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Resilience of the US National Airspace System Airport Network

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***Abstract*— 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 U.S. 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.**

***Index Terms*— U.S. national airspace, robustness, recovery, hazards resilience, network science**

I. Introduction

MULTI-MODAL transportation systems are part of the critical infrastructure which serve an important role in ensuring essential societal functions [1], [2]. 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 [3]. As highlighted in the correspondence piece [4, 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" [5]. 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 [6]. 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

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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 [7], and identify useful measures for recovery prioritization [8]. A time series analysis is used to depict the cascading impact of an event and its far reach from region of origin.

A. Literature Review

Researchers have used complex network description to understand the topological characteristics of air transportation systems [9], [10], making network science as a tool of choice to describe resilience of the NASAN. Houssain *et al.* [11] (2013) presented research based on network analysis of Australian airport network (AAN). 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 *et al.* [12] (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). 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. [12] 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.

Fleurquin *et al.* [13] (2013) analyzed the delay propagation in U.S. airport network as a consequence of technical, operational or meteorological issues. 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 [14]. However, as noted in [8], 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.* [14] (2010) evaluated the relationship between network attributes and robustness and introduced network rewiring scheme to boost resilience to different levels of perturbation. 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 [15]. While researchers have proposed the qualitative description of resilience centric framework with risk as a central component [3], and formulation of various models to quantify resilience [7], [16], we argue that comprehensive description of resilience for infrastructure systems require understanding of underlying dynamics and operational characteristics [17]. 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.

B. 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 [18]. A daily time series comparison of flight operation for 8 major hubs around the U.S. during both these events is presented in Figure 1, for the snow event, note the dip in operations in January for New York and how it cascades to Atlanta and Chicago airports. From observation, the amplitude and frequency of the event drive

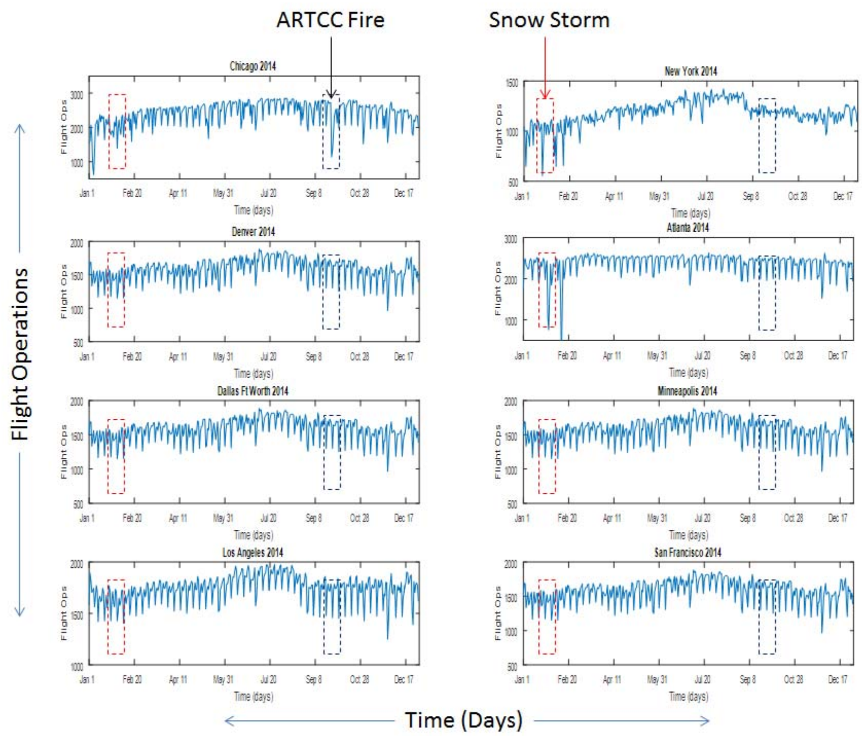

Fig. 1. Time Series of 2014 Flight operations at selected hub airports are shown. Flight operations, defined as aircraft arrivals and departures, are shown along Y-axis. The red box for New York's JFK airport (Row 4, Column 1) signifies a major snow storm that struck the airport in January. There is a significant reduction in number of flight operations. Although the storm strikes New York's JFK, we see a sub sequential drop in flight operation during the same time period at Atlanta and Chicago.

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 [19]. 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 [20]. 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 [9], [15], 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.

C. Methodology and Datasets

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 [21], 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 [7], [9], [10], [14], [15], 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

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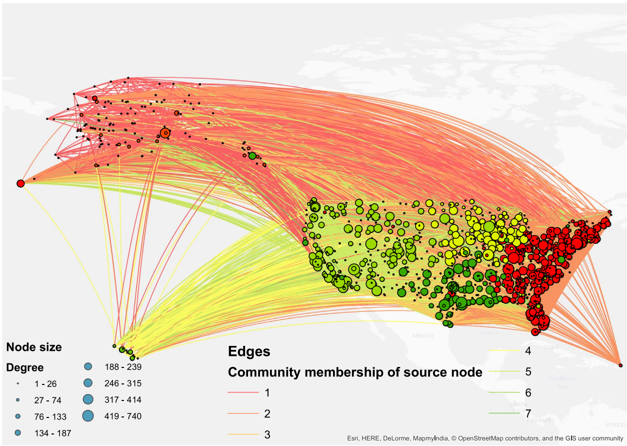

Fig. 2. Complex network visualization of The United State National Airspace System Airport Network (USNASAN)Connectivity map of USNASAN for year 2014. 7 largest communities, identified through modularity based Louvain algorithm, each of which map to a color, capture about 95% of the airports. Communities are clustered together geographically with the community members with high betweenness centrality maintaining connections with the nodes of other communities.

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 [22] . 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.

2) Airport Network Topology: Figure 2 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 :

$$P\left(k > K\right) = 1 - \sum\nolimits_{k=k_{min}}^{K} p\left(k\right) \tag{1}$$

here $p(k)$ 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

$$k_i = \sum_{j=1}^{n} a_{ij} \tag{2}$$

Where a_{ij} is the element of adjacency matrix, $\mathbf{A}$, 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 $<k>$:

$$< k_i >= \frac{1}{n}\sum_{i=1}^{n} k_i \tag{3}$$

The weighted counterpart of degree is strength, here indicated by the traffic volume between two connected airports. It is represented as:

$$S_i = \sum_{j=1}^{n} a_{ij}\, w_{ij} \tag{4}$$

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

a) 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 [23]. Several centrality measures are available but relevant for our purposes are *closeness, betweenness*, and *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

$$c_{CL}\left(i\right) = \frac{1}{\sum\limits_{j\in V}^{n} dist\left(i,j\right)} \tag{5}$$

where *dist(i,j)* is the network distance between the airports j, 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

$$c_B\left(i\right) = \sum_{s\neq t\neq i\in V}^{n} \frac{\sigma\left(s,t|i\right)}{\sigma\left(s,t\right)} \tag{6}$$

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. Park *et al.* [17] defined this centrality measure of the form of:

$$c_{Ei}(j) = \alpha \sum_{\{i,j\}\epsilon E}^{n} c_{Ei}(i) \tag{7}$$

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 [24], [25]. 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 [9], [14], [25].

To understand the patterns in connectivity, we use the modularity based Louvain community detection [26]. Throughout the manuscript, "communities" and "modules" are used interchangeably.

b) 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 [27], [28]. We apply the network regrowth model proposed in [8], 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 [29]. 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 [30] and railroad systems [8] is also evident in the present case (Figure 3), which happens to be a consequence of the recovery model. Recovery after disruption is done in the following steps:

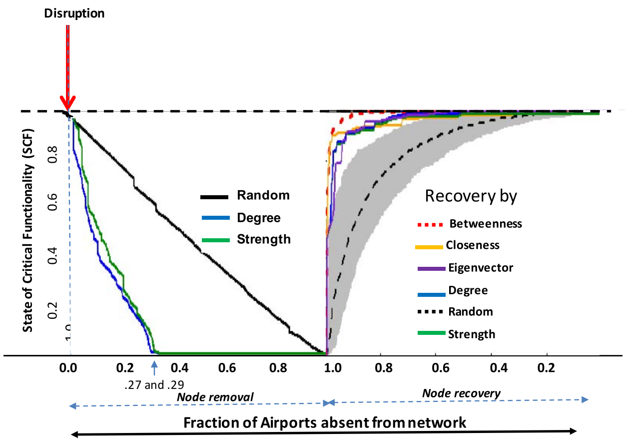

Fig. 3. Average nearest neighbor Degree and Degree Distribution (Left) Robustness of United States National Airspace System Airport Network in response to targeted disruptions in order of decreasing degree (# connections) and strength (traffic volume). State of Critical Functionality (SCF) is measured 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.

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 hosts 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.

II. Results

A. 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 3 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 [27], influence maximization approach and non-greedy algorithms [31]. 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 3 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 3 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.

We evaluate three categories of recovery strategies. To begin, a baseline of 1000 random ensemble sequences is established for comparison. We note that while total of N! recovery sequences are possible. However, we consider 1000 ensembles as a baseline as generating N! sequences is time and computational cost prohibitive. Moreover, the results from random recovery are used as baseline to compare performance of various strategical restoration against each other. Hence, increasing size of random recovery ensembles would not change key insights of the experiments. The next strategy is founded on airport profiles and characteristics

TABLE I

Top 20 Airports by Degree, Strength, Closeness, and Betweenness

	Degree		Strength		Closeness		Betweenness	
Rank	Comm, GA, & Mil.	Commercial	Comm, GA, & Mil.	Commercial	Comm, GA, & Mil.	Commercial	Comm, GA, & Mil.	Commercial
1	Teterboro	Chicago Midway Intl	Atlanta Intl	Hartsfield Jackson Atlanta Intl	Teterboro	Chicago Midway Intl	Teterboro	Ted Stevens Anchorage Intl
2	Van Nuys	Eppley Afld	Chicago Ohare Intl	Chicago Ohare Intl	Van Nuys	Eppley Afld	Ted Stevens Anchorage Intl	Phoenix Sky Harbor Intl
3	Dallas Love Fld	Dallas Love Fld	Dallas Fort Worth Intl	Dallas Fort Worth Intl	Chicago Midway Intl	Dallas Love Fld	Van Nuys	Eppley Afld
4	Chicago Midway Intl	Minneapolis St Paul Intl	Denver Intl	Denver Intl	Dallas Love Fld	Mc Carran Intl	Dallas Love Fld	Salt Lake City Intl
5	Washington Dulles Intl	Mc Carran Intl	Charlotte Douglas Intl	Los Angeles Intl	Washington Dulles Intl	Minneapolis St Paul Intl	Houston George Bush	Wichita Mid Continent
6	Westchester Co	William P Hobby	Los Angeles Intl	Charlotte Douglas Intl	Westchester Co	Wichita Mid Continent	Westchester Co	Dallas Love Fld
7	Mc Carran Intl	Wichita Mid Continent	Houston George Bush	Detroit Metro Wayne Co	Nashville Intl	William P Hobby	Chicago Midway Intl	Jackson Hole Airport
8	Nashville Intl	Washington Dulles Intl	Phoenix Sky Harbor Intl	Phoenix Sky Harbor Intl	Mc Carran Intl	Washington Dulles Intl	Mc Carran Intl	William P Hobby
9	William P Hobby	Westchester Co	Detroit Metro Wayne Co	Philadelphia Intl	William P Hobby	Westchester Co	Washington Dulles Intl	Chicago Midway Intl
10	Omaha, Eppley Airport	Tulsa Intl	Philadelphia Intl	George Bush Intercontinental	Eppley Afld	Tulsa Intl	Gary Chicago Intl	Fairbanks Intl
11	Minneapolis St Paul	Salt Lake City Intl	Minneapolis St Paul	Minneapolis St Paul Intl	Minneapolis St Paul	Salt Lake City Intl	Salt Lake City Intl	Youngstown Warren Rgnl
12	San Antonio Intl	Nashville Intl	Mc Carran Intl	San Francisco Intl	Austin Bergstrom Intl	Nashville Intl	William P Hobby	Westchester Co
13	Austin Bergstrom Intl	Indianapolis Intl	San Francisco Intl	Mc Carran Intl	Louisville Intl	Indianapolis Intl	Nashville Intl	Mc Carran Intl
14	Louisville Intl	San Antonio Intl	La Guardia	La Guardia	Indianapolis Intl	Austin Bergstrom Intl	Minneapolis St Paul Intl	Minneapolis St Paul Intl
15	Indianapolis Intl	Des Moines Intl	Newark Liberty Intl	Newark Liberty Intl	Memphis Intl	Lincoln	Charlotte Douglas Intl	Los Angeles Intl
16	Charlotte Douglas Intl	Austin Bergstrom Intl	Boston Logan Intl	Ronald Reagan Washington Natl	Charlotte Douglas Intl	Des Moines Intl	Atlanta Intl	Chicago Ohare Intl
17	Memphis Intl	Louisville International Airport	Seattle Tacoma Intl	Seattle Tacoma Intl	Raleigh Durham Intl	Louisville International Airport	Palm Beach Intl	Seattle Tacoma Intl
18	Palm Beach Intl	General Mitchell Intl	Reagan Washington Natl	Orlando Intl	Lambert St Louis Intl	General Mitchell Intl	San Antonio Intl	Norman Y Mineta San Jose Intl
19	Raleigh Durham Intl	Lincoln	Salt Lake City Intl	General Edward Lawrence Logan Intl	Palm Beach Intl	Chicago Ohare Intl	Raleigh Durham Intl	San Francisco Intl
20	Lambert St Louis Intl	Chicago Ohare Intl	Orlando Intl	Washington Dulles Intl	Salt Lake City Intl	George Bush Intercontinental	Lambert St Louis Intl	Panama City-NW Florida Bea.

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. Table 1 summarizes the rank of airport facilities according to multiple strategies considered in this study.

B. Topological Sensitivities

Delineation of hubs and their connectivity characteristics is crucial to understand resilience of infrastructure systems [32]. Figure 4A 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 [33].

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 4B 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

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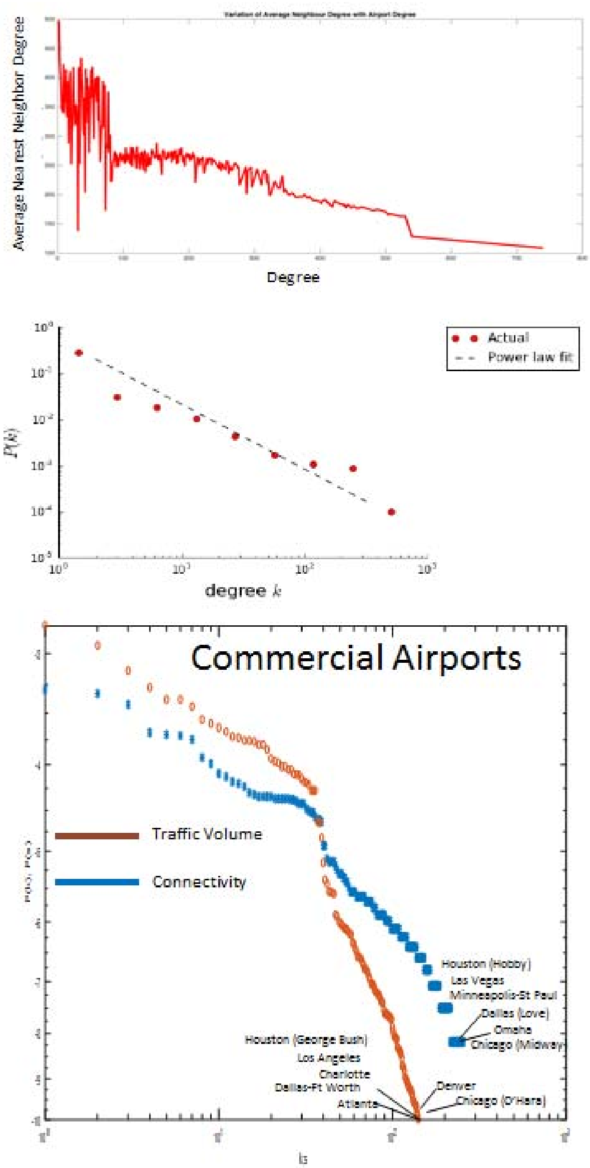

Fig. 4. Average nearest neighbor Degree and Degree Distribution (A) Average nearest neighbor degree exhibits the negative trend with increase in degree with high variability for airports with less than degree of 100. Airports with degree greater than 300 have tendency to connect too many small airports giving rise to hub and spoke arrangement for these nodes. Nodes with degreeless 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.

distribution which signals a high level of heterogeneity in the network. It was a phenomenon also found in [34] and [35]. The Average degree <k> for our network is calculated to 75.32. Figure 4C 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

Since researchers in the past have hypothesized that network centrality measures such as Betweenness, Closeness and

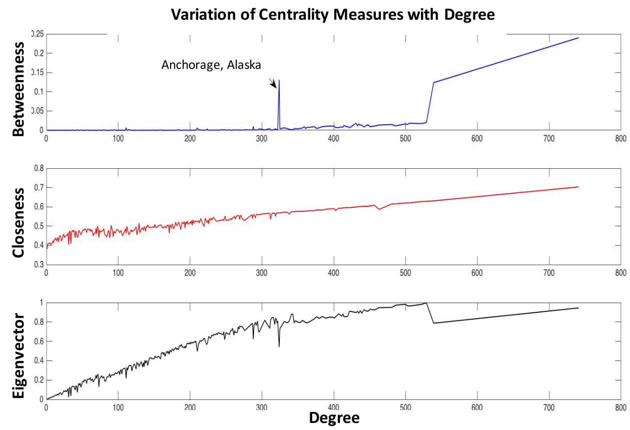

Fig. 5. Relationship between centrality measures and node degree shows that while degrees and centrality measures are strongly correlated, certain anomalies (such as Anchorage, Alaska exhibiting high betweenness centrality despite moderate degree) results in varying recovery rates under different strategies. 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.

Eigenvector centralities exhibit significant positive correlation with the degree centrality [36], 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 5). 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 preempting 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

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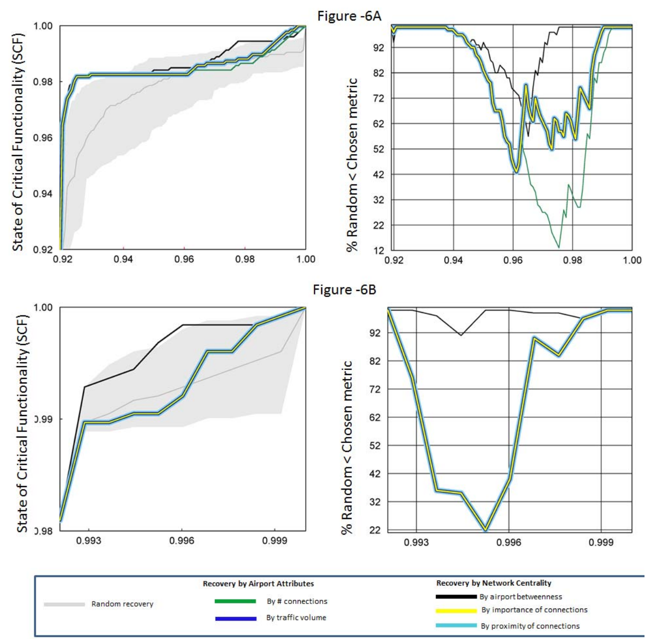

Fig. 6. **A.** (left) Similar to figure 3 but for partial loss of functionality due to simulate tsunami event along the western coast (right) at each recovery curve, the percentage of ensemble members that a given metric is larger than in terms of SCF is plotted. In some cases, recovery (and hence percentage lines) overlap with each other. This overlap is shown by thicker lines. **B.** Same as 6A but for cyber-physical attacks.

more aligned with economic markets and population centers [37].

C. 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 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 6A 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 6B 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.

III. Conclusion

A. 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 [8], the new adaptation to the US airspace system generates novel engineering and policy relevant insights, besides offering further evidence for the general applicability.

B. 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 [38].

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 and dynamic resource allocations [31].

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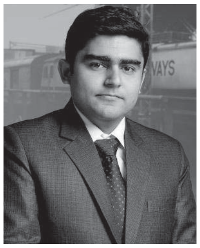

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