components and Characteristics of MTS Resiliency ......................................................... 9
  2.5 Alternate Methods of Assessing Infrastructure Resiliency ................................................ 12
    2.5.1 Time Resiliency (RT) ................................................................................................ 13
    2.5.2 Transit Count Resiliency (RTC) ................................................................................. 14
    2.5.3 Cost Resiliency (RC) ................................................................................................ 16
    2.5.4 Environmental Resiliency (RE) ................................................................................ 16
  2.6 Automatic Identification System (AIS) Technology .......................................................... 17
  2.7 Applications of Nationwide Automatic Identification System (NAIS) Data ..................... 18
  2.8 Summary of Literature Review ......................................................................................... 19

CHAPTER 3. METHODOLOGY ................................................................................................. 20
  3.1 Data Collection and Processing ....................................................................................... 20
  3.2 Metrics and Parameters of Resiliency .............................................................................. 21
  3.3 Time-Dependent Resiliency Analysis .............................................................................. 22

CHAPTER 4. EMPIRICAL APPLICATION .................................................................................. 29
  4.1 Galveston Channel Closure ............................................................................................... 29
  4.2 New York / New Jersey Channel Closure ......................................................................... 38
CHAPTER 5. CONCLUSIONS

REFERENCES

VITA
ABSTRACT

The United States Marine Transportation System (MTS) makes large contributions to the nation’s economy, security, safety, and quality of life. Strategic investment, planning, administrative and operational decisions by government at all levels are necessary to maintain the marine transportation system performance at all times, which in turn requires a technical approach and professional leadership based on research. This study describes the approach and results of an ongoing research effort to assess the resiliency of port operations following major disasters and other disruptive events. The work presented in this research uses a set of archival data from the United States Coast Guard’s Nationwide Automatic Identification System (NAIS) to quantify the state of resiliency by investigating the operation of coastal navigation systems before, during and after disruptive events.

To illustrate the ability of proposed methodology to assess the resiliency of a marine transportation system, two case studies representing two different types of infrastructure disruption are presented. The first case study involves the disruption that resulted from a collision in March 2014 in Texas in the Houston Ship Channel as a no-notice event. The second was a disruption caused by Superstorm Sandy in 2012 on the greater Port of New York/New Jersey as a pre-notice event. The results of this study revealed the importance of AIS data as a source of quantitative data when seeking post-disaster measures of resiliency. From an application viewpoint, the methods and results presented herein can be adapted and implemented to quantitatively evaluate the amount of port specific service loss and the levels of port activity following disruptive events.
CHAPTER 1. INTRODUCTION

Worldwide, marine transportation networks facilitate the movement of nearly 90 percent of total world trade and 60 percent of global fuel and oil delivery[1]. In 2011, U.S. foreign and domestic waterborne trade totalled more than 2.1 billion metric tons of goods, with 62.5 percent of this total bound for international destinations [2]. This total also accounted for about 15 percent of total global waterborne trade activity. Waterborne shipping has increased at an average annual rate of nearly one percent between 2009 and 2012 [3]. This trend is expected to continue, if not increase significantly, as emerging markets enter the global economy.

The United States Marine Transportation System (MTS) is a complex network consisting of hundreds of deep-draft coastal ports connected to thousands of miles of inland river channels and other navigable waterways. As with most interdependent, dynamic networks, domestic and international supply chains are susceptible to disruptions, because even a single severe event can have cascading effects that can disrupt freight transportation throughout the overall system. Similar to traffic backups on interstate freeways, disruptions in navigation channels can also cause delays and congestion that propagates rapidly and widely throughout the broader MTS. This leads to concerns that even a single, isolated, disruptive event such as a storm, terrorist act, or shipping accident can have devastating system-wide impacts.

The threat of natural disasters and human-caused disruptions has driven the need for robust and objective performance evaluation methods to quantify the resiliency of maritime transportation systems. The term resiliency, as used in this research, refers to how “system functionality” is affected due to a disruptive event and how the “system” is able to recover over time from a distressed state into normalcy [4]. Previous work in this area has found that, in general, measures
of time, cost, capacity, and environmental impact should be included to evaluate overall MTS performance [5]. However, the real challenge has been in recognizing quantifiable and reliable parameters which are consistently collected and archived to enable the initial disruptive impacts to be quantified and also allow the subsequent recovery characteristics of maritime systems to be analyzed in terms of resiliency.

In this vein, the work presented here introduces new methods for the assessment of MTS resiliency using archival data from the U.S. Coast Guard’s (USCG) Nationwide Automatic Identification System (NAIS), which collects real-time traffic data on waterborne vessels that operate in the U.S. territorial waters (USCG Acquisition Directorate, 2013). Automatic Identification System technology was primarily developed to aid in the improvement of marine safety and maritime domain awareness. Transceivers on board the vessels broadcast an AIS signal via very high frequency (VHF) band radio waves, which relay their position, heading, speed, and other identifying information to shore-based towers with a reporting interval of only several seconds. Thus, NAIS data is primarily intended for collision avoidance and general maritime domain awareness (MDA) to improve safety and security, support search and rescue efforts, and enhance environmental stewardship [6]. In addition to provide a “live picture” of waterway traffic conditions, the NAIS provides an archive of MTS activity covering several years of individual vessel position reports. Among other valuable research endeavors, this large archived dataset enables rigorous, quantitative analysis of vessel patterns and waterway performance trends in both coastal and inland navigable waterways.

The research summarized in this study has adapted a set of archival NAIS data for resiliency analyses of coastal port operations following disruptive events. As part of this effort, archival vessel position reports were used to establish a baseline of navigation channel and port
operations under routine non-event conditions. Observed losses in system functionality following a major disruption were used to quantify the resiliency of the waterway using a time-dependent performance analysis. This type of analysis is critical when investigating the efficacy of the recovery process protocols and management strategies employed in the days and weeks following a major disruptive event.

The new metrics adopted in this study to assess the resiliency of marine transportation systems are followed by two case studies representing two different types of infrastructure disruption. These illustrate the ability of the methodology developed in this research to estimate the resiliency of waterway infrastructure in pre and post-event conditions. In the case studies, the measurement of system resiliency was expressed in terms of vessel dwell time and net vessel transit counts into and out of the port area, respectively. Recent disruptions experienced in critical, high-use commercial ports were analyzed: the closure of the Houston Ship Channel in Texas in March 2014 following a collision of a bulk carrier with an underway barge tow, and the disruptions to the Port of New York-New Jersey after Superstorm Sandy in October 2012.

1.1 Research Motivation

When an infrastructure system faces a disruptive event, substantial losses occur not only in the affected system, but also in other infrastructures, since these systems are interdependent. Therefore, it is necessary to make the infrastructure network system less susceptible to disruptions, by increasing the shock-absorbance capacity (decreasing vulnerability & increasing survivability) of the system at the time of disruption and improving the recoverability of the system after the disruptive event; that is to incorporate resilience into infrastructure systems. To provide insight into the current resiliency-level of the system, resiliency metrics need to be identified and quantitatively evaluated. [7]
1.2 Research Approach

Several studies have been conducted to define resiliency in infrastructure network. Prior studies have also investigated methods to improve the resilience of MTS at an abstract level. However, little work has been contributed toward identifying and establishing quantifiable metrics to measure the resiliency level of infrastructure systems at various stages. This study adopted a method to estimate the resiliency levels of a Marine Transportation System before, during, and after-disruption, through a set of quantitative metrics based on system specific performance: dwell time and transit count. This study used summary of archival NAIS data to analyze resiliency levels of coastal port operations (dwell time and transit count) in pre and post-shock conditions. Two types of disruptive events were studied in this research: no-notice event (closure of the Houston Ship Channel in Texas in March 2014), and pre-notice event (disruptions to the Port of New York-New Jersey after Superstorm Sandy in October 2012). In the two case studies, two metrics were introduced to measure the system resiliency levels in pre and post-event conditions: vessel dwell time (RDT), and net vessel transit counts (RTC) into and out of the port area, respectively. The proposed resiliency metrics can be used to evaluate on a practical level the resiliency level of an infrastructure system after the occurrence of a disruptive event.
CHAPTER 2. LITERATURE REVIEW

Much of the existing body of knowledge on disruptive events for infrastructure systems has focused on security policies such as protective action, prevention, and risk mitigation [8]. Fundamentally, this approach overlooks the need to design systems which adapt to disruptive events while maintaining a desirable level of service [9]. For a system to be better prepared for a disruption, it is desirable to mitigate the likelihood of an event occurrence and design for adaptive and robust systems which maintain some level of service during and after a disruptive event. To this end, Attoh-Okine et al., (2009) [10] developed a resiliency index for urban infrastructure. Li and Lence (2007) [11] used the ratio of the probability of failure over recovery as a measure within water resources systems to formulate a resiliency index. For telecommunications networks, Omer et al., (2009) [12] proposed a quantitative approach to measure resiliency using the ratio of value delivery of a system after disruption to the value delivery before disruption. Reed et al (2009) [13] used power outages and restorations after Hurricane Katrina in 2005 to estimate the resiliency of interdependent systems after a natural disaster.

From the few examples outlined above, it is clear that there is no consistent, quantitative approach to define resiliency among the many fields and disciplines of infrastructure networks. To address this issue, Henry and Ramirez-Marquez (2012) first proposed a fundamentally quantitative approach to estimating resilience that is applicable to various disciplines. They proposed resiliency as a time-dependent function where system deliverables are quantified for the duration encompassing before, during, and after a disruptive event. This approach was also applied to stochastic systems in subsequent work [14] [15]. This chapter covers three major components of this study, as follows: (Figure 1a)
• Marine Transportation System network (MTSN): this section explains the role and components of MTSN in international and national scales; as well as potential risks, threats and disruptions to MTSN that affect the MTS performance.

• Resiliency: in this section, the concept of resiliency in general and in MTS specifically; components and characteristics of MTS resiliency; and alternate methods to evaluate MTS resiliency are described.

• Automatic Identification System (AIS): this section describes the AIS technology, and applications of NAIS technology (Nation-wide Automatic Identification System) in general and in MTSN specifically.

Figure 1a. Summary of literature review

2.1 Marine Transportation System Network (MTSN)

To clearly provide dimensions of Marine Transportation System (MTS) resiliency in the next sections, it is instructive to summarize total number and types of vessels in operation to clarify the importance of MTS in transportation: The total number of world ships were reported to be 46,222 in 2005, including 18,150 cargo ships, 11,356 tankers, 6,139 bulk carriers, 3,165 container ships, and 6,139 passenger ships. In 2011, 7,836 U.S. oceangoing vessels made 68,036 calls at
U.S. ports, of which 35 percent were by tankers, 32.5 percent were by containerships, 16.1 percent dry bulk vessels, 9.1% were by Roll-On/Roll-Off (Ro-Ro) vessels, and 5.9 percent were by general cargo ships [2]. The increase of waterborne shipping from 30,686 billion ton-mile in 2006 to 33,000 billion ton-mile in 2008 represents an average annual increase rate of approximately 4 percent increase in shipping, which is expected to increase at a similar trend. Table-1 compares the rate of change of total waterborne trade shipping (inbound and outbound) between 2006 and 2012 in the U.S. and world, respectively. As shown in the table, waterborne trade shipping was affected by the great recession of 2008-9.

Table 1. Waterborne shipping [3]

<table>
<thead>
<tr>
<th>Waterborne Trade</th>
<th>Year</th>
<th>Waterborne Trade Tonnage (millions of tons)</th>
<th>Rate of Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Loading</td>
<td>Unloading</td>
</tr>
<tr>
<td>U.S.</td>
<td>2006</td>
<td>545.4</td>
<td>1,148.7</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>632.9</td>
<td>1,122.7</td>
</tr>
<tr>
<td></td>
<td>2008</td>
<td>692.5</td>
<td>1,034.5</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>646.1</td>
<td>883.6</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>682.5</td>
<td>909.9</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>778.0</td>
<td>895.5</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>850.2</td>
<td>885.4</td>
</tr>
<tr>
<td>World</td>
<td>2006</td>
<td>7,700.3</td>
<td>7,878.3</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>8,034.1</td>
<td>8,140.2</td>
</tr>
<tr>
<td></td>
<td>2008</td>
<td>8,229.5</td>
<td>8,286.3</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>7,858.0</td>
<td>7,832.0</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>8,408.9</td>
<td>8,443.8</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>8,784.3</td>
<td>8,797.7</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>9,165.3</td>
<td>9,183.7</td>
</tr>
</tbody>
</table>

2.2 Potential Threats, Risks and Disruptions to MTS

Any significant delay, interruption, or stoppage in the flow of waterborne trade caused by natural disaster, heightened threat level, an act of terrorism, or any Transportation Security Incident (TSI) are defined as a transportation disruption, as stated by U.S. Coast Guard Strategy
Sources of disruptions were categorized by Mansouri et al into the following groups: [7]

- Natural factors: disruptions due to damage caused by nature, such as hurricane
- Human factors: disruptions caused by humans operating or using the system, such as human errors or terrorist attacks
- Organizational factors: disruptions that occur due to events at organizational level, such as worker strikes
- Technical factors: failure in system components, such as faulty or outdated equipment

2.3 Definition of Resiliency

The term resiliency comes from the Latin verb resilire, meaning to rebound or recoil (Concise Oxford Dictionary, Tenth Edition). There is no evidence of scholarly work in resiliency until Thomas Tredgold introduced the term in 1818 to outline the properties of timber as a construction material in tolerating various loads. In 1860’s, Robert Mallet developed the concept of resiliency in marine transportation by incorporating the two newly introduced ideas of resiliency and sustainability in the design and construction of navy ships. Mallet’s work focused on assessing the ability of materials used in different parts of the vessel to withstand sudden forces and severe conditions. One of the other early studies of resiliency was done as a system property in the ecology area by C.S. Holling, who initially defined it as “the ability of ecological systems to absorb changes of environment variables and still persist”. Used widely in different disciplines from environmental research and socioecological systems to material science, psychology, construction and computer science, resiliency is often described as the ability of a system to bounce back after a disruptive event and return back to its normal functional condition within the least amount of time, cost, and
effort. Fiksel depicted resiliency in the system that has the “ability to return to a stable equilibrium state after a perturbation” [16]. Rose and Liao defined resiliency as the “ability of the system to apply adaptive responses in the face of disruptions in order to avoid potential losses” [17]. It is noted in the Infrastructure Security Partnership that a resilient infrastructure sector would “prepare for, prevent, protect against, respond, or mitigate any anticipated or unexpected significant threat or event” and “rapidly recover and reconstitute critical assets, operations, and services with minimum damage and disruption” [18]. Focusing on natural disasters and specifically on post-event response, Comfort (1999, p. 21) defines resilience as “the capacity to adapt existing resources and skills to new situations and operating conditions”. The use of term resiliency in such context implies both system’s strength in reducing post-event network failure probabilities as well as system’s flexibility in coping with and minimizing hazard-related losses while maximizing recovery.

2.4 Components and Characteristics of MTS Resiliency

The initial target of the MTS was to provide safety and efficiency of waterway systems, mostly in the case of natural disasters. After the terrorist attacks of September 2011, however, the Critical Infrastructure Protection (CIP) program was implemented into MTS by the Department of Homeland Security in which the focus of the MTS was shifted from safety to security to protect the infrastructure system from both natural and manmade hazards. Since the complete protection of systems against all disasters is impossible, the MTS focus is being changed from CIP to Critical Infrastructure Resiliency (CIR), in which instead of trying to reduce the occurrence of the disasters, the probability of system’s vulnerability to natural and manmade disasters is reduced.

The two main components of CIR in MTS are summarized as system’s vulnerability and system's coping capacity [19] or adaptive capacity [20]. Systems with lower vulnerability are less
influenced by disruptions and thus are less susceptible to harm, while systems with higher response capacity have greater “ability to adjust to a disturbance, moderate potential damage, take advantage of opportunities, and cope with the consequences of a transformation that occurs” [21]

Previous studies introduced techniques to reduce vulnerability and increase coping capacity of the MTS to optimize the system’s resiliency. The vulnerability reduction strategies include the implementation of the following characteristics into the system: [7]

- Robustness
- Redundancy
- Diversity
- Modularity
- Rapidity

whereas the scenarios to increase the coping capacity of the system cover the employment of the following qualities into the system: [22]

- Resourcefulness
- Collaboration
- Preparedness
- Cognition

Figure 1b shows the performance levels of a resilient system at three stages of original, disrupted, and recovered state in the face of a disruption.
Resiliency can be interpreted as a quality framework within which lies a system that shows the following characteristics during and after a shock-event: [22]
• Minimized probabilities of system failure

• Minimized consequences of partial or full failure of system if it occurs, in terms of hazard-related damages to the network, and negative economic and social impacts

• Optimized (quick) recovery

In summary, a resilient system can be explained as a system with the ability to reduce the probabilities of being affected by a shock, increase the shock absorbance capacity if a shock ever occurs to the system, maintain and ideally maximize quantifiable portions of the system’s serviceability and adaptive capacity during and after event, and develop a quick recovery to the normal or above-normal conditions. [7]

2.5 Alternate Methods of Assessing Infrastructure Resiliency

Previous studies suggest a post-event loss assessment method as a mean to determine the current resiliency stage of the system to establish resiliency improvement techniques based on the identified system resiliency level. Different MTS-related disruptive events including hurricanes, vessel collisions, or oil spills can cause various shocks to the system network and consequently impact the system’s ability to function. In this paper, port resiliency measurements were defined in terms of normal MTS performance capacity, remaining adapted post-event performance, and the amount of MTS serviceability loss. Building upon previous studies by M. Omer et al., the following metrics have been introduced in the literature to quantify MTSN resiliency:

• Time Resiliency (RT)

• Capacity Count (Loading) Resiliency (RL)

• Cost Resiliency (RC)

• Environmental Resiliency (RE)
Following a disruption, not only is the time needed to travel to and from the disrupted port increased, but also the amount of freight loads being transported between the origin and destination ports and the total cost of shipping are negatively impacted based on the size of back-log. After conducting vessels dwell time analysis as a means of quantifying the port resiliency, the loss assessment method is proposed in this study to monetarily translate the corresponding loss of the four resiliency metrics after a disruptive event in to precisely identify the current resiliency level of the network system. In the following sections, each of the four MTS resiliency metrics is briefly discussed.

2.5.1 Time Resiliency (RT)

Time resiliency of a port consists of two components: dwell time resiliency (RDT), and disruption duration resiliency (RDD). Dwell time (DT) represents the time a vessel spends in the same position, area, or stage of a process within the port or its extension. It fundamentally refers to the timeframe from the moment the cargo arrives in the port to the time it leaves the port (difference between time of entrance and time of departure). Representing the "capability of the port to efficiently handle cargo flows at the terminals and beyond" [23], dwell time in ports accommodates vessels waiting time for berth, mooring time in, waiting time for gangs, working time, preparation for sailing, and mooring time out [24]. Various ports allow for different DT averages for each of the inbound and outbound vessel categories, depending on the port performance, capacity and demand. A decrease in the port performance capacity following a disruption confines the number of vessels to be processed at any given post-event time unit, which consequently extends vessels dwell time. Dwell time resiliency can be calculated as follows: [7]
Where;

\[ RDT = \frac{\varphi_0}{\varphi_i} = \frac{DT_0}{DT_i} \]  

(EQ. 1)

Dwell Time Resiliency (RDT) ranges from 0 to 1, where the smaller ratio represents a less resilience implemented port. RDT results greater than 1 represent a system that recovers to an above-normal condition.

Disruption duration (RDD) is the other component of the MTS time resiliency (RT). Ranging from a few days to several weeks, the length of the disruption absorbed by the port quantifies the resilience quality of the infrastructure network. The more resilient the MTSN, the shorter the time the port performs under disrupted quality or partial failure.

2.5.2 Transit Count Resiliency (RTC)

The capacity of the port in sending and receiving shipments loads decreases after the occurrence of a disruptive event. Regulatory information on the normal load processing capability of the port in both inbound and outbound shipping flow is required to quantify the amount of port’s load processing loss during disruption. Figure 2.1 and 2.2 show the changes in port loading (transit count) capacity and dwell-time at different time segments of before, during, and after a disruption. As shown in the figure, maximum dwell time (bottom figure) occurs when the port performs at its lowest loading capacity (top figure), due to a disruptive event.
Transit count resiliency (transit count resiliency, loading resiliency) of a port can be calculated using the following equation [7]:

\[
RTC = \frac{\varphi_0}{\varphi_i} = \frac{TC_0 \ast t_{\text{total}}}{TC_i \ast t_i}
\]  

(EQ. 2)

Where:

- \( \varphi_i \) = port transit capacity following a disruption
- \( \varphi_0 \) = port transit capacity under normal conditions
- \( TC_0 \) = transit count under normal condition
- \( t_{\text{total}} \) = duration of the disruptive event
- \( TC_i \) = transit count after disruption
- \( t_i \) = transit count during the time period I after disruption
- \( n \) = number of time periods in a disruptive event
2.5.3 Cost Resiliency (RC)

A disruptive event negatively impacts the cost of shipping and waterway transportation by increasing the cargo dwell time (wait time) and decreasing the port’s freight flow capacity (service capacity). This imposes other indirect and overhead costs and results in an increased cost of waterway freight transportation per mile-ton following a disruption. Cost resiliency of a port can be calculated using the following equation:

\[
RC = \frac{C_0}{C_i} = \frac{C_0}{C_0 + C_x} = \frac{C_0}{C_0 + (C_{dep} + C_{ovh} + C_{alt})}
\]  

(EQ. 3a)

\[
C_x = C_{dep} + C_{ovh} + C_{alt}
\]  

(EQ. 3b)

Where;

- \(C_0\) = transportation cost under normal condition
- \(C_i\) = transportation cost during disruption
- \(C_x\) = loss due to disruption
- \(C_{dep}\) = value depreciation cost
- \(C_{ovh}\) = overhead cost
- \(C_{alt}\) = alternate transportation cost

The loss cost (\(C_x\)) due to disruption includes the depreciation of the value of goods during transportation, overhead costs such as administration, security, scans, customs, and the cost of transport by alternative means per mile-ton.

2.5.4 Environmental Resiliency (RE)

A disruptive event in most cases causes damages to the natural environment. A damaged ecosystem requires a lot of effort, time and money to recover from disturbances and return to the normal pattern. Environmental resilience is defined as the amount of disturbance that an ecosystem can withstand without changing self-organized processes and structures. For example, in the
March 22, 2014, Galveston bay oil spill took over 40 days to completely collect the oil from the water surface, which resulted in threatening several underwater species. In many cases, it is very difficult and sometimes impossible to evaluate the costs resulting from damages to biological and natural existence. These assessments, typically taking several years, involve the design and development of a plan to restore damaged areas, and require some negotiation with the responsible parties[25]. In addition to the complexity of assessing the costs associated with the environmental damages, developing a plan to restore these areas is usually another big challenge.

2.6 Automatic Identification System (AIS) Technology

Automatic Identification System (AIS) technology has developed in recent decades primarily as a means to improve marine safety and maritime domain awareness (Tetreault, 2005). The AIS technology uses the VHF radio spectrum to broadcast and receive (ship-to-ship, ship-to-shore, and shore-to-ship) real-time information concerning vessel identities, dimensions, positions, speeds, and headings among other fields (USCG Navigation Center: http://www.navcen.uscg.gov/). The Maritime Transportation Security Act of 2002 (MTSA) (46 USC §§70113, 70114) mandates AIS carriage requirement by commercial vessels operating in or bound for U.S. waters. The U.S. Coast Guard has implemented this requirement through regulations in 33 CFR § 164. The Coast Guard also enforces these and other equipment carriage requirements, is involved in developing standards for AIS message formatting, and has established an archive of historical AIS data as part of its NAIS program.

MTS travel time statistics for maintained navigable waterways can be compiled for different classes of vessel and by direction (inbound/outbound; upstream/downstream) via a straightforward comparison of the time-stamped position reports as unique vessels move through the various geo-fenced watch areas of interest [5]. Some recent examples of archival AIS data
applied in this fashion, as well as practical methods for dealing with some of the issues encountered with travel time outliers can be found in [26] [27] [28]. A similar treatment of AIS data can also be applied to derive dwell time estimates for vessels within a defined bounded region [29]. This can be done by comparing the time stamp of the first observed vessel position report within a defined area to the time stamp of the subsequently first observed report outside the defined area. This approach can be applied at a variety of spatial scales, from specific berthing terminals or waterway segments to entire port zones, though care must be taken to ensure the AIS data coverage in the area is thorough and reliable.

2.7 Applications of Nationwide Automatic Identification System (NAIS) Data

The use of archival NAIS records as a remote-sensing technology to infer aspects of navigation system performance has become more frequent in recent years. Numerous studies have used archival AIS position reports to measure or estimate environmental impacts of shipping, such as air emissions [30] [31] and whale strikes [32]. Schwehr and McGillivary [1] explored the use of the AIS to track illegal oil releases from vessels and provide real-time monitoring of traffic to improve incident response times and management. Hatch et al.[33] used AIS data to estimate the impact of large ocean-going vessels on noise levels near shipping lanes in a national marine sanctuary off the coast of Massachusetts. Dobbins and Langsdon [16] used AIS data as proof of concept for vessel trip generation to improve on existing data sources (e.g., U.S. Army Corps of Engineers Waterborne Commerce statistics and Lock Performance Monitoring System) in the vicinity of Paducah, Kentucky, along the lower Ohio River. Shu et al. [34] used Show Route software, developed by the Marine Research Institute, Rotterdam, The Netherlands, to investigate forcing factors that affected ship path and speed. For its Atlantic Coast Port Access Route Study, the USCG used aggregated NAIS data to provide a detailed map of shipping lanes along the
Atlantic coast [35]. Calder and Schwehr [36] investigated the use of NAIS data to inform risk management strategies across a variety of spatial and temporal domains. Mitchell and Scully [6] used archival NAIS data to assess tidal influence on vessels that call at deep-draft coastal ports as well as to conduct waterway transit time analysis over a range of spatial and temporal domains.

2.8 Summary of Literature Review

Considering the importance of the Marine Transportation System on the nation’s as well as international economy, such systems must be designed to be resilient. Previous studies introduced techniques to reduce vulnerability (increase survivability) and increase coping capacity of the system as a means to improve system’s resiliency. The vulnerability reduction strategies include the implementation of robustness, redundancy, diversity, modularity, and rapidity into the system network, whereas the scenarios to increase the coping capacity of the system cover resourcefulness, collaboration, preparedness and cognition [22]. Along these lines, MTS resiliency can perhaps best be measured in terms of time, capacity, cost, and environmental impact. By quantifying these measures both before and after a disruptive event, it is possible to measure the full impact of the disruption on serviceability (performance level and/or performance loss) and recoverability of MTS, by which resiliency level of the system can be measured (resiliency as the ratio of recover to loss is furthers discussed in the next chapter). Archival NAIS records as a remote-sensing technology have recently been used in several studies to infer aspects of navigation system performance, and can be used in quantifying the resilience of MTS.
CHAPTER 3. METHODOLOGY

This research proposes a new methodology to quantify MTS resilience by plotting time-dependent resiliency figures for commercial ports using a summary of archival AIS data. The research methodology in the following section describes what types of data were used for the resiliency analysis of marine infrastructure facility, and how the data were collected, organized and adopted. Then various metrics and parameters by which resiliency can be measured are discussed and examined. Among the several resiliency metrics, this chapter concludes with the introduction of time-dependent resiliency analysis of ports. Each of the above methodology component was described in the following section.

3.1 Data Collection and Processing

Historical AIS data is developed by U.S. Coast Guard as part of its NAIS program. Archival AIS data sets used in this study were obtained by the U.S. Army Corps of Engineers (USACE) through a suite of NAIS web services, made available to the Corps as part of a standing interagency service agreement (ISA). Manual real-time and archival data requests can be made to the Coast Guard’s Navigation Center, pursuant to agency terms concerning requesting entity, intended use of the data, and disclosure to third parties (www.navcen.uscg.gov/?pageName=NAISdisclaimer). There are also numerous commercial vendors of both real-time and archival AIS data, and transceiver units needed to broadcast and receive AIS messages are readily available for purchase to those seeking to collect their own data. The adapted archival NAIS data in this study were used to analyze resiliency levels of port operations experiencing disruptive events at three stages of pre-event, during-event, and post-event. Two metrics were introduced to measure the system resiliency levels at different stages: vessel dwell time resiliency (RDT), and net vessel transit count resiliency (RTC) into and out of the port area, respectively.
3.2 Metrics and Parameters of Resiliency

Vessel location information from onboard AIS transceivers is used to generate two performance indicators, average “vessel dwell time” within the port areas of interest and net “vessel transits” into and out of the port areas of interest. Dwell time represents the continuous length of time a vessel spends within the port area or associated regions such as offshore anchorages. In terms of freight throughput efficiency, dwell time indicates the “capability of the port to efficiently handle cargo flows at the terminals and beyond” [37]. Decreases in port performance following a disruption tend to limit the rate at which vessels can be processed, thereby extending the overall average vessel dwell time within the greater port area. The net number of vessels within a port area is obtained from a running tally of vessels both entering and departing the port area and surrounding zones. In the case of port terminals handling cargo, this quantity can indicate relative rates of freight throughput (loading and unloading of vessels) at any point in time; whereas in the case of anchorages where vessels typically wait for berthing slots to open within the port area, this quantity can indicate backlogs and excessive delay owing to disruptions in port operations. It should be noted that there may also be external factors influencing the resiliency performance measures, such as use of anchorages by vessels for reasons (e.g. bunkering and lightering operations) unrelated to the MTS disruption. Here the two performance measures (average vessel dwell time and net vessel transits into and out of the port) provide general trends in the efficiency of overall port operations and the associated maintained waterways. By estimating and plotting the resiliency in terms of these two metrics for the days and weeks before and after major disruptive events, additional analysis can be conducted on the recovery efforts and their impact on overall port resiliency and performance.
3.3 Time-Dependent Resiliency Analysis

Figure 3 illustrates a general description of different states a system undergoes after occurrence of disruptive events. A generic time-dependent resiliency plot is shown in figure 3a for an increasing service system and figure 3b for a decreasing service system [15]. An increasing service system is one where network output is positively correlated with service; that is, as the output increases, so too does the service provided. An example of this is a production process where output, in terms of units built increases with the overall service of the production line. A decreasing service system is one where the network output is negatively correlated with the service. An example of this is dwell times; if a system is performing well, then dwell times should be minimized. In Figure 3a and 3b, a system, noted as $S$ is analyzed before, during, and after a disruptive event. System $S$ experiences three steady states (the original state $S_o$, the disrupted state $S_d$, and the stable state $S_r$), and two transitional states (where the systems transitions from normal steady state to the disrupted state and another from the disrupted state back to the recovered stable state). These transitions are marked by two events; the first is the onset of the disruptive event ($e^j$) and the second is a recovery action. The figure illustrates how the initial system, as measured by its output performance $F(t)$, initially exists in a steady state. Then, due to the onset of a disruptive event $e^j$, transitions into a disrupted state. Finally, after the start of a recovery event, the system transitions back into a stable state.
Figure 3a. Increasing service system function [15]

Figure 3b. Decreasing service system function [15]
Furthermore, Figure 1 points out four behavioral features of a resilient networked system in the face of a shock, as described below: [38]

- **Reliability**: refers to the system’s behavior during time period \((t_0 - t_e)\), while there is no external disruptive event. It corresponds to the system time to failure in the face of a disruption at time \(t_d\).

- **Survivability**: refers to the system’s behavior after the occurrence of a disruptive event. A more resilient system maintains system service continuity so that potential disruptions are minimized. Several techniques have been developed to increase a system’s survivability in the face of a shock, or in other words, to help the system become robust to external attacks [39], through general architecture features like adaptability (ability to change as to better accommodate new condition) and flexibility (ability to adapt to a range of adverse unexpected events).

- **Vulnerability**: refers to the interaction between a disruptive event and the system performance in order to size the specific system performance loss (Crucitti et al, 2005), (Zhang et al, 2011), (Nagurney and Qiang, 2008), (Zio et al, 2008). By addressing such negative impacts, those system elements generating the highest damage when disrupted can be identified. Diagnosis of these points of system vulnerability, which are essentially responsible for the maximum reduction of service performance, has been the subject of many recent studies.

- **Recoverability**: refers to the ability of the system to recover after a disruptive event. Rose (2007) describes dynamic recoverability as “the speed at which a system recovers from a severe shock to achieve a desired state”. While there are several studies in this area, there
is still a gap in research related to the stochastic behavior of recovery in general networked systems [38].

Based on the previous discussion and to help fill current research gaps, this study adopted the resiliency equation developed by Henry and Ramirez Marques (2012) to estimate the resiliency levels of waterborne infrastructure systems in the face of a given shock. In the Ramirez-Marquez equation (EQ.5), resilience is given the notation of $\mathcal{Y}$ (as R is already used for reliability) and computed at any time $t_i$ after disruptive event $(e_j)$ as the ratio of the system’s specific performance $(F)$ recovered by time $(t_i)$ over the maximum service loss of the system occurring at time $(t_d)$. The Ramirez-Marquez equation can be used if and only if the system is hit by an external disruptive event $(e^j)$ capable of affecting system’s original state $(S_0)$. As seen in Figure 1, once the system is disrupted by an event $(e^j)$ at time $(t_e)$, a period of specific service degradation of length $(t_d – t_e)$ shifts the system down from its original stable state $(S_0)$ with corresponding performance $F(t_0)$ to a disrupted state $(S_d)$ with the corresponding performance $F(t_d)$. Once entering the disrupted state $(S_d)$ at time $(t_d)$, the system continues to function under the maximum disrupted state for a length of time $(t_s – t_d)$, after which the system restoration begins until it reaches a recovered stable state $(S_r)$ with corresponding performance level $F(t_r)$. In his equation, Ramirez-Marquez calculated the system resiliency at any time $t_i$ after event $e^j$, as follows: [4]

\[
\mathcal{Y}_F(t_i) = \frac{\text{Recovery}(t_i)}{\text{Loss}(t_d)} \quad \text{(EQ. 4)}
\]

\[
\mathcal{Y}_F(t_i|e^j) = \frac{F(t_i) - F(t_d)}{F(t_0) - F(t_d)} \forall e^j \in D \quad \text{(EQ. 5)}
\]

Where,

$\mathcal{Y}_F(t_i|e^j)$ = the resiliency of system $S$ at any time $t_i$, resulting from the disruptive event $e^j$
\[ F(t_i) = \text{the performance of the system at time } t_i \]
\[ F(t_d) = \text{the performance of the system at time } t_d, \text{ corresponding to the time of maximum system service loss} \]
\[ F(t_0) = \text{the performance of the system at time } t_0, \text{ corresponding to the original state} \]
\[ D = \text{set of all disruptive events which could hinder service} \]

Henry and Ramirez-Marquez (2012) made several important observations regarding the resiliency formulation \( \mathcal{R}_F(t_i|e^j) \): (1) \( \mathcal{R}_F(t_i|e^j) \) indicates the proportion of service which has been recovered by time \( t_i \), keeping in line with the meaning and intent of resiliency; (2) the minimum value of \( \mathcal{R}_F(t_i|e^j) \) is zero, indicating that the system has not recovered from its disrupted state; (3) when the value of \( \mathcal{R}_F(t_i|e^j) \) is equal to one the system has fully recovered at time \( t_i \); (4) \( \mathcal{R}_F(t_i|e^j) \) is undefined when \( F(t_0) = F(t_d) \), this indicates that no drop in performance was measured as a result of event \( e^j \), and therefore \( e^j \) is not an element of disruptive state \( D \). This model enables quantifying and tracking the changes in the network state as a function of time and accurately observing the network response to the recovery strategies employed. Using this metric, decision makers can dynamically assess their resilience-building decisions during the after-math of a disruption [4].

The degree of disruption is used as a mean to quantify resiliency in the context of this study. Figure 3d plots the hypothetical rate of change of system’s specific performance over time (before, during and after disruption), or in other words, illustrates the derivative of the resiliency function.
The derivative of the resiliency function is a measure of the rate of change of specific service output by the system. Initially the system is operating in the original stable state, and the derivative of the resiliency function \( \frac{dR}{dt} \) is equal to zero during this original stable state. The transitive vulnerable state begins after the occurrence of the disruptive event and when the derivative of the resiliency function drops to less than zero \( \frac{dR}{dt} < 0 \) in an increasing service system. A larger negative magnitude derivative (steeper negative slope) in the transitive vulnerable state indicates an inability of the system to absorb and withstand the shock without being impacted. This suggests that the higher the absolute magnitude of the derivative during this transitive state, the less resilient the system is. The disrupted state is immediately preceded by a negative derivative resulting from the initial loss of service, and is marked by a derivative equal to zero when entering the stable
disruptive state. The system will remain in the stable disruptive state with the derivative equal to zero \( \frac{d\eta}{dt} = 0 \), until a recovery action is taken. At this point, the derivative will then increase from zero \( \frac{d\eta}{dt} > 0 \), indicating the impacts of the recovery action on the system’s performance. The higher the magnitude of the derivative (steeper positive slope) during the transitional recoverability state, the more responsive the system is to the recovery action taken, and the more resilient the system is. After this point, the system begins entering the stable recovered state, marked by a decreasing derivative \( \frac{d\eta}{dt} < 0 \), and the derivative returns to zero, indicating system service stability.
CHAPTER 4. EMPIRICAL APPLICATION

To demonstrate the versatility of the proposed methodology, two empirical case studies are presented here. The first applies the methodology to a no-notice event (an event with no warning time) which was triggered by a collision between an oceangoing bulk carrier vessel and a tow of fuel barges in the Houston Ship Channel on March 22, 2014. The second case study demonstrates the methodology on a pre-notice event (warning time is greater than 24 hours), the closure of harbor operations in the greater Port of New York/New Jersey resulting from Superstorm Sandy on October 28, 2012.

4.1 Galveston Channel Closure

On March 22, 2014, the 607-foot long bulk carrier *Summer Wind* collided with a tank-barge being pushed by the *Miss Susan* near the end of the Texas City Dike in Lower Galveston Bay. The collision was caused primarily by heavy fog in the area, and it resulted in about 4,000 barrels (168,000 gallons) of fuel oil spilling into the waterway [40]. During the ensuing channel closure for cleanup operations, pilot services were suspended and oceangoing vessels began queuing up in the various anchorage areas near the entrance to Galveston Bay. This study uses a set of NAIS data covering January-June 2014 for cargo and tankers transiting in the vicinity of the intersection of the Houston Ship Channel with the Gulf Intracoastal Waterway (GIWW). To keep data file sizes and processing times manageable, the temporal sampling rates vary from 5 minutes to 1 hour, depending on the amount of time each vessel was within range of shore-based AIS towers. In Figure 4a, density plots of vessel traffic are shown for the overall Galveston Bay port area (inset) as well as the offshore anchorages where vessels queue up while waiting for pilots and/or berthing slots to open at the various port terminals in Galveston, Texas City, or Houston. The small box in the inset map shows the general location of the collision in March 2014. It should be noted that
the density plots reflect the relative number of AIS position reports per unit area, but they do not necessarily indicate higher numbers of unique vessels. The inbound and outbound traffic fairways can also be seen bisecting the two offshore anchorage areas.

A large watch area encompassing both of the offshore anchorage areas seen in Figure 4a was used as the basis for AIS-derived dwell time observations and a rolling vessel entrance/exit tally during the 6-month study period. As previously described, the dwell time observations are taken as the difference in the time stamps of vessel position reports when first appearing within and subsequently outside of the watch area. Some (manageable) dwell time error is introduced by the differing sampling rates used for unique vessels, which vary between 5 minutes and 1-hr for vessels
within range of AIS receiving towers. Figure 4b shows the total number of days that the port was closed during the 6-month study period. Note that some of the closure times in the figure represent service disruptions in different parts of the greater Galveston Bay port area, and do not necessarily represent closures of the entire waterway system. The post-collision disruption that is the focus of this study is indicated by the red arrow. Presumably, the fact that this closure was continuous and affected the entrance to the entire Houston-Galveston-Texas City port zone led to the significant disruptions to overall vessel traffic seen by the average dwell time and net transit count increases in the outer anchorages. Note that the multiple closures during February, likely due to foggy weather conditions, also appear to have taken their toll on the overall port area performance.

![Figure 4b. No. of days Galveston bay was closed during the 6-month study period](image)

Figure 5 shows the weekly average vessel dwell times and the number of inbound and outbound vessels within the offshore watch area for the six-month period encompassing the vessel collision. The disruptive event date (March 22, 2014) is shown on the figure with a solid line. This period coincides with an imbalance in the number of inbound and outbound vessels and subsequent increases in the average vessel dwell time. An unexpected finding of note includes an earlier
increase in average vessel dwell time (noted by the dotted-dashed line) five weeks prior to the collision event. Channel closure records obtained from officials with the Houston-Galveston Vessel Traffic Service (VTS) show that cumulative weekly closure durations were actually higher in February 2014, mostly due to fog, than they were in March 2014, even after taking the post-collision closure into account.

![Figure 5. Six-month vessel traffic summary for Galveston offshore anchorage area](image)

Some of the closures represent service disruptions in different parts of the greater Galveston Bay port area, and they do not necessarily represent closures of the entire waterway system. The post-collision disruption that is the focus of this study is indicated by the solid line. Presumably, the fact that this closure was continuous and affected the entrance to the entire Houston-Galveston-Texas City port zone led to the significant disruptions to overall vessel traffic seen by the average dwell time and net transit count increases in the outer anchorages.

Figure 6a shows the daily average dwell times in the Galveston entrance outer anchorages from March 7, 2014 until April 14, 2014. The event date is shown with a solid line and corresponds
to the closure of the channel for a four-day period. On March 27, 2014 (shown with a dotted line) the channel was partially reopened and then completely opened on April 7, 2014 (shown with a dashed line). The figure shows that prior to the event, the outer anchorage area was in the original state condition. The system reached the full disrupted state starting on March 23, 2014. On March 27th a recovery action was taken (the partial reopening of the channel), which began the transition between the disruptive state and the stable state. Finally, the system reached the stable state around April 7, 2014.

Figure 6a. Galveston Dwell Times

Figure 6b shows the resiliency, as calculated from Equation 1, for each day after the disruptive event. This analysis demonstrates that the recovery action (dotted line) was effective as a means of increasing the resiliency of the system. Then, over the ensuing days the resiliency of the system fluctuates until it again reaches its stable state (dashed line). For this demonstration, the original state is quantified as the average vessel dwell time the day prior to the incident. Future
work will incorporate a more statistically robust measure of steady-state, pre-disruption port operations.

Figure 6b. Galveston Dwell Time Resiliency

Figure 6c shows the derivative of the Galveston dwell time resiliency, or in other words, changes in port dwell time performance per day as the unit of time. As expected, the figure represents a dwell time in an initial stable state before the event date, which then transitions into a disruptive state with a negative derivative value. It appears that the transition occurred on March 22nd and continues until a day after. On March 23rd, the system begins to enter the stable disruptive state, as noted by a spike in the derivative value. Once in the stable disrupted state, the derivative is shown varying between +0.20 and -0.22, indicating that stochastic systems performance is essentially unchanged during this interval of nine days. The derivative function then indicates that effects of the recover action taken on March 26th were not observed to have an impact on port operations until April 2nd, six days later. After this recover action the system stabilizes once again.
until April 7th, when the port is reopened, which corresponds to another spike in the derivate function.

Figure 6c. Rate of change of system’s dwell time resiliency, Galveston Bay, oil spill of March 2014

Figure 6d shows the daily number of inbound and outbound vessels through the Galveston offshore anchorages for the same period. Also shown in the figure (with solid, dotted, and dashed lines) are the event day, partial reopening, and full opening of the channel. Looking at the cumulative inbound and outbound number of vessels, a sharp drop is seen on the incident day. This drop continues (marking the start of the transitional state) until March 25, 2014, where the systems enters the disruptive state. It is important to note that the beginning and ending of the disruptive state occur on the same days as shown in Figure 6a. After March 26, 2014 the system begins transitioning, and by the time of the full reopening on April 7, 2014, the system is in its stable state.
Figure 6d. Galveston Net Vessel Transit Counts

Figure 6e displays the daily net vessel transit count (capacity usage) resiliency, as calculated from Equation 1, based on vessels entering and exiting the offshore anchorages. In general, the net transit count resiliency of the system performed in a similar manner to the dwell time resiliency, with corresponding peaks and valleys, to some extent. This is an expected finding considering the relationship between dwell time and the number of inbound and outbound vessels.

Figure 6e. Galveston Net Vessel Transit Count Resiliency
Figure 6f shows the derivative of the Galveston net transit count resiliency, or in other words, changes in port transit count performance per day as the unit of time. As shown in the figure, the system transitions from a normal stable state into a disruptive state on the day of the event, with 72 percent decrease in total number of vessels processed by the port on March 22\textsuperscript{nd}. Once in the disrupted state, the derivative is shown varying between -0.19 and +0.22 in the first four days after the event. Then after the recovery action taken on March 26\textsuperscript{th}, the derivative is shown to have a major fluctuation between March 27\textsuperscript{th} and March 30\textsuperscript{th} (varying between -0.67 and +0.78), indicating the impacts of the recovery actions on the system’s performance. Four days after the initial recovery action, the derivative is shown to be almost steady (-0.14) for three days, indicating that the system’s performance is unchanged between March 30\textsuperscript{th} and April 1\textsuperscript{st}. After another set of fluctuations between April 2\textsuperscript{nd} and April 6\textsuperscript{th} (varying between -0.44 and +0.33), which might be due to another phase of recovery action- the system stabilizes once again until April 7\textsuperscript{th}, when the port is reopened, which corresponds to another spike in the derivate.

Figure 6f. Rate of change of system’s transit count resiliency, Galveston Bay, oil spill of March 2014
4.2 New York / New Jersey Channel Closure

The Port of New York and New Jersey, which spans both the New York and New Jersey sides of New York harbor, is the third largest port in the U.S. and the largest port on the Atlantic coast (PANYNJ n.d.). In late October 2012, New York harbor was significantly disrupted and damaged by Superstorm Sandy as that unusual extra-tropical system moved slowly up the U.S. eastern seaboard. In preparation for the storm, the port was shut down in the evening of October 28, 2012 and remained closed for almost 8 days. This is an example of the pre-notified event in which vessels were notified about the closure of the port facilities in the following days due to the big storm.

For this study, NAIS data was used and the data was filtered for analysis of cargos and tankers transiting the Arthur Kill area of New York Harbor during a 6-month period (August 2012 – January 2013) encompassing the landfall of Superstorm Sandy. The sampling rate for unique vessels ranged from 5-minutes to 15 minutes, depending on the amount of time each vessel was within range of AIS receiving towers.

Figure 7 shows the AIS density plot of vessel traffic and position reports within the greater New York area based on the summery set of NAIS data obtained for this study. The small red box near the center of the figure shows the area that was queried for NAIS archival data; all vessels transiting this box were tracked for the full 6-month study period. The larger bounded region indicated by the gray polygon encompassing the greater New York metropolitan area shows the larger port area that was used for the post-Sandy resiliency analysis.
Figure 7. Density plot of AIS position reports in greater New York Harbor, watch area used for post-Sandy resiliency analysis, and bounded region (red box) used for NAIS data collection

Figure 8 shows the weekly average vessel dwell times and the number of inbound and outbound vessels for New York Harbor during the six-month study period. The day of the closure (October 28, 2012) and the day the harbor was reopened (November 4, 2012) are shown with solid and dashed lines, respectively. In the week leading up to the closure, a drop in the number of vessels can be seen, likely due to vessels routing away from the harbor in advance of the storm. Also shown prior to the closure is an increase in vessel dwell time, also likely due to storm preparations. From the figure it can be seen that the port returns to “normal” operations by the third or fourth week in November.
Figure 8. Six-month vessel traffic summary for New York harbor area

Figure 9a shows New York Harbor average daily dwell times from October 15, 2012 to November 20, 2012. The closure of the harbor began on October 28 (shown with a solid line), Superstorm Sandy made landfall the following day on October 29, and the port reopened on November 4 (shown on the figure with a dashed line). From the figure it can be seen that vessel dwell times started to decrease a week prior to the incident and that the vessel average dwell times did not immediately increase following the closure. This is in contrast to the no-notice event which took place in Galveston Bay, which saw a drastic increase in dwell times immediately following that incident. However, in the ensuing days after Sandy, average dwell times for the greater New York port area increased as vessels begin to queue, waiting for the port operations to reopen. By November 9, 2012 the port area appears to have returned back to a stable dwell time performance.
Figure 9a. Greater New York Port Area Dwell Times

Figure 9b shows the dwell time resiliency for each day after the harbor closure. The figure begins on October 23, 2012, a few days prior to the closure to provide a reference. The day of the port closure, the reopening day of the port, and the day by which the port were fully recovered are shown in the figure with a solid, dashed, and dotted line, respectively. After the closure of the port, the system transitions into a disruptive state, reaching its maximum disruptive state between October 29 and October 31, 2012. The ultimate recovery event was the reopening of the harbor, after which the vessel activity began the transition into a stable state, and essentially normal operating daily average dwell times.
Figure 9c shows the derivative of the New York port dwell time resiliency, or in other words, the rate of change of port dwell time resiliency per day as the unit of time. The figure shows a drop from the initial stable state two days prior to the incident day, due to vessels notified to route away from the port. The system then transitions into a disruptive state on October 28th and enters the steady disrupted state on October 30th. The system remains in its fully disrupted state from October 30th to November 2nd, with the derivative varying between -0.03 and +0.15, indicating that stochastic systems performance is almost unchanged during this interval of four days. After the recovery action taken on November 4th, the system transitions from a disrupted state to stabilize once again until November 7th, when the port is fully reopened. The derivative function also indicates some fluctuations in port dwell time resiliency for another week until November 12, 2012, when it completely bounces back to its normal service condition.
Figure 9c. Rate of change of system’s dwell time resiliency, NY/NJ Harbor, 2012

Figure 9d shows the daily number of inbound and outbound vessels through the greater New York port area between October 15 and November 22, 2012. The figure displays the harbor closure and reopening with solid and dashed lines, respectively. Looking at the cumulative inbound and outbound number of vessels, a sharp drop is seen on the day of the closure.

Figure 9d. Greater New York Port Area Net Vessel Transit Counts
Figure 9e displays the daily net vessel transit count resiliency, as calculated from Equation 1, for the New York Harbor. Again, as seen during the Galveston Bay disruption, the starting and ending days of the various states in the resiliency process (stable state, disruptive state, and transitive states) are the same between the dwell time and net vessel count resiliency figures.

Figure 9e. Greater New York Port Area Net Vessel Transit Count Resiliency

Figure 9f shows the derivative of the New York Port transit count resiliency. Similar to the dwell time resiliency derivative diagram, the figure shows a drop from the initial stable state prior to the incident, due to vessels routing away from the port. The system then transitions into a disruptive state on October 28th, with an 88 percent decreasing rate from its normal serviceability. The system enters into its fully disrupted state on October 30th and remains almost fully disrupted until November 2nd. During the stable disrupted state, the derivative is shown varying between -0.06 and +0.12, indicating that stochastic systems performance is relatively unchanged during the interval of October 30th to November 3rd. Once the recovery action is taken on November 4th, the system transitions from a disrupted state to stabilize once again until November 7th, when the port is fully recovered.
When comparing these two events from a resiliency stand-point, several notable differences can be seen. First, in the days leading up to Superstorm Sandy, there was a gradual increase in the number of exiting vessels. This shows that many of the large tankers and cargo ships evacuated prior to the arrival of the storm. No such evacuation was possible prior to the incident which took place in Galveston Bay. Also, since the New York Harbor closure was scheduled in preparation for the storm, the drop off in port performance was drastic. This is in contrast to the Galveston Bay example, in which vessels were still able to access the anchorage areas offshore of the Galveston Entrance channel both before and after the incident. This manifested itself in a more gradual drop off in port system performance. Furthermore, it would appear that approximately 48-72 hours after the New York Harbor was reopened, the vessel traffic and dwell times returned to pre-event levels. The same cannot be said for the no-warning event in Galveston Bay, where normal port operations did not resume until several days later.
CHAPTER 5. CONCLUSIONS

Despite best efforts to mitigate the risks and effects of catastrophic events, future disruptions will continue to cause significant losses to maritime infrastructure and efficiency. For this reason, it is essential that MTS stakeholders continue to improve the design and operation of port and waterway facilities and their associated infrastructure to minimize losses and maintain functionality in cases of disruption and major disasters. A key aspect in improving system resiliency is to identify robust and objective performance evaluation methods. To this end, the research presented herein has been developed from USCG Automatic Identification System (AIS) data to create new methods and metrics for the assessment of resiliency in maritime systems. This methodology advances the field of disaster science by expanding on the concepts first proposed by Henry and Ramirez-Marquez (2012) and Baroud et al. (2014), and applying these methods to empirical observations.

In general, the results of the research show that AIS, which collects information from nearly all commercial vessels on a semi-continuous basis data, is an excellent source for quantitative data when seeking post-disaster measures of resiliency. The time-dependent performance models developed from this data show the cascading effects of disruptions and demonstrate how it can be used to quantify the MTS resiliency levels in terms of dwell time metric and net transit counts. One of the more interesting findings of this effort was the manner in which the data show, in quantifiable terms, reductions in performance resulting from incremental, less-publicized disruptions (Feb. 2014 at Galveston Bay) and evidence, albeit limited, of the benefits of advanced warning prior to a disruptive event. It is worth noting that the proposed approach can also be applied toward longer-period disruptions. The recent West Coast labor dispute and
associated port slowdowns in late 2014 and early 2015 provide a prime example of the need for unbiased analysis and can be studied within the context of this research in future work.

This study adopted a summary of AIS data and employed the resiliency equation introduced by Remirez-Marquez to obtain empirical observations. Using this methodology, the purpose of this study was to quantify the resiliency level of a specific waterborne facility after the occurrence of a particular disruption. The methodology employed in this study can further be used to carry out an economic impact assessment of the disruptive event by estimating the likely economic costs associated with the disruption, including the economic impact of MTS closures. The methodology herein did not account for the severity of the disruptive event, as the disruption and the disrupted port were both assumed to be known and given for the purpose of this study. The author may expand the formulation of resiliency used in this study in her future work to reflect the impacts of different disruptions in port performance by introducing other factors in the current resiliency equation such as the magnitude of disruptive event and the significance of the shock.
REFERENCES


VITA

Nafiseh Farhadi, daughter of Mahdi and Mahnaz, was born in Tehran, Iran, in June of 1984. Nafiseh has one younger sibling, Farzaneh. Nafiseh arrived to the United Stated in 2009 to study Architecture at Kent State University in Ohio. Nafiseh completed her B.S. in Architecture in May 2012 and her Masters of Architecture in December 2013. After graduating from KSU, Nafiseh started working as an intern architect in a firm in New Orleans, Louisiana. One year later, Nafiseh started her graduate studies in Civil Engineering at Louisiana State University in January 2015. Entering the Master’s program as a research assistant for Dr. Brian Wolshon, Nafiseh is now a candidate for the degree of Master of Science from The Department of Civil and Environmental Engineering at Louisiana State University.