2023 IEEE/AIAA 42nd Digital Avionics Systems Conference (DASC), 1-5 October 2023, Barcelona, Spain
DOI:10.1109/DASC58513.2023.10311258

Analyzing Fragility of the Advanced Air Mobility System and Exploring Antifragile Networks

Arinc Tutku Altun
School of Aerospace, Transport and Manufacturing
Cranfield University
Bedford, UK
arinc.altun@cranfield.ac.uk

Yan Xu
School of Aerospace, Transport and Manufacturing
Cranfield University
Bedford, UK
yanxu@cranfield.ac.uk

Gokhan Inalhan
School of Aerospace, Transport and Manufacturing
Cranfield University
Bedford, UK
inalhan@cranfield.ac.uk

Michael W. Hardt
Airspace Operational Efficiency and Autonomous Operations
Boeing Research and Technology
Madrid, Spain
michael.w.hardt@boeing.com

***Abstract*—Future Advanced Air Mobility (AAM) is a concept that envisions to transform the current air transportation system into a more agile, flexible, and accessible system. Yet, the considered transformation and integrated system is not easy to achieve since it involves providing a high level of safety as well as efficiency. For that purpose, in this paper, we explored the fragility and antifragility concepts to analyze the AAM traffic network and provide an understanding of a system where it can benefit even under adverse conditions such as contingency events. For the analysis, first, a complex AAM traffic network is built via various AAM vehicles and possible vertiport locations that are analyzed for the Northern California area. After that, the AAM network is modeled via queue theory to simulate the considered flight plans, obtain the actual departure and arrival times under different conditions, and observe the delay propagation. Then, metrics from network theory based on targeted node and edge removals are studied to analyze the fragility of the AAM network and used for antifragility analysis. The methodology is used to analyze different disruptive cases over an AAM network such that disruptions at vertiports and over origin-destination pairs. Finally, an analysis of making the considered traffic antifragile through flight cancellations and its trade-off based on flight cancellation costs is provided.**

***Index Terms*—AAM, fragility, antifragility, network modeling, network analysis**

I. Introduction

Future Advanced Air Mobility (AAM) is an emerging concept for air transportation which is expected to revolutionize the current air transportation system by providing air taxi and cargo operations to urban, sub-urban, and rural areas. Besides extending air transport operations to places that are not served before, the considered transformation will bring accessibility, flexibility, and resiliency to the current system. Yet, there are still various aspects to consider such as infrastructure, technology, safety, efficiency, scalability, and so forth, for integrating AAM into everyday life. Various industry leaders discuss how the future of air transportation should be by considering those aspects and came up with various concepts of operations to create a roadmap for realizing the AAM system [1]–[5].

The expected complexity of the traffic with AAM is another issue since it is expected to be very high once the concept is mature enough. For fully achieving and showcasing the aforementioned aspects, the traffic environment has to be built for both accommodating complexity and providing harmony in operations. Apart from that, the traffic network has to be built and managed in a way that it gets less affected by disruptions/contingencies or not affected at all for the sake of safety and efficiency. Therefore, developing a reliable and effective air traffic network and management system for AAM is important and for building such a system, a proper analysis has to be conducted focusing on the weaknesses and potential of the traffic network.

Networks are the building blocks for ensuring systems that can withstand to failures at some extent [6]. There are many research efforts towards analyzing the networks with numerous metrics such that robustness and resiliency. In terms of robustness, most of the studies are defining that metric through the size of the largest connected component (LCC) of a network. Network robustness is analyzed with the LCC size over various optimized networks through different types of link attacks where the number of network nodes and edges remains the same in [7]. In [8], a methodology that provides robustness to any type of network is elaborated. In this method, the robustness term is based on the LCC size of the network after targeted attacks and network efficiency is taken into account via the shortest path between nodes. There are some other approaches for quantifying the robustness of a network which are used especially in the air transportation domain. For example, in [9], extensive robustness analysis is conducted via targeted node (airport) attack strategies based on various network metrics and comparisons on the US and EU air traffic networks are given. Also, numerous robustness metrics and attacking strategies are compared and analyzed especially based on passenger's perspective via a worldwide airport network in [10]. From a resiliency perspective in air transportation, epidemic models are studied to model the delay propagation dynamics in [11] and the control strategy for providing a more resilient system through epidemic modeling is covered in [12].

Last but not least, fragility and antifragility concepts are defined and detailed in [13], [14], which will be the main focus of this paper. In [15], the fragility concept and tail risks are quantified and applied to bank stress testing and public debt cases in finance. The mathematical breakdown for the considered ideas is provided in [16]. These concepts are very important and useful to create synergies for building beyond resilient systems such that the system starts taking advantage of disruptive events at some point. Thus, antifragile systems can be extremely beneficial to build reliable and sustainable systems, especially in engineering problems [17].

In this study, we examine the ways to implement the fragility/antifragility concept from economics into the air transportation domain, especially for AAM and analyze the initially developed AAM traffic network via those metrics. For simulating the daily flight plans a queue network model is built and for analyzing the fragility/antifragility of the AAM network, some metrics from network theory are benefited. Finally, the network is analyzed for different cases such as disruption at a node or on an edge through those metrics and a method to make the considered network antifragile is explored.

II. Fragility and Antifragility of a Network

The fragility concept refers to the negative sensitivity of a system where the system suffers due to variability in the considered environment after a particular threshold. Antifragility, on the other hand, is a term for representing the positive sensitivity of a system where the system benefits from the variability [13], [16]. These concepts, especially antifragility, were introduced and used in economics to better analyze the sensitivity of a system under a disruption. Therefore, these concepts can be formally defined as below where the exposed payoff to an event is given with positive values.

Fragility can be represented with a convex payoff function which shows a negative sensitivity to rare events/disruptions. That negative sensitivity may even result in a complete failure in the considered system.

Antifragility shows a concave behaviour in terms of its impact where a positive sensitivity is observed after a rare event/disruption. Positive sensitivity refers to a gain in the considered system even under extreme conditions.

In financial markets, the price of an option gets more affected with less likely to happen disruptions that have a higher impact, in other words, ”Black Swan” type of events, compared to the cumulative effect of small disruptions occurring with high frequency [15]. Assuming that the frequency of those disruptive events can be modeled with a distribution, the tail parts matter the most rather than the mean part for analyzing the sensitivity of a system.

Those ideas resemble with the delay propagation dynamics in air transportation systems. Therefore, fragility and antifragility concepts can be utilized for analyzing the air traffic networks or even developing one which allows to have a reliable traffic system that may gain from disruptive events. That can play a crucial role especially to build a safe and efficient AAM environment which may require such an approach due to the expected complexity in the future.

III. Traffic Network Modeling and Analysis

In this section, the data that is generated for building a proper AAM traffic network by considering various types of AAM vehicles, is detailed. Moreover, we elaborated on the simulation environment which is built for simulating the generated flight plans and replicating the actual flight data.

A. Data Preparation

We created an AAM traffic network on a daily basis using a direct routing option meaning direct trajectories from the departure point to the arrival point. For generating detailed traffic and considering many aspects of the AAM, the traffic network creation is based on various parameters such as possible vertiport locations, demands, and capacities; vehicle types and their operational specifications; possible origin-destination (O/D) pairs, their frequencies, and possible departure times.

The vertiport network is built over the Northern California area following the research efforts in [18] which analyzes the historical transportation patterns to obtain the possible UTM demand trend. Therefore, 75 different vertiport locations are considered for Northern California.

For the AAM vehicles that are operating within the traffic network, three different types of passenger carrying vehicles are considered as Wisk Cora 5, Ehang 216, and Lilium Eagle. The specifications of those vehicles and used parameters are given in Table I [19]. For setting the feasible O/D pairs, the maximum range and flight time limitations for the vehicles are taken into account as a constraint.

TABLE I
Vehicle Specifications for the AAM Traffic

			
Vehicle Type	**Wisk Cora 5**	**Ehang 216**	**Lilium Eagle**
Configuration	Lift & Cruise	Multicopter	Vectored Thrust
Cruise (km/h)	177.03	99.78	299.34
Range (km)	99.78	35.41	299.34
Flight Time (min)	19	21	60
Opr. Altitude (m)	900	300	900
DOC/h ($)	439	638	341

Furthermore, current traffic data of commercial aviation is used to decide on the O/D pair frequencies and departure times within the AAM traffic network. The reason behind this approach is to create a logical basis for modeling the traffic flow between vertiports which represent the system nodes and obtaining the daily demand profiles at vertiports. When the departure times are set, complete trajectories are generated through vertical take-off and climb, cruise at operational altitude, and vertical landing phases for each individual flight.

An AAM traffic with 19795 flights over 75 vertiports is generated to analyze the fragility and antifragility of an AAM traffic network. Figure 1 represents the obtained daily traffic over Northern California for the analysis where the node size gives information on the vertiport demand and edge thickness refers to the number of daily flights for the considered O/D pair.

B. Queue Network Model

For modeling the AAM traffic network, there are several studies focusing on queuing network models to represent air

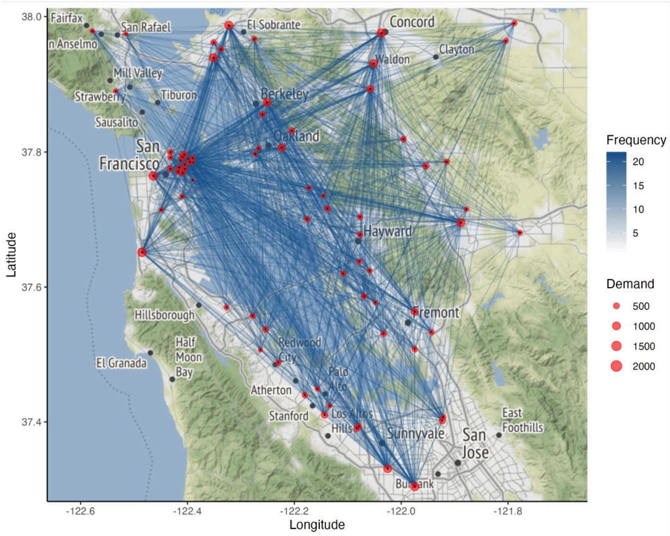

Fig. 1. Generated AAM traffic in Northern California.

traffic networks and analyze the delay propagation process [20]–[23]. Therefore, the AAM traffic network is built through the queue theory for simulating the generated flight plans and obtaining the actual departing and arriving times of the flights.

A queuing model is comprised of servers and customers and estimates the waiting times of customers to get service. Therefore, a queuing network model is built to simulate the flight plans that are generated and observe the actual departure and arrival times and delays. In the considered model, vertiports and AAM vehicles represent servers and customers, respectively.

The key parameters for such a model are service and inter-arrival times. Service time refers to the service duration at a vertiport which has a unique value for each vertiport and can include uncertainty. For this model, service times are defined as proportional to the demand expectation at each vertiport and the uncertainties in service times are modeled based on the deviation at corresponding airports scaled to the relevant vertiports. After obtaining the shape and scale parameters accordingly, the service time at each vertiport is modeled through Gamma distribution $\Gamma(k, \theta)$. The vertiports are managed via a first-come first-served policy. On the other hand, inter-arrival times are generated considering the flight duration between O/D pairs with a random uncertainty added. The travel duration between vertiports is not based on a specific distribution, thus they are named as general distribution which refers to any type of distribution. Finally, the queue network model built for an AAM traffic can be represented as $G(t)/\Gamma(t)/1$ where inter-arrival time is modeled with a generalized distribution $G(t)$, the service time is modeled with a Gamma distribution $\Gamma(t)$, and each resource has a single server.

The developed queuing network model consists of three main processes: the departure vertiport queue, the transition between departure and arrival vertiports, and the arrival vertiport queue. In this model, all the scheduled flights of an AAM vehicle are simulated one by one. Flights are simulated concurrently within the system. For each flight, the departure queue, transition, and arrival queue processes are repeated which are detailed as below.

The first part represents the queuing process during departure. In the departure vertiport queue, first, a candidate departure time is selected by considering the scheduled departure time (SDT), previous arrival time (PAT) and turnaround time (TAT) of the simulated vehicle. Thus, the candidate departure time (CDT) is calculated as follows.

$$CDT = max(SDT, PAT + TAT) \tag{1}$$

Basically, if the arrival time from the previous flight of the vehicle is greater than the proposed departure time of the current flight, then the previous arrival time is set as the new candidate departure time. Otherwise, if the previous flight is completed before the currently scheduled departure time, then the vehicle has to wait for its next flight until the scheduled departure time. When the departure time comes, the considered AAM vehicle requests service from the departure vertiport to take-off. If there is not any queue at the departure vertiport, the AAM vehicle waits for the amount of service time and after the completion of the service, the AAM vehicle departs.

The second part refers to the transition; in other words, flight duration between departure and arrival vertiports. Once the AAM vehicle departs, it continues to its destination vertiport with an uncertainty included travel duration. Thus, the travel duration for each flight differs due to uncertainties and different O/D pairs.

The last part comprises the queue process for arrivals at the destination vertiport. An AAM vehicle that is completing its flight duration, lines up for the arrival vertiport queue. The flight requests service when the arrival vertiport is available and waits for the particular service time which is specific to each vertiport. The AAM vehicle completes its flight once the service is done.

The developed algorithm for the explained data-driven queuing network model above is as shown in Algorithm 1.

Algorithm 1 Algorithm for Queuing Network Model

```
Get vertiport (resource) info.
Simulate AAM flights concurrently
for each flight of an AAM vehicle do
    if flight is not the first flight then
        CDT = max(SDT, PAT + TAT)
    end if
    if current time < CDT then
        wait until CDT
    end if
    request, wait for service, release (dep. vertiport)
    wait for travel duration
    request, wait for service, release (arr. vertiport)
end for
```

In the algorithm, flight information for all flights, travel duration uncertainties and service time distributions of each vertiport are given as inputs. After the simulation, real departure and arrival times of the flights, therefore the delays are obtained as outputs.

C. Fragility / Antifragility Analysis

For the fragility and antifragility analysis, two approaches are followed. First, different network attacking strategies are considered to see which elements of the network are the main contributors to determining the fragile point of the built AAM traffic. Then, the simple heuristic measure that is defined in [14], [15] for tail risks is used to understand if our AAM network has a tendency to be fragile or antifragile.

For the following definitions, consider a weighted directed graph that is defined as $G = (V, E, W)$ where V is a set of nodes (vertiports) $V = \{v_1, ..., v_N\}$, E is a set of edges (flights) $E \subseteq V \times V$, and W is the weight matrix for the edges of the graph. Each element in W is also corresponding to the adjacency matrix A of the considered graph where $a_{v_i,v_j} = 1$ if $w_{v_i,v_j} > 0$ and $a_{v_i,v_j} = 0$ if $w_{v_i,v_j} = 0$. In the considered directed graph, there are 75 nodes which are connected through 2246 edges. If the graph is considered as an undirected graph, then the number of edges reduces to 1379.

1) Robustness analysis for capturing the fragile behaviour: Robustness can simply be defined as an ability of a system to maintain its desired state. An extremely disruptive event on a robust system may lead to a complete failure which brings fragility. Since the robustness and fragility concepts have a correlation, metrics related to robustness can be utilized for analyzing the fragility of a network. Therefore, the considered AAM traffic network's robustness is measured through targeted attack strategies on both nodes and edges to analyze the fragility of the network.

Network robustness after targeted node removals is quantified as in [24].

$$R_n = \frac{1}{N} \sum_{i=1}^{N} S(i) \tag{2}$$

where $S(i)$ is the size of the LCC of the system after removing i number of nodes from the network which has N number of total nodes.

For the targeted node attacks on a weighted directed graph such as an air traffic network, degree centrality, strength centrality, and betweenness centrality based attacking strategies are considered.

Degree centrality is a metric that measures the total number of connections of a node. The total degree of each node is quantified by considering the summation of the in-degree and out-degree of a node which represents the number of incoming and outgoing connections to/from a node, respectively.

$$d_{v_i} = \sum_{v_x \in V} a_{v_x,v_i} + \sum_{v_x \in V} a_{v_i,v_x} \tag{3}$$

Strength centrality is a metric that takes the total weights connected to a node into account rather than the total number of connections which is the main difference with the degree centrality. The total strength of a node is calculated by summing up all the weights of all the edges connected to that node considering both the in-strength and out-strength of a node.

$$s_{v_i} = \sum_{v_x \in V} w_{v_x,v_i} + \sum_{v_x \in V} w_{v_i,v_x} \tag{4}$$

Betweenness centrality is defined as the level of impact that a node has over the network connection. Each node receives a score considering the number of shortest paths they are involved in between the considered node pairs.

$$b_{v_i} = \sum_{v_x, v_y \in V} \frac{\sigma(v_x, v_y | v_i)}{\sigma(v_x, v_y)} \tag{5}$$

where $\sigma(v_x, v_y|v_i)$ is the total number of shortest paths between the nodes v_x and v_y passing through the node v_i and $\sigma(v_x, v_y)$ is the total number of shortest paths between v_x and v_y.

The robustness of the graph is measured through the LCC size of the network. Figure 2 shows the LCC size change in the AAM traffic network after going through vertiport removals which are obtained considering degree, strength, and betweenness centrality measures. The prepared AAM network is strongly connected and built based on having at least one connection between nodes if the constraints permit. Therefore, significant failure in the robustness of the network is observed at later stages of the node removal process.

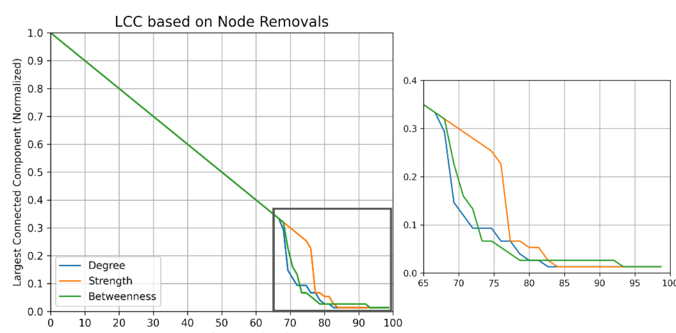

Fig. 2. LCC size of the considered AAM traffic network after each targeted node removal obtained via different network metrics.

Network robustness after targeted edge removals is quantified as in [25].

$$R_e = \frac{1}{M} \sum_{j=1}^{M} S(j) \tag{6}$$

where $S(j)$ is the LCC size of the system after removing j number of edges from the network which has M number of total edges.

For generating an attacking strategy on the edges of the considered graph and analyzing the robustness of the network afterwards, the edge betweenness centrality metric is focused.

Edge betweenness centrality represents the level of impact that an edge has over the network connection. Each edge receives a score based on the number of shortest paths that go through that edge.

$$b_{e_{v_i,v_j}} = \sum_{v_x,v_y \in V} \frac{\sigma(v_x, v_y|e_{v_i,v_j})}{\sigma(v_x, v_y)} \tag{7}$$

where e_{v_i,v_j} is an edge between the nodes v_i and v_j within the graph, $\sigma(v_x, v_y|e_{v_i,v_j})$ is the total number of shortest paths between the nodes v_x and v_y, passing through the edge e_{v_i,v_j}, and $\sigma(v_x, v_y)$ is the total number of shortest paths between v_x and v_y.

Similar to the node removal analysis, the network's LCC size is utilized for the edge removal analysis. LCC size change in the traffic network after O/D pair removals which are obtained considering edge betweenness centrality metric is depicted in Figure 3.

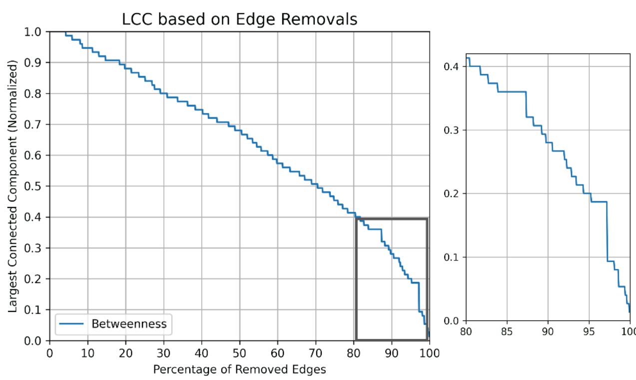

Fig. 3. LCC size of the considered AAM traffic network after each targeted edge removal obtained via different network metrics.

2) Simple heuristic for analyzing the antifragility concept: The simple heuristic is a measure to detect the convexity effects, especially on tail risks. Therefore it can be useful for the fragility/antifragility analysis of a system. The method involves a second-order testing and benefits from Jensen's inequality for observing the convexities/concavities in tail parts, rather than direct outputs of the considered model. Jensen's inequality is given as below.

$$E[g(X)] \geq g(E[X]) \tag{8}$$

where it represents the relationship between the expectation of a convex function g and the function of the expectation of a random variable X.

The main idea for the simple heuristic is to enhance the outputs obtained through stress testing, by focusing on the small variations in potential losses especially for the rare events. This approach provides an understanding on if the system is doing better or worse rather than providing an exact output for the considered situation. The simple heuristic can mathematically be defined as follows.

$$H = \frac{f(a-\delta) + f(a+\delta)}{2} - f(a) \tag{9}$$

where f is the payoff function for the system and δ is the small disturbance on the variable a which is the considered state.

For a payoff function where the larger values represent more adverse cases, $H = 0$ means that the payoff function is linear and the output is robust. If the heuristic becomes larger than zero $H > 0$, that case refers to a fragility in the output. Such a system gets more fragile with increasing variability in uncertainty meaning that the system loss will be larger with disruptive events. Lastly, $H < 0$ means that the output is antifragile and the system has a tendency to gain under disruptive conditions.

IV. Case Studies and Results

In this section, the implementation of the considered metrics from a fragility/antifragility perspective is elaborated and an analysis on the generated AAM traffic network through different case studies is provided. Case studies cover a capacity reduction case at vertiports based on targeted node removal strategies and a disruption case on an O/D pair considering the edge removal method. Lastly, a method to improve the network in terms of antifragility is discussed and analyzed.

A. Capacity Reduction at Vertiports

This case covers the analysis over vertiports that suffer from an adverse condition which leads to a disruption and uncertainty in capacity usage. In our queuing network model, this situation affects the service time parameter. Thus, both local and global effects of such a disruption are analyzed and their impact to network fragility/antifragility are discussed.

For the analysis, the capacity usage of a vertiport is gradually reduced and the network-wide outcomes of the contingency situation are observed through the developed queue network model. The vertiport for each situation is selected considering the degree centrality, strength centrality, and betweenness centrality based node removal strategies.

Figure 4 shows the fragility/antifragility analysis of the AAM traffic network after targeted node attacks and the corresponding delay propagation over the network after performance reduction/improvement situations. Based on the degree and strength centrality measures, vertiport NC72; based on the betweenness centrality measure, vertiport NC17 is focused on having a performance reduction due to an adverse event. Some service time improvement cases are also tested. As it is observed in local and network impact figures, there is a positive payoff function where the total delay at considered vertiports and over the network is increasing.

For testing whether the system is antifragile or not, the small perturbation δ is selected as a 1% change in the service time and analyzed both at the selected vertiports and traffic network at 50% capacity reduction situation. Once the simple

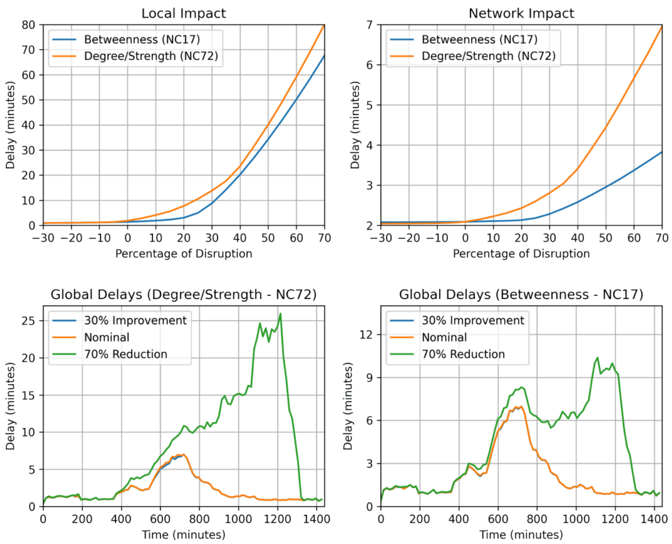

Fig. 4. Fragility and delay analysis of the AAM traffic network based on vertiport disruptions.

heuristic is implemented for the considered network, H scores are observed as in Table II to decide if the network is fragile or antifragile. For the global cases, especially after around 40% capacity degradation, network delay has a linear behaviour. Therefore, the simple heuristic scores are very close to zero which refers to having a robust system after that point. Yet, they are still positive thus they stay on the fragile side.

TABLE II
FRAGILITY/ANTIFRAGILITY ANALYSIS FOR VERTIPORT CASES

Local/Global	Metric	Heuristic	Fragile/Antifragile
Local (NC17)	b_{v_i}	0.0075	Fragile ($H > 0$)
Global	b_{v_i}	0.0016	Fragile ($H > 0$)
Local (NC72)	d_{v_i}, s_{v_i}	0.0145	Fragile ($H > 0$)
Global	d_{v_i}, s_{v_i}	0.0003	Fragile ($H > 0$)

B. Disruption on O/D Pairs

Effects of a contingency event over an O/D pair are analyzed. An increase in the uncertainty of the flight duration and resulting delay are covered with this scenario. This situation corresponds to a disruption in the inter-arrival time parameter of the queuing network model. Similar to the previous case, the impact of such disruption is quantified and discussed via fragility/antifragility concepts.

Travel duration on the selected O/D pair is decreased step by step to analyze both the local and network impact of the disruption. The O/D pair selection is done based on the edge betweenness centrality metric.

Analysis on if the AAM traffic network is fragile or antifragile after a targeted edge attack and the corresponding delay propagation over the network after an increment/decrement in the flight duration are given in Figure 5. Considering the edge betweenness centrality measure, the edge between the nodes NC60 and NC72 is selected as the considered O/D pair for analyzing the travel duration variation case. It is observed that the variation on an O/D pair over the whole traffic network is not impactful, yet it can be effective under multiple O/D pair disruptions. Since the impact is not very significant, especially at busy vertiports such as NC72 and the complete traffic network, delay-event relationship is not obvious. But for the relevant vertiports that are less busy such as NC60, O/D pair variation creates an observable impact.

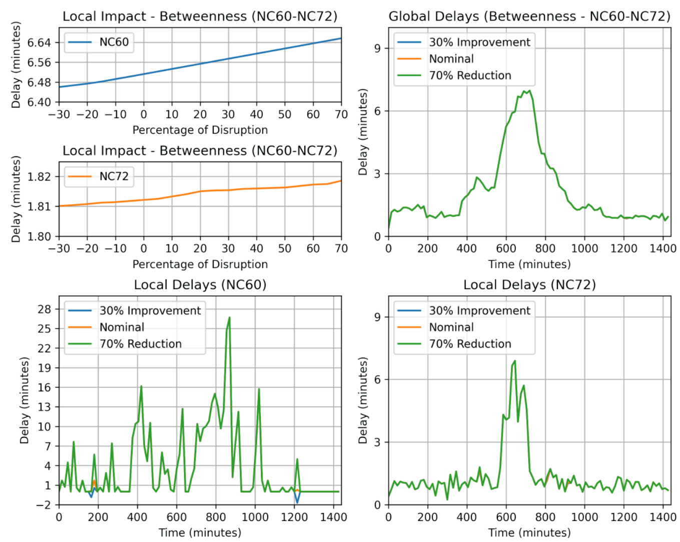

Fig. 5. Fragility and delay analysis of the AAM traffic network based on an O/D pair disruption.

For the global cases, especially after around 40% capacity degradation, network delay has a linear behaviour. Therefore, the simple heuristic scores are very close to zero which refers to having a robust system after that point. Yet, they are still positive thus they stay on the fragile side.

For the antifragility analysis, the small perturbation δ is chosen as a 1% change in the flight duration around the 30% increase in the inter-arrival time case. Heuristic scores H are obtained as in Table III. Around the selected point, delay behaviour at NC60 and the traffic network shows linearity. Therefore, NC60 and the traffic network show robustness for such an individual O/D pair disruption. On the other hand, NC72 seems fragile with a slight difference around the 30% disruption in flight duration between NC60 and NC72.

TABLE III
FRAGILITY/ANTIFRAGILITY ANALYSIS FOR O/D PAIR CASES

Local/Global	Metric	Heuristic	Fragile/Antifragile
Local (NC60)	$b_{e_{v_i,v_j}}$	$\simeq 0$	Robust ($H = 0$)
Local (NC72)	$b_{e_{v_i,v_j}}$	0.00002	Fragile ($H > 0$)
Global	$b_{e_{v_i,v_j}}$	0	Robust ($H = 0$)

C. Antifragility Improvement on the AAM Network

In this part, an approach to make the existing AAM traffic network antifragile, is studied. Considered approach deals with canceling flights based on their delay levels. Simply, the flights that are expected to have more than 15-minute delays are canceled and the behaviour of the network is observed. This method is analyzed through one of the vertiport capacity disruption cases. The vertiport is selected based on the degree centrality metric. Thus, the service time disruption case at vertiport NC72 is focused on for the simulations.

Figure 6 depicts the local and network-wide results before and after the improvement on the antifragility. After the improvement, delay levels at higher disruptions are less than the ones have lower disruptions. This refers to the built AAM traffic network becoming antifragile where it benefits from the adverse conditions.

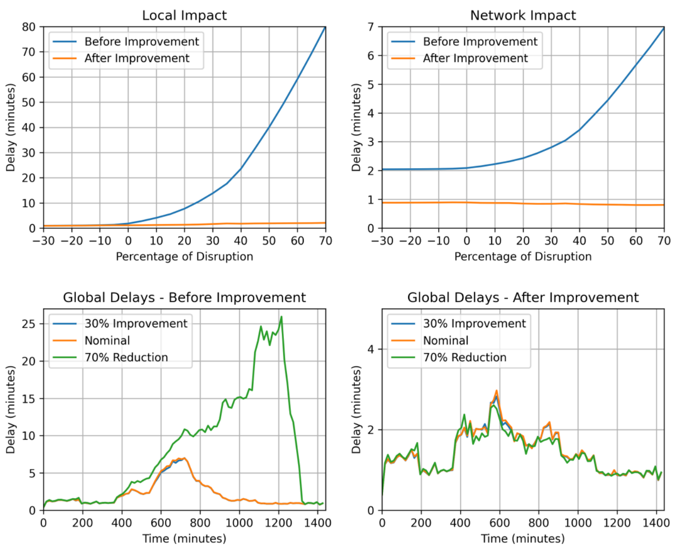

Fig. 6. Fragility and delay analysis of the AAM traffic before and after the improving action via a delay-based flight cancellation policy.

Simple heuristic scores are also taken into account to assess whether our AAM network became antifragile or not. Table IV shows the antifragility analysis after the flight cancellation action. It is observed that the network becomes antifragile at both local and global levels.

TABLE IV
FRAGILITY/ANTIFRAGILITY ANALYSIS AFTER THE IMPROVING ACTION

Local/Global	**Heuristic (15-min)**	**Fragile/Antifragile (15-min)**
Local (NC72)	-0.00026	Antifragile ($H < 0$)
Global	-0.00022	Antifragile ($H < 0$)

Since flight cancellations are used as an improving action, it is important to consider the cost of that approach as well. For the simple cost analysis, direct operating costs of the AAM vehicles are used as in [19]. It is assumed that the passengers are meeting the operating costs to receive such a service. The total cost of flight cancellations for each considered disruption is shown in Figure 7. Even though flight cancellations work well for obtaining an antifragile network, it may cause a big cost for daily operations. In other words, it provides an antifragility for the traffic in terms of delay but creates a fragility for the network in terms of costs. For example, the total cost of cancelling flights that suffer from 15-minute or more delay (2973 flights) is around \$300.000 under 60% service time disruption at NC72. Instead of having the same procedure for the flight cancellation policy over the network, the policy can vary for each vertiport based on their operational limits and procedures. This approach may also help to optimize the expected total costs.

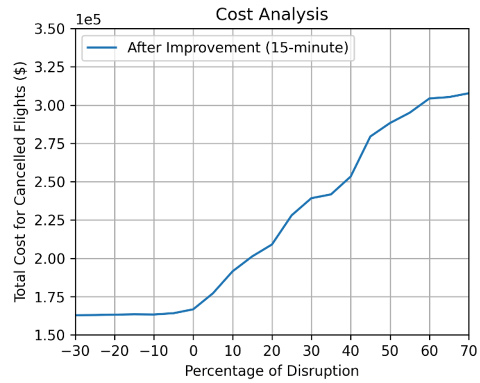

Fig. 7. Cost analysis for the improving action.

V. Conclusion

In this study, we covered the antifragility concept which is mainly utilized for financial markets and adapted that concept for the air transportation systems, especially for the future AAM system. For that purpose, an AAM traffic network is built considering different types of AAM vehicles and possible vertiport locations over Northern California. For simulations, the queue network model is considered and ways to analyze antifragility in AAM are explored. Finally, an analysis over an AAM traffic network is provided for both vertiport and O/D pair related variations and an approach for improving the antifragility of the considered AAM traffic is given which is a flight cancellation policy based on a maximum delay threshold. Lastly, a cost analysis of that policy is provided considering the direct operating costs of each AAM vehicle.

As a future work, to build an antifragile AAM network for the future, we will explore new strategies that will reduce the cost of having such a system. Those new strategies may involve not only flight cancellation policies but also using vertiport locations in a different manner to contribute to the traffic network or considering additional infrastructures for the system. Also, we will focus on the development of antifragile networks from scratch, especially for building a safe, reliable, and sustainable AAM traffic network.

Acknowledgment

Arinc Tutku Altun is funded by Boeing Research and Technology Europe under the Engineering and Physical Sciences Research Council (EPSRC) Doctoral Training Programme (DTP) for the research project entitled Contingency Management of the Advanced Air Mobility System of Systems: UAS/UAM, Integrated ATM/UTM and Infrastructures.

REFERENCES

[1] FAA NextGen, "Urban air mobility (uam) concept of operations v1.0," 2020.

[2] SESAR JU CORUS, "U-space concept of operations ed 03.00.02," 2019.

[3] Airservices Australia and Embraer Business Innovation Center, "Urban air traffic management concept of operations v1.0," 2020.

[4] G. Price, H. Dougles, K. Jenkins, M. Kvicala, S. Parker, and R. Wolfe, "Urban air mobility operational concept (opscon) passenger-carrying operations," NASA, Tech. Rep., 2019.

[5] Boeing and Wisk, "Concept of operations for uncrewed urban air mobility," 2022.

[6] A.-L. Barabási, "Network science," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 371, no. 1987, p. 20120375, 2013.

[7] B. Duan, J. Liu, M. Zhou, and L. Ma, "A comparative analysis of network robustness against different link attacks," *Physica A: Statistical Mechanics and its Applications*, vol. 448, pp. 144–153, 2016.

[8] V. H. Louzada, F. Daolio, H. J. Herrmann, and M. Tomassini, *Generating robust and efficient networks under targeted attacks*. Springer, 2015.

[9] B. Başpınar, K. Gopalakrishnan, E. Koyuncu, and H. Balakrishnan, "An empirical study of the resilience of the us and european air transportation networks," *Journal of Air Transport Management*, vol. 106, p. 102303, 2023.

[10] X. Sun, V. Gollnick, and S. Wandelt, "Robustness analysis metrics for worldwide airport network: A comprehensive study," *Chinese Journal of Aeronautics*, vol. 30, no. 2, pp. 500–512, 2017.

[11] B. Baspinar, E. Koyuncu *et al.*, "A data-driven air transportation delay propagation model using epidemic process models," *International Journal of Aerospace Engineering*, vol. 2016, 2016.

[12] B. Baspinar, A. Tutku Altun, and E. Koyuncu, "Event-based air transport network resiliency management with meta-population epidemic model," *Journal of Aerospace Information Systems*, vol. 18, no. 9, pp. 632–644, 2021.

[13] N. N. Taleb, "Antifragile: Things that gain from disorder," *New York City: Random House & Penguin*, 2012.

[14] N. N. Taleb and R. Douady, "A map and simple heuristic to detect fragility, antifragility, and model error," *NYU-Poly working paper, SSRN*, 2011.

[15] N. N. Taleb, E. Canetti, T. Kinda, E. Loukoianova, and C. Schmieder, *A new heuristic measure of fragility and tail risks: Application to stress testing*. International Monetary Fund, 2012.

[16] N. N. Taleb and R. Douady, "Mathematical definition, mapping, and detection of (anti) fragility," *Quantitative Finance*, vol. 13, no. 11, pp. 1677–1689, 2013.

[17] K. H. Jones, "Engineering antifragile systems: A change in design philosophy," *Procedia computer science*, vol. 32, pp. 870–875, 2014.

[18] M. Rimjha, M. Li, N. Hinze, S. Tarafdar, S. Hotle, H. Swingle, A. Trani, and J. C. Smith, "Demand forecast model development and scenarios generation for urban air mobility concepts," 2020.

[19] R. J. Howard, E. Wright, S. V. Mudumba, N. I. Gunady, B. E. Sells, and A. Maheshwari, "Assessing the suitability of urban air mobility vehicles for a specific aerodrome network," in *AIAA AVIATION 2021 FORUM*, 2021, p. 3208.

[20] N. Pyrgiotis, "A stochastic and dynamic model of delay propagation within an airport network for policy analysis," Ph.D. dissertation, Massachusetts Institute of Technology, 2012.

[21] N. Pyrgiotis, K. M. Malone, and A. Odoni, "Modelling delay propagation within an airport network," *Transportation Research Part C: Emerging Technologies*, vol. 27, pp. 60–75, 2013.

[22] B. Baspinar, N. K. Ure, E. Koyuncu, and G. Inalhan, "Analysis of delay characteristics of european air traffic through a data-driven airport-centric queuing network model," *IFAC-PapersOnLine*, vol. 49, no. 3, pp. 359–364, 2016.

[23] B. Baspinar, E. Koyuncu, and G. Inalhan, "Large scale data-driven delay distribution models of european air traffic flow network," *Transportation research procedia*, vol. 22, pp. 499–508, 2017.

[24] C. M. Schneider, A. A. Moreira, J. S. Andrade Jr, S. Havlin, and H. J. Herrmann, "Mitigation of malicious attacks on networks," *Proceedings of the National Academy of Sciences*, vol. 108, no. 10, pp. 3838–3841, 2011.

[25] A. Zeng and W. Liu, "Enhancing network robustness against malicious attacks," *Physical Review E*, vol. 85, no. 6, p. 066130, 2012.

2023-11-10

Analyzing fragility of the advanced air mobility system and exploring antifragile networks

Altun, Arinc Tutku

IEEE

Altun AT, Xu Y, Inalhan G, Hardt MW. (2023) Analyzing fragility of the advanced air mobility system and exploring antifragile networks. In: IEEE/AIAA 42nd Digital Avionics Systems Conference (DASC) 2023, 1-5 October 2023, Barcelona, Spain

https://doi.org/10.1109/DASC58513.2023.10311258