SCALE-FREE NETWORKS AND COMMERCIAL AIR CARRIER TRANSPORTATION IN THE UNITED STATES

Sheila R. Conway
Old Dominion University, NASA Langley Research Center

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Abstract

Network science, or the art of describing system structure, may be useful for the analysis and control of large, complex systems. For example, networks exhibiting scale-free structure have been found to be particularly well suited to deal with environmental uncertainty and large demand growth.

The National Airspace System may be, at least in part, a scalable network. In fact, the hub-and-spoke structure of the commercial segment of the NAS is an often-cited example of an existing scale-free network After reviewing the nature and attributes of scale-free networks, this assertion is put to the test: is commercial air carrier transportation in the United States well explained by this model? If so, are the positive attributes of these networks, e.g. those of efficiency, flexibility and robustness, fully realized, or could we effect substantial improvement?

This paper first outlines attributes of various network types, then looks more closely at the common carrier air transportation network from perspectives of the traveler, the airlines, and Air Traffic Control (ATC). Network models are applied within each paradigm, including discussion of implied strengths and weaknesses of each model. Finally, known limitations of scalable networks are discussed. With an eye towards NAS operations, utilizing the strengths and avoiding the weaknesses of scale-free networks are addressed.

1 Introduction

Changes in the demand for air transportation are inevitable, and indeed seem to be upon us. The National Airspace System (NAS) improvement initiatives currently being pursued are focused on incremental improvements in today's Air Transportation System (ATS), but it is becoming clear these will not satisfy future demand. In June of 2001, Federal Aviation Administration (FAA) spokesman William Shumann told the San Francisco Chronicle, "Even if the [FAA] plan attains the goal of a 30 percent increase in air traffic, it will not completely close the gap between supply and demand... There is no obvious solution." More dramatically, Transportation Secretary Norm Minetta recently called for tripling the air traffic capacity of the United States in the next 15 to 20 years because of growing demand in the airline sector and the introduction of new transportation modes such as jet taxies and unmanned aerial vehicles. He stated, "The changes that are coming are too big, too fundamental for incremental adaptation of the infrastructure... We need to modernize and transform our global transportation system, starting right now."[1]

Unfortunately the revolutionary changes required to accommodate a large and rapid increase in capacity will be very difficult to implement, and the operational consequences of introducing the changes difficult to predict. The ATS is a very large, complex "system-of-systems" that evolved in response to powerful social, political, economic and technological pressures. The technological infrastructure alone is enormous, and represents a substantial investment.

If researchers are to provide meaningful alternatives to policy makers regarding this urgent national problem, they will need methods to rapidly and reliably model the characteristics and performance of ATS innovations as they are developed. The complexity of the task suggests that the system design and transformation will likely be iterative in nature, levying constraint on the investment of any single iteration, particularly in the early formative phases. However, researchers also need to rigorously verify that any suggested changes meet minimum criteria, such as safety and reliability. [2]

Traditional parametric modeling techniques meet the requirement for rigor, but they can be complex and costly to develop[3 4]. They are also inherently unable to predict dynamic and higher-order behaviors of complex systems unless all of those behaviors are fully understood and incorporated into the model[5 6 7]. Kutaka and Fursova assert "the complexity of real systems does not allow one to construct 'absolutely' adequate [traditional] models." [8] Even more importantly, these deterministic models can not, by themselves, be used for establishing sensitivity to uncertain demand, or generalizing behavior of a yet undefined future system.[9 10] Given the complexity of the ATS, developing a sufficiently comprehensive model of all higher-order behaviors is unlikely.

System engineering methods may be useful in this complex, multi-objective realm. Daniel[11] suggests that, of the many systems modeling techniques described in the literature, soft systems methods are particularly well suited to context-rich, non-linear problems that can not be expressed by a single set of objectives or goals. These methods have, however, been criticized for being unverifiable, non-quantifiable, and lacking in rigor.[12]

For a safety-critical system with minimum performance criteria, mental constructs (and the flexibility they provide as "controlling" qualities) are not sufficient. In fact, Moss[13] goes so far as to say that neither "current social theory, nor any similar construct, will ever support an effective policy analysis." How then to address complex systems in both a rigorous but sufficiently realistic and tractable way? Moss provides a suggestion as he continues; "However, adaptive agent modeling is an effective substitute when embedded in a wider policy analysis procedure."

Bonabeau[3] claims that Agent-Based Modeling (ABM) is "by its very nature the canonical approach to modeling emergent phenomena" of complex systems, necessary for analysis of nonlinear behaviors, localized phenomena, and heterogeneous populations. However, he also acknowledges difficulties in building ABMs of large systems because of the myriad low-level details and the "extremely computation intensive and therefore time consuming" model that results.

While full-scale ABMs can be as complex and costly to develop as a large-scale parametric model, there may be a means of validating the model and educing a number of higher-order effects without constructing and running a full-scale agent-based simulation: Network analyses, developed in the field of network science (an extension of graph theory) could be applied to a network defined by the agents' communications demands. These may provide a relatively simple and reliable means of evaluating the aggregate performance of proposed ATS.

For some time, network models have been recognized as valuable aids "in the analysis and synthesis of systems."[14] Whitehouse mentions the ease of model formation, the inclusion of communications between model elements, and a means of specifying data requirements and nominal system state as important attributes of the technique. By modeling the ATS as a network or series of networks, we may be able to elucidate complex system attributes, e.g. system dynamics and emergence without having to develop a full agent-based simulation.

2 Network types and their attributes

2.1 What is a Network?

Networks are mathematical descriptions of systems using nodes (e.g. airports) and links to connect the nodes (e.g. routes). All networks are interconnected in some way or another, and are often categorized by their structure. In turn, this structure imparts peculiar characteristics to both the system as a whole and to the individual nodes. Following specific connectivity rules, some networks have some nodes that are highly connected while others have only a few connections. Other networks' links are randomly formed, though they still obey statistically generalizable patterns.[15]

Wuchty, et al state that all networks can be classified by some basic, quantifiable measures. These include their degree distribution, P(*k*), and the average clustering coefficient, C(*k*)[16] as summarized in figure 1.

Figure 1: Basic Network Features

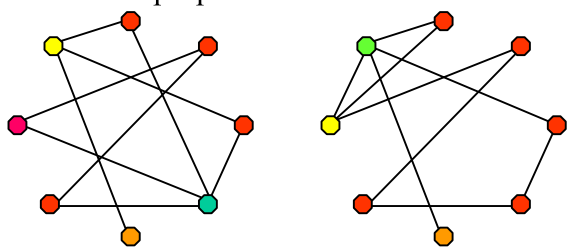
- Degree (Connectivity)
  - # of links (interactions) at each node n : k
  - Mean: <k>
  - Degree Distribution: P(*k*), to capture potential variation
- Path length
  - Shortest path from node i to node j: ij
  - Mean: <ℓ>
- Clustering Coefficient (measuring connected triangles)
  - Degree of click-ness for each neighbor: Ci
  - Mean for each node: <C>
  - Average clustering coefficient, denoting structure: C(*k*)

Stemming from these basic metrics, networks often exhibit higher-order dynamic functions, thought to be associated with their unique structures. These include robustness, fragility, percolation and searchability. Due to the relatively small number of nodes in air traffic networks, nodal separation distance and searchability tend to be straightforward. However because of the criticality of the application, resilience to cascading failure, percolation, and congestion robustness are of utmost interest in the ATS.

2.2 Random Networks

As the name implies, random networks are those created by linking a collection of nodes together by random chance. In a random network, the degree or average number of connections emanating from any single node, *k*, is determined by a probability p(*k*).

Barabasi credits Erdos and Renya with first generalizing the behavior of such structures. They noted that as random networks become more highly connected, the average mean path length tended towards log(n), where n is the number of nodes. It is also characteristic of such networks for their degree distribution to be Poisson distributed, centered about <*k*>. Their clustering coefficient also tends to be very low, and independent of *k,* since each neighbor is linked to a random destination. In Figure 2 we see two examples of very simple random networks, b derived from random "rewiring" of a. Though b looks somewhat more organized, it still exhibits properties of a random network.



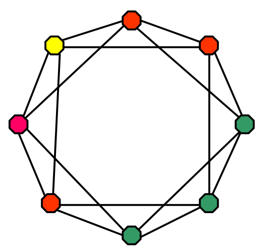
L(p) = 2.18
C(p) = 0.00
Fig 2 a **Random Network** **Fig 2 b**
L(p) = 1.98
C(p) = 0.02

2.3 Regular Networks

Regular networks are those whose nodes have "nearby" nodes designed with a uniform number of connections, thus exhibiting recurrent connectivity. By definition, "distant" nodes with larger degree have few or no direct connections (green relative to yellow, Fig. 3).

Since they follow rigid rules, regular networks are difficult to generalize, as they can be designed with specific attributes. But they are commonly highly clustered due to a high density of connections between nearby nodes, and in extensive networks, often have long path lengths due to a lack of short cuts to far-off system areas.

These networks have an associated "scale" related to the relative size of nearby nodes vs. the entire network volume.



L(p) = 1.43 C(p) = 0.50
Fig 3: Regular Network

2.4 Scale-Free Networks

Recently there has been an explosion of work in the area related to "scale-free" networks and their associated properties. Much of this work has been related to internet expansion, but the properties of such networks have been observed in biological as well as man made systems of many types. Scale-free networks are special constructions that, unlike regular networks, do not have a single characteristic degree. Networks having these particular attributes can be formed relatively easily from either random or regular networks by inclusion or rewiring of only a small fraction of connections complying with simple rules.

The term scale-free was coined to highlight that, when magnified, smaller portions of this type of network resemble the whole. This attribute goes hand-in-hand with multi-scale connectivity, i.e. having connectivity at all scales simultaneously (e.g. worker to worker as well as worker to president). Scale-free networks have "small world" properties in that they exhibit short typical path lengths and good searchability characteristics. Additionally, they also have high clustering coefficients (not expected in random networks) and, by definition, a distribution of degree connectivity that follows a power law.[5] In other words, scale-free networks have a unique trait that N(k), the number of nodes with k links, follows ~$k^{-\gamma}$.

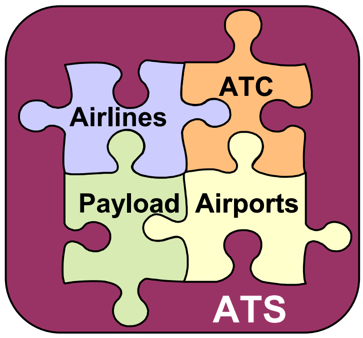
Multi-scale is a meta-structural property that has been characterized in many natural and man-made systems. Dodds et al[17] described its importance in susceptibility to cascading failures and congestion robustness. Callaway et al[18] express caution due to potential network fragility and percolation mechanisms (non-linear growth). Watts and Strogatz[19], on the other hand, describe "small world dynamics" of such systems, including the speed of transport across a large network, and the ability to search the space for the shortest, most efficient paths.

3 Air Transport Networks and *Complementarity*

Keating and Varela define a fundamental system concept of *complementarity* which acknowledges that different perceptions of a single system can exist simultaneously and be correct from each observer's point of view[20]. We cannot assume any single network model of the ATS to be a wholly complete or accurate depiction of the environment from the various perspectives of all ATS participants.

As travelers, perhaps the most familiar ATS structural element is airlines' route structures, though they are many others. Airline routes are frequently (and almost exclusively) cited as an example of network structure within the ATS. They are a good starting point for investigating airline strategy and service coverage. With some relatively simple analysis, it is possible to uncover fundamental mathematical differences in airline routing strategies.

However, one does not have to look too hard to uncover other network structures in the ATS. In fact from every participant's vantage, one could argue for a functionally different network. To illustrate the variety and breadth of complementary network structures within the ATS, a selection of observational points of view are described below.



3.1 The Airlines

3.1.1 Routes

Route maps are familiar to most people who have ever booked a flight on a commercial airline. They graphically depict all cities served by an airline, its affiliates and, depending on the complexity of the route structure, the links as well. Indeed, visual inspection of route maps alone may reveal different market strategies. While America West connects nearly all flights to either Las Vegas or Phoenix (more typical of

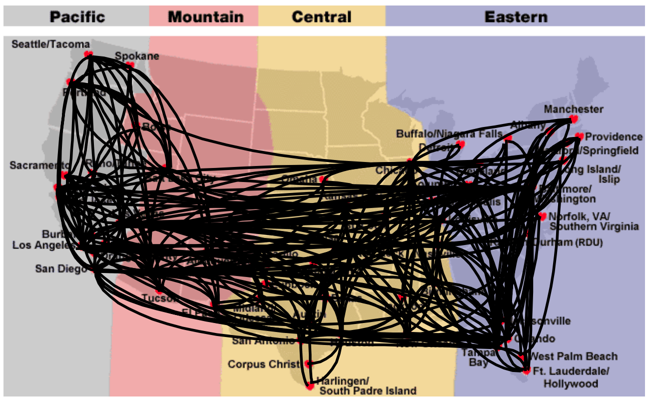
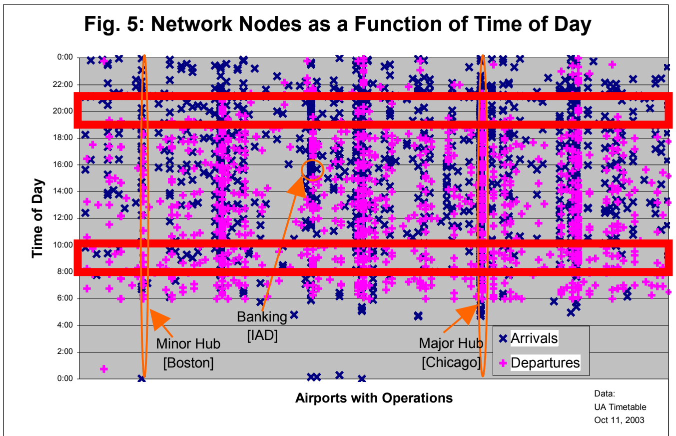


Figure 4: Southwest Airlines Non-stop Routings (2003)

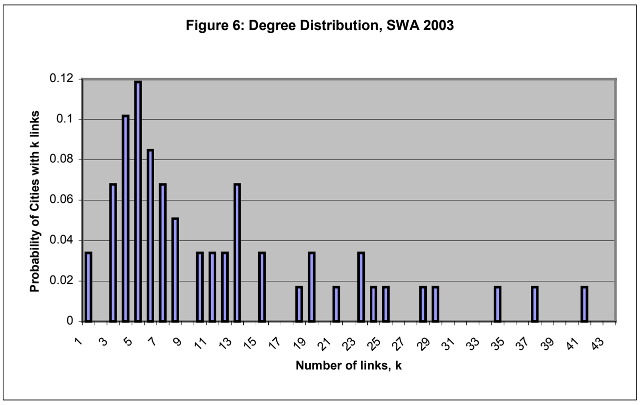
a dual-centralized system than a scale free one), Southwest Airlines (SWA) has a different strategy, as evident by their destination map augmented with their non-stop routes (Fig 4).

An analytical model, even one based on a relatively straightforward system depiction, requires operational context. For example, concentrating on a particular airline's own flights rather than all of those available to customers through code sharing or other contract carrier agreements will greatly affect the extent of the network. (e.g. though the United Airlines (UA) route map shows over 650 destinations worldwide, they themselves fly non-stop between only 104 cities[21]). The "appropriate" nodes for analysis are dependent on the vantage point of the network user: e.g. for fleet and crew management, only UA destinations are relevant. For customers, the entire accessible network plays a role (although not always seamlessly). Because airlines trade routes cooperatively in some markets[22] and compete amongst themselves in others, models developed for business planning purposes must selectively incorporate routes from code share partners and subsidiaries in addition to the airline's own.

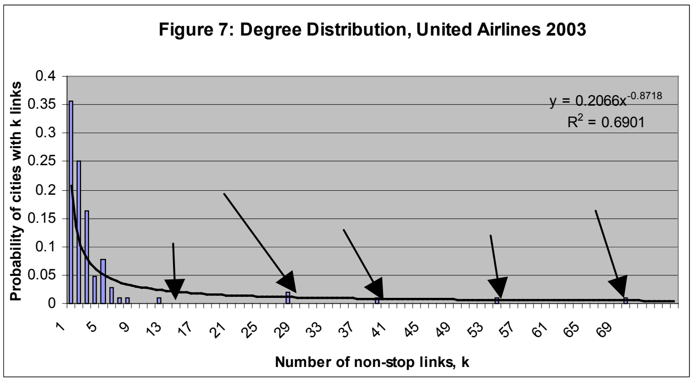
Similarly, time segmentation of the schedule must be accounted for, because the network changes during the course of the day as a result of the intermittent nature of flights. The red-boxed areas in figure 5 show two different effective network structures in the same airline, dependent on the time of day considered. Also evident is banking of flights.



Often offered as an example of a point-to-point (PtP) route structure, a large portion of the SWA route structure does follow scale-free principles: a few cities, such as Las Vegas and Phoenix, are highly connected by non-stop service, while many others are connected only to a few cities in the network. Analysis of the aggregate route map shows the clustering coefficient, C(p), a measure of the connectedness of a node's neighbors, is predictably high at 0.641 (compared to a predicted C(p) = 0.195 for a similar-scale random network), leading us away from a random network model. However, SWA does not have nearly as many singularly connected cities as a scale-free model predicts, as shown by Fig. 6 SWA's degree distribution.



Jaillet et al[23] studied the natural emergent tendency for hub-and-spoke (HaS) strategies and found that indeed they can be a preferred solution, but only under specific sets of demand conditions. They concluded that for optimality, hub placement would be geographically driven. In fact, using Phoenix, Las Vegas and Albuquerque as hubs for airlines serving mainly the southwest United States as SWA does is supported by their results: these cities are near the geometric centers of their routings, and they have the additional benefits of reliable weather and little congestion. Their results also support UA hubs at SFO and ORD despite their continuous weather and congestion problems (figure 7). However, unlike SWA, little if any of UA's degree distribution is well explained by a power law function. In fact, it is more bimodal like America West, with cities either highly or modestly connected.



3.1.2 Business Case

Of course, the airlines are in the business of transportation for profit, not connecting all cities to everywhere (the latter perhaps being a part of a strategy for the former). The business case for airline operations is made with standard qualities of price of operations vs. cost as well as still-significant regulatory control and government subsidies of various kinds. Additionally, alliances among airlines greatly influence their ability to support their business case by affording access to larger markets and reducing direct operating costs for any single entity. The network of alliances and contracts that represent these business entities is substantially different both in structure and function that that of the airlines' route network, yet are closely related as Brueckner and others imply.

Price/Demand

Airline pricing is not a reflection primarily of cost, but rather a complex interplay of cost, competition, demand mix (time vs. cost sensitive passengers), and network strategy. The industry collectively refers to these pricing strategies as "yield management." Resulting in as much as a 1000% disparity in fares for the same class of service on the same flight, yield management strives to maximize the revenue generated per flight and guide route scheduling decisions. In a series of articles, Barlow[24] reports that passengers have begun to spurn fully flexible, high cost fares in such numbers that yield management assumptions regarding people's preferences are no longer valid, and that the full-fare business traveler is largely a thing of the past. Other popular press suggests that the market is split: one segment that is still service/convenience oriented, the other that is extremely cost sensitive.[25] [26] Mann, an often-quoted airline industry analyst, summarized this trend, saying, "The market . . . is simply not demanding an industry composed of hub-and-spoke clones, certainly not as many as exist today."[27] What then is the market looking for, and what airline topologies could it support?

When demand is low from any one city to another, HaS makes sense, as the number of flights to connect a large number of cities is minimized. However, when demand grows, HaS looses efficiency, as multiple flights to the hub are made when in actuality some passengers could be taken directly to their destination more efficiently. Not only is the travel time shorter for direct routing, there are fewer connections (less hassle, better value) and less schedule risk, as point-to-point (PtP) flights avoid unnecessary traffic delays at the hub. There is no single equation as to when this crossover occurs, because it is dependent on the seat-revenue-cost of carrying passengers, the demand, the need to move equipment to more profitable routes, etc. Schedule profit optimization is a complex problem unto itself, but there is evidence that the market is aware of the advantages of PtP.

Business literature is rife with articles regarding the vanishing business case for the HaS operational model.[28] [29] In fact, Brancatelli[30] lists many reasons why he sees HaS as "frighteningly expensive to operate and prone to frequent mechanical and meteorological meltdown."

Though there is a large volume of research regarding yield management and its influence on the airlines, until recently, little attention has been paid to its effects on the NAS. This is beginning to change, as evidenced by the recent de-banking of flights during rush periods at airports such as DFW. These issues are beginning to be addressed together as a single optimization problem, as the airlines find it in their own interest to consider the NAS and the larger ATS.[31]

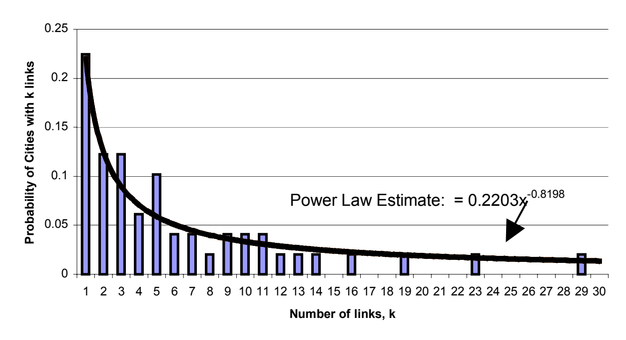
Subsidies and Deregulation

Profit, not revenue is the goal of any industry. Airlines, with extremely thin profit margins, large gross receipts, and very high operating costs[32], are especially sensitive to government intervention: regulation and subsidy.

Deregulation and Essential Air Service

Deregulation and subsequent legislation has had a measurable effect on airline network structure. TWA's March/April 1976 route system was analyzed as a representative sample of routing before deregulating the industry in 1978. Interestingly, even in the heavily regulated environment of the time, this PtP schedule's probability distribution function was highly correlated to a power law model (R^2=0.926, Figure 8), and the measured clustering C(p)=0.47 is far from that of a random network. As we saw above, the majority of today's airlines do not exhibit these same scale-free attributes so clearly.

Figure 8: Degree Distribution, TWA 1976



The US DOT[33] reports that at the time of deregulation, there was concern that smaller markets may lose service because of their relatively low traffic volume and the airlines' concentration on more lucrative markets. As part of the act, the Essential Air Service (EAS) program was formed to ensure a "minimum level of service" in each community. Where necessary, EAS was to subsidize a carrier to provide connectivity to the rest of the airline network. Though the intent of the program was to retain service levels (and degree distributions) near to those prior to deregulation, even roughly $50 million in yearly subsidies has proven insufficient to support roughly a third of those communities originally eligible. Currently, the airlines are guaranteed payment (in part) to fly to 105 otherwise presumably non-profitable communities.

Civil Reserve Air Fleet

Another source of financial guarantees available to the nation's largest air carriers is participation in the Civil Reserve Air Fleet. As the name implies, some civilian air carriers are paid to operate a fleet with particular capabilities. In return, they promise to provide military airlift service if called upon. According to the General Accounting Office[34], a major benefit of the CRAF program is that it provides up to half of the nation's strategic airlift capability without the government having to purchase additional aircraft, pay personnel costs, or fly and maintain the aircraft during peacetime. They report that replacing the CRAF capability with military aircraft would have cost DOD about $1 to $3 billion annually over the past 30 years, implying a "win-win deal." For the airlines, this equates to financial support for a larger fleet, reducing the downside risk (net expenditures), thus supporting an extensive-route strategy such as HaS.

Mail Contracts

Additional sources of guaranteed airline income that influences route choices are the U.S. mail contracts. In 2001, commercial carriers were paid to carry 4,000,000+ tons of mail[35] on existing but specific revenue flights.

3.1.3 Complementarity within the Airlines

These and other regulatory actions have a marked effect on route topology and therefore ATS operations. For example, if EAS funds were grantable to on-demand air taxi providers, would this provide sufficient seed money to kick-start this service sector? Future policy and political climate will continue to influence both the business case (for the airlines as well as air taxi and general aviation interests) and the performance of the NAS (e.g. delays due to hub congestion).

Addressing the network route structure vs. yield problem, Brueckner et al[36] studied the relationship between routes, flight frequency, fares, aircraft choices and costs. He explains when and why HaS strategies can be preferred over PtP networks from a purely static business case (e.g. avoiding issues of crew/fleet incompatibilities and maintenance of a diverse fleet). He stops short of including other network construction limitations, such as congestion or traffic constraints at the hubs.

Effects of these other system traits can be teased out by modeling other network structures, such as airline support and NAS infrastructure. In that vein, even from the airlines' perspective, other networks beyond the familiar route maps may be worthy of study.

3.2 Air Traffic Control and the NAS

Air Traffic Control (ATC) is a primary objective of the FAA In furtherance of this objective, the FAA seeks to "develop air traffic rules, assign the use of airspace, and control air traffic".[37] The FAA operates and maintains the NAS, but also "maintain other systems to support air navigation and air traffic control, including voice and data communications equipment, radar facilities, computer systems, and visual display equipment at flight service stations." Together, these intertwined networks of operational facilities and technology infrastructure provide for ATC services. What might a model of these services look like? Each sub-component of ATC could in itself be modeled as a network, though some portions are more amenable to such a representation than others. The FAA[38] themselves recognize the "diversity and challenge" they have in improving the system due to complexity of this "collection of systems."

What is the NAS and how does it differ from the ATS? The United States Department of Transportation definition[39] describes the NAS as technical infrastructure and facilities. It does not encompass other aspects of the ATS, such as flight operations; regulatory procedures; over 23,000 daily flights and their crews; and of course, the 600 million annual passengers and 14.5 million tons of freight and mail that travel using air. It is important that when considering changes to the NAS, we don't become myopic and restrict our analysis to the infrastructure alone. Improvements to the infrastructure for their own sake may have a limited, or even a negative impact on transportation quality.

A functional rather than physical network model of the NAS can be generated by using nodes to represent required actions and links to represent communication requirements. Unfortunately, a static representation of this system does not provide an adequate picture. Aircraft carry integral components and perform various functions related to their operating conditions, equipment, etc. that change as a flight progresses. A single aircraft can be in contact with many different ground and air targets along a flight, filling different rolls in each pair-wise encounter. Also, all of the communication channels are dissimilar in their form and functions, making the dynamic (real-time) behavior difficult to model.

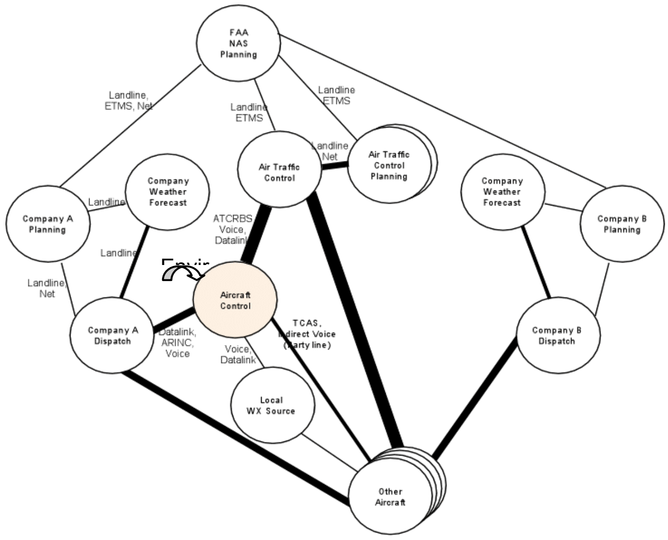


Figure 9: ATC Network of Functions Supporting a Flight

Figure 9 is offered as a model for flight operations within the ATC domain. The shaded element represents the aircraft under control for analysis. Other aircraft operating in the vicinity are shown as multiple elements that may or may not be from the same airline. As example, one other airline's function relative to this flight under study is included in the figure. Typically there would be many other participatory airlines (The Collaborative Decision Making website[40], where much of the NAS planning is coordinated, lists 37 airlines in the program). The weight of the links is meant to give rough approximations of the relative communication bandwidth necessary to support the functions. A comprehensive functional model has not yet been completed, but from the initial model, the ATC functions indeed exhibit small world characteristics, L(p)=2.0 and a very high clustering coefficient of 0.86. However, a power-law degree distribution isn't apparent. Perhaps this is an artificial artifact of the constraints already put in place to limit traffic at any ATC node (e.g. rerouting around busy sectors or ground delay programs).

3.3 Payload: Passengers and Freight

For passengers, flight routing is only part of the story. Because of the proliferation of HaS networks, more and more passengers are required to make connections. Though airline and ATC delays are well characterized, Barnhart and Bratu[41] suggest that using these same data to draw conclusions regarding passenger service is misleading. Among the issues they raise is that passenger delays can significantly outpace aircraft delays due to the increasing number of connecting passengers, more frequent flight cancellations, and increased load factors (more passenger delay for the same flight delay). They suggest analyzing the network from the passengers' perspective to assess in impact of network topology on passenger-centric metrics.

Guimera et al[42] recently characterized the worldwide airport network and the non-stop links that connect them. Viewed en mass, they found that indeed this network of 3883 cities connected via 531,574 flights has small world properties, and has degree probability density functions following power law distributions. Interestingly, they also found that the most connected cities were not the most geographically "central" cities on this global scale, at odds with Jaillet's condition for optimality. They continue to say that network topology is dependent on many factors, including demand profile, distance between cities, and geo-political restrictions. Their models demonstrate the substantial influence these factors can have on otherwise nominally optimal networks. This then leads one to conclude that other factors, perhaps some mentioned above such as the availability of ATC facilities, may also constrain the growth and operation of the air transport network. Indeed, Guimera et al postulate that the domestic multi-hub network is a compromise for a star (centralized) configuration that has adapted "to the loss of efficiency that arises due to overloading of the hubs."

Aggregate topology studies are critical to establish effects like "artificial" problems created by pseudo-hub locations related to politics rather than demand, and establish their effect in system growth and overall efficiency. However, it may also be useful to take a more local look at service provided for a particular community, and how this measures up to demand and compares to other communities of comparable size.

3.4 Airports / Communities

An analysis of a local network, even from a small hub like Norfolk, Virginia (ORF), reveals that, even restricting the network to non-stop and one-stop destinations, surprisingly good connectivity is possible (see Fig 10). 24 cities, including 18 large and 6 medium size hubs are served from ORF with non-stop service at least once daily. An additional 75 international one-stop connections are listed in their Flight Guide.[43] After augmenting the ORF schedule with data from SABRE, a well-established air-travel scheduling consortium, the clustering coefficient for ORF was found to be 0.928, meaning that the directly reachable cities out of ORF create a nearly-fully connected cluster.

Figure 10: Non-stop and One-stop Cities from ORF, Norfolk, VA

This is an important feature for a municipal airport because the airport's value to the community is improved from the implicit full network access this clustering provides. However, for a particular passenger, the network may not be fully accessible due to the fare restrictions of their tickets regarding itinerary changes and transference to other airline connections. For some communities, these restrictions can be very important, as there are many airports where a single carrier has the lion's share of the business.

Data show that when a single airline has a very large market share percentage in a particular city (a "fortress hub") they can, and do, adjust prices more widely than in more demand-responsive markets. [44] Sometimes this means dramatically reducing fares to exclude competition success, or other times inflating prices for profit-taking in the face of limited competition. This can strongly limit the consumer choice for specific communities, effectively controlling the size and cost of access for the entire scheduled air transport network.

4 ATS Network Models: Strengths and Weaknesses

Using network depictions of ATS elements may prove to be a practical way to understand the system dynamics of the ATS, particularly under environmental stresses. Since these models will largely generalize classes of system behaviors rather than mimic individual entities, the results will have to be used accordingly, to help set systemic policy regarding conflicts, shared resources, etc. At this time, it is not plausible to expect network theory to aid with localized problems, as it is oriented towards regulating system-wide, conglomerate behaviors. Of course, the system elemental models themselves must be validated, and their underlying assumptions must be understood.

A critical issue related the use of networks in both air traffic system modeling and operation is that of constructing a distributed, safety-critical real-time control system. Though today's system has some shared functional responsibilities, there is still substantial central planning authority and clear roll delineation. Short of these, the skies are still relatively empty, putting little stress on the system. As demand grows, safety attributes will be tested or traded for capacity as the probability of air-to-air and ground resource conflict rise. We can look to the work of Nicholson[45] and others[46] for answers regarding the use of non-deterministic systems in safety-critical applications. The implication is, with careful system structuring and judicious data demand, much of the safety application issue can be averted.

On the other hand, the robustness to localized failures is a general strength of many network constructions. Some operational models are able to deal with issues such as airport weather closures better because they are more flexible and can utilize alternate links in their network. Some of this flexibility is inherent in a multi-hub operation, where passengers can be re-routed away from problem areas. Nevertheless, without an ability to also adjust resources across routes, the flexibility of extensive networks operating at near-full capacity is limited.

The downside to such constructions is vulnerability to disruption. Networks with hubs that have a high probability of experiencing problems also have a high probability of proliferating those problems across the entire network. Particularly in the area of air traffic management, where the hubs are largely constructions of the operational control mechanisms (e.g. multiple aircraft to a controller), diversification of the control task could lower the vulnerability to a disruption.

The effect of the partite nature of the nodes (e.g. as sets or communities) in these model constructions needs to be explored. Strogatz warns that a uni-partite representation (treating all nodes as members of the same set) of a multi-partite system may suppress important information and conflate different structures.[47] For example, functions of the various ATS participants may have unique properties (ATC, pilot, airline company, etc.) that are potentially essential to understanding the system dynamics.

Since air traffic management, the needs of passengers, and running a cost-competitive airline are such different, yet clearly intertwined aspects of the ATS, it is likely that a uni-partite functional network model can not properly capture the dynamics of the system.

5 Conclusion

In 1999 Eric Scigliano[48] stated, "Five years ago the FAA set out to revolutionize air traffic control. Its comprehensive plan failed…" A contributing factor may have been that they had no reasonable way of predicting the impact of large-scale, revolutionary procedural changes. It may also be argued that the changes that were implemented could not affect radical change within the context of the ATS political, economic and regulatory environment. Though there has been progress in setting some technology standards in recent years, we are not much closer to implementing truly radically new operations such as user-preferred routing or self-separation. Possibly we have habitually taken[49], and continue to take, too narrow a view of research and development in air transport.

A fully system-wide model of the ATS seems to be what is called for, but where do you draw the system boundary, and how to develop a comprehensive, dynamic model? Using appropriately selected idealized network models may be an affordable way to build tractable, understandable models that can still provide insight regarding this large, complex system.

Scale free networks have been suggested as useful models of the commercial air transportation system. At first blush, airline route maps appear to have this structure, and indeed, systemic scale-free behavior has been quantified. After some investigation within the context of specific observers, however, it becomes clear that scale-free structure is not as ubiquitous as implied.

Though other topologies may better explain portions of the system, the general notion of network characterization used to identify systemic properties that scale-free models bring to the forefront appears quite powerful. The ATS may be best characterized as a system-of-systems, each with their own goals. All ATS components interact to a large degree, so interconnections between elements and their representations appear to be critical to uncovering dynamic behaviors. Exploiting network science may facilitate sufficiently comprehensive yet tractable models to provide insight into the ability of the NAS to deal with a likely future ATS robustly, and provide an attainable basis for governmental NAS/ATS policy decisions.

References

[1] Transportation Secretary Minetta, Aero Club of Washington, Jan 27, 2004. Reported by Wald, "Tripling of Capacity for Air Traffic Is Sought" *New York Times*, January 28, 2004

2 Odoni, Bowman, Delahaye, Deyst, Feron, Hansman, Khan, Kuchar, Pujet, and Simpson, "Existing and Required Modeling Capabilities for Evaluating ATM Systems and Concepts" ICAT, MIT. NASA Technical Report, NAG2-997, 1997.

[3] Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems", *PNAS* 99/3 p. 7280-7287, May, 2002.

[4] Wieland, Wanke, Niedringhaus and Wojcik, "Modeling the NAS: A grand challenge for the simulation community" Society for Computer Simulation, 1/2002, San Antonio, TX

[5] Jennings, "On Agent-based software engineering" *Artificial Intelligence* 117 (2000) 277-296

[6] Macdonald & Bologna, "Advanced Modelling and simulation methods and tools for critical infrastructure protection" ACIP deliverable D4.5, the EU, 1/2003.

[7] Parunak, Savit, Riolo, "Agent-Based modeling vs. equation-based modeling: a case study and user's guide" Proc. of Workshop on Multi-agent systems and Agent-based Simulation, Paris. Springer 1998.

[8] Kutakh and Fursova, "A simulation modeling system for estimation of the efficiency of new technologies and organization of railroad transportation", *Cybernetics and Systems Analysis*, v. 39, n.6, 2003.

[9] Schaefer Wojcik Berry Wanke, "Decision Support for advanced aviation concepts", Winter Simulation Conference, INFORMS, San Diego, CA 12/2002.

[10] McLucas, "Choice and decision making in engineering and architecting of complex systems", *Journal of Battlefield Technology,* v.4 , n.3, 11/2001.

[11] Daniel "Hard problems in a Soft World" *Project Management in R&D*, v. 8, n. 2, 1990.

[12] Andrews, “Restoring Legitimacy to the Systems Approach” *IEEETechnology and Society Magazine*, v. 19 n.4, p.38-44, winter 2000/2001.

[13] Moss, “Policy analysis from first principles”, *PNAS* v.99 suppl.3, p.7267-7274, May, 2002.

[14] Whitehouse, *Systems Analysis and Design using Network Techniques*, Prentice-Hall, Englewood Cliffs, NJ, 1973

[15] Albert and Barabasi, “Statistical mechanics of complex networks”, *Reviews of Modern Physics*, v.74 Jan 2002.

[16] Wuchty, Ravasz and Barabasi, "The Architecture of Biological Networks", in Deisboeck, Yasha Kresh and Kepler (eds.), *Complex Systems Science in Biomedicine*, Kluwer Academic, New York, 2003

[17] Dodds, Watts and Sabel, “Information exchange and the robustness of organizational networks,” PNAS, vol. 100 no. 21, October 2003

[18] Callaway, Newman, Strogatz, Watts, “Network Robustness and Fragility: Percolation on Random Graphs” Physical Review Letters, v.85, n.25, 12/2000

[19] Watts and Strogatz, “Collective dynamics of ‘small world’ networks”, Nature, v.393, n.4, June 1998.

[20] Keating and Varela, *Project Management Systems*, 23rd Annual American Society for Engineering Management, Tampa, Florida, October 2- 5, 2002

[21] UA Timetable, from www.united.com/page/ middlepage/0,1454,1891,00.html, October, 2003

[22] Atlanic Coastal airline press release http://www.atlanticcoast.com/PressRelease Archive/2001/IADCVand3ORD.shtm

[23] Jaillet, Song, Yu, “Airline Network Design and Hub Location Problems” *Location Science*, Vol. 4. No 3, pp.195-212, 1996

[24] Barlow, “Airlines face big changes as business travelers rebel” *Houston Chronicle*, June 5, 2002, and “The full-fare business flyer: an endangered species?” *Houston Chronicle*, April 29, 2002

[25] Sharkey, “Business travel: Seeking new model for air travel”, *New New York Times*, April 30, 2002.

[26] Leonhardt & Markels, “The Days of Coasting are Gone; Airlines Face Reality. It’s Time For a New Flight Plan.” New York Times, Late Edition, Final, Section 3 p.1, 8 December, 2002.

[27] Mann, “It’s the business model stupid”, R.W. Mann & Company, Inc Airline Industry Consulting, February 2002. www.rwmann.com/Network.html

[28] Schepp, D. “United’s future in limbo”, *BBC news online*, 9 December, 2002.

[29] Grossman, D. “Restrucutre the Airline Industry? Dream On” *USA Today,* 26 February, 2003.

[30] Brancatelli, “Bruning Down the House”, *USA Today,* 25 February, 2003.

[31] C. Barnhart, T. Kniker, and M. Lohatepanont. “Itinerary-Based Airline Fleet Assignment”. 2000. submitted to Transportation Science.

[32] Van Wijk, “The Value Chain”, World Air Transport Summit Annual Meeting, Washington, D.C., 6/2003.

[33] Office of Aviation Analysis “What is Essential Air Service?” US DOT, May 1998.

[34] http://www.fas.org/man/gao/ns96125.htm

[35] US DOT Bureau of Transportation Statistics, National Transportation Statistics, 2002.

[36] Brueckner, Dyer and Spiller, “Fare determination in airline hub-and-spoke networks” *Rand Journal of Economics,* v.23, p.309-333, 1992.

[37] FAA, www1.faa.gov/aboutfaa/Activities.cfm

[38] FAA Office of System Architecture and Investment Analysis, pp. 21, 2003. www2.faa.gov/asd/cip03/FY03CIP_final.pdf

[39] US DOT, *The Changing Face of Transportation,* BTS00-007, Washington, DC 2000

[40] http://www.metronaviation.com/cdm/index.html

[41] Barnhart and Bratu, “National Trands in Airline Flight Delays and Cancellations, and the Impact on Passengers,” MIT Global Airline Industry Program Briefing, Cambridge, MA, March 2001

[42] Guiemera, Mossa, Turtschi, Amaral, “Structure and Efficiency of the World-Wide Airport Network” awaiting publication, October, 2003. available @ http://amaral.northwestern.edu/roger/

[43] Norfolk Airport Authority, “Norfolk International Airport Flight Guide”, 10/2003.

[44] US General Accounting Office, “Airline deregulation: Changes In Airfares, Service Quality, and Barriers to Entry”, GAO-RCED-99-92, 3/1999.

[45] M. Nicholson. and. A. Burns, "Emergence of an Architectural Topology for Safety-Critical Real-Time Systems," University of York, England, York YCS-97-292, November 1997

[46] P. Conmy, M. Nicholson, Y. Purwantoro, J.A. Mcdermid J.A. "Safety Analysis and Certification of Open Distributed Systems", International Conference on Computational Science 2002

[47] Strogatz, “Exploring Complex Networks”, *Nature*, Vol 410 p.268-276, March 2001.

[48] Scigliano, “Delayed Takeoff”, *Technology Review,* p. 44-52, September/October 1999.

[49] Fraser, Donheiser, Miller, “Civil Aviation Development: A policy and Operations Analysis”, Arthur D. Little in support of contract DOT-OS-00083, “Management and Finance Options” DOT/NASA Civil Aviation Policy, pp.17, 1970.