Mitigating Infrastructure Risk: Reducing Uncertainty in Resilience Modeling

A Dissertation Presented

By

Kevin Luther Clark

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ABSTRACT

The National Airspace System (NAS) is a complex system of systems which plays a vital role in sustaining economic and personal growth in America. As part of the transportation critical infrastructure the NAS like other lifeline substructures is impacted by shocks caused by both man-made and natural phenomenon. The U.S. airport network (USAN) continues to show signs it is operating at capacity, and its supporting facility infrastructure is aging and is some cases operating in poor conditions. Recently critical infrastructure resilience has emerged as an essential research topic for academia, public and private industries. This is in reaction and perception of the range of shocks and stresses correlated with natural and man-made pressures on transportation infrastructure which are compounded by the uncertainty of climate variability and resource constraints. Measuring critical infrastructure resilience is challenging and requires an approach which focuses on the robustness of infrastructure. Here we develop and demonstrate a framework which utilizes the integration of network science based analysis, and system dynamics analysis to quantitatively characterize the airport network and supporting infrastructure resilience. This research was structured in three parts. The first focused on a developing metrics to measure the robustness and to analysis recovery strategies of the USAN. The second focused on a specific policy concerning sustainment of the USAN supporting infrastructure. The third part focused on one specific airport and it’s recovery from two extreme weather events.
ACKNOWLEDGEMENTS

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In 2016, disruption of flight operations due to weather related factors accounted for 32.9% (Bureau of Transportation Statistics (BTS)) of delays. Extreme weather events accounted for 4.4% (BTS) of flight cancelations. From the time the passenger leaves home to the time he/she returns weather often has been the biggest influence on their travel 70%-80% (Rosenberger et al. 2002) and a major cause of lost revenue for commercial airlines (Lan et al. 2006).
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CHAPTER 1 - INTRODUCTION

1.1 Background

The Next Generation Air Transportation System (NextGen) has transformed the National Airspace System (NAS) from a radar based ground centric control system to a satellite based air centric control system. Some of the capabilities enabled by NextGen have included Area Navigation (RNAV), Trajectory Based Operations, and text-based clearance instructions or data communications (DataComm). Airport renovations along with Air Traffic Control (ATC) facilities modernization have played a key role in the transformation of the NAS also. Airport communication and network improvements have enable automated access, real-time monitoring of logistics, and swift response to emergencies. Given these enhancements, an airport still remains one of the most vulnerable transportation infrastructures, both physical and functional. In the future policy makers will be required to look beyond standard risk mitigation methods for acquisition and life-cycle sustainment practices for modernization. New performance and resilience quantification methods and innovations in visualizing system interdependencies will drive the change needed to deal with the increase in unpredictable weather and other disruptive events impacting flight operations and airport logistics.

Drilling down from a national aspect, observations show the primary choke point for operational efficiency will be the airport. An airport operating near capacity is susceptible to collapse or severe degradation during a disruptive event putting the NAS at risk. Looking beyond the identification of vulnerabilities there is an issue with aligning performance variables with the hazard. For example, a departure delay is the result of an event, but what change in NAS parameters occurred that initiated the causal factors resulting in that delay. Thus, applicable tools and metrics to investigate and identify the causal factors are lacking or difficult to understand due to their technical nature. In the case of a cyberattack determining the specific system interdependencies
and constraints support development of a better model which support better understanding for stakeholders. This research applies network analysis (graph theory) and system dynamics, to develop a methodology which characterizes the robustness of the U.S. Airport Network (USAN) and supporting facility infrastructure. In addition, this research analyzes recovery strategies and quantifies the relationship between airport availability/traffic flow performance indicators and the evolution of disruptive events.

Network science based analysis (Graph theory) has emerged as a useful tool in the evaluation and analysis of transportation networks. It provides a mathematical transcript of pairwise dependencies and interrelationships. The concept was originally used in the fields studying human communication and social networks. (Abert, 2001) Here the term network refers to a framework of routes (links) within a system of locations, identified as nodes. The mathematics of “nodes” and “links” provide the analysis of relation and importance in terms of statistical mechanics of network topology and dynamics. Applied to complex transportation systems, network analysis provides characterization and problem solving for routing, flows, and node interdependencies. (R. Guimera`, 2005) In addition, it provides measurement for degree of accessibility and connectivity, spatial extent, and influence of one node to other nodes in the network.

Despite these attributes, however, network analysis has limitations when applied to non-planner networks where multifaceted factors derive link or “edge” configuration. (i.e. airport, TRACON, En Route control) This will be dealt with by the approach taken in development of our network model. In addition, our application of system dynamic analysis will cover those non-linear aspects of the intersection of physical deterioration and policy. Note system dynamics is a facet of system theory as a method to understand the dynamic behavior of complex systems. The basis of the method is the recognition that the structure of any system, the many circular, interlocking,
sometimes time-delayed relationships among its components, is often just as important in
determining its behavior as the individual components themselves. (Spicar, 2014) For this
research, development of a system dynamics model provides a means to understand the dynamics
of the policy aspects of infrastructure investment funding decision making.

1.2 Dissertation Outline

In this research, we apply an innovative approach for demonstrating the effectiveness of
resilience modeling for reducing overall risk and uncertainty. The outline of this research will be
divided into 5 distinct chapters.

- Chapter 1 Introduction, research objectives, organization of dissertation. This includes
  background information, descriptions of the NAS architecture;
- Chapter 2 Problem statement; discuss research challenges, motivation and impacts on
current and future aviation infrastructure. Recent research and relevant literature discussed;
- Chapter 3 Resilience of the U.S. Airspace System Airport Network; characterization of
  interdependencies, development of system indices, centrality metrics, robustness, recovery
  strategies;
- Chapter 4 Developing Policies Which Optimize Long-term Service for Vulnerable
  Infrastructure, discuss aging facility infrastructure, facility condition index, deferred
  maintenance, system dynamics;
- Chapter 5 ; Time series analysis; blizzard of 2015, the impact on the National Airspace
  System, Resiliency Issues;
- Chapter 6 Conclusion and future work; discuss multi-faceted quantification methods
CHAPTER 2 – PROBLEM STATEMENT

2.1 Airports and Weather

There are 506 commercial airports providing passenger and cargo service across the United States (U.S.). Within this group are primary hub airports and in 2017/2018, extreme weather shutdown or hampered operations for a significant portion. The loss of operational efficiency and capacity rippled across the country affecting smaller non-hub airports. These extreme weather events included the Gulf Coast hurricanes; the Midwest tornado outbreak; the Southwest heatwave; and recent east coast winter storm. Most surprising to national and state officials was location and frequency of these events, such as rare occurrences of snow accumulating at airports in Charlotte, Atlanta, and Jacksonville. The common impact theme of these events to aviation infrastructure was the temporary loss of airport functionality. Several investigations have analyzed air traffic operations and correlated flow reductions and delay patterns based on weather, however, there is scarce number that have applied quantitative methods to measure loss of functionality and robustness to an event.

Of the many stressors to the U.S National Airspace System (NAS) extreme weather is one of the most impactful where air traffic disruptions at one airport could cause a cascading effect nationally. Quantifying the impact of extreme weather events on transportation infrastructure continues to be a major effort of academia, public and private researchers. (Freeman, 1979) Showed from a historical perspective drawing inference on vulnerabilities based on typical meteorological values even when applying a valid statistical sampling process is uncertain due to climate volatility and variability. From the literature there are several studies of the impact of weather on airport operations. Weather impact common theme is depicted in Figure-1. Strong winds, rain, and snow hamper flight operations and airport logistics. Temperature changes can damage
runways/taxiways and impact aircraft performance. While duration and intensity often quantifies the weather as extreme, it should also be qualified by its hostile work environment for personnel, primarily airport workers, air traffic controllers, and pilots. Personnel efficiency decreases and often to compensate workload is reduced (i.e., volume of traffic and/or certain airport services reduced). For airport operations extreme weather is the events that cause severe disruption of flight operations, utilities, and logistics. Depending on location, this can also include sea level rise resulting in the total loss of the airport infrastructure. Stakeholders understand the risk involved but evidence has shown a lack understanding in regards to airport/ATC interdependencies. This can lower preparedness and increase the time of recovery.

*Figure 1 – Typical Airport Operations and Weather Impact*
Extreme weather frequently denotes distinct meteorological conditions or climate events measured by means of physical accumulation or magnitude. For example, precipitation, or wind speed. Extreme weather by definition, typically, fluctuates with the characteristics of the event and could be centered on effects on property and infrastructure (Garschagen, 2014). For instance, heat waves often lead to reduced flight operations due to reduced air density, which may cause operators to take longer takeoff rolls to generate lift, provided the runways are long enough.

In 2016, disruption of flight operations due to weather related factors accounted for 32.9% (Bureau of Transportation Statistics, 2017), of delays Extreme weather events accounted for 4.4% of flight cancelations. From the time the passenger leaves home to the time he/she returns weather has been the biggest influence on their travel 70%-80% (Rosenberger et al. 2002) and a major cause of lost revenue for commercial airlines (Lan et al. 2006). If there is continued warming at its current pace research describes significantly stronger and more frequent extreme weather events. A heatwave in the context of aviation operations limits aircraft performance, stresses airport/ATC data center cooling capacity, and afflicts airport tarmac work conditions. A recent study published in the journal of Climate Change examined 19 airports around the world and found the rising temperatures will make it harder for aircraft to take off. (Coffel, 2017)

In early January 2018, the National Weather Service (NWS) Weather Prediction Center (WPC) assessed the probability of snow based on easterly and northward tracking areas of low pressure. Airports from Washington DC to Portland ME took preemptive action to ensure low impact and quick recovery from the expected storm. The NWS later designated winter storm Helena as a blizzard. During the storm operations data indicated typical air traffic delays and cancellations for the Northeast. Similarly, airports in the south in Little Rock, AR, Knoxville, TN, and Charlotte, NC, experienced major delays and cancellations, but the denigration was quicker and recovery
slower. Observations indicate these airport officials did not expect the accumulation levels of snow that was reached. (Cantore, 2018) See Figure-2. NOAA (Krasting, 2013) indicated the lack of statistically significant trends in these regions due to high variability of snow accumulation could hamper resource planning. (i.e., de-icing and snow removal equipment, man-hours) Comparably, (Dennis, 2016) statistical evidence revealed a 27% increase in heavy rain events in southeast from 1958-2012. For the northeast the increase in heavy rain events is 71% for the same time period. (Chui et al, 2013) denoted the strong storms such as hurricanes could make landfall more frequently in diverse locations. Based on simulations of 10,000 storms with different climate conditions results revealed a 500-year event may occur every 25 to 240 years. For the airport and FAA manager the challenge is how to mitigate the variability of these strong storms.

*Figure 2 – Snow and Ice Accumulation for Winter Storm Helena*

![Image of Snow and Ice Accumulation](image.png)

### 2.2 Research Challenge

Characterizing infrastructure resilience is challenging requiring cross-sector understanding of complex interdependencies. Several studies have been performed quantifying natural and man-
made infrastructure hazards, especially when it comes to the transitioning of new technologies. However, the foundation for a majority of these studies rely on event correlation designed for monitoring and detecting known risk patterns. In addition, most of these reports fail to bridge the gap between the theoretical to the operational. Complexities in the research often hinder the transition of methodologies. Spatial epidemic models show promise for characterizing threshold behavior (i.e., spread of initial disruption) but lack in providing the long-distance interactions and detail scale interaction. For instance, literature suggest there is no ideal model for measuring cyber risk indicating there is still a need for better quantification methods. It is rare to integrate two quantitative methods for uncertainty mitigation. Risk vulnerability analysis methods rarely map the event data to preparation or operationalize concepts beyond the theoretical. Even with the demonstrated influence of shocks on airport operations there has been little research into the impact on demand within the scope of the NAS of the future where the need for understanding complex system relationships that cut across domains will be necessary to provide adaptive resilience when dealing with uncertainty.

Researchers who study resilience across infrastructure sectors draw a similar distinction between metrics and lessons learned. Data suggest the highest gain in resilience comes when managers are able to integrated lessons learned from passed extreme events. Still more real world-based empirical research needs to be done to validate theoretical concepts such as predictive approaches to mitigating uncertainty. Multidimensional hazards evolve with a stored potential to transverse all aspects of the NAS impacting airports, facilities, and flights; thus, the importance of developing new resiliency quantification methods is recognized by both private and government stakeholders. (Moore, 2007) However, prevalent lack of applicable tools and metrics to investigate readiness and susceptibility hinder development of effective strategies. This lack of applicable tools and
metrics can be traced to the inability to adapt theoretical methods to real world constraints. First, when a constraint is not properly factored into the model subsequent outcomes are highly suspect and trust in an approach can be lost. Second, the more complex the model the higher the difficulty level is in translating the metrics to non-technical operators limiting their understanding, which could reduce readiness and false judgement of impact level of a potential event. Third, lack of iterative methods to inject lessons learned from prior experience constrains adaptive opportunity and can heighten user misconceptions and impact decision-making. These resiliency quantification issues have been castigated for their model limitations and inability to predict and visualize system robustness. Table-1 describes some of these research themes.

2.3 Motivation

From the literature there are several studies which deal with the impact of weather on airport operations. However, there is a lack of knowledge in research into the impact of extreme weather variability on the USAN and NAS interdependencies, and how miscalculations and bad decisions prior to and during the event ripple across the transportation infrastructure. This requires a better understanding of functional relationships, automation, forecast processes, traffic flow models, and better dissemination of traffic and weather information to controllers and decision support systems. An airport that is better prepared to respond to weather hazards operates more efficiently for passengers and airlines, and can avoid significant negative impact to the NAS as a whole. Hurricane Sandy, which hit the New York area on October 29, 2012, caused severe infrastructure destruction including major flooding of runways at LaGuardia (LGA), John F. Kennedy (JFK), and Newark (EWR) airports.
**Table 1-Research Areas**

<table>
<thead>
<tr>
<th>Theme</th>
<th>Research Area</th>
<th>Author</th>
<th>Known</th>
<th>Unknown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster Resilience; Disaster Risk Management (DRM); Complex Network Analysis</td>
<td>Air transportation networks; Conceptual framework for examining life-line networks; Interpretations of resilience in DRM; Measuring transportation network resilience under earthquake uncertainty.</td>
<td>R. Guimera et al. (2005); Bhatia, et al. (2015); MacAskill &amp; Guthrie (2014); Duan et al. (2016)</td>
<td>Use of centrality measures show positive indications for recovery analysis; Resilience concept is context-dependent; Quantitative risk measures based on transportation corridor selections and pattern response.</td>
<td>Mapping of event data to preparation. How is DRM and resilience concepts operationalized from the theoretical? Recovery impact of comprehensive effects of disaster given key chokepoints are removed simultaneously.</td>
</tr>
<tr>
<td>Modeling Critical Infrastructure (CI); Information Flow</td>
<td>Modeling Congestion Transition in Air Traffic networks; Modeling dynamics of disruptive events for impact analysis; Understanding System of Systems; Systematic analysis of resilience using an integrated review of literature. Flexibility of Networks: a new measure for network design space analysis; Network analysis of air transport delay propagation.</td>
<td>Bernardo et al. (2015); Canzani (2016); Eusgeld et al. (2014) Palliyaguru et al. (2014, p45); Bhamra et al. (2011); Y.Y Haines et al., (2005); Keller et al. 2015: Zanin et al.(2017); Song and Yeo, (2017)</td>
<td>Input-Output flow models connect the inability of CI to produce as planned with demand perturbations; Theoretical constructs have had a positive impact understanding the disaster phenomenon; Complexity of interdependency modeling place constraints on efforts to model anything above a single infrastructure.</td>
<td>Input-Output flow models are unable to capture nonlinear feedback loops; More real world-based empirical research needs to be done to validate theoretical constructs. Integrated dependency analysis methods for tolerance and flexibility validations. Sub-level interactions and impacts</td>
</tr>
<tr>
<td>Sustainability Assessment; Infrastructure Modernization &amp; Policy</td>
<td>Impacts of Climate Change and Variability on Transportation Systems and Infrastructure; Development of methodologies to assess complex environmental problems; System Dynamics Archetypes</td>
<td>Halog and Manik, (2011); Radim Špicar (2014); Seyhani et al, (2015)</td>
<td>Linear estimation methods based on system or structure configuration and age.</td>
<td>Information regarding functionality measures are not represented in the outcome. Unpredictable behaviors among elements with numerous interactions.</td>
</tr>
</tbody>
</table>

Airport and ATC facility equipment and system damages resulted in loss of critical flight navigation aids, radio transmitters allowing communication between pilots and controllers, airport lighting, and airport pumping stations.\(^1\) This extreme weather event caused air traffic delays across the country, but it did not only impact affected passengers; it threatened the recovery. Cargo aircraft were needed to carry tons of relief supplies and emergency replacement equipment. Aircraft were also needed to deliver emergency workers critical to the recovery effort. In assessing and restoring destroyed FAA equipment at the airports team members noted many of the parts needed for repair or replacement were unavailable adding to the recovery time. All three airports

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reopened November 1, 2012. For better understanding of the impact, JFK serves about 100 airlines from more than 50 countries operating all over the world. LGA and EWR serve 50 airlines each.

2.4 Problem Statement

The randomness of disruptive events requires a significant amount of flexibility in planning the allocation of resources to mitigate risk and enhance resiliency.

Figure 3-Overview of NAS Resilience Problem

Figure 3 is a generic depiction of the NAS that over time will experience multi-hazard stresses which impact operations and resiliency. From the NAS, a model was created of the airport network consisting of commercial, general aviation, and military airports connected by their air traffic flow. This model provided the framework for the quantitative analysis of the airport network’s resilience. To complete the analysis we focused on a segment of the airport network in
examination of a specific policy aspect. All indicators show that air travel in the U.S. is strong according to the FAA Aerospace Forecast Fiscal Years 2018-2038. U.S. airlines passengers will increase from 840.8 million in 2017 to 1.28 billion in 2038. The FAA forecasts total landings and take offs at FAA and contract towers to reach 51.0 million in 2018, growing to 60.5 million in 2038.

*Figure 4- Delayed Flight Operations & SDP CI Failures*

These demands will continue to stress an already strained USAN. Delayed and canceled flight cost the airlines billions of dollars per year. (Monechi, 2015). Figure 4, depicts airport flight delays and service delivery point critical infrastructure failures trending up at selected airports. Thus we arrive at our problem statement:

**The frequency of disrupted flight operations impacting U.S. Airports has raised concerns the system and/or supporting infrastructure has reached capacity and lacks tolerance to even minor shocks.** Even with the transition of the NAS to NextGen the impact of unpredictable shocks to a highly exposed and vulnerable infrastructure require further understanding and quantification. In
summary, there is a requirement for an enhanced understanding of interdependencies, constraints, and a structured approach to identifying, modeling, and effectively communicating relevant real world resiliency assessment. More specifically, the following research questions need to be addressed:

- What is the robustness of the airport network?
- What is the fragmentation of the airport network given a simulated event?
- Following hurricanes Harvey and Irma, and snowstorm Grayson did the airport network perform within tolerance level specified by FAA?
- What is the effectiveness of linear regression estimates for Policy decisions on the allocation of airport network infrastructure sustainment funding?

The first three questions examine our network as a whole. Here we are generating knowledge on quantifying network capacity (functional and physical), adaptability, and cohesion (that is characterization of the airport network to act as a unified whole to mitigate the shock). In addition we generate insights on recovery strategies for the airport network.

The remaining questions focus on at a specific segment of the airport network. Here we advance understanding on the broader impacts of policy on the airport network, specifically operations and maintenance analytical approaches used in decision making and the impact on resilience.
3  CHAPTER 3 - RESILIENCE OF THE U.S. NATIONAL AIRSPACE SYSTEM AIRPORT NETWORK

Kevin L. Clark¹, Udit Bhatia², Evan A. Korda³, and Auroop Ganguly⁴

¹Sustainability and Data Science Lab, Northeastern University, Boston, MA, kevin.clark@dot.gov
²Sustainability and Data Science Lab, Northeastern University, Boston, MA, Bhatia.u@husky.neu.edu
³Sustainability and Data Science Lab, Northeastern University, Boston, MA, evan.kodra@risq.io
⁴Sustainability and Data Science Lab, Northeastern University, Boston, MA, a.ganguly@northeastern.edu

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3.1  Chapter Summary

Natural hazards such as hurricanes and winter storms, computer glitches and technical flaws, and man-made terror or cyber-physical attacks, can lead to localized perturbations of the US National Airspace System Airport Network (NASAN), which can in turn percolate across the interconnected system. Here we develop and demonstrate an approach to quantitatively characterize the robustness of NASAN, defined as loss of critical functions owing to perturbations, and a quantitative framework to select the most efficient and effective post-hazard recovery strategies. The system-level robustness and recovery strategies rely on network science methods and associated attributes. New insights include the central role of network attributes to robustness and optimal recovery sequences. Characterizations of robustness and fragility can inform what-if plans and proactive design, while recovery strategies developed in advance can support systematic, reliable and timely bounce-back from hazard-related perturbations. The framework can serve as a baseline over which local information or cost optimization can be superposed.
3.1.1 Introduction

Multi-modal transportation systems are part of the critical infrastructure which serve an important role in ensuring essential societal functions (Santumtira, 2010). The National Airspace System (NAS) is a spatial multi-layered system of sectors, and altitude blocks built on a network of airports and Air Traffic Control (ATC) facilities. As a system, it is one of the most important driving forces of economic and business changes, justifying constant global investments in operational upgrades. Airports are vulnerable to adverse events which impact public and private industry operations, budgets, and business attraction. While reducing the impact in most cases is difficult due to unforeseen and turbulent nature of these adverse events, resilience framework with risk as the central component can potentially inform infrastructure managers to plan-for and recover from these events in an efficient way (Linkov et al, 2014). As highlighted in the correspondence piece (Fisher, 2015 p. 70), more than 70 definitions has been proposed in the literature, which makes characterization of resilience a non-trivial task. National Academy of Sciences define resilience as an ability of the system to “plan and prepare for, absorb, respond to, and recover from disasters and adapt to new conditions” (National Academies Press, 2012). In the context of air transportation system, resilience is the ability to prevent or mitigate impact to air traffic operations. The Federal Aviation Administrator’s (FAA) efficiency target is to achieve 90% of normal operations after a disruptive event within 24 hours at core airports, or 96 hours at en-route ATC Centers. The NAS’s ability to tolerate the disruptive event and transition and adapt defines its robustness.

After the events of September 11th, 2001, following considerable restructuring, the U.S. airline industry recovered but with slightly reduced demand (Guimerá et al, 2005). Profitability for both the airlines and airports can be traced to the introduction of fuel-efficient aircraft, diversified hubs, and flexible routing. System perturbations caused by expected and unexpected ‘disruptive events’ drastically cut in to these profits. We define a ‘disruptive event’ as any off-
nominal occurrence, which effects airport and air traffic operations. In terms of NAS robustness, it defines a threshold where below a specific value, further capacity loss brings critical functionality (airport operations & air traffic flow) into an unacceptable region. NAS interdependency and unpredictability, intensified by rapid technology change, is urging the need for new quantitative approaches for quantitative description of resilience.

As an introduction to the concept, we model the airport system as a network with nodes and edges. In present study, the commercial, General Aviation (GA), and military airports, which constitute the important elements of the NAS, constitute the nodes, and a pair of nodes are connected if there is at least one direct flight between them. We have chosen combined network for study as General aviation, military and commercial airports are all part of the NAS. As past events have shown, their resilience and sustainability supports robustness and recovery. True they may serve different customers but during disruptive events, the components that characterize a Commercial from a GA airport may be required to change. During 9/11, ATC Command Center restricted all flights over the U.S. and cleared the airspace, diverting aircraft to the closest suitable airport.

Risk vulnerability analysis methods rarely map the event data to preparation or operationalize concepts beyond the theoretical. Even with the demonstrated influence of disruptive events on airport operations and capacity there has been little research into the impact on demand within the scope of the NAS of the future where the need for understanding complex system relationships that cut across domains will be necessary to provide adaptive resilience when dealing with uncertainty. Even under nominal conditions it is important to address why certain airports experience demand exceeding its capacity. Researchers who study resilience across infrastructure sectors draw a similar distinction between metrics and lessons learned. Data suggest the highest
gains in resilience comes when managers are able to integrate lessons learned from passed extreme events. Still more real world-based empirical research needs to be done to validate theoretical concepts such as predictive approaches to mitigating uncertainty. The findings from our network analysis characterize the U.S. Airport Network in terms of robustness (Derrible, 2010), and identify useful measures for recovery prioritization (Bhatia et al, 2015). A time series analysis is used to depict the cascading impact of an event and its far reach from region of origin.

3.1.2 Literature Review

Researchers have used complex network description to understand the topological characteristics of air transportation systems (Zanin, 2013), and (Barrat et al, 2004), making network science as a tool of choice to describe resilience of the NASAN. Houssain, Alam, and Rees presented research based on network analysis of Australian airport network (AAN) (Hossain et al, 2013). This investigation focused on the assessment of level of vulnerability to which AAN can be exposed through random and targeted failures. Their disruption scenario and cost analysis was based on standard flight schedule. Although sufficient, it doesn’t allow for location and volume dynamic manipulation which provides more realistic economic analysis and impact as our model will show.

(Utne, 2011) simulated a class of connected infrastructures to measure to what extent disruptions ripple through complex networks, with the goal of displaying a process for evaluating mutually reliant critical infrastructures, based on cross domain risk and vulnerability analysis (RVA) (Utne et al, 2011). A challenge in his work was identifying key stakeholder responsibilities, interests, and contributions to the analysis. In addition, difficulties with access and use of proprietary or classified data could hindered RVA of issues relating to societal changes. Gopalakrishnan et al (2016) considered clustering air traffic delay networks. (Gopalakrishnan et al, 2016) Their approached identified delay states and a methodology for characterizing these states in the NAS. Their use of directed networks was unique in that the edge weights used were departure delays.
The findings showed their approach could helped identify airports driving network delays. However, evidence has shown delays, as an informal measure of forecast on impact of aviation operations, do not provide forecast quality nor do they accurately predict the ripple impact on airport capacity.

Fleurquin et al. (2013) analyzed the delay propagation in U.S. airport network as a consequence of technical, operational or meteorological issues (Fleurquin et al, 2013). They noted that there is “non-negligible” risk of systematic instability not only under disruption scenarios but also under normal operating conditions, highlighting the need to have predetermined post-hazard restoration strategies for immediate response and service recovery after cascading failure across the network. Furthermore, multiple previous studies have hypothesized that optimal recovery strategy should be the mirror image of the sequence of nodes loss that generated the maximum damage to the network (Wuellner et al, 2010). However, as noted in (Bhatia, 2015), while the sequence of recovery may or may not be same as optimal path for disruption, the rate of recovery is not the mirror image of rate of collapse.

Wuellner et al. (2010) evaluated the relationship between network attributes and robustness and introduced network rewiring scheme to boost resilience to different levels of perturbation (Wuellner et al, 2010). While rewiring and restructuring schemes can aid in informing the design of new facilities, implementation of the same is non-trivial task in day-to-day operations for large scale infrastructure systems such as U.S National Airport System (Bertsimas, 2000). While researchers have proposed the qualitative description of resilience centric framework with risk as a central component (Linkov et al, 2014), and formulation of various models to quantify resilience (Bhatia et al, 2015), (Ganin et al, 2015), we argue that comprehensive description of resilience for infrastructure systems require understanding of underlying dynamics and operational
characteristics (Park et al, 2013). In present study, we attempt to bridge the gap that exists in identifying and understanding specific geometric properties and configurations which drive the comprehensive resilience of critical infrastructures and highlight the asymmetry that exists between robustness and recovery of NASAN.

3.1.3 Motivation

In January 2014, in the space of four weeks, the U.S was hit by a Nor’easter, two polar vortexes, record cold temperatures, and heavy snow. 49,000 flights were canceled by U.S airlines, and another 300,000-delayed affecting 30 million passengers. The delays and cancelations ranged in cost to the industry from $75 million to $150 million. The cost to traveling passengers was estimated at $2.5 billion. It should be noted that regional airlines accounted for about two thirds of the cancellations. On September 26, 2014, the Chicago Air Route Traffic Control Center (ARTCC) went offline for seventeen days due to a fire set by a disgruntled contractor, to ARTCC’s intricate communications network that controls some of the busiest airspace in the country. 1,750 flights were canceled and ninety-one thousand square miles of airspace were affected as workers scrambled around the clock to restore functionality to the center (Flying Magazine, Feb 2017). A daily time series comparison of flight operation for 8 major hubs around the U.S. during both these events is presented in Figure 5, for the snow event, note the dip in operations in January for New York and how it cascades to Atlanta, Chicago, and Denver airports. From observation, the amplitude and frequency of the event drive the duration and spread of a symmetric ripple in airport flight operations. In contrast, the fire event at Chicago ARTCC in September, although it caused major disruptions at Chicago’s O’Hara airport, it did not appear to cause a ripple effect to other hubs. In general terms following a disruptive event, the interaction of many periodic (totally predictable) airport flight schedules make a chaotic (unpredictable) system. Our metrics (connection and traffic volume behavior) are outcomes of interactions among the airports, and not
from their average behavior. Therefore, resolving uncertainty in predicting and planning for natural and man-made disruptions to airports require research to develop effective risk models that support design and implementation of resilient infrastructures. As evident, there is a research requirement to quantifiably measure and characterize the interactions and couplings between infrastructures. As fixed assets, an airport hub consisting of physical infrastructure and ATC facilities are highly exposed, vulnerable, expensive to replace, and hard to repair if damaged. In 2008, the Office of Inspector General (OIG) reported that 59%
of FAA ATC facilities were over 30 years old, and identified structural deficiencies and maintenance-related issues at many facilities (OIG, 2017). Therefore, the potential for an unwanted outcome resulting from a disruptive event could elevate a hazard to a disaster.

On August 8, 2016, failure in electrical component in Atlanta rippled through the entire system as a consequence of loss of power to a transformer that provided power to the airport data center of one of the major carriers (Carey, 2016). The situation didn’t get any better after backup systems were engaged because not all the servers were connected to this power source amplifying the problem. 2,100 flights were canceled and it took four days to restore operations to normal levels.

Given the importance of air transportation system of the United States to both global and regional transportation of freight and passengers (Barat et al, 2004), (Bertsimas, 2000), efficient recovery response after disturbance in the operations is imperative. In present study, we demonstrate the application of network science based framework to illustrate response of hazards and effectiveness of proposed recovery strategies for US National Airspace System Airport Network.

3.2 Methodology and Data Sets

3.2.1 Airport and Air Traffic Flow Data

For this study, city pair traffic flow data is obtained from Federal Aviation Administration (FAA) open-source database (FAA, Feb 2017), to verify origin to destination airport connection and flight counts for calendar year 2015. Since network science based frameworks and metrics have been used to understand the structure of transportation systems operating at various spatial scales (Bhatia et al, 2015), (Barrat et al, 2004), (Hossain et al, 2013), (Wuellner et al, 2010), (Bertsimas, 2000), we model United States National Airspace System Airport Network (USNASAN) as origin-destination network with airports representing the nodes and a pair of nodes are considered to be connected if there is at least one flight between the pair. (i.e., a flight
originates at one airport and terminates at the other). With the exception of three Canadian and one Puerto Rican airport, the airport network consists of domestic airports and is modeled as an origin-destination network, meaning the traffic volume (strength) and number of connections (degree) of each airport network “node as the number of aircraft that originate and terminate at an airport.

We considered commercial, military, and general aviation (GA) airports with at least one originating or terminating flight, resulting in 1261 airports. Based on FAA and airline data, close to 90,000 flights are in the sky over the U.S. On a typical day, Air Traffic Control (ATC) manages nearly 30,000 commercial flights, 27,000 General Aviation flights, 24,000 air taxi flights, 5,000 military flights, and 2,000 air cargo flights (Bureau of Transportation Statistics, Feb 2017). To build our model, we make these assumptions:

- Flights are scheduled at a series of airports during a given period (i.e., standard operations and procedures vs. ad hoc);
- Duration and intensity of adverse events are unpredictable and uncontrollable in advance;
- Hub failure (collapse) at one or more airport may or may not cause consequential proportional flight service issues such as delays, diverts, or cancelations at other airports;
- Based on specific cases, an adverse event may impact full utilization of major airports and surrounding airspace.

3.2.2 Airport Network Topology

Figure 6 depicts our network model. For our network, all flight connections are bi-directional. Here note, a symmetric matrix for aircraft flow is feasible without substantial distortion of the network, by choosing the higher non-zero quantity per airport pair. Thus, our airport network is evaluated as an undirected weighted network. Since our network is undirected, the interdependent
connection can point in two possible directions. To understand the topology of the NAS airport network we determine the distributions for degree and strength of airports.

The cumulative degree distribution \( P(k > K) \) provides the proportion that an airport has more than \( K \) links to other airports, and is defined as:

\[
P(k > K) = 1 - \sum_{k=kmin}^{K} p(k)
\]  

(1)

where \( p(k) \) is the number of airports having degree \( k \) divided by total number of airports, and \( k_{min} \) is the minimum degree found over all nodes in the network. Likewise, the cumulative strength distribution \( P(S > s) \) gives the probability that an airport has more than \( s \) originating (or terminating) aircraft, i.e., traffic volume. Nodal degree indicates the number of edges shared with other nodes, in our case airports

\[
k_i = \sum_{j=1}^{n} a_{ij}
\]  

(2)

Where \( a_{ij} \) is the element of adjacency matrix, \( A \), which is equal to 1 if two airports are directly connected and 0 otherwise.

The average degree of a network is the average number of neighbors a node has which is denoted by \( <k> \):

\[
<k> = \frac{1}{n} \sum_{i=1}^{n} k_i
\]  

(3)

The weighted counterpart of degree is strength, here indicated by the traffic volume between two connected airports. It is represented as:
Figure 6 – U.S. Airport Network - Connectivity map of USNASAN for year 2014. 7 largest communities, identified through modularity based Louvain algorithm, each of which map to a color, capture about 95% of the airports. Communities are clustered together geographically with the community members with high betweenness centrality maintaining connections with the nodes of other communities.

\[ S_i = \sum_{j=1}^{n} a_{ij}w_{ij} \]  

(4)

where \( w_{ij} \) is the weighted adjacency matrix representing the traffic volume between airport \( i \) and \( j \) for calendar year 2014-2015.

3.2.3 Centrality Measures

Understanding the importance an airport in the network is vital to design for enterprise level resiliency development. Here, we apply measures of centrality to help us quantify airport importance (DeLaurentis et al, 2008). Several centrality measures are available but relevant for our purposes are \textit{closeness}, \textit{betweenness}, and \textit{eigenvector centrality}. 
Closeness centrality measures the concept an airport \(i\) is ‘central’ if it is ‘close’ to several other airports. Mathematically, it is expressed as

\[
c_{CL}(i) = \frac{1}{\sum_{j \in V} \text{dist}(i, j)}
\]  

where \(\text{dist}(i, j)\) is the network distance between the airports \(j, \text{and } i\) in our network graph. For comparison with other centrality measures, \(C_{CL}\) is normalized to lie between \([0,1]\).

Betweenness centrality measures allow us to surmise the degree such that an airport is located ‘between’ other pairs of airports. The idea here ‘significance’ ties to where an airport is positioned in relation to paths in the network graph. We depict these paths as traffic lanes that allow air traffic flow, airports that sit on many routes are more likely more critical to air traffic flow. For our calculations we used betweenness introduced by defined as

\[
c_B(i) = \sum_{s \neq t \neq i \in V} \frac{\sigma(s, t|i)}{\sigma(s, t)}
\]  

where \(\sigma(s, t|i)\) is the total number of shortest paths between \(s\) and \(t\) that pass through \(i\), and \(\sigma(s, t)\) is the total number of shortest paths between \(s\) and \(t\) regardless of whether or not these pass through \(i\).

Eigenvector centrality is based on ‘status’ or ‘prestige’ or ‘rank’. Here it captures the notion, the more central the neighbors of an airport are, the more central the airport itself is. Katz (Park et al, 2013) defined this centrality measure of the form of:
\[ c_{ Ej}(j) = \alpha \sum_{(i,j) \in E} c_{ Ei}(i) \]  \hspace{1cm} (7)

The vector \( c_{ Ei} = (c_{ Ei}(1), \ldots, c_{ Ei}(N_j))^T \) is the solution to the eigenvalue problem \( Ac_{ Ei} = \alpha_{-1} c_{ Ei} \) where \( A \) is the adjacency matrix for our airport network graph (Kolaczyk, 2014). We use network science based centrality measures as multiple researches have attempted to assess the importance of nodes in infrastructure systems using centrality metrics for both weighted and unweighted networks (Barrat et al, 2004), (Wuellner et al, 2010), (Tamvakis, 2013).

To understand the patterns in connectivity, we use the modularity based Louvain community detection (Blondel et al, 2008). Throughout the manuscript, “communities” and “modules” are used interchangeably.

### 3.3 Robustness and recovery metrics

For air transportation systems, we perform the robustness and recovery analysis of USNASAN. We assume that multiple rerouting options are available between a pair of airport since no physical infrastructure is involved (other than ATC centers) between take-off and landing, and primary cause of delays and cancellation in most of the cases are ground delay problems at airports which lead to flight delays and cancellations. Hence, we restrict our analysis to node vulnerability.

Evaluating resilience requires measuring collapse and recovery processes. The first step is identifying a measure for critical functionality. Utilizing the giant component (most linked group of airports in our network) we define Total Functionality (TF) as the number of airports in the giant component when the airport network is completely functional. For our network TF = 1261. Fragmented functionality (FF) is the number of airports in the giant component at any given time after one or more airports collapse due to disruptions. We calculate the state of critical
functionality (SCF) for our airport network as SCF=FF/TF. This methodology is based on percolation theory. Immediately after the disruptive event the SCF is calculated, and a prioritization order is determined for the progression of airports to fully recovery or regain total functionality (Xiao, 2011), (Albert et al, 2000). We apply the network regrowth model proposed in (Bhatia et al, 2015), according to which a priority list of restoration is obtained by looking at various flow and topological metrics such as traffic volume, connectivity, and network centrality measures (Bonacich, 1987). The node which has higher rank receives the priority for restoration. The selected node is then restored to its full functionality by restoring all its outgoing and incoming connections. It is noted that to restore the full functionality of a node, all other nodes at one network distance from that node should at least be partially functional to accommodate the connections to fully functional node. This process of prioritization and restoration is repeated until network regains the desired level of functionality (which is equal to 100% in present case). The time reversal asymmetry in recovery, that was observed for the recovery of systems such as financial systems (Jiang et al, 2013) and railroad systems (Bhatia et al, 2015) is also evident in the present case (Figure 7), which happens to be a consequence of the recovery model. Recovery after disruption is done in the following steps:

1. State of Critical Functionality (SCF) is computed for the unperturbed network.

2. A prioritization sequence of airports is determined using traffic volume, connectivity and topological measures. Restoring an airport A to full functionality requires restoring all connections to the airport by partially restoring the host airport to accept the incoming connections. Airports that are partially activated may not have full functionality since for these airports, only the edges that directly lead to functional airports are recovered.

3. The process of full and partial restoration is continued till SCF reaches 1.
The recovery in airport network is different than subway networks in a sense that in a subway network with stations connected serially, say “A”, “B”, and “C”, requires “B” to be functional for “A” to connect to “C”. However, if A, B, and C are airports and B loses functionality A can still connect to C by bypassing the collapsed node. For the purposes of this evaluation however, we sustain that an order of recovery must follow the sequence of connections to restore airports to a hub in the network. For large airport hubs like Chicago, Atlanta, and Denver, this logic holds true for certain stakeholders that deal with cargo versus passenger movement. In general, all carriers develop operations and business strategies based on a sequential order of flight initiation and termination to hold down cost and optimize profits.

Figure 7 - Robustness & Recovery Plot - Average nearest neighbor Degree and Degree Distribution (Left) Robustness of United States National Airspace System Airport Network in response to targeted disruptions in order of decreasing degree (# connections) and strength (traffic volume). State of Critical Functionality (SCF) is measured using relative size of largest connected cluster in the network. (Right) Recovery response of USNASAN. Airport recovery prioritization is done using centrality measures such as strength, betweenness, closeness, eigenvector, degree centrality. Grey bounds on right side represent the 99% confidence interval for recovery scores obtained from 1000 ensembles of random recovery.
3.4 Results

3.4.1 Robustness and Recovery

As discussed earlier, the analysis of robustness of our network has mainly focused on visualizing loss and recovery of critical functionality based on strength and degree. These given performance metrics are affected when airports are removed according to random and targeted attack. Figure 7 demonstrates the networks tolerance to airport loss. We quantify robustness of our airport network as it reacts to random and targeted disruptions. That is, airports are systematically removed based on their number of connections and traffic volume. Here targeted disruptions are driven by either airport degree or strength. We note that removing nodes in descending order of number of connections and traffic volume computed for the intact network may not be the fastest way to damage the network. Many researches in the past have explored the optimal way to efficiently damage the network using percolation theory (Xiao, 2011), influence maximization approach and non-greedy algorithms (Morone, 2015). However, in this study, our focus is to illustrate the application of recovery framework for US National Airspace System Airport Network subjected to disparate hazards. We note that node removal according to dynamic centrality measures can result in even faster collapse rate, but we have used intuitive measures (such as connectivity, and traffic volume) that can be judged through preliminary analysis of traffic maps and open-source datasets. Secondly, for natural hazards, we have used random sequence to trigger the collapse because natural hazards, such as Tsunami, do not affect the airports/facilities in any specific order but impact the facilities falling within effected area.

Based on random removal of nodes, close to 99% of the airports would need to be disrupted for loss of total functionality. For degree and strength based targeting loss of total functionality occurs at 27% and 29% respectively. Note that nearly 30% of the airports must be disrupted for the complete collapse of airport network.
The right section of Figure 7 depicts recovery rates computed using multiple strategies with random recovery as benchmark. Here, these are analyzed for the scenario in which the airport network status is at SCF = 0, i.e., complete failure or no connections, traffic flow. Although Figure 7 provides the quantitative description of resilience of the USNAS, it may not be realistic for a real-life network to begin recovery from state of complete collapse. This motivates the testing of framework on realistic hazards that only partially incapacitates the USNASAN.

Table 2 – Topological Rankings

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Table 1. Top 20 Airports by Degree, Strength, Closeness, and Betweenness

Table 2 summarizes the rank of airport facilities according to multiple strategies considered in this study. We evaluate three categories of recovery strategies. To begin, a baseline of 1000 random ensemble sequences is established for comparison. The next strategy is founded on airport
profiles and characteristics including connectivity and traffic volume. The final strategy is based on network centrality measures, specifically eigenvector, closeness, and betweenness. The results show that for our airport network, the path to optimal recovery for most phases of partial and full recovery takes place when betweenness centrality is selected as for generating a recovery order. Performance of each recovery strategy is measured by the rate of change of SCF with respect to the airports restored to full functionality.

3.4.2 Topological Sensitivities

Delineation of hubs and their connectivity characteristics is crucial to understand resilience of infrastructure systems (O’Kelly, 1986). Figure 8A depicts log average of the neighbor’s degree vs the degree in airport network, and suggest that while there is a tendency for airports of higher degree to connect to comparable airports, airports of lower degree show a tendency to connect to airports of both lower and higher degrees. Given the presence of hub and spoke arrangement for the airports with large degree, these higher degree nodes, although disproportionately less in number in comparison to the airports with average degree less than 100 (O’Kelly, 2015). A cumulative probability distribution of node degree, on a log-log scale profile the distributional properties of the airports. The distributions follow truncated power law models, wherein most airports have a small number of connections, except for a few hubs.

Figure 8B depicts the cumulative probability distribution of airport degree (connectivity) on log-log scale. The plot depicts linear decay in the log-frequency as a function of log-degree. The distribution follows a truncated power law model, indicating airports such as Richmond and Fort Walton Beach having fewer connections with similar and larger airports come more closely to the fitted line plot showing a scale-free power law degree distribution slope, in contrast to the airports having several connections, such as Atlanta follow an exponential decay. Hossain et al. (2013) showed that the AAN cumulative strength distribution indicated the presence of a right-skewed
distribution which signals a high level of heterogeneity in the network. It was a phenomenon also found in (Bagler, 2008), (Wang et al, 2011). The Average degree $<k>$ for our network is calculated to 75.32. Figure 8C displays a cumulative probability distribution of commercial airport degree and strength. For commercial airports, the average degree is 14.1 and the average path length 2.276.

Figure 8 – Topological Sensitivities - Average nearest neighbor degree exhibits the negative trend with increase in degree with high variability for airports with less than degree of 100. Airports with degree greater than 300 have tendency to connect too many small airports giving rise to hub and spoke arrangement for these nodes. Nodes with degree less than 100 have tendency to connect to both large and small airports resulting in amplified fluctuation along the negative trend. Given the presence of hub and spoke arrangement for the airports with large degree, these higher degree nodes, although disproportionately less in number in comparison to the airports with average degree less than 100 (Fig 4B), have considerable impact on robustness and recovery characteristics of the network. Figure C, cumulative probability distribution of node degree and strength of commercial airport only, on a log-log scale, profile the distribution properties of the airports.

8A – Average nearest neighbor degree

8B – Cumulative probability distribution of airport degree on log-log scale

8C – Cumulative probability distribution of airport degree and strength
Since researchers in the past have hypothesized that network centrality measures such as Betweenness, Closeness and Eigenvector centralities exhibit significant positive correlation with the degree centrality (Valente et al, 2008), it gives rise to another question: if the centrality measures are indeed correlated, then why various recovery strategies yield different recovery rates? To understand this, we plot the variation of average measure of the three centrality measures with degree centrality (Figure 9). We observe that centrality measures are indeed strongly correlated to degree. While this positive correlation is clear for higher degree nodes, certain airports exhibit anomalously high (or low) centrality measures in comparison to their degree. For example, airport in Anchorage, Alaska is ranked 62 out of total of 1261 airports per degree (# of connections) but its betweenness centrality is ranked second among all the airports. Furthermore, airports with degree 320 or less exhibit large deviation from the linear relationship and hence are ranked differently by different recovery strategies.

Many decisions in the airline industry depend on the formation of traffic demand and development of connections. Whether an airport becomes an important hub in the network may be driven by competition, but as we have shown, an airports centrality characterization can play a crucial role in understanding resilience and the airport’s criticality to the network. Even without disruptions, ATC managers are concerned with airport criticality. Recent observation of procedures applied by FAA and airport managers aim to lessen the impact of severe weather on airport performance by pre-empting the severe weather by reducing arrival and departure volume, and taking non-critical systems off-line until the storm passes.

Congestion in almost all parts of the U.S. have created higher interest in the airport network route problems. The relative importance of various airports in the NAS allows for better planning and mitigation of traffic conflicts. Unlike surface and maritime transportation networks that
develop gradually for commercial and other social/geographical reasons, air transportation networks are based on hub networks more aligned with economic markets and population centers (Buldyrev et al, 2010)

Figure 9 – Variation of Centrality Measures with Degree - Relationship between centrality measures and node degree shows that while degrees and centrality measures are strongly correlated, certain anomalies (such as Anchorage, Alaska exhibiting high betweenness centrality despite moderate degree) results in varying recovery rates under different strategies. Note the sharp increase in betweenness centrality as degree increases beyond 550 which also drives the state of critical functionality during recovery according to betweenness centrality.
3.4.3 Tolerance and Recovery

As discussed earlier, the U.S. airport network is robust needing approximately 30% of airports to be removed in order for total loss of SCF. That said, given a larger scale loss, such as west coast airports from the Seattle-Tacoma (SEA) to San Diego (SAN) the perturbations to the network would be severe. A tsunami hitting the coast trigged by the Cascadia or San Andreas faults could implement such a scenario. Returning to our network model we simulate this event by removing those nodes with the highest probability of being impacted. The resulting airport

Figure 10 –Tolerance and Recovery Simulated Scenarios - (left) Similar to figure 7 but for partial loss of functionality due to simulate tsunami event along the western coast (right) at each recovery curve, the percentage of ensemble members that a given metric is larger than in terms of SCF is plotted. In some cases, recovery (and hence percentage lines) overlap with each other. This overlap is shown by thicker lines. B. Same as 6A but for cyber-physical attacks.
network fragments into 14 components of which six large components make up 98.04% of the network. The remaining eight components comprise less than 2%. Translating this into recovery, we see our centrality results concur with our earlier plot; i.e., restoring airports in order of betweenness would provide the quickest recovery for restoring SCF. Figure 10A depicts the airport network robustness and recovery plot based on our simulated Tsunami. The x-axis describes: Fractions of stations recovered. The y-axis for left plot describes: SCF and for right plot: percent random < Chosen metric. Figure 10B depicts the recovery plot based on a Cyber-attack on the 10 largest hub airports in the Midwest. Comparing plots of both scenarios, note the slightly larger Impact Area for the Cyber-attack. As with the full collapse and recovery, betweenness centrality out performs other measures for recovery of network. Although there are far less airports removed after the Cyber-attack, due to their attributes, number of connections and traffic volume, the impact on the entire airport network is more severe. Figure 11, depicts a time series for airports flight operations impacted by recent hurricanes. Note, the proximity of the results to our airport network simulations.

3.5 Conclusion

3.5.1 Summary

Evaluation of the dynamic response of the NAS to airport disruptions allows for assessment of system robustness and resiliency, and measuring resilience is the first step in improving it. This paper presented a methodology to describe and analyze the functional relationships between the airports in terms of air traffic flow. The proposed approach to airport system resilience characterization following a disruptive event provides key metrics for stakeholders to better understand vulnerabilities.
The knowledge gained in a network analysis context demonstrated that centrality measures are a good platform for supporting restoration. It allows researchers and system developers to manage and apply disruptive scenarios to pre-existing data and network structures for predictive analysis. It supports an integrated and interoperable way of stepping through phases of an event based on fragmentation and recovery. This is clean separation from risk based and probabilistic methods of the past.

Interesting to note that two general aviation airports, Teterboro and Van Nuys Airports, had the highest number of connections. Teterboro is in the New Jersey Meadowlands, 12 miles (19 km) from the middle of Manhattan, making it efficient and in demand for corporate and private aircraft. Globally and nationally it is the primary hub for several charter aviation companies severing the private sector. Van Nuys Airport located in the San Fernando is one of the busiest general aviation airports in the world. While the network science based framework proposed here was originally developed in the recent paper (Bhatia et al, 2015), the new adaptation to the US airspace system generates novel engineering and policy relevant insights, besides offering further evidence for the general applicability.

3.5.2 Future Study

In addition to informing decision makers about the resource prioritization, the proposed strategy also highlight how recovery will propagate which can then be translated into “$ saved” by computing the revenues generated restored operations. While demonstration of the same for US Airlines require ticketing data for various passenger and freight carriers, our group has demonstrated the applicability of similar algorithm for post Sandy recovery of New York’s Mass Transit System to compute how measure of State of Critical Functionality (SCF) can be translated to revenue saved in operations (Bhatia et al, 2015).
Analysis of dynamic responses with high accuracy is an important factor in developing methodologies, process improvements, and designs that enhance system resiliency. Particularly, in the case of airport networks and NAS service threads, a new concept will be introduced characterizing system resilience and performance at the local and global level by the change in capacity ratio over a given time. Future directions to network resilience quantification needs to go beyond heuristic measures such as network centralities and account for the optimal recovery strategies such as influence maximization approaches (Morone, 2015).

3.6 Acknowledgements

This research was performed at Northeastern University’s Sustainability Data Science Laboratory (SDS Lab). KLC acknowledge his affiliation with the VOLPE - The National Transportation Systems Center, while EAK, a former member of the SDS Lab, acknowledges his current role as CEO of risQ Corp. The authors thank and Mary Elizabeth Warner; Stephen Flynn, Director of Northeastern's Center for Resilience Studies; the Volpe Center Director Emeritus Richard John, Principal Technical Advisor (PTA) Walter Gaza; for helpful discussion. This research was funded by VOLPE and Northeastern (for KLC), risQ (for EAK) and an NSF SBIR (# 1621576) project (for EAK), as well as three National Science Foundation projects (for UB and ARG): NSF BIG DATA (# 1447587), NSF Expeditions in Computing (#1029711) and NSF Cyber SEES (#1442728).
3.7 Addendum to the published paper

To answer our research question concerning 2017, hurricanes Harvey and Irma, and 2018, snowstorm Grayson did the airport network perform within tolerance level specified by FAA?

Figure 11, depicts a time series for airports flight operations impacted by recent hurricanes. Note, the proximity of the results to our airport network simulations. Results from snowstorm Grayson are also depicted. Criteria, per Presidential Policy Directive (PPD-21) achieve 90% of normal operations after an event within 24 hours at core airports. (See Appendix A for core airports listing)

Figure 11 – Time series of flight operations during hurricanes Harvey and Irma

- Did the airport network perform within tolerance level specified by FAA?
  - (Criteria: In accordance with PPD-21, achieve 90% of normal operations after an event within 24 hours at core airports)
  - Harvey – 97% of core airports
  - Irma – 86% of core airports
  - Grayson – 80% of core airports
  - AN Hurricanes – 98.5% (9)
  - AN Snowstorm – 96.9% (15)
4  CHAPTER 4 - DEVELOPING POLICIES WHICH OPTIMIZE LONG-TERM SERVICE FOR VULNERABLE INFRASTRUCTURE

Kevin L. Clark1, Udit Bhatia2, Auroop Ganguly3, and Matthias Ruth4

1Sustainability and Data Science Lab, Northeastern University, Boston, MA, kevin.clark@dot.gov
2Sustainability and Data Science Lab, Northeastern University, Boston, MA, Bhatia.u@husky.neu.edu
3Sustainability and Data Science Lab, Northeastern University, Boston, MA, a.ganguly@northeastern.edu
4Public Policy and Urban Affairs, Northeastern University, Boston, MA, a.ganguly@northeastern.edu

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4.1  Chapter Summary

The Mission of the U.S. Department of Transportation is to ensure all Americans are served by a fast, safe, efficient, accessible and convenient transportation system that meets the nation’s vital national interest and enhances the quality of life today and in the future. Airports and National Airspace System (NAS) play a key role in achieving this mission. In cases of outdated and aging infrastructure it is essential that managers identify facilities that merit further investment and those that do not, allowing resources to be allocated to other important efforts. The difficulty is to ensure the facility infrastructure continues to meet the requirement in all localities and regions including areas of high vulnerability. This, in turn, requires proper assessment of conditions and determination of the required investment to maintain the proper balance of services to large hub and non-hub airports is an ongoing problem policy makers must confront. This paper presents a System Dynamics model to visualize the impact of investment policies on operations and communities. The methodology applied allows variable manipulation for assessing simulation outcomes based on set parameters, and identifying incentives and compromises that meet broad requirements.
4.1.1 Introduction

One of the Federal Aviation Administration’s (FAA) primary modernization goals is to implement policies that ensure their 1,230 facilities enable robust Air Traffic Control (ATC) services to meet air traffic demand requirements in a safe and efficient manner for all citizens. These facilities provide the lifeline for airports and are the foundation on which the Next Generation Air Transportation System (NextGen) programs are built. Local incidents such as a chiller outage could have regional effect on airports but also depending on interdependencies and duration, have cascading impacts on airports nationally. The challenge of maintaining complex airport and facility infrastructure is in the assessment of needs and the implementation of a clear modernization and sustainment prioritization strategy that supports those needs. Evidence has shown policy changes display their impact in long-term gains or losses, not short-term. (Toyoda, 1991)

The purpose of this research is to investigate modernization investment policies and their long-term impact on ATC service availability. Modernization investments are meant to improve operations and efficiency primarily by reducing risk of facility and infrastructure failures. Facility infrastructure modernization should meet two goals which are higher service availability and improved resilience. General observations, however, have shown such investments have most often not yielded desired results. Thus, it is imperative to conduct a thorough analysis of policies driving the infrastructure procurement lifecycle. The analysis should identify the important factors that are crucial to make the investments beneficial and what policy conditions the behavior dynamics of the process. The criteria and factors involved require that the model captures the dynamics of investment decisions and the prevailing tendencies fundamental to the uncertainties policy makers confront. The system behavior must be revealed in a manner that specific policies could be analyzed with respect to their system impact.
The importance of this research progresses to the new normality of an aging infrastructure. Recent events initiated by extreme weather have shown how a simple infrastructure failure such as a water-main break can cause a critical outage and disrupt both local and national traffic operations. Considering the extensive damage caused by weather, much attention has also been focused on trends describing increases in frequency and intensity of weather events and their impact on infrastructure. Garschagen (Garschagen, 2014) gave testament to this in his research findings in Can Tho City, Vietnam. Vulnerability increases as capacity to adapt to change decreases. He also describes the socio-economic and political influences to recovery. Focusing primarily on gulf coast we note the population, airport facilities, and the issues of an increased likelihood of weather hazards (see Figure 12).

Figure 12- Gulf coast airports and population density – Although many communities in the gulf coast region are exposed to risk of natural hazards there has been a population migration and growth in recent years in areas of Houston, TX, Mobile, AL, and St Petersburg, FL. Climate and robust industries related to energy, aerospace, agriculture, and tourism provide incentives for population sustainment and the need for reliable air transportation.
A survey of failure data for instrument landing systems (ILS) indicated facilities located on airports within 50 miles of the gulf coast had a 31% of the outages for the combined Eastern and Central Service Areas. The ability to provide enhanced services to these areas will improve with modernization, however, given funding limitations in the era of continuing resolutions and sequestration, managers may be forced to forego upgrades or replacement in order to maintain operations. Thus, challenges to both operations and maintenance require that policy maker consider tactical and strategic objectives when determining the resource allocations.

The FAA is bound to use appropriated funds in accordance with public law for modernization and sustainment. (FAA, 2006) FAA policy makers responsible for infrastructure and facility management use weighted criteria to identify potential areas of risk. (Federal Aviation Administration, 2016) A September 2013, GAO Audit, (U.S. Government Accountability Office, 2013) however, found variation in methods used to determine facility conditions made data comparison and assessment of needs difficult. According to the report, most federally maintained facilities are in “Good” to “Fair” condition. However, 409 terminal facilities had not been inspected and had no estimates of their facility condition index (FCI). Because the FAA’s estimates for these uninspected facilities had substantial errors, the GAO did not present condition data for them. A comparison of FAA and GAO estimate results is listed in Table 3. This table was regenerated based on data from GAO-13-757. These non-hub and small airport facilities serve airports like Corpus Christi, New Orleans, and Tallahassee. These facilities, in most cases identified as Tier 2-4 facilities are most vulnerable when policy decisions delay required maintenance and modernization funding. Deterioration ultimately precedes system and/or

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2 GAO Report to Congressional Committees, “GAO-13-757”
structure fragility increasing the likelihood of outage or failure. This study describes an approach to policy analysis through the development of a system dynamics model.

Table 3 – Comparison of results for FAA & GAO Estimates.

<table>
<thead>
<tr>
<th>Facility</th>
<th>Facility Age (years)</th>
<th>Facility Replacement Value (000)</th>
<th>Deferred Maintenance - Actual (000)</th>
<th>Deferred Maintenance - FAA Estimate (000)</th>
<th>Deferred Maintenance - GAO Estimate (000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dallas-Ft Worth TRACON</td>
<td>36</td>
<td>$42,112</td>
<td>$2,893</td>
<td>$524</td>
<td>$3,143</td>
</tr>
<tr>
<td>Greensboro Tower</td>
<td>36</td>
<td>$7,506</td>
<td>$1,173</td>
<td>$524</td>
<td>$592</td>
</tr>
<tr>
<td>Teterboro Tower</td>
<td>36</td>
<td>$4,215</td>
<td>$289</td>
<td>$524</td>
<td>$349</td>
</tr>
<tr>
<td>Woodring Tower</td>
<td>36</td>
<td>$3,129</td>
<td>$150</td>
<td>$524</td>
<td>$269</td>
</tr>
</tbody>
</table>

4.1.2 Previous Research

Studies have linked economic development and environmental issues to inadequate polices on infrastructure improvement and sustainability. A milestone study titled “Our Common Future”, (Brundtland Commission, 1987) described situations of increasing environmental problems correlated with lack of support for infrastructure modernization. A major focus of the report emphasized the identification of elements that due to societal needs must be sustained. The report also discussed the importance of placing a value on what must be sustained. The report did not discuss however, effects on multiple stakeholders and the consequences rendered by separate but interdependent investment actions, specifically, actions taken by agencies to bring facilities up-to-date. By not linking the actions taken to the effects or impact it is unclear which specific legacy restoration actions succeeded. Lemer (Lemer, 1996) characterized infrastructure aging and obsolescence as the inability of legacy systems to meet changing performance requirements. He stressed that the complexity of the facility infrastructure system made it difficult to be assessed by a single parameter. His framework for performance assessment included effectiveness, reliability,
and cost, where maximum effectiveness is reached when supply of services equals demand requirements. Reliability was measured as that probability of in which effectiveness would be sustained for an extended period of time. Cost or life-cycle cost includes planning, design, installation, operation, maintenance, and demolition. The noted facility longevity, ranging from 30 to 70 years in some cases, justify high re-investment cost, but unlike computers and automobiles, innovation is slow and the business case for return on investment may not be achieved. From a perspective of ATC service, innovation and business opportunities will be tied to increased capacity and growth. Rissmiller (Rissmiller, 2000) reached similar results but emphasized the importance of applying a causal prototype in public policy development. What these studies did not discuss were methods to quantifiably measure the impact of investment decisions, or issues evolving from poor policies. Friedman, (Friedman, 2006) raised this issue in his study of policy impacts on the national highway system. He found that modernization and preventative maintenance policies intended to improve road conditions, reduce congestion, and reduce accidents were actually increasing accidents due to increase speeds enabled by better roads and less congestion. He noted the importance of setting boundaries and testing assumptions. Friedman also questioned the mental model and reasoning used by policy makers given the unexpected short-term consequences. Saleh et al. (Saleh, 2010) also identified how false assumptions can lead to policy decisions that translate to inadequate results. He outlined a framework for performing a structured policy analysis based on the use of linking model processes to system modes of behavior expressed as the eigenvalues of a linearized model. The framework aids in focusing analysis on behavior patterns that directly impact outcomes, desirable or not. His research showed the value of applying feedback loops to explore policy intervention, allowing variable adjustments that impacting near-present behavior. What he did not stress was that this
approach only provides for a partial policy analysis, meaning evaluating the effects of changing only one policy parameter at a time.

The Budget Control Act of 2011 implemented by Congress saw federal agencies impacted by extensive funding reductions. Many researchers predicted the cuts to these agencies would significantly undermine the government’s ability to maintain essential infrastructure modernization efforts. Sustainability related studies such as that by Halog (Halog, 2011) emphasized the need for the development of new integrative tools and methods to better support policy in the transition of new regulations. Given complex needs but limited resources, he proposed integrated modernization assessments, life-cycle analysis, and multi-criteria decision making. The effectiveness of this approach is questioned given the stress placed on stakeholders to reach a collaborative outcome. Multi-stakeholder engagement is time consuming due to the levels of involvement and iterations required to reach consensus, thus, hampering policy implementation. In the era of ‘big data’ and data science there are methods to resolve these multi-stakeholder complexities. Network analysis is often used to identify decision path lengths and key stakeholders. Pruyt (Pruyt, 2014) elaborated on this and the use of ‘big data’ and system dynamics as beneficial for policy analysis. His research included reducing data sets to manageable proportions by filtering, clustering, and selection methods. Pruyt’s crime fighting application example showed how this approached enabled strategic policy development where high-levels of uncertainty existed. Although this method is promising he points out that multi-method and hybrid modeling approaches should be further developed to make the approach appropriate for a range of system characteristics, spatial and network aspects and risks. Chen (Chen, 2017) used computable general equilibrium modeling of economic consequences to aviation system disruptions. There are some synergies to our approach in the aspect of running simulations and varying key parameters,
but Chen focuses on event disruptions impact on system failures and economic consequences. Of interest to our work is the use of system dynamics to envision the facility infrastructure modernization process and outcomes based on the simulation of reaching different policy investment decisions.

What is absent from many policy investigations are upstream variables that effect processes and behavior. Barlas (Barlas, 2009) discussed common errors made in structuring problems. Missdiagnosis of dependencies or lack of weight given to a key parameter may skew results from the optimum decision. For non-linear relationships this is especially true. Our objective of achieving a preferred outcome, where modernization increases and infrastructure vulnerabilities decrease, requires a mechanism for the two to be linked. That is the choice of measures or indicators should be linked to the issue needing change. Boussauw (Boussauw, 2017) discussed how ‘sustainable transport’ policies may result in benefits for one stakeholder while resulting in unsustainable outcomes for another. Our approach addresses this by holistic observation of the process, defining the causal relationships, and capturing key components and variables in the model.

4.2 Data

Information and data for this research was obtained from several sources including discussions with ATC terminal facility subject-matter-experts, and the following FAA websites www.faa.gov/regulations_policies/faa_regulations; http://gisserver/apps/faa/tbfm/map.aspx; technet.faa.gov; and www.faa.gov/data_research/aviation.

Congress authorizes all funding for the FAA. In its history, FAA funding has been the subject of budget cuts challenging policy makers and forcing managers to grapple with the establishment of a long-term sustainable framework. The two primary sources of funding include the General
Fund and the Airport and Airway Trust Fund. (U.S. DOT, 2016), covering the following four main budget accounts:

- **Operations**: Funds the administration, operation, repair, and maintenance of the National Airspace System (NAS) and Aviation Safety Oversight

- **Facilities & Equipment (F&E)**: Provides for current infrastructure, modernization, and the advancement of NextGen Air Traffic Control

- **Research, Engineering, & Development (RE&D)**: Funds the research and development of products and services that ensure a safe, efficient, and environmentally compatible air transportation system

- **Grants-in-Aid**: Funds FAA’s Airport Improvement Program (AIP), which supports the development of a nationwide system of public-use airports to meet the current needs and the projected growth of civil aviation

Figure 13, generated from enacted FAA budgets, depicts the breakdown of FAA Budget History\(^3\). For our study we are primarily concerned with the Operations and F&E budgets which are the sources for facility infrastructure maintenance, modernization, and replacement. Policy for funding allocation is updated annually in the Capital Investment Plans (CIPs) covering the Facilities Infrastructure Portfolio (FIP). The purpose of these plans is to identify planned capital investments for a five year period consistent with FAA budget submissions. In simple terms, F&E funding is budgeted for predicted maintenance, and Operations funding is allocated to facilities “to keep things running”. In other words, to mitigate risks of unforeseen outages and infrastructure failures.

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\(^3\) Gahart, Karen, *FAA Budget Overview, October 26, 2016*
As of 2017, the FAA operates 264 Air Traffic Control Towers, 162 Terminal Radar Approach Controls (TRACONs), 246 contract Towers and six Operations Support Facilities. (FAA, 2017) In 2016, the FAA requested $464 million to move forward the “state of good repair” for infrastructure facilities. The funding request corresponded to a deviation to re-invest needed capital into essential infrastructure in an attempt to reduce the deferred maintenance (DM) backlog and thus reduce operational uncertainties. Here we can gain our first insight into sustainment policy by inquiring, how upgrades and maintenance priorities line up with airports in vulnerable gulf coast areas. Do they fall into “the backbone” of the NAS category for funding urgency?

*Figure 13 – FAA budget breakdown and history.*

FAA classifies airport facilities by Tiers. Characteristics of the division and guidance on maintenance priority are listed in Table-4. This table was regenerated from FAA Facility Group documentation. As an example, Chicago O’Hara Airport (ORD) Tower is a Tier 1 facility. In 2016, ORD served 39,589,899 passengers. New Orleans Airport (MSY) Tower is a Tier 2 facility,
and served 5,569,705 passengers. Tallahassee Airport (TLH) Tower a Tier 3. In 2016, TLH served 345,404 passengers. (Air Carrier Activity Information System (ACAIS), 2017)

The FAA uses maintenance records and facility condition assessments (FCA) for their FIP management process and decision making. This includes an asset priority model (APM) score based on FCI, Service Delivery Point (SDP) and annual operations. As defined by the FAA, FCI is a value that defines maintenance, repair and replacement deficiencies of a facility divided by its current replacement value. The resulting fraction is then subtracted from 1 to express FCI as a percentage. A facility with an FCI above 95 is considered in “good” condition, 90 to 95 in “fair” condition, and below 90 in “poor” condition. For uninspected facilities, representing more than half of Terminal Facilities, the FAA uses assumptions about facility deterioration along with statistical methods based on age to estimate the condition of facilities in that year.

Table 4 – Facility Tier Classification - Presently 568 Facilities are characterized by FAA Tier structure. Note only 77 Facilities are classified as Tier 1

<table>
<thead>
<tr>
<th>Tier (568 Facilities)</th>
<th>Threshold</th>
<th>National Guidance - NAV Services/Equipment</th>
<th>National Guidance - All Other Services/Equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tier 1 (77 Facilities)</td>
<td>Airport with &gt; 1.0% Total Annual Enplanements; ARTCCs; CCF, Combined TRACONS w/Tier 1 Airports; Andrews AFS/NAG OR Cargo Bds. &gt; 100</td>
<td>Maintain, Repair, Restore, &amp; Sustain all equipment to all runway ends.</td>
<td>Maintain, Repair, Restore &amp; Sustain all equipment</td>
</tr>
<tr>
<td>Tier 2 (88 Facilities)</td>
<td>Airport with 0.25% -1.0% Total Annual Enplanements OR Standalone TRACONS w/Tier 2-4 Airports OR Airports with &gt; 150K Annual ATCT Operations OR &gt; 400 GA Based Aircraft</td>
<td>Maintain, Repair, Restore, &amp; Sustain all equipment to up to 4 runway ends. Delay repair &amp; restoration of other equipment up to 5 days.</td>
<td>Maintain, Repair, Restore &amp; Sustain Comm. Power. Delay repair &amp; restoration of other equipment up to 5 days.</td>
</tr>
<tr>
<td>Tier 3 (109 Facilities)</td>
<td>Airport with 0.5% -0.25% Total Annual Enplanements OR Airlines 100K - 150K Annual ATCT Operations OR 200-599 GA Based Aircraft</td>
<td>Maintain, Repair, Restore, &amp; Sustain all equipment to up to 2 runway ends. Delay repair &amp; restoration up to 30 days; Defect sustained for 1 year; Equipment OTS &gt; 180 days is decommissioned</td>
<td>Maintain, Repair, Restore &amp; Sustain Comm. Power. Delay repair &amp; restoration of other equipment up to 30 days; Defect sustained for 1 year; Equipment OTS &gt; 180 days is decommissioned</td>
</tr>
<tr>
<td>Tier 4 (254 Facilities)</td>
<td>Airport with 0.25% -1.0% Total Annual Enplanements OR Standalone TRACONS w/Tier 2-4 Airports OR Airports with &gt; 150K Annual ATCT Operations OR &gt; 400 GA Based Aircraft</td>
<td>Maintain, Repair, Restore, &amp; Sustain all equipment to up to 1 runway end. Defect repair, restoration, sustainment of other equipment; Equipment OTS &gt; 180 days is decommissioned</td>
<td>Maintain, Repair, Restore &amp; Sustain Comm. Power. Delay repair, restoration, sustainment of other equipment; Equipment OTS &gt; 180 days is decommissioned</td>
</tr>
</tbody>
</table>

4 FAA-AJW-2A, Air Traffic Control Facilities and Engineering Services
As discussed earlier, GAO has pointed out flaws in the methodology. For example, an uninspected ATC Tower at San Diego Airport, CA and one at Tampa Airport, FL could have the same FCI due to their age even though the Tower in Tampa may have a higher number of maintenance issues. This could be critical given the Tampa Tower is more exposed and vulnerable to extreme weather. Thus, the process may overlook needed repairs and upgrades without considering that the frequency and amplitude of extreme weather may be having on facility condition and deterioration. Also, compared to other locations, the gulf coast of Florida is highly susceptible to multiple hazards with a higher number of facilities in vulnerable communities. (Petkova, 2015) 39 airports along the gulf coast are exposed to some degree of hazards including Key West; Tampa; Tallahassee; Mobile; New Orleans, and Houston. As noted in Table-4, Tier 1 facilities are given the highest consideration for funding. Driven by mission needs, the CIP and FIP processes, maintenance and modernization activities are executed. The measurement of the success of the implementation however, is not immediate. Consider a facility serving Atlanta Airport, GA, has a need for carpet replacement while a facility serving Corpus Christi, TX, has a need for roof replacement. Based on current policy the carpet in Atlanta would be replaced while the roof replacement would be deferred. Assume that a year passes and the roof hasn’t been replaced, and a Hurricane hits southern Texas causing roof collapse and severe water damage to vital equipment. There is a high probability air traffic services will be significantly degraded to a point the facility goes ATC zero. Airport and airline stakeholder complaints are heard, and the FAA pulls funding from the operations budget, allocated to another project, to have the roof replaced. It is estimated that large portion of Tier 3 facilities receive their project funding in this manner. Note, this funding is allocated from the operations budget, which draws from planned projects and reduces available funds for programs such as NextGen and New Horizons 2045. Yet,
from a benefit/cost reference there may be no business case for upgrading certain Tier 3 facilities. The estimated gains in operations and resilience may not equal an acceptable return on investment. Thus, how can modernization requirements be met with a process architected for underinvestment?

The current decision policies based on estimates from linear regression models are insufficient and will not deliver what is required for modernization. The FAA’s goal is to reduce DM and increase FCI for all facilities but unless the approach to funding policy changes lower Tier facilities will become unsustainable, which adversely impacts ATC services. A methodology is required that is holistic, measurable, and adaptable based on feedback. Specifically there is a need to understand interrelationships among variables and what mechanisms are driving the process behavior and decisions.

4.3 Methodology

System dynamics methodology (Sterman, 2001) is appropriate for modeling complex systems. It has been applied across various natural science studies but is also relevant for modeling government policy interdependencies. In generating an approach based on system dynamics we must first understand the process framework and next identify what systemic policy is conditioning the behavior of the process. Figure-14 depicts the boundaries of our framework. With this framework in mind we develop a model that represents the variables, system, and process. We examine the linkages, actions, and consequences that are rendering the process/policies unsustainable. Causal relations here are of greater interest than simple correlations. This is presented through a causal loop diagram (CLD). The CLD links entities by causal associations and as the diagram matures feedback loops become discernable. Feedback loops are either positive (self-reinforcing) or negative (balancing/self-correcting). Reinforcing loops magnify what is
occurring in the process, such that an increase in one quantity leads to an increase in another. Balancing loops resist change such that an increase in one quantity leads to a decrease in another.

*Figure 14 – Sustainment Planning Framework - This framework is guide for executing a focused planning process relying on assessment tools and indicators mitigate risk and support decision-making aligned with goals.*

If we configure our model with both these loops a dynamic equilibrium can be reached. Once developed, we examine our CLD to identify which loop’s influence on process behavior has the greatest impact on all others at specifics time intervals. Hence we can design a simulation that depicts how key variables will evolve based on interaction and identify changes required to generate sustainable benefits. *Figure 15 shows the simplistic CLD for Tier 3 facility sustainability.*
Depending on the degree, misdiagnosis of behavior causality may invalidate outcomes or reduce the effectiveness of point-to-point comparisons.

As illustrated by (Moore, 2007), the “+” and “-”, arrows characterize the activity interdependencies, where the sign designates pair-wise effect of the variable at the source of the arrow on the target of the arrow. In general terms, an arrow labeled with a (+) indicates the source and the target variables move in the same direction; and an arrow labeled with a (-) indicate the value of the source and target are moving in opposite directions. (Moore, 2007)

*Figure 15 – Causal Loop Diagram for Facility Condition - Note capability influences pressure on both Operations and F&E Budgets.*

Focusing on the dynamic behavior orientation verses the event orientation, we see as facility condition improves facility deterioration decreases and, vice versa, as deterioration
increases the condition decreases. Stepping through our CLD, facility condition increase causes an increase in level of service and in turn causes an increase in capability. An increase in capability leads to a decrease in need for F&E budget spending. Level of service increase causes decrease in need for planned repairs & upgrades. An increase in repairs and upgrades causes a decrease in need for modernization spending. An increase in modernization spending causes a decrease in deferred maintenance. An increase in deferred maintenance causes a decrease in facility condition. Looking at the service loop, an increase in level of service causes an increase in outages but an increase in outages causes a decrease in level of service. An increase in outages also increases the need for repairs and upgrades. An increase deferred maintenance increases FCI decreases. As FCI increases pressure to increase the budget decreases. As level of service increases pressure to increase the budget decreases. Note, as deferred maintenance increases the pressure to increase the budget increases. Adverse environmental conditions increase deterioration and outages. In summary we have a positive loop linking facility condition and deterioration, indicating that if a cause increases, the effect amplifies the outcome. Note, an increase in level of service or FCI decreases pressure to increase the budget. An increase in deferred maintenance however increases pressure to increase the budget. There is a negative loop linking facility condition, level of service, repairs and upgrades, modernization spending, and deferred maintenance indicating that if a cause increases, the effect opposes or decreases the outcome. Because of the influences on process behavior of this loop it is deemed most dominant.

The next step in our methodology is to chart our CLD dynamics into a stock and flow model composed of four main components: stocks, flows, converters, and connectors (see Figure 16). The following definitions were regenerated from Dynamic Modeling text book. (Hannon and Ruth, 2012)
In general terms the facility condition is our primary stock. Deterioration causes a state change in our facility condition with respect to time, in this case draining the stock and thus worsening the condition. Upgrades and repairs cause a state change by adding to the stock or improving the condition. The equations below describe the basic calculations involved with stock and flow modeling.
The rate of state change in a stock variable is determined based on the difference between inflows and outflows:

$$\frac{d(stock)}{dt} = Inflow(t) - Outflow(t)$$

In our case the rate of change in facility condition will be proportional to the amount of upgrades subtracted by the amount of deterioration over time. The specific value of a stock variable at any time (t) over the simulation time can be determined by:

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)] ds + Stock(t_0)$$

Once fully developed our stock and flow model describes all system variables and behavior relationships (see Figure 17). The model distinguishes three functional areas: providing facility services, sustaining facility condition, and funding facility sustainment. Note, unlike the CLD our stock and flow model also includes Tier 1 and Tier 2 components and parameters. Conceptually it is an integrated problem moving toward equilibrium given limited time and resources. Based on current policies Tier 1 facilities receive the majority of F&E funding not leaving much for projects to be planned at Tier 2 and 3.

The results of the simulation will be compared with current FCI and DM regression model estimates. Expectations are our plot will indicate a nonlinear decline in Tier 3 facility condition over a time given deterioration is nonlinear. (Rashedi, 2016) The factors that go into driving modernization determine the steepness of the curve. In addition, we expect that the manipulation of parameters of the most dominate loop will allows us to reach equilibrium and thus the most optimum investment policies for long-term service sustainment. Shocks to the system in terms of adverse environmental conditions allow us to simulate the disruption and recovery of an operating facility, and how this disruption impacts airport services.
The following section describes simulation results obtained by executing the model shown above. For our simulation we used an estimate of $4 billion dollars as the replacement value for terminal facility infrastructures for Tier 3 federally staffed facilities. The model consisted of three
segments: facility condition, modernization funding, and services segment. Each segment was divided into three identical sub-segments to represent Tier 1, 2, and 3 facilities. This allowed for establishing a baseline for specific parameters prior to inserting estimates for key variables into our simulation. As discussed, expectations are given a positive loop for facility condition and deterioration FCI and DM results will be nonlinear in decay and growth. Also, given a negative loop effecting facility condition, repairs, modernization, and DM we should see funding move toward the center to balance the offsets of projects, outages, and maintenance actions between the facility types (Tiers), thus balancing resources and sustaining facilities at all levels. For are simulations Tier 1 facility parameters were not changed to simulate an outage or repair requirement.

4.4 Results

Age, level of service, frequency of outages, and number of maintenance projects is sufficient in estimating DM and FCI for facilities between 20 to 50 years of age. FCI is used as indicator that drives the need to increase sustainment funding. Given a failure or outage at a Tier 2 or 3 facility, in 100 simulations results showed an increase in Tier 2 or 3 spending offset by a decrease in Tier 1 spending. In our scenario, age, deterioration, and operations led to outages and an increase in required maintenance projects. The increase in projects increased DM. The increase in DM reduced FCI putting pressure on stakeholders to increase spending. Increase spending increased maintenance and repairs activities reducing DM and increasing FCI. Table 5 provides a comparison with FAA FCA and regression model estimates. From the aspect of current policies and process, it is evident that when an assessment of a facility can be conducted an accurate and decision relevant FCI is attained. South Florida International Airport, serving the Fort Myers community, has a Tower facility 35 years old and an FCI based on FCA of 90.4, meaning the
facility is in fair condition. Our model provided an estimate of 88.7 which identifies the condition as poor. Here there is a 2% error with our method. Consider Sarasota International Airport’s 30 year old Tower facility which has not had a FCA. An FCI of 90.5 (fair) was given based on a linear regression estimate. Our model estimate was 85.8 (poor). A critique of the age-based regression model is its lack of consideration for the physical changes involved with environment. (i.e., deterioration and outages will differ from lax to harsh environments)

Table 5 – Selected gulf coast airports system dynamic model results - The APM score is based on asset criticality index, weighted FCI, and maintenance score. For FY16 APM used a 130-point scale. Note: The higher the APM score the higher the priority, whereas for FCI the lower the FCI the higher the need for upgrade and repair.

<table>
<thead>
<tr>
<th>Airport</th>
<th>CY 16 Explanements</th>
<th>Hub (Large, Medium, Small, None-hub)</th>
<th>Facility Type</th>
<th>Tier</th>
<th>AGE</th>
<th>FIP APM Value</th>
<th>FCI Regress. Est.</th>
<th>FCI Sys. Dynamics Ext.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austin Int (AUS)</td>
<td>6,095,545</td>
<td>M</td>
<td>Combine TRACON &amp; Tower</td>
<td>2</td>
<td>19</td>
<td>96.9</td>
<td>95.7</td>
<td>92.7</td>
</tr>
<tr>
<td>Corpus Christi Int. (CRP)</td>
<td>325,815</td>
<td>N</td>
<td>Combine TRACON &amp; Tower</td>
<td>3</td>
<td>15</td>
<td>81.8</td>
<td>98.39</td>
<td>94.8</td>
</tr>
<tr>
<td>Daytona Beach Int (DAB)</td>
<td>342,495</td>
<td>N</td>
<td>Combine TRACON &amp; Tower</td>
<td>2</td>
<td>31</td>
<td>124.8</td>
<td>89.75</td>
<td>94.8</td>
</tr>
<tr>
<td>Ft Lauderdale Int (FLL)</td>
<td>14,263,270</td>
<td>L</td>
<td>Tower with Radar</td>
<td>1</td>
<td>34</td>
<td>116.3</td>
<td>94.72</td>
<td>93.3</td>
</tr>
<tr>
<td>Gulfport -Biloxi Int. (GPT)</td>
<td>305,157</td>
<td>N</td>
<td>Combine TRACON &amp; Tower</td>
<td>3</td>
<td>5</td>
<td>77.7</td>
<td>100</td>
<td>96.6</td>
</tr>
<tr>
<td>Houston Intcont. (IAH)</td>
<td>20,062,072</td>
<td>L</td>
<td>Tower with Radar</td>
<td>1</td>
<td>20</td>
<td>98.3</td>
<td>95.37</td>
<td>93.3</td>
</tr>
<tr>
<td>Miami Int (MIA)</td>
<td>20,896,813</td>
<td>L</td>
<td>Combine TRACON &amp; Tower</td>
<td>1</td>
<td>15</td>
<td>119.3</td>
<td>94.5</td>
<td>93.3</td>
</tr>
<tr>
<td>Mobile Regional (MOB)</td>
<td>288,209</td>
<td>N</td>
<td>Combine TRACON &amp; Tower</td>
<td>3</td>
<td>28</td>
<td>108.6</td>
<td>93.85</td>
<td>83.8</td>
</tr>
<tr>
<td>New Orleans Int (MSY)</td>
<td>5,569,709</td>
<td>M</td>
<td>Combine TRACON &amp; Tower</td>
<td>3</td>
<td>22</td>
<td>93.3</td>
<td>95.85</td>
<td>89.2</td>
</tr>
<tr>
<td>Orlando Int (MCO)</td>
<td>20,283,541</td>
<td>L</td>
<td>Tower with Radar</td>
<td>1</td>
<td>15</td>
<td>88.6</td>
<td>97.98</td>
<td>94.7</td>
</tr>
<tr>
<td>Pensacola Int. (PNS)</td>
<td>792,916</td>
<td>S</td>
<td>Tower with Radar</td>
<td>3</td>
<td>22</td>
<td>102.7</td>
<td>93.38</td>
<td>87.3</td>
</tr>
<tr>
<td>Sarasota Int (SAR)</td>
<td>589,880</td>
<td>S</td>
<td>Tower with Radar</td>
<td>3</td>
<td>30</td>
<td>102.2</td>
<td>90.5</td>
<td>83.8</td>
</tr>
<tr>
<td>South Florida Int (RSW)</td>
<td>4,239,261</td>
<td>M</td>
<td>Combine TRACON &amp; Tower</td>
<td>2</td>
<td>35</td>
<td>114.3</td>
<td>90.44</td>
<td>83.1</td>
</tr>
<tr>
<td>Tallahassee Int (TLH)</td>
<td>345,404</td>
<td>N</td>
<td>Combine TRACON &amp; Tower</td>
<td>3</td>
<td>21</td>
<td>87.1</td>
<td>96.29</td>
<td>89.8</td>
</tr>
</tbody>
</table>

Therefore, executives considering decisions concerning Tier 2-3 facilities which have no FCA may benefit from having even a minimal survey done to ascertain the condition rather than using the regression number. This approach drives the process/system to equilibrium, meaning sustainment funding is allocated to the need (see Figure 18). There is lag in the process varying between 1-2 years based on available funding. In scenario’s where we limited available F&E and
Ops funding for the 30 year timeframe, sustainment was moving toward equilibrium but did not reach it. Also, a simulated increased in weather induced deterioration and outages without a proportional increase in spending proved unsuccessful in the system reaching equilibrium. Thus, the uncertainty of climate conditions should be a driver of change for how the FAA services certain assets and asset locations. We used HVAC and Chiller data for our study due to the higher number of maintenance issues the FAA has experienced with them in recent years. (FAA, 2017) As the facility infrastructure ages those services relying on mechanical systems tend to be at higher risks of outage and failure. With this in mind, future facility modernization or replacement policy must consider changing environments and more frequent and higher intensity weather.

Figure 18 – FCI Comparison - Depending on the degree of deterioration, amount of deferred maintenance, or outages, FCI provides a reliable driver for allocation of funding resources. On the top right as expected FCI is most sensitive to deferred maintenance and bottom right FLOS to outage duration.
4.5 Conclusion

This research applied an innovative approach to identify and reduce barriers to modernization and sustainment funding for medium to non-hub airport facility infrastructure. The ability to manipulate parameters in our model enabled configuration of realistic relationships between variables for behavior, impact and effect observation. Given that a worsening facility condition is amplifying deterioration it cannot be a linear function, thus a linear regression model to determine FCI is questionable. FCI is an effective measure for adapting investment policy. FCI produced from FCA data is the most accurate and effective allowing policy makers the opportunity to intervene in the process and make essential choices to sustain the system. Our findings indicate using system dynamics to derive an FCI estimate can also be effective. For aging Tier 2 and 3 infrastructure the policy of using linear regression estimates for uninspected infrastructure is ineffective for meeting long-term modernization and sustainment requirements.

Without marginalizing Tier 2 and Tier 3 facilities policy makers should continue to focus modernization funding on direct-mission related facilities to ensure a high level of service. As part of this strategy policy makers must make funding available to recover from asset failures along with targeted allocations to reduce DM. Pulling funding from the Operations budget is not an efficient way of providing a reserve funding reservoir. Using available data funding should be assigned to specific facilities based on operation priorities. Figure 19 depicts a funding strategy distribution based on simulations. Here hub class ranges from 1 – 4 where a 1 equates to a large airport and a 4 to a non-hub small airport. For airports like Sarasota, FL and Mobile, AL, renovated facilities and infrastructure improves community resilience and encourages economic growth. Although communities will still be susceptible to several hazards, increasing economic growth reduces social vulnerabilities. Translating this work into a practical application requires
further decomposition of the facility infrastructure where specific facility assets to the large component level are assigned a FCI. The manpower to perform these tasks however may prove to be not cost-effective.

A final thought, during the second term of the Obama Administration congressional policy makers expressed their proposal to transition the functions of the FAA to a private organization. Although there was much resistance within the Administration, lawmakers produced examples of successful private entities that took over government functions. At issue is the objective of on non-public organization managing ATC operations which are profitable at large and medium size airports but not at small. Those airports and facilities may not survive due to operations tempo or obsolescence. As the U.S. armed forces closed and abandoned bases in the 1990’s to save cost, the FAA could go the same way. In their case however, the DOT’s mission would be compromised by not serving and making accessible convenient transportation.

4.6 Acknowledgements
This research was performed at Northeastern University’s Sustainability Data Science Laboratory (SDS Lab). KLC acknowledge his affiliation with the VOLPE - The National Transportation Systems Center. The authors thank Professor Stephen Flynn, Director of Northeastern University’s Center for Resilience Studies; Volpe Center’s Steve Bransfield and John Hadley. This research was funded by Volpe Fellow’s Program and Northeastern University (for KLC).

4.7 Addendum to the submitted paper
Increasing resiliency by developing new adaptive policies based on system dynamics provides a mitigation against physical, functional, and economic hazards. In 2017, cumulative deferred maintenance for Tier-1 facilities was $208 million, for Tier-2 $120 million, and for Tier-3/4
combined $298 million. Based on our simulated results Figure 19 depicts a funding distribution for Tier1-4 driven by FCI. Note, the lighter the color the higher the funding amount.

*Figure 19 – Funding strategy distribution based on simulation and percent increase in FCI. Note, Hub Class (HC) 1 refers to a Tier 1 facility serving core and larger airports, HC 2 refers to Tier 2 facilities serving smaller hubs airports. HC 3 & 4 refers to Tier 3 and 4 facilities serving smaller non-hub airports.*
5 Chapter 5 A Time Series Analysis of the Impact of Extreme Winter Weather on Airport Operations

Excerpts from this chapter were submitted and published in Bhatia et al, Climate Hazards and Critical Infrastructure Resilience, Encyclopedia of GIS 2015 and reproduced doi: 10.1007/978-3-319-23519-6_1634-1.

5.1 Summary

FlightAware\(^5\) reported that 1,200 flights were expected to be cancelled on January 26, 2015, to reduce air traffic volume in the Northeast prior to a forecasted heavy winter storm. Delta airlines pre-emptively cancelled 600 flights; furthermore, a dozen flights from London Heathrow to New York, Philadelphia and Boston were cancelled on the same date. These are just a few of the steps commercial airlines, the Federal Aviation Administration (FAA), State Officials, and Airport Authorities took in preparation for the January 27, 2015, blizzard, designated “Juno” by the National Weather Service (NWS). Across New England contingency plans were implemented to sustain critical functions and return air transportation to normal operations as soon as possible. The impact of the storm was felt locally and nationally. This study addresses air traffic delays, diversions, and flight cancellations caused by extreme winter weather events and system recovery. An airport that is better prepared to respond to weather hazards operates more efficiently for passengers and airlines, and can avoid significant negative impact to the NAS as a whole. It has been hypothesized reducing flight operations and taking systems “offline” prior to extreme weather reduces uncertainty and improves response and recovery to nominal conditions. This

\(^5\) FlightAware is a global aviation software and data services company. Based in Houston, it is best known for the flightaware.com web site, the first to offer free flight tracking of both private and commercial aircraft in the United States, Canada, Australia, and New Zealand. It is currently the largest flight tracking website in the world in terms of users.
investigation will use time series analysis as a method to give a basic evaluation of the performance of contingency planning for Juno at Boston Logan compared to previous blizzards.

5.1.1 Introduction

As of August 21, 2014, there were 507 commercial airports in the U.S. Six Five of the busiest are located in the Eastern Service Area (ESA) of the National Airspace System (NAS): Atlanta, New York’s JFK, Boston, Miami, and Washington DC. While a significant number are locally controlled, the airport system’s predictability and dependability are critical to the efficient operation of the NAS. Numerous studies have shown that convective weather in/around airports is a major cause of flight delays and a significant causal factor in aircraft accidents. In 2012, FlightStats.com issued a report stating that from October 27th to November 1st in North America alone, 20,254 flights were canceled due to Hurricane Sandy. Roughly 9,978 flights were canceled at New York area airports alone. United stands as the airline with the most cancellations by Sandy (2,149), followed by JetBlue (1,469), US Airways (1,454), Southwest (1,436), Delta (1,293) and American (759). In an examination of weather events over the past seven years, Sandy comes in second in terms of total number of cancelled flights, behind the North American Blizzard of February 2010 (22,441 flights), for which the Blizzard of January 2015, designated “Juno” is compared in this report. Airport system capacity directly relates to NAS capacity, and Juno adversely affected airports and air traffic in the system. (Bureau of Transportation Statistics, 2012) Literature is filled with various analytical processes and models for investigating weather phenomenon. A useful predictive analysis technique for identifying load points and stress on a system is time series analysis.

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6 U.S. Dept. of Transportation, Bureau of Transportation Statistics, Table 1-3, U.S. Airports
5.1.2 The Topic

The management of air traffic flow at an airport or in a given airspace is required to sustain safe, efficient, and effective guidance of aircraft. Safety implies aircraft separation and traffic flow without conflicts. Meeting these needs requires dividing controlled airspace into smaller segments based on air traffic intensity and complexity. En route airspace is made up of segments. Here aircraft are monitored and handed-off as they transit across sector boundaries. Within 40-50 miles of an airport, known as the Terminal airspace, arrival and departure of aircraft is managed. Airport Terminal airspace is the primary location where operational efficiency is measured. Balancing demand with available capacity is a key indication on how well the NAS is meeting requirements. (FAA, 2015) Statistical analysis of operations by means of time series can provide a clear visualization of trends, operational influences, diverse impacts, and forecasting of future series.

A time series is a sequence of data points, typically consisting of successive measurements made over a time interval. Time series analysis covers processes for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. For our study, time series analysis is a good methodology to determine response patterns in flight and service operations. Time series analysis supports depicting the impact of weather on local and national flight operations. (Nury, 2012) In addition this process supports development of Autoregressive Moving Average (ARMA) and AR Integrated MA (ARIMA) models to carry out short-term predictions of flight delays and the ripple effect on the NAS. (Folorunso, 2013) Long traffic delays typically involve cascading ground holds and flight cancellations. We assume that with enhanced information from predictive models a large number of delays could be avoided, mitigated and/or reduced. From this study data could also be used to support design of response plans and enhanced strategies for future storms.
5.1.3 Research Problem

Weather of all types can cause air traffic delays and frustration for customers. Weather delays occur due to uncertainty of future departure and landing capacity over a several hour interval. Using five years of FAA and NWS data a time series analysis was conducted to describe the impact of Juno on air traffic capacity at Boston Airport (BOS) and the ripple effect on Chicago International Airport (ORD) and Atlanta International Airport (ATL). Evidence from the literature indicates significant research has been conducted in the area of weather forecasting and predicting the impact on transportation infrastructures. There is a gap or lack of knowledge however, in research into impact of extreme weather on airport and NAS interdependencies and how miscalculations and bad decisions prior to and during the event ripple across the transportation infrastructure. This requires a better understanding of forecast processes, operations, traffic flow models, and better dissemination of traffic and weather information to controllers and decision support systems. An airport that is better prepared to respond to weather hazards operates more efficiently for passengers and airlines, and can avoid significant negative impact to the NAS as a whole. Nearly 35-years of aviation and air traffic control experience were utilized to collect, clean, and correlate data for this examination. Due to the scope of the study the number of locations, (ESA vs National), were limited to: Boston, New York (JFK), Buffalo, Chicago, Atlanta, and Washington, (National).

5.1.4 The Cost of Delays

The randomness of weather and its impact on air traffic require a significant amount of flexibility in planning for extreme weather events such as blizzards and hurricanes. (Brunetti, 2004) The NAS in general encounters a high frequency of delays caused by weather, but rare extreme weather events like Juno, which disrupted travel in all transportation modes was especially hazardous to air travel due to the effect on navigation, communication, and surveillance
capabilities along with creating reliability issues with facilities and systems. Delayed and
canceled flight cost the airlines billions of dollars per year. In 2013, the cost of aircraft block (taxi
plus airborne) time for U.S. passenger airlines was $76.22 per minute, 1.4 percent less than in
2012. Fuel costs decreased 6.0 percent to $36.36 per minute. Crew costs are estimated to have cost
$16.92 per minute, followed by maintenance and aircraft ownership ($11.94 and $8.29,
respectively) and all other costs ($2.72). Table 6 is regenerated airline operations data and lists
the breakdown of direct operating cost for airlines and cost of delays. Not described this paper is
the ripple (cascading) effect of the delays and corresponding influence on the logistics of moving
people in out of airports. Part of the ripple effect is the FAA losing tax revenue from unoccupied
boarding gates.7

Table 6-2013 Airline Operating Delay Cost.

<table>
<thead>
<tr>
<th>Calendar Year 2013</th>
<th>Direct Aircraft Operating Cost per Block Minute</th>
<th>Δ vs. 2012</th>
<th>2013 Delay Costs ($ millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel</td>
<td>$36.36</td>
<td>-6.0%</td>
<td>$3,847</td>
</tr>
<tr>
<td>Crew – Pilots/Flight Attendants</td>
<td>16.92</td>
<td>5.9%</td>
<td>1,790</td>
</tr>
<tr>
<td>Maintenance</td>
<td>11.94</td>
<td>0.2%</td>
<td>1,263</td>
</tr>
<tr>
<td>Aircraft Ownership</td>
<td>8.29</td>
<td>3.8%</td>
<td>877</td>
</tr>
<tr>
<td>Other</td>
<td>2.72</td>
<td>1.0%</td>
<td>287</td>
</tr>
<tr>
<td>Total Direct Operating Costs</td>
<td>$76.22</td>
<td>-1.4%</td>
<td>$8,064</td>
</tr>
</tbody>
</table>

7 1. Costs based on DOT Form 41 data for U.S. scheduled passenger airlines 2. Arrival delay minutes (Arr:00) reflect operations at 77 U.S.
airports as captured in the FAA ASPM database
As discussed, the most direct impact of severe weather is on commercial airline profits in the loss in customer sales as well as the increase in maintenance expenses. Recently policies and procedures adopted by FAA and airport managers aim to lessen the impact of severe weather on airport performance by pre-empting the severe weather by reducing arrival and departure volume, and taking non-critical systems off-line until the storm passes. It has been hypothesized that the drop in capacity will be moderate and the mean time to return to nominal operations will be reduce. To test this theory this study analyzed 72 months of flight data, facility data, and weather data, focusing on blizzards that impacted municipalities in the Eastern Service Area (ESA).

\[ H_0: u_0 = u_1, \]
\[ \text{executing contingency plans prior to forecasted event did not improve recovery} \]

\[ H_1: u_0 \neq u_1, \]
\[ \text{executing contingency plans prior to forecasted event did improve recovery} \]

Histograms of the different variables were taken to acquire an estimate of the probability density function. A summary of the data collected is depicted below Figure 18. As expected the flight operations data follows a rough estimated of the extreme value distribution. All other distributions appear to be exponential.
5.2 Data Set and Methodology

Time-series analysis methods are largely based on the assumption that historical patterns will continue, and they rely heavily on the availability of historical data. The Federal Aviation Administration’s (FAA) Operations Network (OPSNET) and Aviation Systems Performance Metric (ASPS) holds air traffic operations performance data for all domestic flights and international flights originating in the United States. For our analysis arrival and departure data was retrieved for BOS, BUF, and JFK. The blizzards of February 2010, “Snowicane” and January 2015, “Juno” were similar in that they both covered a large area of the Northeast.
The relationship between variables contributing to a disrupted flight operations, (weather, outages, etc...), can be expressed in terms of a liner combination, given random variables, $X_1, X_2, ..., X_p$, and constants $c_1, c_2, ..., c_p$,

\[ Y = c_1X_1 + c_2X_2 + ... + c_pX_p, \]

can be modeled for defining the characteristics in the process under study, without attempting to identify the nature of the relationships between the various relevant interacting variables. The dynamics of the physical systems can be expressed in terms of the differential equation of the form (4)

\[ (1 + c_1D + c_2D^2 + ...)Y = (1 + d_1D + d_2D^2 + ...)X \]

Where $Y$ is the output variable,

$X$ is the input variable,

$D$ is the differential operator, and the $c$’s and $d$’s are the constants.

Weather observations on one variable in time may be used to explain the variation in another series (flight and facility operations, etc,...) which help us understand the mechanisms that generated a given time series. For our study an Autoregressive Moving Average $(1,1)$ ARMA$(1,1)$ process was used for evaluation.

\[ X_t = \phi X_{t-1} + \varepsilon_t - \theta \varepsilon_{t-1} \]
Where $X_t = \phi X_{t-1}$ equals

- flight operations in the Eastern Service Area (ESA)
- and $\epsilon_t = $ municipalities effected by blizzards in the ESA

$Y_t = \phi Y_{t-1} + \epsilon_t - \theta \epsilon_{t-1}$

- Where $Y_t = \phi Y_{t-1}$ equals comm facility operations
- and $\epsilon_t = $ facilities effected by blizzards in the ESA

Data consisting of monthly flight operations, facility related delays, and municipalities hit by blizzards were evaluated as a time series. The time series are plotted in Figure 21 and 22 and depict the flight operations time series and trend line and 90% confidence interval. As expected, only the flight operations data depicted seasonality with a downward trend. Because of seasonality it was difficult to discern any immediate correlation between the blizzards and flight operations or facility related flight delays.

Figure 21 – Time series of flight operations
The difference plot in Figure 23 along with autocorrelation function and partial correlation function for the flight operations data is depicted Figure 24. Note taking one lag decays the function to approximately zero. For the time period examined flight operations are found to be a stationary process with a mean, variance, and autocorrelation structure not changing over time. The time series has a slight but clear downward trend which appears to be stochastic. Taking a first difference of the series to remove the trend,

$$\nabla X_t = X_t - X_{t-1} = (1 - B)X_t$$

Transformation of the series to a new time series where the values are the differences between consecutive values.
Figure 23 - Difference plot of time series

Figure 24 – Autocorrelation and partial correlation plots ESA Flight Operations
Differencing will often create negative correlation, if the time series first indicates high positive autocorrelation, then the non-seasonal difference will diminish the autocorrelation. As with the earlier plot the time series show significant seasonal pattern. In summer, the odds of high delay is much higher than in other seasons, while in fall the odds of high delay is much lower than in other seasons. Significant correlation with blizzard or equipment related delay data is not noted. Higher resolution hourly data is required and collected for Boston, Buffalo, New York City (JFK), airports. In addition, service interruption data (communication system) is collected and analyzed. The results of the analysis are discussed in the following section.

5.3 Results

For the three airports discussed, an analysis of the hourly data for both arrival and departure data indicated significant delays, diversions and cancelations during both blizzards, February 2010, and January 2015. Figure 25 (2010) and Figure 26 (2015) depicts Boston airport hourly flight departure data prior to, during, and after each blizzard. The blue line on the plots depict scheduled flights, the red line depicts actual flights. Note, forecast for both extreme weather events predicted snow accumulations greater than 6 inches. For the February 2010, blizzard event the drop in flight departures is significant but gradual and does not completely shut down flight operations. The interval between the drop in departures and return to normal flight operations is 47 hours. For the January 2015, blizzard event flight departures were canceled prior to the storm on the 27th. Boston’s flight operations returned to normal level 44 hours later. The snow total and duration of Juno was higher but the interval for recovery was similar. Although the total is higher the similarities in recovery may be based on decisions manager took to cancel flight operations.
Figure 25 – Boston airport hourly flight departure during blizzard 2010

Figure 26 - Boston airport hourly flight departure during blizzard 2015
From the statistics gathered the flight operation means for both time periods showed no significant difference. Table 7 depicts statistics for the hourly data. P-Value is significant, and the data is inconclusive both means lie inside a 95% confidence interval. Figure 27A depicts normalized scatter plot for arrival data and Figure 27B a normalized scatter plot for departure data. For the normal plot, both scatters approximately follow straight lines through the first and third quartiles of the samples, indicating approximate normal distributions. The 2010 sample (the right-hand line) shows a slight departure from normality in the lower tail. A slight shift in the mean from 2010 to 2015 is evident.

Table 7 – Statistical Data for Blizzards 2010 and 2015

<table>
<thead>
<tr>
<th>Blizzard - February 2010, BOS Departures/Hour</th>
<th>Blizzard - January 2015, BOS Departures/Hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Mean</td>
</tr>
<tr>
<td>16</td>
<td>14.20560748</td>
</tr>
<tr>
<td>Standard Error</td>
<td>Standard Error</td>
</tr>
<tr>
<td>1.213634184</td>
<td>1.346032547</td>
</tr>
<tr>
<td>Median</td>
<td>Median</td>
</tr>
<tr>
<td>15.5</td>
<td>10</td>
</tr>
<tr>
<td>Mode</td>
<td>Mode</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>12.95806716</td>
<td>13.92346893</td>
</tr>
<tr>
<td>Sample Variance</td>
<td>Sample Variance</td>
</tr>
<tr>
<td>167.9115044</td>
<td>193.8629871</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>Kurtosis</td>
</tr>
<tr>
<td>-1.100594524</td>
<td>-1.208469785</td>
</tr>
<tr>
<td>Skewness</td>
<td>Skewness</td>
</tr>
<tr>
<td>0.323457069</td>
<td>0.449295902</td>
</tr>
<tr>
<td>Range</td>
<td>Range</td>
</tr>
<tr>
<td>47</td>
<td>43</td>
</tr>
<tr>
<td>Minimum</td>
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Figure 27- A & B depict normalized arrival and departure data

Figure 27A

Figure 27B

Figure 28 depicts an ARIMA forecasts for 180 hour period for 95% confidence interval. Trial and error attempts to get a close depiction of expected flight operations were unsuccessful. A high order polynomial or trigonometric function was not attempted.

Figure 28 – ARIMA forecast
5.4 Conclusion
Weather is a significant factor in aircraft operations and blizzard Juno significantly impacted the NAS. The logical output $h = 1$ indicates a rejection of the null hypothesis at the default significance level of 5%. The time series plot show a significant delay in a return to normal flight levels following Juno, the exact opposite of what was hypothesized. There was no correlation between the storms and the number communication service outages. As shown in figure 6b, outages were random with no pattern of seasonality. Not considered was the change in policies and attitudes for taking bold approaches to increase safety and protect property. Decision makers are sensitive to being labeled as “slow to take action”, thus the quick decision to cancel flight operations on January 27th. An area that was not covered in this study deals with the impact of blizzards on airports outside the affected area. Ripple events from the storm could be felt nationally. For example, delays in the effected airport caused delays and grounds holds airports waiting on aircraft or pilots. There are other impacts also, the National Basketball Association postponing two games scheduled to take place on January 26, both in New York City. In the future the cascading impacts of the blizzard will be considered in the study.
CHAPTER 6 – CONCLUSION, DISCUSSION, AND FUTURE WORK

This chapter summarizes the dissertation, discusses its results and contributions, points out limitations of the current work, and also outlines directions for future research. This research addressed mitigating risk by quantifying infrastructure resilience. Innovative methods applied to the aviation transportation sector analyzed and demonstrated to be effective model for understanding the state of critical functionality and physical condition. However, integrated and multi-faceted analysis research deserve further consideration. The chapter is divided into three sections:

- Section 6.1 is a summary of the dissertation;
- Section 6.2 presents a discussion of the contribution and limitations of the current work;
- Section 6.3 discusses the future work;
- Section 6.4 brings the dissertation to a conclusion.

6.1 Summary of the Dissertation

This research describes the resiliency of a transportation infrastructure sector as a complex network and system of system through unique and innovative robustness and fragility characterization methods. Based on the application of the methods the state of critical functionality can be determined and recovery strategies applied. The long term goal of this research is to develop a quantifiable and understandable measures for the NAS airport network and its facility infrastructure. The development of network and system dynamic analysis methods as defined herein was the process of identifying, classifying, modeling, and resolving interdependencies and constraints.
Understanding infrastructure interdependencies and operational relationships is key to reducing uncertainty and improving critical infrastructure resiliency. This study used a quantitative assessment to characterize the impact of extreme weather on the aviation sector based on network science analysis. Although not new, research has shown that centrality metrics are more than adequate indicator of infrastructure robustness and fragility. This research, simulated the fragmentation and recovery of the airport network, and provided a visualization of the complexities of the infrastructure, and given an event, which airports are key to quick and sustained recovery. It is these locations national and state policy makers should invest in for future infrastructure improvement and to ensure adequate resources are allocated annually.

6.2 Contribution and limitations of the current work

Demand and capacity imbalances impact almost all infrastructure sectors. Characterizing complex relationships and interdependencies supports development of performance indicators across the transportation modes. Do we need metrics and progressive quantification methods? Yes, if you cannot measure it you cannot improve it. Answering the relationship question between airport availability/traffic flow performance indicators and disruptive events allows us to better define processes and/or identify priorities for quicker recovery. Note, this research focused on the physical infrastructure and the analytical methods in our framework development, but it is understood air traffic control service and pilots play a role in the equation. Without ATC and pilots working together disruptive situations can become hazardous leading to potential disasters. Also, there is always a trade-off between capacity and resilience. For an airport that schedules to a level near to or at its capacity, the level of resilience is going to be lower than an airport the plans in a measure of spare capacity or breathing room.
Unlike other researchers we developed quantitative methods for the U.S National Airspace System (NAS) that include all operating airports commercial, military, and general aviation. In addition we described an approach for characterizing the NAS state of critical functionality, showing empirical result defining NAS Critical functionality based on degradation of airport and/or ATC facilities. The enhancement of facility infrastructure condition assessment through system dynamics analysis utilizes causal relationships in determination of behavior response. This approach performed better than linear regression models for determining FCI. NAS Dynamic models, from a system perspective allowed us to apply realistic scenarios for generation of quantitative results.

6.3 Future Work

The implementation of NextGen technology such as satellite-based navigation, data communications, voice over IP, and intelligent decision-aiding will allow consolidation of resources and improve efficiency. In addition, new applications of bi-directional remote monitoring of systems provide constant vigilance on technical performance. In 2020, we will see the mandatory requirement for all aircraft to equip with Automated Dependent Surveillance-Broadcast (ADS-B) in order to fly in most controlled airspace. This transformation will enable real-time precision, shared situational awareness, and advanced applications for pilots, controllers, airlines, and airports. Note, these four groups represent the key positions responsible for managing the airport and system wide flow of air traffic. A decision made at any of these positions usually results in a change in the NAS. As the future will reveal these new technologies can compensate for human vulnerabilities, but also create unknown risk due to misperceived relationships between system components. Figure 29 depicts the interdependencies of these relationships in regards to NextGen. Future analysis methods must be multi-level and multi-faceted to quantifiable
characterize the state of critical functionality of the NAS in the future, given a disruptive event. Recovery based on centrality metrics may not be the best strategy as more virtual and autonomous systems are introduced to the NAS. Based on recent history there is compelling data that indicate a shock could exceed the ability of automation causing disruption to complex interactions across domains and loss of system critical functionality.

*Figure 29 NextGen Integration Framework by Phase of Flight*

6.4 Conclusion

There are thousands of airports providing passenger, military and cargo service across the United States (U.S.). Within this group are primary hub airports and we have shown a disruptive
events like extreme weather can shutdown them down or hampered operations for a significant majority. The loss of operational efficiency and capacity can rippled across the country affecting smaller non-hub airports. The common impact theme of these events to aviation infrastructure was the temporary loss of airport functionality. Several investigations have analyzed air traffic operations and correlated flow reductions and delay patterns based on weather, however, there is scarce number that have applied quantitative methods to measure loss of functionality and robustness to the event. This research has shown it is not the magnitude of the stressor, in this case extreme weather that matters in evaluating airport robustness and recovery but the relationships or interdependencies of the component in the network as it is impacted. Thus the magnitude of the event may not correlate to a ripple impact nationally or the fragility of the network. Applying network science based analysis has shown significant benefit for identifying the most essential infrastructure components in a system or network, the infrastructure or network’s ability to absorb shocks, and which strategies are best suited to quicken recovery.
REFERENCES


Available at: www.faa.gov


Available at: https://www.bts.gov/topics/airlines-and-airports
[Accessed Tuesday February 2015].

Available at: https://www.bts.gov
[Accessed 1 December 2017].


Dennis, M., 2016. *Another 100 Year Storm*, Amsterdam: ACADIS.


[Accessed 19 February 2015].

Available at: www.faa.gov/about/office_org/headquarters_offices/ato/service_units/terminal/


Available at: https://www.faa.gov/data_research/
[Accessed 1 12 2017].


Xiao H. and Yeh, E. M. “Cascading Link Failure in the Power Grid: A Percolation-Based Analysis,” in *2011 IEEE International Conference on Communications Workshops (ICC)*, 2011, pp. 1–6.


### Core Airports

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