METHODS TO INTEGRATE MULTIPLE STAKEHOLDER PERSPECTIVES INTO AIR TRASNPORTATION EFFICIENCY METRICS

Tatsuya Kotegawa, Daniel DeLaurentis and Galen Harden
Purdue University School of Aeronautics and Astronautics

Keywords: *Air Transportation, decision support, aircraft design, system-wide performance*

Abstract

The Air Transportation System (ATS) can be viewed as a collection of multiple, heterogeneous and independent systems operating in networks under the control of various stakeholders. Each stakeholder has a different perspective on the relevant efficiency metrics, making analysis as well as subsequent system-wide design decision-making very difficult. This paper analyzes the potential performance boundaries and trade-offs between efficiency metrics established around the passenger, airline and network-centered perspective by varying the service route network topology. The paper further initiates the formulation of aircraft design and resource allocation based on system-wide network efficiency of the ATS.

1 Introduction

Transforming national (and international) Air Transportation Systems (ATS) to meet future travel demand has been the focus of many researchers, technologists and policy-makers. This challenge has become further complicated by increased emphasis on noise and emissions reductions and by increased economic pressure due to volatile fuel prices. Improving individual aircraft efficiencies (e.g., CO_2, NO_X) and air traffic management (ATM) practices have been common approaches to satisfy increasing travel demand while reducing environmental impacts. While these efforts are important and appropriate, they may not be sufficient. Other high-level factors beyond these largely determine the system-wide performance of air transportation, such as the airline service route network topology, aircraft fleet mix and resource allocation. These factors are wide in scope and complex in nature making analysis as well as subsequent design decisions extremely difficult.

The lack of a universal definition that describes the overall performance of the ATS exacerbates the problem. This is mainly due to the distributed control and heterogeneous structure of the ATS which is composed of multiple stakeholders (e.g., passengers, airlines, airports, etc.) operating under a unique set of objectives, timescales and domains (e.g., economical, operational, and political) [1]. The unique stakeholder objectives, in turn, generate unique objectives, they also have their own perception of what "ATS performance" means. For example, ATS performance for an airline may be based on the economical effectiveness of meeting passenger travel demand. However, from a passenger point of view, performance may also be based on required travel time or number of connections, which does not necessarily coincide with an ATS architecture designed for economical effectiveness. Further, ATS performance defined by levels of noise or emissions may conflict with metrics for either the passengers or the airlines.

2 Technical Approach

2.1 Overview

Research reported in this paper describes an heuristic approach to evaluate various ATS network types via several stakeholder-centered performance and efficiency metrics. The ATS architecture is simplified into a network of service routes interconnecting airports and the impact of network topology characteristics to performance is explored. The approach is extended to an initial formulation of aircraft design and allocation based on system-wide efficiency of the ATS.

2.1 Network Theory Background

Network theory has produced powerful results from multiple domains (e.g., physics, information, social science, biology) in recent years concerning how real-world networks are structured. Random and scale-free networks are the two most discussed types of network topologies. Scale-free networks are similar to the hub-and-spoke networks of the ATS where few nodes with high degree (i.e., number of links) maintain much of the connectivity throughout the network. Similar structure is also seen in protein networks, social networks and the World Wide Web [2]. The prime benefits of this structure are that all nodes are connected via relatively few links, and new nodes can be easily integrated as long as the hub nodes are functional. On the other hand, the main drawback of a scale-free network is that as the hub nodes become larger, the potential damage that can be caused by disabling the hub node significantly increases. Scale-free networks can be constructed using the Barabási-Albert (BA) model [2] which operates under the precept of a preferential attachment. In preferential attachment nodes with higher importance are granted a higher probability to attain a new link. In the BA model, importance of a node is valued by its local degree compared to the total degree of the network. In another words, the probability of node *A* linking with newly arrived node *B* is

$$P_{connect}\,(A, B) = \frac{k_A}{\sum_{i=1}^{j} k_i} \qquad (1)$$

where j is the total number of nodes in the network and k is nodal degree. For random networks, links between nodes are constructed based on a uniform probability distribution function which remains constant for all node pairs that may form a link. While random networks require more links for equal connectivity compared to a scale-free, propagation of disruption throughout the network is much lower since nodal importance is more equally distributed than scale-free [2].

Some researchers have applied the analysis techniques developed in the network theory community to explore the structure of the ATS. Guimera, et al. analyzed the worldwide air transportation network topology and computed measures which characterized the relative importance of cities and airports [3]. Further, Bonnefoy and Hansman used the weighted degree distribution for light jet operations to understand the capability of airports to attract the use of very light jets [4]. In general, network theory has been very successful in aggregating the complexity of the ATS to better understand its fundamental characteristics. However, applying network theory not only as an analysis tool but also for designing the future ATS has been a continuing topic for our work [5, 6].

2.2 Network Topology Generator (NTG)

The unit of analysis in this study is the service route network, consisting of airports interconnected by airline routes. Links in the service route network are weighted by the number of passengers using the link to travel from their origin to destination airports (nodes). The particular network examined here assumes a single, monopolistic airline with an annual operation time scale.

Different network topologies are generated by the network topology generator (NTG) and the correlation between topology characteristics and performance metrics defined in the later section is analyzed. More specifically, the NTG constructs a network with varying ratio of scale-free and random characteristics, based on the user input. Fig. 1 shows the flow chart of this process. The NTG algorithm first generates two networks, random and scale-free with equal total degree for the same node set. The NTG then arbitrarily selects links from the scale-free and random network and places it in the final network; the number of links chosen from either the scale-free or random network depends on the user input mix ratio mentioned earlier. For example, if the mixture ratio was 80% scale free, the NTG will chose 80% of the final links from the scale-free network generated in the initial step, while extracting the remainder 20% from the random network. Networks blending scale-free and random topology features will be examined for the impact on the various stakeholder centered efficiencies.

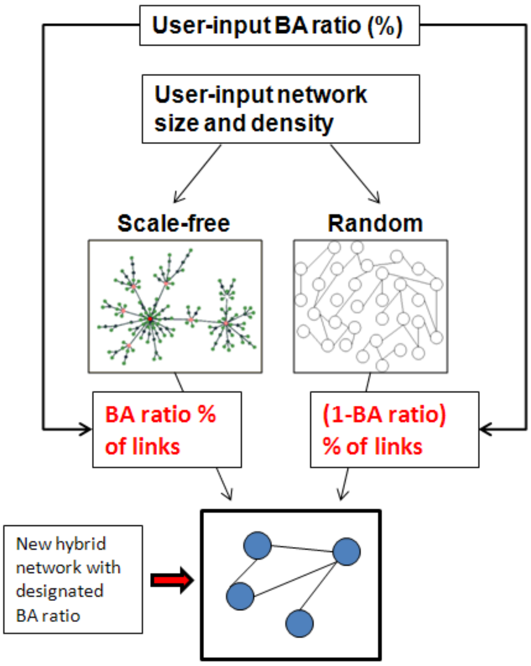

Fig. 1. Network Topology Generator logic flowchart.

The network is instantiated with historical data on passenger demand and airport operations extracted from the 2005 DB1B Survey and T-100 Domestic Segment data respectively, both available from the Bureau of Transportation Statistics [7]. The number of nodes in the network is kept constant at 304, representing active airports only in the continental US. Once the network is constructed by the NTG, passengers are allocated to service route(s) with the shortest travel distance, according to their origin and destination location extracted from DB1B.

2.3 Performance Metrics

Stakeholders seek to optimize their operation with regard to their own objective metrics to extract maximum benefit from the system [8]. For instance, airlines use the hub-and-spoke system to reduce costs by aggregating passengers from various origins and transporting them to a wide number of destinations. Such efficiently gained by the airlines come at the price of increased passenger travel time and network service fragility in case of a disruption. In the present study, metrics to representing the airline, passengers and regulatory agent stakeholders were created, as defined in the following subsection.

2.3.1 Passenger Centered Efficiency

Passenger travel distance efficiency (τ) describes the impact of airline service route network topology on travel distance for passengers.

$$\tau = \frac{d_{ij}}{d_{tot}} \tag{2}$$

d_{ij} is the distance between the passenger's origin and destination where d_{tot} is the total distance traveled by the passenger, which includes connections, if any. In this formulation, $\tau \leq 1$. The number of connections required to complete the passenger itinerary was also computed. A new metric which combines τ and the number of required connections to formulate total passenger travel time is currently under development but it is not part of the work in this paper.

2.3.Network Centered Efficiency

A wide variety of aspects contribute to network efficiency; one of the especially critically one is robustness. However, one cannot speak generally about robustness; instead, a class of possible disturbances must be specified in order to measure or estimate a particular robustness level of the system. Two general types of network disturbances are targeted and random. These disturbances disable the function of a node (airport) and either temporarily or permanently removes it from the entire network, along with any associated links. Random attacks are arbitrary failures that occur equally likely to any node within the network; they may represent incidents such as weather, accidents, and aircraft malfunctions. Targeted attacks, on the other hand, are failure of specific nodes which are usually due to an intentional cause. In the real world, targeted attacks may occur as terrorism, strike, or war-related issues. Robustness of each network topology configuration is examined by measuring the degradation in τ and percent of passengers unable to travel after certain nodes are removed, mimicking targeted and random attacks. For targeted attacks, nodes with the highest degree are removed while for the random attack, nodes are removed according to a uniform random distribution.

2.3.3 Airline Centered Efficiency

The amount of fuel required to transport the passengers was used as the airline centered efficiency; fuel used well represents direct operating cost. Three aircraft types differentiated by seat class (CRJ200, B737-300 and B757-200) were sized in the Flight Optimization Software (FLOPS) provided by NASA [9]. Fuel burn lookup tables were created using the number of passengers and range of the mission. An example look-up table for the CRJ200 is shown in Table 1 below. For each route, a single aircraft with the best fuel efficiency was assigned. All aircraft models assume a constant load factor of 0.7 and passengers are evenly distributed among all flights.

Table 1: Fuel Burn (lbs) look-up table for CRJ200

		Number of Passengers		
		10	30	50
Operation Range	300	2,044	2,119	2,202
	600	3,242	3,371	3,523
	900	4,453	4,641	4,870
	1200	5,678	5,928	6,246
	1500	6,918	7,236	7,651
	1700	7,754	8,121	8,606

However, since the current approach does not include any flight scheduling and or frequency modulation, larger aircraft are preferred on almost all routes due to higher fuel efficiency per passenger. In reality, larger aircraft on hub-to-spoke routes will be less efficient since in general, the number of passengers aboard is less per flight compared to a hub-hub flight. Further, in order to produce realistic results, the total number of operations should reflect historical and known benefits of smaller aircraft in terms of scheduling and turnaround time [10]. To do so, a penalty function was introduced in the fuel burn efficiency if the aircraft fails to maintain a minimum number of flights using a constant load factor of 0.7 and even distribution of passengers across all flights. The minimum number of operations required in a route is determined by its passenger volume. Fig. 2 shows a box plot for number of operations that were carried out in a route with respect to the total number of passengers that traveled through that route in 2005. Based on this data, a penalty is added to aircraft which will have fewer operations than -1 sigma for routes with corresponding number of passengers in Fig. 2, such that

$$\rho_{i,j} = \frac{ops\ \ by\ \ aircraft_{i,j}}{ops\ required_{i,j}} \qquad (3)$$

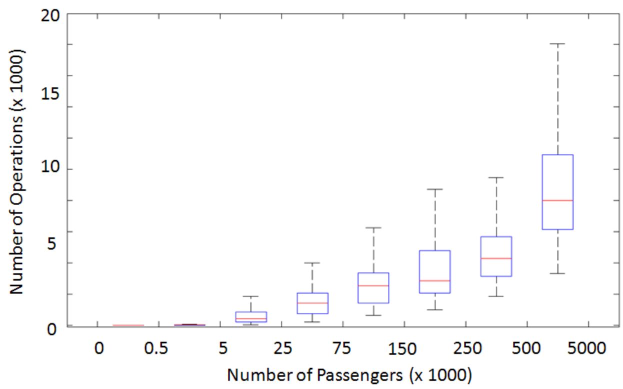

Fig. 2. Box plot of annual operations and passenger volume in air service routes for 2005.

where i, j refers to a particular route. For example, if a certain route has a 50,000 annual passenger volume and the B757 requires 294 operations (under 0.7 load factor) but the -1 sigma for a route with that range of passenger volume is 1000, there will be a 29.4% reduction in the final fuel efficiency for the B757 for this particular route as a penalty for generating reasonable frequency.

3 Results

Twenty-four networks are generated by the NTG: topologies with six scale-free / random mix ratios and four different network densities. Network density is the ratio between the total number of links and the number of possible links that can exist. Using 6% density (2612 links) which was observed in the 2005 ATS network as a baseline, networks with 12%, 3% and 1% density were also considered. For some of the lower density networks, not all passenger trips were completed due to route unavailability. However, in all cases at least 99% of the passengers in the DB1B database were able to complete their trip with the network topologies constructed for this study. Further, since the NTG is a stochastic simulation, each network topology type was generated and analyzed ten times. Results presented in the next several sections are the average over those ten runs.

3.1 Individual Stakeholder Efficiency

3.1.1 Passenger Results

Fig. 3 displays the τ for each topology type. Each column shows the different network mix ratios. For example, “BA80” means 80% of the links came from the BA (i.e. scale-free) logic while the remaining 20% is from the random network logic. As expected, τ increases for topologies with higher density and more scale-free characteristics. However, the difference in τ was considerable between the higher and lower density networks. For example, τ in a network with 1% density was 37% less compared to a 12% density network under the BA100 mix ratio. In a network with 304 nodes, this 10% difference in density is equivalent to approximately 5000 links. Since most demand is still satisfied, the service route network with 1% density was able to transport the same amount of demand with about 5000 fewer links, in exchange for lower travel distance efficiency. However, higher network density significantly decreases the minimum number of connections required on the shortest distance route [11], which brings more convenience to passengers. Additional analysis between degree, number of connections and travel distance efficiency may be a useful study for future ATS transformation efforts if links are considered as resources in constructing a network. Increasing the network density at first may seem like an effective way to increase τ. However as Figure 4 shows, the effectiveness for increasing τ by adding more links decreases exponentially.

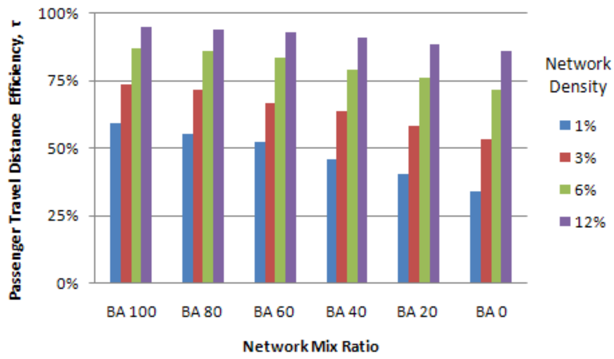

Fig. 3. Passenger travel distance efficiency for different network topology types and degree.

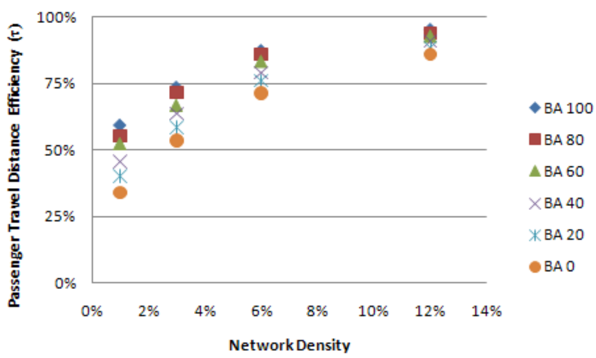

Fig. 4. Passenger travel efficiency with respect to network degree.

3.1.2 Network-centered Efficiency Results

For both random and targeted disturbances on each of the 24 network configurations, five, ten and fifteen nodes were removed to observe the degradation in the overall network performance. Tables 2 and 3 display the amount of performance degradation of the networks after the disruptions in terms of τ and percent of passengers unable to travel (due to their origin / destination airport being disabled or completely isolated), respectively. The τ in Table 2 applies only to passengers that are able to complete their trip after the disturbance and does not include stranded passengers depicted in Table 3. While both scale-free and random networks are fairly resistant towards random disruption, it can be observed that networks with the slightest scale-free characteristics are extremely fragile towards targeted attacks until a certain network density is attained. This phenomenon is due to the hub airports being located in highly populated regions. Areas with higher population are more likely to generate air travelers and utilize its hub airport. Any scale-free characteristic in the network topology develops the metropolitan airports as "hubs", which impacts a great number of passengers when taken down by a targeted disruption.

Table 2: Percent reduction in passenger travel efficiency after disruption

Network Density	Disruption Type	Disbled Nodes	BA100	BA 60	BA 40	BA 0
3%	Random	5	0.1	0.4	0.5	0.5
		10	1.1	0.3	0.6	0.9
		15	0.0	0.4	1.0	1.2
	Targeted	5	10.0	8.0	6.7	1.5
		10	19.2	13.5	11.0	2.3
		15	25.1	17.2	13.9	3.3
6%	Random	5	0.0	0.3	0.1	0.2
		10	0.2	0.1	0.5	0.5
		15	0.4	0.6	1.1	0.9
	Targeted	5	2.9	3.3	2.3	1.0
		10	7.0	6.7	5.5	1.7
		15	12.4	11.0	8.7	2.5
12%	Random	5	0.1	0.2	0.3	0.4
		10	0.2	0.1	0.2	0.4
		15	0.1	0.3	0.2	0.7
	Targeted	5	1.1	1.0	1.1	0.4
		10	2.1	2.3	1.9	0.8
		15	3.7	3.5	3.1	1.1

Table 3: Percent of passengers that cannot be served after disruption

Network Density	Disruption Type	Disbled Nodes	BA100	BA 60	BA 40	BA 0
3%	Random	5	3.1	3.6	3.8	4.0
		10	7.3	6.4	7.8	8.2
		15	7.1	10.0	10.3	7.8
	Targeted	5	20.3	21.2	20.9	3.0
		10	36.5	37.6	38.5	8.1
		15	49.3	50.3	47.6	11.4
6%	Random	5	2.1	3.2	2.6	3.1
		10	5.6	6.2	5.0	5.6
		15	12.3	10.6	10.3	8.7
	Targeted	5	17.6	20.5	15.9	5.1
		10	34.6	34.7	33.4	8.5
		15	49.1	48.5	48.2	13.0
12%	Random	5	3.6	4.2	4.3	3.3
		10	7.8	5.1	6.2	7.9
		15	9.0	9.5	7.0	10.2
	Targeted	5	17.5	17.4	16.4	2.1
		10	32.0	33.2	32.2	5.5
		15	44.4	46.0	44.5	8.1

On the other hand, while a large number of passengers were unable to travel after targeted attacks on networks that exhibit the slightest scale-free characteristics, a fully random topology is able to maintain routes to travel approximately 90% of the passengers for any network density setting.

3.1.2 Airline Results

Fig. 5 displays the amount of fuel required to transport passengers based on the logic for aircraft allocation to routes described in section 2.3.3. As expected, networks with lower density require significantly more fuel due to the lower τ resulting from the higher number of connections needed to complete a passenger's trip. However, it was quite interesting to observe that as the network density increases, the significance of the network topology type decreases in determining the amount of fuel required. For example, there is nearly a 50% increase in fuel requirements from BA100 to BA0 for networks with degree of 653, but only a 14% increase for networks with 5224 links. Similar phenomena can be seen in τ from Fig. 2. It is hypothesized that the network is reaching a saturation point where it is becoming more of a small world network [2] as total degree approaches somewhere between 2612 to 5224 links, in conjunction with the travel demand pattern seen from the DB1B database.

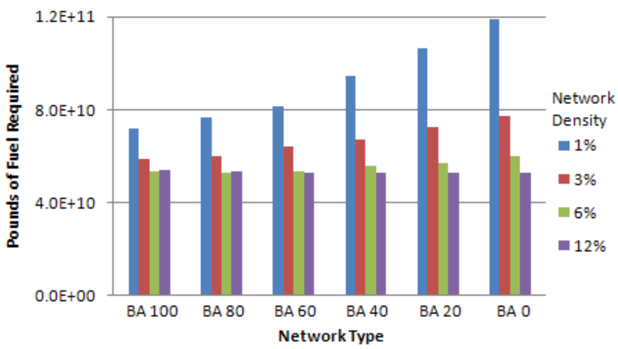

Fig. 5. Fuel required to transport 2005 demand for different network topology type and degree.

Fig. 6 and 7 show a more detailed breakdown of operations by aircraft seat-class for the 1% and 6% density network, respectively. The CRJ200 becomes a more preferred seat-class (vs. the B757-200) as the network density increases. The same phenomenon is also observed when the distribution of aircraft seat class assignment in terms of routes is investigated, as depicted in Fig. 8 and 9. In general, larger aircraft are preferable as the network density decreases due to the higher passenger volume on the routes. Compared to network density, network type has a smaller impact on the preferred aircraft type; however, networks with higher BA value seem better suited to smaller aircraft, due to higher frequency in hub-spoke type routes with relatively low passenger volume. This structure is also seen in the current US ATS network.

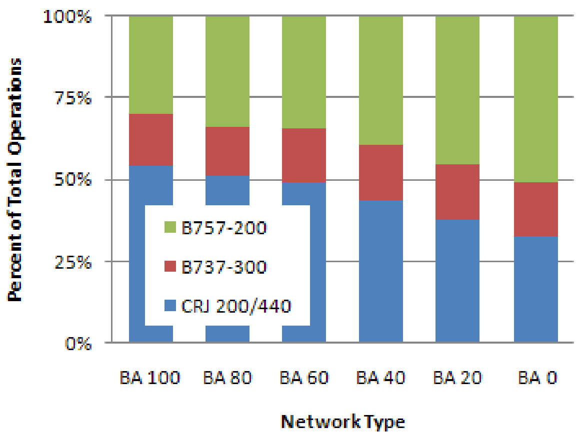

Fig. 6. Aircraft use frequency for networks with 1% network density.

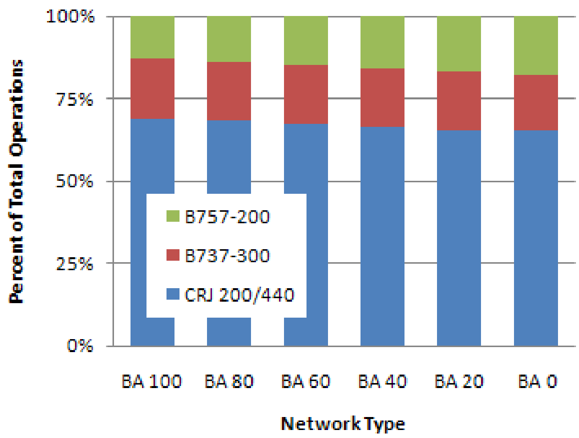

Fig. 7. Aircraft use frequency for networks with 6% network density.

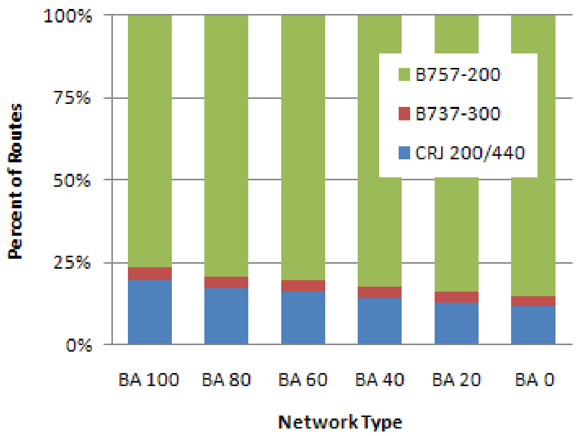

Fig. 8. Distribution of aircraft on routes for networks with 1% network density.

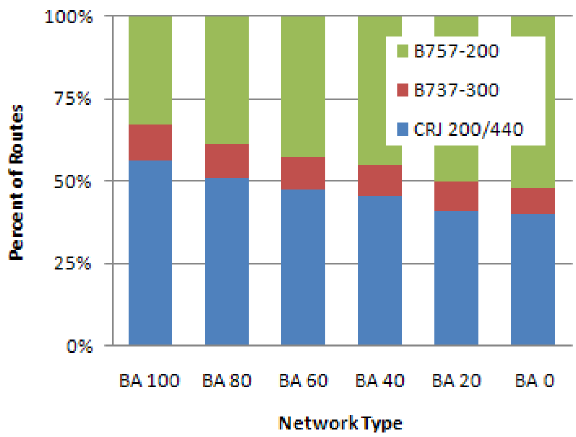

Fig. 9. Distribution of aircraft on routes for networks with 6% network density.

3.2 Comprehensive Analysis of Results

The prior section’s results have demonstrated that the ATS service network “efficiency” depends on the stakeholder metric. From the perspective of τ and amount of fuel required, a network that shows strong scale-free characteristics seems more suitable, as it has been known from practice. However, a random network configuration seems to be more ideal from a robustness standpoint, as it is more resistant to both targeted and random attacks compared to a topology with any scale-free characteristics. Further, if a certain threshold network density can be attained, the scale-free advantages on τ and fuel requirements are so negligible that a random topology becomes more preferred from its resilient features against targeted and random disruptions. To understand the trade-offs better, we can examine the various metrics all together. Fig. 10 and 11 shows an example of this approach by utilizing the data generated in the previous section to visualize the trade regions.

Fig. 10 shows the relationship between network topology type, network density, τ and resistance features against targeted disruptions. Increasing the scale-free characteristics (the BA value for the NTG) significantly increases τ even for a low density network, but also increases the potential damage from a targeted disruption. Within the options available in the scope of analysis presented here, the only method to simultaneously attain high τ and resistance against targeted disruptions is to increase the total network degree. Otherwise, the appropriate trade-offs to maximize the utility of the overall network by the decision-makers. This process usually requires sacrifice in some performance dimensions, and appropriately defining the design objectives become extremely important especially under any strict constraints or restrictions.

Similar analysis regarding correlation between total fuel burn, τ, network topology and density (degree) is shown in Fig. 11. Under the aircraft assignment logic, an almost linear relationship with a short tail between τ and fuel burn is observed. Higher τ is essential in lowering the total fuel burn required to transport the passengers, and to do so, the network degree or the network's scale-free characteristics need to be increased. Similar to results displayed on Fig. 3 and 4, the effectiveness to increase τ (thus lower fuel burn) by changing the network topology exponentially decreases as the density is increased. Further, the ATS network seems to approach diminishing returns at 12% density where further fuel savings cannot be expected by changing network type or density.

In summary, comprehensive analysis such as the ones shown in Fig. 10 and 11 allows the designers and decision-makers of the ATS to recognize the minimum level of network density or network topology type required to attain a certain objective, such as τ, fuel burn or resistance against failures. At the same time, this line of analysis can point out some of the performance boundaries rooting from limitations due to current technology or available resources. For example, with potential performance boundaries seen in fuel consumption reduction by changing network topology type and degree, more focus may need to be put on smarter aircraft route assignment strategies or tailor the aircraft design to make it more suitable for a specific network type.

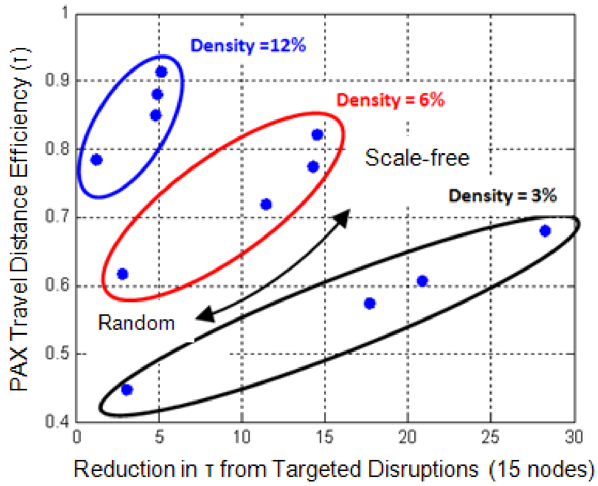

Fig. 10. Trade-off between passenger travel efficiency and network resistance against targeted failures (15 node removal).

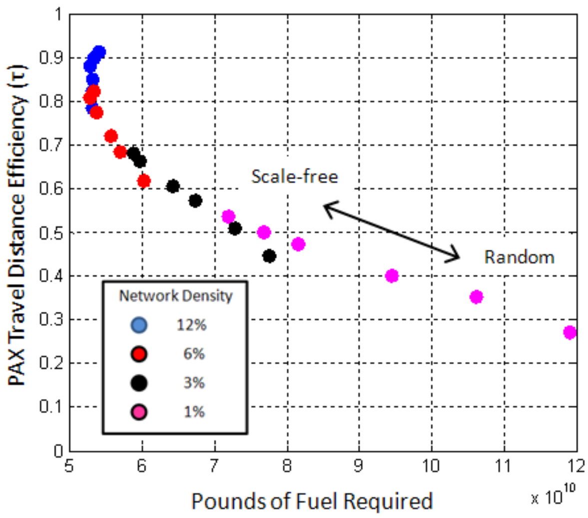

Fig. 11. Trade-off between fuel consumption and passenger travel efficiency for different network types.

4 Initial Methods for Aircraft and Fleet Design based on Service Network Topology

Usually when designing a new aircraft, a specific market area which the aircraft is going to be deployed is first researched and defined. This market description is later formulated into a set of specific requirements that the aircraft design revolves around. However, in order to effectively improve overall performance of the ATS, aircraft design requirements should also stem from a system-wide perspective. In this section we propose a top-down approach on aircraft and fleet composition design based on the service network topology type. More specifically, the type of aircraft and fleet mix that will maximize the overall efficiency from an environmental standpoint for the different network topologies described in Section 3 is pursued.

Aircraft efficiency is typically evaluated for each mission or flight independently but for the purpose of the network centered aircraft design, a simple yet effective metric to describe the cumulative efficiency to compare various aircraft, fleet mix and network topology combination was necessary. Payload Range Efficiency (PRE) [12] shown in (3) was extended to develop the network-wide PRE (PRE_{net}) in (4). Given the aircraft specs, PRE describes aircraft efficiency for a particular service route by taking the ratio between W_{pay}, R, and W_{fuel} which is the payload weight, flight distance and weight of fuel required to fly the payload with W_{pay} lbs for R miles, respectively. Higher PRE indicate higher efficiency. On the other hand, PRE_{net} first normalizes the PRE for each route between node *i* and *j* with number of passengers using that route compared to the total number of passengers traveling in the entire network. This process will avoid highly efficient routes that are hardly utilized to have lower impact in the final PRE_{net} value. After the normalized PRE for every service route is calculated, PRE_{net} is calculated by simply summating the PRE for each route.

$$PRE = \frac{W_{pay} * R}{W_{fuel}} \tag{3}$$

$$PRE_{net} = \sum_{i=1}^{k} \sum_{j=i+1}^{k} \left(\frac{W_{payload,i\,j} * R_{i,j}}{W_{fuel,i\,j}} \right) \frac{P_{i,j}}{P_{net}} \tag{4}$$

All aircrafts modeled in this study uses the Boeing 737-300 as a baseline with tailored payload and range capabilities using Raymer's sizing method for preliminary aircraft design and the Breguet range equation [13]. To determine the fleet composition, a heuristic search is employed to find the most efficient combination of aircraft with range up to 3600 miles and 400 seats, at 100 miles and 5 seat intervals. A constant weight of 200lbs per passenger is assumed for the payload and load factor is fixed at 0.7 for all ops. The penalty function for not producing enough operations discussed in Section 2.3.3 is also employed here. In addition, the resulting fleet is required to serve all passengers that are able to travel from their origin to destination.

Fig. 12 and 13 displays the aircraft fleet composed of two and three aircraft which maximize PRE_{net} for the various network constructed by the NTG. Each entry in Fig. 12 and 13 represents an aircraft preferred for the six network topology types (BA value) categorized by different marker types according to the network density shown in the legend. Surprisingly, network density and topology type had little impact on the preferred range for the aircraft in the fleet. Higher BA value topologies have a tendency to prefer a smaller seat size, but the network density had a significantly larger effect. Networks with higher density seem to prefer aircraft with smaller seat size most likely due to passenger volume being more spread out among the routes compared to the lower density networks. Table 4 shows the PRE_{net} for both the two and three aircraft fleet in the different networks. PRE_{net} can be slightly increased by ~5% if a third aircraft type is introduced to the fleet. When increasing the number of aircraft type, the aircraft with the longest range remains relatively unchanged since it needs to serve passengers with the longer range trips.

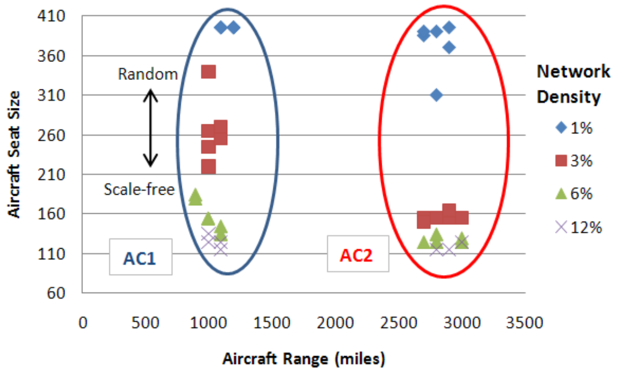

Fig. 12. Fleet with 2 aircraft that maximize PRE_{net} for various network topologies

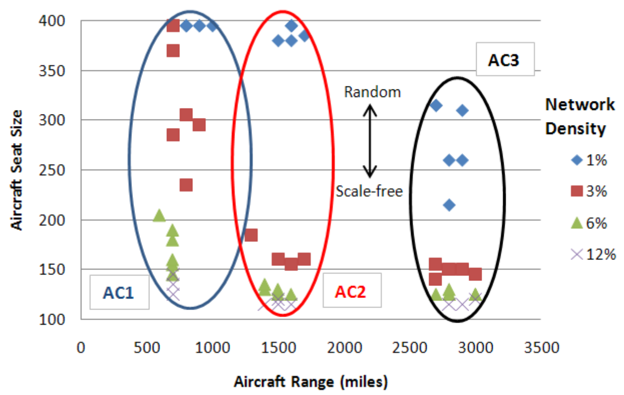

Fig. 13. Fleet with 3 aircraft that maximize PRE_{net} for various network topologies

Table 4: Percent of passengers that cannot be served after disruption

Network Density	BA Value	Avg. 2AC PRE_{net}	Avg. 3AC PRE_{net}	Network Density	BA Value	Avg. 2AC PRE_{net}	Avg. 3AC PRE_{net}
1%	100	1292.2	1348.3	6%	100	1038.6	1082.6
	80	1269.5	1309.8		80	988.4	1034.4
	60	1258.0	1304.4		60	992.3	1031.2
	40	1258.1	1306.7		40	1014.9	1057.6
	20	1256.7	1307.2		20	974.7	1019.1
	0	1275.9	1327.8		0	978.2	1021.9
3%	100	1120.9	1166.2	12%	100	1032.7	1076.6
	80	1105.4	1153.2		80	1001.4	1046.0
	60	1097.0	1147.7		60	965.5	1011.4
	40	1096.7	1145.5		40	948.9	990.9
	20	1084.7	1140.7		20	934.5	977.8
	0	1100.1	1151.8		0	910.2	954.4

7 Conclusions

Research reported in this paper provided an initial investigation on how the preferable architecture configurations for large scale systems like the ATS may differ depending on stakeholder viewpoints. A rudimentary trade-off among different service network configuration was examined for efficiency in processing travel demand, fuel consumption, resistance to various failure modes and preferred aircraft types. Current results presented throughout the paper show that the favorable network configurations may lie on opposite extremes depending on the different objectives examined. We do recognize that the control of the actual service route network structure is distributed among the various airlines; there is no central route-allocating architect. However, the results reported here provide quantitative bounds on the efficiency and robustness of different network configurations that could serve as targets for system transformation. Given these targets, policymaking bodies, as well as airline enterprises, can use the influence factors they do control to drive overall system behavior towards these preferred network configurations. Before further work in ATS transformation is commenced, objectives need to be prioritized in order to clarify the ideal configuration of the future ATS.

References

[1] DeLaurentis, D.A., “Understanding Transportation as a System-of-Systems Design, Problem,” *AIAA Aerospace Sciences Meeting and Exhibit*, 10-13 Jan. 2005.

[2] Albert, R., Barabási, A., 2002. Statistical mechanics of complex networks. *Rev. Mod. Phys* 74, pp. 47-97

[3] Guimera, R., Mossa, S., Turtschi, A., Amaral, L., 2005. “The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. *Proc. Nat. Acad. Sci. U.S.A.*, 102(22), pp. 7794-7799.

[4] Bonnefoy, P., Hansman, R., 2007. Potential Impacts of Very Light Jets in the National Airspace System. *Journal of Aircraft*, 44(4), pp. 1318-1326.

[5] DeLaurentis, D., Han, E-P., Kotegawa, T., 2008. Network-Theoretic Approach for Analyzing Connectivity in Air Transportation Capacity Networks. *American Institute of Aeronautics and Astronautics Journal of Aircraft*, 45(5), pp. 1669-1679.

[6] Kotegawa, T., Han, S., DeLaurentis, D., Implementation of Enhanced Network Restructuring Algorithms and Scenarios for Improved ATO Forecasts, *9th AIAA Aviation Technology, Integration and Operations (ATIO) Conference and Aircraft Noise and Emissions Reduction Symposium (ANERS)*, Hilton Head, SC, 21-23 Sep. 2009.

[7] “Transtats,” *Bureau of Transportation Statistics (BTS)*, accessed on 1 Dec. 2009, from http://www.transtats.bts.gov/homepage.asp

[8] Hileman, J., Katz, J., Mantilla, J., Fleming, G., “Payload Fuel Energy Efficiency as a Metric for Aviation Environmental Performance”, 26th International Congress of the Aeronautical Sciences, Anchorage, AK, 14-19 Sep. 2008.

[9] FLOPS, Flight Optimization System, Software Package, Release 7.01, NASA Langley Research Center, Hampton, VA, June 2006.

[10] Wang, Donohue, Oseguera-Loh., Analysis of Air Transportation for the New York Metroplex: Summer 2007. 3rd International Conference on Research in Air Transportation, Washington D.C., June 2008.

[11] Kotegawa,T., Fry, D., Puchaty, E., DeLaurentis, D., Impact of US Airline Network Topology on Air

Transportation System Performance. 4th International Conference on Research in Air Transportation, Budapest, Hungary, June 2010.

[12] Nangia, R., "Commercial Aircraft Efficiency Considerations & Meeting Environmental Challenges using Air-to-Air Refuelling & Close formation Flying," *AIAA Aviation Technology, Integration and Operations Conference*, AIAA, Belfast, Northern Ireland, 2007.

[13] Raymer, D. P., *Aircraft Design: A Conceptual Approach*, 4th ed., AIAA Education Series, AIAA, 2006.

Contact Author Email Address

Tatsuya Kotegawa tat@purdue.edu
Galen Harden gharden@purdue.edu
Daniel DeLaurentis ddelaure@purdue.edu

Copyright Statement

The authors confirm that they, and/or their company or organization, hold copyright on all of the original material included in this paper. The authors also confirm that they have obtained permission, from the copyright holder of any third party material included in this paper, to publish it as part of their paper. The authors confirm that they give permission, or have obtained permission from the copyright holder of this paper, for the publication and distribution of this paper as part of the ICAS2010 proceedings or as individual off-prints from the proceedings.