Ninth USA/Europe Air Traffic Management Research and Development Seminar (ATM2011)

Impact of Commercial Airline Network Evolution on the U.S. Air Transportation System

Tatsuya Kotegawa and Daniel DeLaurentis
School of Aeronautics and Astronautics
Purdue University
West Lafayette, IN USA
{tat, ddelaure}@purdue.edu

Kimberly Noonan and Joesph Post
Air Traffic Organization
Federal Aviation Administration
Washington D.C., USA
{kimberly.noonan, joseph.post}@faa.gov

***Abstract*—The air traffic forecast method for future schedules used by the United States Federal Aviation Administration (FAA) assumes a static route network operated by airlines; that is, new routes will not be added nor existing ones removed. However, the competitive nature of the airline industry is such that routes are routinely added or dropped between cities depending on passenger demand and airline business choices. This represents a significant gap between the forecasted and likely actual state of the US National Airspace System (NAS) in the long term, thus hampering stakeholders and decision-makers in their consideration of major policy, technology and infrastructure changes. To address this gap, a series of algorithms which forecast restructuring of the US commercial airline network were developed and tested. One restructuring algorithm produces discernible differences in the NAS of 2020 as compared to the FAA's primary forecast. The impact of these network structure differences on NAS-wide delay are assessed via the National Airspace Performance Analysis Capability (NASPAC) simulation. Both average flight delay and total delay is reduced in the modified schedule versus the FAA's original.**

Keywords-forecasts; network; air traffic; simulation.

I. INTRODUCTION

To synthesize long term plans for new technology, infrastructure improvements, policy enhancements, and regulations for the Air Transportation System (ATS), an understanding of air traffic dynamics—how, when, and where air traffic arises or shifts in the future—is needed. The official forecast of aviation activity at Federal Aviation Administration (FAA) facilities is the Terminal Area Forecast (TAF). FAA's Air Traffic Organization (ATO) Office of Performance Analysis and Strategy (AJG-6) uses the TAF to produce forecasted air traffic schedules. These future daily schedules help to project future performance, identify operational shortfalls, determine workforce requirements, and estimate the benefits of future investments [1]. The current forecast algorithm applies a boot-strapping technique to the current air traffic schedule to meet the projected growth in the TAF. Therefore the future service route network structure remains static for all forecasted years, precluding the establishment of new routes and limiting the ability to forecast hub formation and deletion [2].

In fact, the service route network structure substantially changes over time [3]. The competitive nature of the airline industry is such that new direct routes are routinely added between cities with significant passenger demand and routes are also removed when demand diminishes. In addition, the location and number of airline hubs are not fixed; within the past several years, two major hubs have been eliminated (St. Louis and Pittsburgh), one airline hub opened and subsequently closed (Washington Dulles), and several other hubs were substantially restructured [4,5]. In order to enhance the NAS network forecast precision, a better understanding of restructuring dynamics is required. An earlier approach to this problem employed and compared artificial neural networks, logistic regression, and a network fitness function approach to forecast restructuring based on topological properties of constituent airports and associated population levels [6]. While each of the three techniques exhibited quality in some portion of forecasting (e.g., correctly identifying new network links, minimizing the number of false positives, etc.), none performed well in the overall task of correctly forecasting network restructuring terms of correct route additions and deletions and the number of new routes. In addition, the changes in network structure developed by the algorithms were not compared to a nominal forecast in the same future year. Motivated by the goal of improved comprehensive forecasts and assessment of their impact, *the objective of research presented in this paper is to construct restructuring algorithms that better capture the mechanisms of service network evolution and assess the impacts of resulting changes on NAS performance*. The improved algorithm still operates on the same network topology data [6], but proceeds in two serial steps employing a support vector machine algorithm followed by a logistic regression for link addition and logistic regression alone for link removal. NASPAC, the FAA-ATO standard system-wide model used for technology and procedure cost-benefit analysis, is employed at the end of the paper to assess the impact of the restructured network on NAS-wide delay.

II. TECHNICAL APPROACH

A. Network Charecterization and Definition of Topology Parameters

The service network consists of airports (nodes) connected by service routes (links) operated by the airlines. The weight on a link represents the number of annual operations that are carried out between the two airports connected by the link. Table I summarizes key metrics used to characterize network nodes. These metrics are employed in the forecast algorithms presented later in this paper. The general implications in Table I indicate how these various measures imply important roles in a network. We attempt to utilize nodal metrics as predictor variables to estimate the likeliness of airport pairs to connect or disconnect based on historical data. In other words, the forecast algorithms seek to "learn" patterns in the types of nodes that were involved in new links (or removed ones) and use this information as a basis to predict future network restructuring.

In particular, the network restructuring forecast algorithm operates on an input topology in two regimes: link addition and link removal. These two activities are performed year-to-year,

TABLE I. KEY NETWORK METRICS

Measure	Symbol and Equation	General Implications
Node	N/A	Represents an airport within the US ATS
Non-weighted adjacency matrix	A	Mathematical expression for a network. The matrix size depends on how many nodes compose the network – if there are *n* nodes in the network, the matrix size will be *n* x *n*. All entries are binary, indicating whether a link between two nodes are present ("1") or not ("0"). For example, if a link between node 1 and 5 exist, the entry in $A_{(1,5)} = 1$
Weighted Adjacency Matrix	A^w	Similar to non-weighted adjacency matrix but instead of a binary value, each link has a corresponding scalar weight that signifies some distinguishing trait such as distance, number of operations, etc.
Node Degree	$k_i = \sum_j A_{ij}$	In the transport network, degree refers to the total number of connection node *i* has with other nodes
Node weight, or strength, is the total load on all its links	$s_i = \sum_j A_{ij}^w \quad (1)$	In the transport network, node weight represents the amount of traffic (operations) associated with the node.
Link Weight	A_{ij}^w	The link weight refers to the amount of traffic that occurs between node *i* and *j*
eigenvector centrality, introduced by Newman (2004), used for weighted networks, is proportional to the linear combination of its neighbors' degree and strength of links	$x_i = \lambda^{-1} \sum_j A_{ij}^w x_j \quad (2)$ In a compact form, Eq. (2) becomes $A^w x = \lambda x$, an eigenvector problem where x is an eigenvector of the adjacency matrix.	In the transport network, the importance of one airport is determined not only by its own number of routes supported, but also the number of routes and traffic level of airports with which it directly connects (i.e., an airport with high eigenvector centrality is likely to be very busy itself and also connected to other busy airports).
clustering coefficient for a given node is the number of triangles centered on that node divided by the number of triples centered on that node.	$C_i = \frac{1}{k_i(k_i - 1)} \sum_{j,k} A_{ij} A_{ik} A_{jk} \quad (3)$	Measure of local cohesiveness for a collection of nodes; A node with higher $C_i > C_{avg}$ is "more interconnected" than the average. This measure has implications on local robustness (or global for the average value). Higher C_i indicates greater robustness since alternate connection paths may exist when a neighboring node fails.

predicting where new links will occur (and with what weight), where links will be removed, and adjusting operations that occur in other existing links due to the change in topology. The resulting network structure contributes to the Future Schedule Generator which produces flight segment schedules for future years in conjunction with the TAF and the Enhanced Traffic Management System (ETMS). The details on how the forecast algorithm, TAF and ETMS integrate to produce a future flight segment schedule is described in Section III.

B. Data Source and Assumptions

The data used for this study is obtained from the Air Carrier Statistics database family maintained by the U.S. Bureau of Transportation Statistics, or BTS. In particular, the Form 41 T-100 Domestic segment (All US Carriers) database was used to construct the network studied [7]. This dataset only includes commercial IFR flights. The BTS monitors 2,627 US airports but we reduced the network size by eliminating relatively inactive nodes in the network evolution. This reduction serves two purposes: it reduces the level of complexity in accurately predicting restructuring and focuses the analysis on the primary mechanisms driving the NAS network evolution. Airports were required to be located in the CONUS, have an average of at least one operation per day and one connection with another airport every year between 1990 and 2008. Application of these criteria reduced the final network size to 304 nodes. The historical data involving these 304 airports from 1990-2008 served as the training data for the forecast algorithms.

C. Link Addition Algorithm

Forecasting particular new links in the NAS network is much like looking for a needle in a haystack. On average over the past 20 years, 140 new city-pair links are introduced to the NAS network. The network is composed of 304 nodes and approximately 1,600 existing links, so there are 46,000 possible candidates that the link addition portion algorithm must consider to find the roughly 140 new links. Further, the over-forecasting nature of the algorithms makes this problem even more challenging. The current NAS network is mainly a hub-and-spoke structure with many small, spoke airports and very few large, hub airports. With abundant spoke airports that show similar network characteristics [6], all link addition algorithms tend to predict connections for too many hub-spoke and/or spoke-spoke type links. To overcome this difficulty, we take a layered approach which combines two algorithms. The first algorithm aims to narrow the search space by correctly filtering out node-pair candidates that are most unlikely to connect. A second forecast algorithm is then used to evaluate and assign a fitness value to the candidates that make it through the first algorithm. New link candidates with the top-ranking fitness values are then connected at the end of each timestep.

The two algorithms chosen for the final link addition process is based on its Type I and II error performance. In the link addition scheme, Type I error refers to the algorithm's rate of not connecting new links that should actually be connected. On the other hand, Type II error is the rate at which the algorithm constructs new links between nodes that should remain disconnected. For the first filter where we want to correctly eliminate as many non-connecting node pair candidates as possible; an algorithm with low Type II error is preferred. A forecast algorithm with low Type I error is favored for the second process in which we are searching for the node pairs to actually connect.

For the first filter in the link addition process, a support vector machine (SVM) algorithm is chosen due to its superb performance in maintaining low Type II error. SVM is a type of supervised machine learning which recognizes and analyzes patterns by constructing an n-dimensional hyperplane that optimally separates data into multiple categories [8]. In the link addition context, the two categories for classification of the unconnected node pairs were: 1) connect or 2) remain disconnected (based on their network characteristics). The SVM model showed spectacular performance in keeping Type II error low for any combination of network metric utilized but the best performance is seen when only eigenvector centrality is used. The results are summarized in Table II. Here, Type II error is calculated by

$$
\begin{aligned}
&\textit{Type II error} = (\textit{New link candidates after SVM filter} \\
&-\textit{Correct new links that pass SVM filter}) \\
&/\ (\textit{Total number of new link candidates}) \qquad (4)
\end{aligned}
$$

When the SVM is trained through eigenvector centrality and a linear kernel hyperplane, Type II error ranges between 14-16% while for other algorithms we tried this value is no less than 50% (and hence, are excluded from this paper). However, even with such low Type II error, more than 6,000 incorrect candidates still pass through the SVM filter. Thus, an additional step, or filter is needed to produce a final number of new links of the same order as the historical average of 140. This is provided by a logistic regression algorithm, for which we are well-experienced from our prior models for network restructure forecasting.

TABLE II. REPRESENTATIVE STATISTICS FOR SVM ALGORITHM

	Year			
	1990-1991	***1998-1999***	***2007-2008***	***Average (1990-2008)***
Total number of new link candidates	44,455	44,369	43,661	44,202
Number of acutal new links	92	106	134	140
New link candidates after SVM filter	6,381	6,303	7,145	6,635
Correct new links that pass SVM filter	79	82	182	117
SVM filter Type II error	14.2%	14.1%	15.9%	14.7%

The logistic regression mode ranks the fitness of each new link candidate based on historical data. Logistic regression is a statistical technique that is used to calculate the probability of a certain even occurring based on historical data. For application in new route addition, the probability of a new link occurring between nodes based on its network characteristics is computed. This probability of node *i* and *j* forming a link is:

$$P_{connect,ij} = \frac{1}{1+\exp(-B_{connect,ij} X_{connect})} \tag{5}$$

The design matrix B in (5) contains the network metrics for the node pair (*i,j*) in the following fashion:

$$\begin{aligned} B_{connect,ij} = [&\max(k_i, k_j)\ \min(k_i, k_j)\ \max(s_i, s_j) \\ &\min(s_i, s_j)\ \max(C_i, C_j)\ \min(C_i, C_j)\ \max(x_i, x_j) \\ &\min(x_i, x_j)] \end{aligned} \tag{6}$$

$X_{connect}$ in (5) is a vector which contains the regression coefficients obtained through the iteratively-reweighted least squares (IRLS) algorithm, a training scheme for the logistic regression [9]. Values for $X_{connect}$ that were used in the final algorithm are

$$\begin{aligned} X_{connect,ij} = [&0.04\ \ 0.16\ \ -2.26e-6\ \ -3.40e-5 \\ &-3.12\ 0.93\ 2.34\ 46.27] \end{aligned} \tag{7}$$

The 140 new link candidates with the highest $P_{connect}$ are selected as new links for that year period. Table III shows the accuracy of the SVM results both with and without the second, logistic regression filter.

TABLE III. NEW LINK ADDITION RESULTS

Algorithm Type	Year			
	1990-1991	*1998-1999*	*2007-2008*	*Average (1990-2008)*
Accuracy for SVM followed by logistic regression	5.7%	7.9%	15.0%	10.2%
Accuracy for SVM followed by a random draw	1.2%	1.3%	1.9%	1.7%
Accuracy for random draw	0.2%	0.2%	0.4%	0.3%

The accuracy shown in Table III as well as the remainder of the Tables in this paper is equivalent to 1-Type I error, or

$$\begin{aligned} &Accuracy = Correctly\ forecasted\ new links \\ &/\ Number\ of\ actual\ new\ links \end{aligned} \tag{8}$$

The accuracy is clearly superior with the SVM and logistic regression used in series. The average accuracy for the training period is 10.2%. Though this value seems low, it actually represents a tremendous improvement over a random selection (last row of Table III) and is a significant capability in light of the "needle in haystack" problem.

D. Link Removal Algorithm

Compared to link addition, forecasting which links will disconnect is somewhat easier since the number of candidates is limited to the total degree of the network: approximately 2,000 compared to 46,000 for link addition. In addition to nodal, the link weights can also be employed to differentiate links that disconnect from those that do not. Various algorithms and parameter combinations were constructed and tested for the link removal process; not all will be described in detail here but a portion of the final accuracy results for those algorithms tested are displayed in Table IV.

After investigating the several approaches, an approach similar to the link addition algorithm demonstrated the best results; the only major difference being the initial filtering process is not necessary since the number of candidates is already relatively small. Equation (5) is used again but the predictor variable is now just the link weight. Thus, the probability for an existing link to be disconnected is:

$$P_{connect,ij} = \frac{1}{1+\exp(0.0019 A_{i,j}^{w})} \tag{9}$$

The coefficient on the link weight is derived by training the logistic regression via IRLS with historical data. After $P_{disconnect}$ has been calculated, the top 93 node pair candidates' links are removed, which is based on the historical average. Table V

TABLE IV. RESULTS OF OTHER LINK REMOVAL ALGORITHMS

Algorithm Type	Year			
	1990-1991	*1998-1999*	*2007-2008*	*Average (1990-2008)*
Node (airport) distance filter	7.4%	6.8%	11.5%	9.7%
SVM using eigenvector centrality	9.1%	17.5%	13.2%	14.17%
Logistic regression using link weights	15.8%	26.4%	19.8%	20.38%

TABLE V. FINAL LINK REMOVAL ALGORITHM RESULTS

	Year			
	1990-1991	***1998-1999***	***2007-2008***	***Average (1990-2008)***
Number of link removal candidates	1,601	1,687	2,395	1,761
Number of acutal links removed	119	55	126	94
Accuracy for logistic regression	41.2%	61.8%	34.9%	42.3%
Accuracy for random draw	7.4%	3.3%	5.3%	5.3%

summarizes the link removal results, indicating a much higher accuracy compared to randomly removing the same number of links as were removed historically in an annual period.

E. Link Weight Adjustment

After links are added and removed using the procedure described in the previous sections, the link weights are adjusted using the following process. First, the projected terminal operations for each airport are calculated from the number of operations in the previous timestep using the TAF. Once this is done, the newly established links are assigned weights using a historical distribution based on the distance between the airports. The Fratar algorithm [10] is then employed to adjust the weights on the links (both new and the ones that remained from the previous time step) so that the projected terminal operations matches the sum of their weights within a certain tolerance level. This network evolution procedure is iterated year by year until the target year for the forecast is reached. The final product of this algorithm is a NAS network in which the link weights represent the amount of annual operations between the corresponding nodes (airports).

III. PREPARING MODIFIED NETWORK FORECASTS FOR NASPAC

The system-wide analysis tool used to assess performance impacts of the modified network is the FAA's modernized National Airspace Performance Analysis Capability (NASPAC) model. As primary input, NASPAC requires a daily schedule. However, the network restructuring algorithms described above operate on an annual scale. Therefore several steps are required to transform the modified network into a daily schedule. First, the links weights of the annual NAS network are normalized by the total link weight. The normalized network is then scaled to the day level by multiplying the total number of operations that take place in the particular day we want to analyze. The FAA's office that produces the original future daily schedules, AJG-6, recommends March 19, 2009 as a uniformly busy, representative day for fiscal year 2009. . The final product is a "network day" corresponding to the modified network structure. Each of the operations in the day-level NAS network requires a flight schedule in order to be processed by NASPAC. The same technique used by AJG-6 is used where the flight segment schedules for future years are produced by bootstrapping historical flight plan data from ETMS [11]. For newly created links with no historical flight plans, we simply copy the flight schedules and other details (such as equipment, waypoints, etc.) from airport pairs with similar distance and have historical ETMS schedules. Lastly, since the forecast algorithm only works with commercial flights, other user classes must be added such as VFR, cargo, general aviation etc. The current approach for this issue is to use the original AJG-6 forecasted schedules for non-commercial operations and combine it with the commercial schedules generated under the new, restructured network topology from the forecast algorithm.

IV. RESULTS

A. Comparison of Network Structure in the Original and Restructured (modified) 2020 schedules

In the presentation of results, "original" refers to the FAA AJG-6's forecasted network/schedule on 3/19/2020 and "modified" refers to the network/schedule for that same day generated as a result of the network restructuring algorithm (and associated corrections) described in the prior sections. Overall, the network restructuring algorithm significantly increased the total degree (size) of the commercial airline network, from 2274 to 3442. The majority of these new links were granted towards the small to medium size airports which originally had degrees ranging among 20 to 60, as it can be seen in Fig.1. This phenomenon is more apparent when comparing the degree distribution between the two schedules, shown in Fig. 2. The original schedule shows the traits of a typical hub-and-spoke type network but the modified schedule displays a significant rise in number of medium-size airports with degree ranging from between 20 and 80. Meanwhile, the distribution in strength of nodes (number of operations) is very similar between the original and modified schedule, depicted in Fig.3.

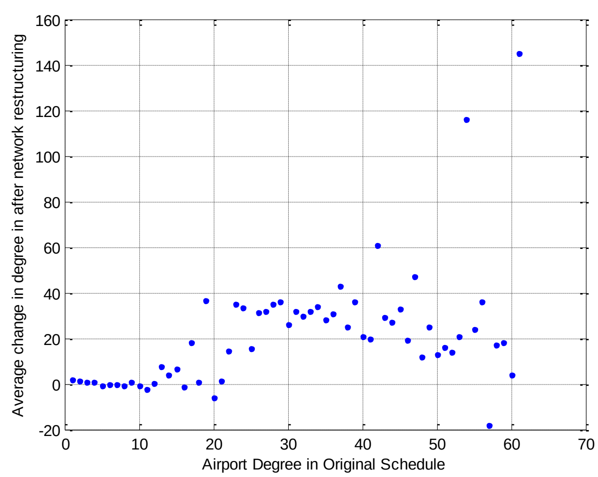

Figure 1. Change in airport degree between original and modified schedule.

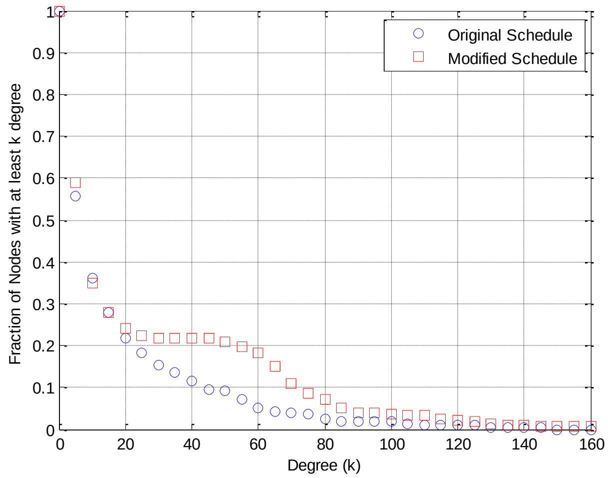

Figure 2. Cumulative degree distribution for the original and modified schedule network.

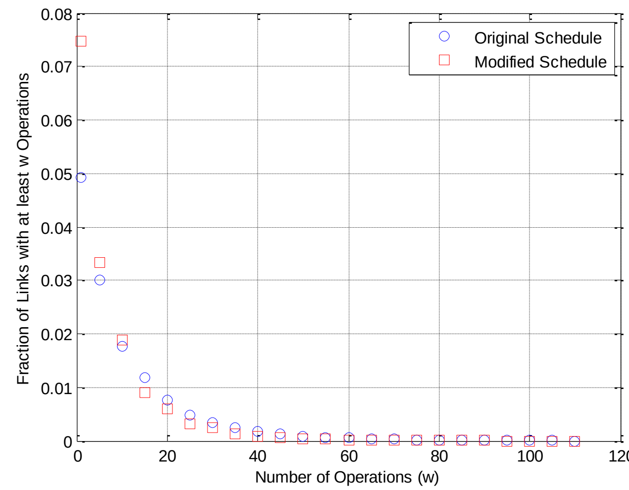

Figure 3. Weighted degree distribution for the original and modified schedule**.**

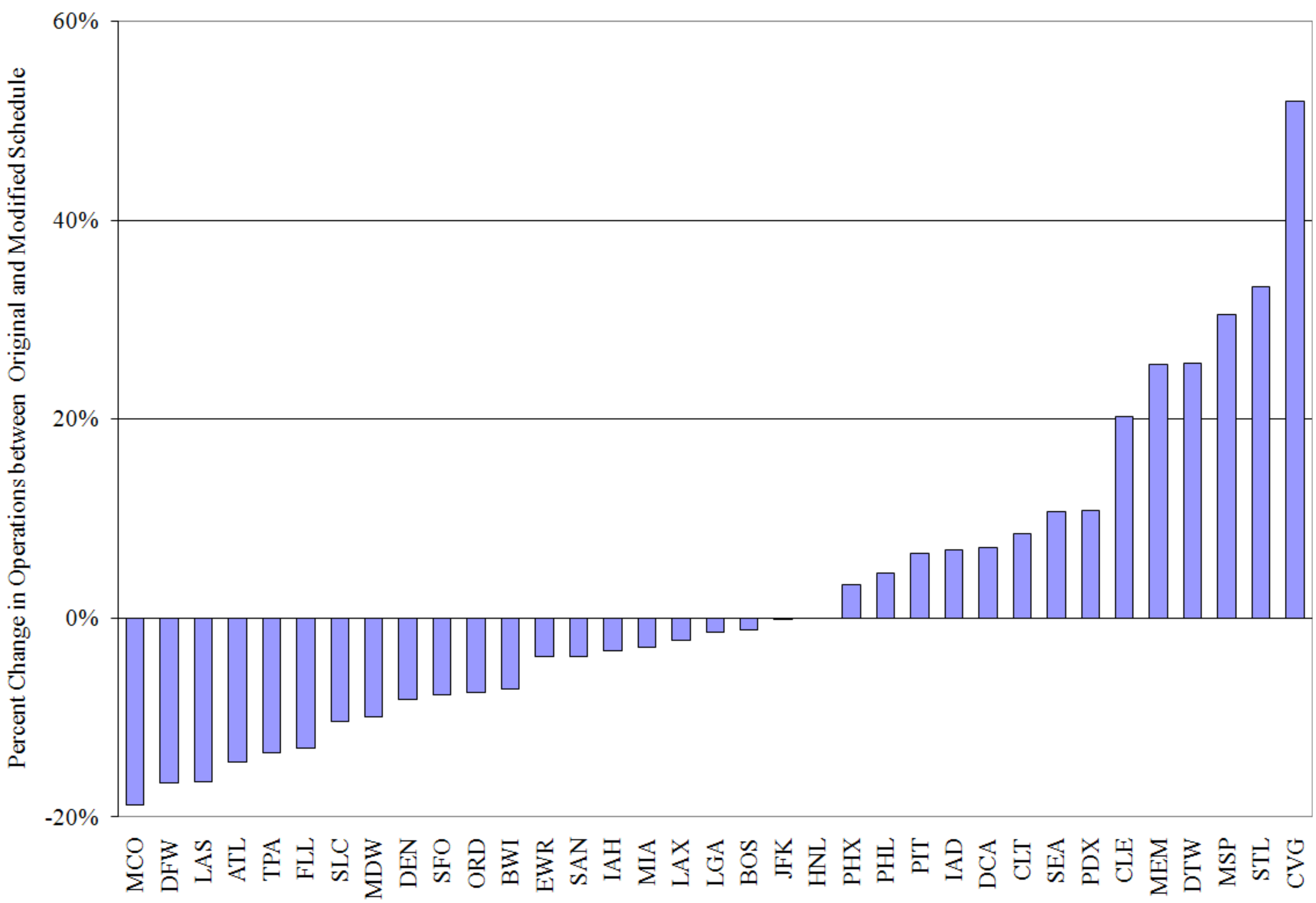

Figure 4. Percent change in operations (weighted degree) at OEP 35 airports.

B. *Traffic at Key Airports*

The network restructuring algorithm reduced the number of operations at some of the largest Operational Evolution Partnership (OEP) 35 airports while increasing at others (Fig. 4). Large hubs like ATL and DFW saw reduced traffic compared to the original while significant increases occurred at STL and CVG. While the restructuring algorithm did not have any direct features that addressed metroplexes, modest, but not dramatic, changes in overall traffic at the two major east coast metroplexes (NY/NJ and Washington, DC) are generated versus the original network. IAD and DCA grow around 7% while BWI is reduced by about 7%. LGA (-2%) and EWR (-4%) are reduced while JFK is nearly unchanged.

A more detailed analysis regarding the change in operations at ATL and CVG was done. The network restructuring algorithm added 139 links to ATL compared to the original 2020 schedule. However, the flight frequency on many existing links was reduced (Fig. 5). Overall, since the total operations at ATL in 2020 were reduced in the modified network by about 13%, the reduction in frequency on common links was reduced enough to overcome the new operations added by via new city pairs. The ATL city-pairs in the modified schedule had an average of only 8.9 operations per city-pair where as in the original it had 16.4 operations per city-pair. CVG was showed similar trends. CVG started out with 104 city-pairs which was increased to 131 in the modified schedule. Terminal operations were also increased from 728 to 1106, resulting in a slight increase from 7 to 8.4 for the average operations per city-pair; this change is also reflected in its weighted degree distribution shown in Fig. 6.

It is interesting to observe that many airports in the modified schedule experienced higher degree but with similar or less amount of traffic on each degree. It is hypothesized that the cause of this stems to the ratio between the degree and operations increase rate within the forecast algorithm. The NAS network degree increases about 2% annually according to the data obtained from the BTS. On the other hand, the average TAF across all airports shows a net increase of 1%. The cause of many airports having high degree with lower operations on each degree may be due to the degree increase rate being larger than the operations increase rate. Further analysis is required to better understand the cause of this phenomenon.

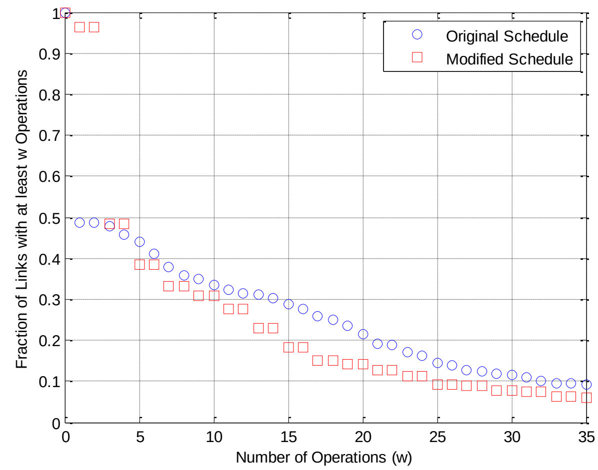

Figure 5. Change in weighted degree distribution at Hartsfield-Jackson Atlanta International Airport (ATL).

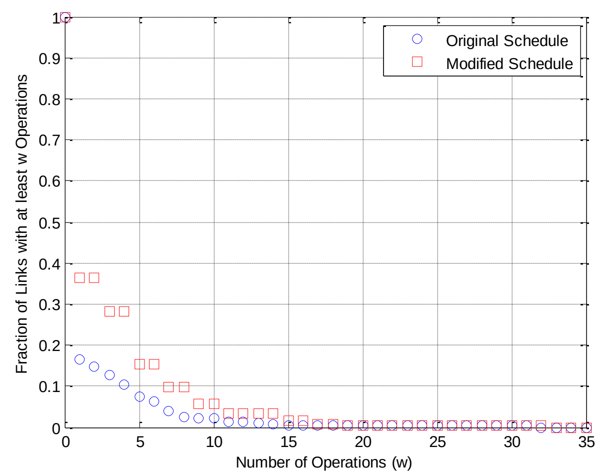

Figure 6. Change in weighted degree distribution at Cincinnati/Northern Kentucky International Airport (CVG).

C. Changes in NAS Performance

Inputs to NASPAC include aircraft itineraries, flight plans, miles-in-trail restrictions, wind/weather data, time-varying airport arrival and departure capacities, and airspace sector geometries and capacities (also time-varying). Model results are typically summarized by the following metrics: delay per flight segment (gate, surface, and airborne) and flights accommodated. The above figures summarize the differences in delay minutes between the original and modified forecasts computed by NASPAC. Total delay is calculated as the sum of gate delay, surface delay and airborne delay. Airborne delay is comprised of departure fix delay, en-route sector delay, arrival fix delay, and arrival queuing delay. Both the average delay per flight and the daily total of delay were lower for the modified network than the original (see Figs 7 and 8). However, when the delay is broken down by flight phase, the modified schedule is seen to exhibit greater delay (both on average and in-total) in the enroute sectors. This result follows from the "spreading of traffic" away from the largest hubs and towards medium to minor hubs after the restructuring algorithm is run. The typical outcomes from overcrowded large hubs (gate, departure, and arrival delays) are reduced at the expense of more traffic in the sectors. However, in aggregate, the total and average delay minutes are slightly lower in the restructured network.

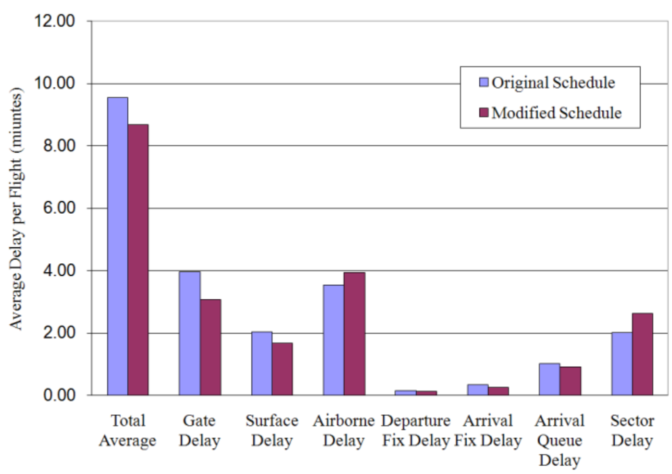

Figure 7. Average delay minutes per flight categorized by source.

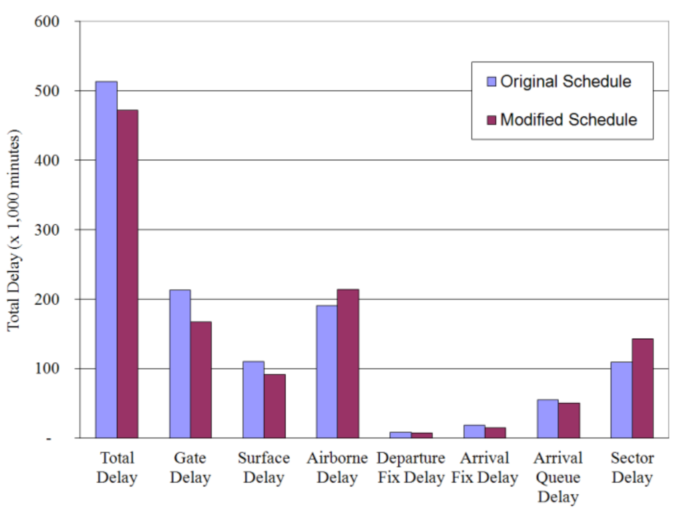

Figure 8. Total delay minutes categorized by source.

This outcome has direct implications for FAA resource planning. If airlines shift their operations from hubs towards the small to medium size airports (as the network forecast suggest), the source of delays will also shift accordingly. Besides increasing the capacity at hub airports to relieve congestion we see in the NAS today, the FAA will also need to allocate resources towards expanding the airspace sector capacity in order to be one step ahead of the game and prevent high delays from occurring in the future.

While the network forecast algorithm cannot give the exact answer on how the NAS network will look like in the future, it can be used to capture the general direction of its evolution. Simulation tools such as NASPAC can then be incorporated to project the change in performance due to the network evolution and therefore identify upcoming operational shortfalls, workforce requirements and most importantly estimate some of the benefits of future investments.

V. CONCLUSION

This paper presented the latest network restructuring algorithm aimed to capture the evolutionary behavior of the U.S. NAS network. The algorithm is capable of estimating where, when and how much air traffic will likely to occur in the future. Compared to some of the previously developed forecasts, the current algorithm shows much better performance.

Traffic forecasts are critical for strategic planning, but many state of the art forecasting techniques assume a static NAS network structure. In reality the NAS network is quite dynamic, changing its characteristics at significant speed. Discernible differences were observed in the 2020 network produced by the restructuring algorithm compared to the FAA's primary forecasts.

By implementing a system-wide analysis capability to the forecast algorithm through NASPAC, operational performance of the future NAS network can now be estimated. Further development of this tool will enable analysts to better point out potential future pitfalls in the system, as well as carry out more accurate benefits analysis for various long term investments.

ACKNOWLEDGMENT

This research was sponsored by the FAA Air Traffic Organization Office of Performance Analysis and Strategy via the PARTNER Center of Excellence. The contribution of James Bonn at the FAA ATO's NAS Modeling Group (AJP-D) in running many NASPAC cases and assisting with algorithm test was instrumental. The contributions over the past several years of Donald Fry, Sricharan Ayyalasomalajula and Shashank Tamaskar from Purdue University are also acknowledged and appreciated.

REFERENCES

[1] Post, P., Gulding, J., Noonan, K., Murphy, D., Bonn, J., Graham, M., 2008. "The Modernized National Airspace System Performance Analysis Capability". 26th *International Congress of the Aeronautical Sciences*, 14-19 September 2008, Anchorage, AK.

[2] Schaufele, R., 2007, *Terminal Area Forecast Summary*. [Online] Federal Aviation Administration. Available at: http://www.faa.gov/data_research/aviation/taf_reports/media/TAF2007-2025Summary.pdf [Accessed 24 June 2009].

[3] Kotegawa, T., DeLaurentis, D., 2007. "Evolution of Service Provider Behaviors via Network-based Analsysis". 7th *AIAA Aircraft Technology, Integration and Operations*. 18-20 September 2007, Belfast, Northern Ireland.

[4] Compart, M., 2009. American Leaving Love Field. [Online] Aviation Week. Available at: http://www.aviationweek.com/aw/generic/story_channel.jsp?channel=comm&id=news/LOVE03169.xml. [Accessed 24 June 2009].

[5] Ssdada Michels, J., 2007. *Pennsylvania Delegation Grills Parker on Philly Slots*. [Online] Aviation Week. Available at: http://www.aviationweek.com/aw/generic/story_generic.jsp?channel=comm&id=news/specpark11097.xml&headline=Pa.%20Delegation%20Grills%20Parker%20On%20Philly%20Slots. [Accessed 24 June 2009].

[6] Kotegawa, T., DeLaurentis, D., Sengstacken, A., "Development of Network Restructuring Models for Improved Air Traffic Forecasts," *Journal of Transportation Research Part C: Emerging Technologies*, Vol.18 (2010), pp.937-949. DOI:10.1016/j.trc.2010.03.004

[7] U.S. Bureau of Transportation Statistics, Air *Carrier Statistics (Form 41 Traffic) – US Carriers*. [Online] Available at: www.transtats.bts.gov. [Accessed 13 Jan 2011].

[8] Cortes, C., Vapnik, V., "Support-Vector Networks," *Machine Learning*, Vol.20 (1195), pp.273-297. DOI: 10.1007/BF00994018

[9] Guitton, A., *2000. Huber solver versus IRLS algorithm for quasi L1 inversion.*[Online] Available at: http://sepwww.stanford.edu/public/docs/sep103/antoine2/paper_html/index.html. [Accessed 18 June 2009].

[10] Fratar, T. (1954), "Vehicular Trip Distribution by Successive Approximation," Traffic Quarterly, Vol.8, 1954, pp. 53-56.

[11] Department of Transportation, "Enhanced Traffic Management System (ETMS) Functional Description Version 8.3," Volpe National Transportation Systems Center VNTSC-TFM-FD-003, Cambridge, MA, January 2007.

AUTHOR BIOGRAPHY

Tatsuya Kotegawa is a graduate research assistant in the System-of-Systems Laboratory and a PhD candidate in the School of Aeronautics and Astronautics at Purdue University. He received his BS and MS in Aeronautical and Astronautical Engineering from Purdue in 2006 and 2008, respectively. His research interest lies in developing foundational methods and tools for addressing problems seen in large-scale, complex systems, often characterized as system-of-systems.

Daniel DeLaurentis is an Associate Professor in Purdue's School of Aeronautics & Astronautics in West Lafayette, IN. Dr. DeLaurentis leads the System-of-Systems Laboratory (SoSL) which includes graduate and undergraduate students as well as professional research staff. His primary research interests are in the areas of problem formulation, modeling and system analysis methods for aerospace systems and systems-of-systems (SoS), with particular focus on air transportation. His research is conducted under grants from NASA, FAA, Navy, and the Missile Defense Agency. Dr. DeLaurentis is an Associate Fellow of the American Institute of Aeronautics and Astronautics, served as Chairman of the AIAA's Air Transportation Systems (ATS) Technical Committee from 2008-2010, and is Associated Editor for the IEEE Systems Journal. He earned a PhD in Aerospace Engineering from the Georgia Institute of Technology (Atlanta, GA) in 1998.

Kimberly Noonan is an operations research analyst in the Federal Aviation Administration's NextGen and Operations Planning Office of Systems Analysis. Ms. Noonan received a bachelor of science degree in mathematics from the University of Richmond, and both a master of science degree in computer science and a master of science degree in mathematics from the University of North Carolina at Chapel Hill.

Joseph Post is the director of systems analysis in the Federal Aviation Administration's NextGen and Operations Planning organization. He received a bachelor's degree in aeronautics and astronautics from the Massachusetts Institute of Technology, a master's degree in electrical engineering from Yale University, and a master's degree in economics from George Mason University. Mr. Post holds numerous patents in the area of automatic flight control systems and is an instrument-rated pilot.