Complex Dynamics of Air Traffic Flow

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Article Outline

Glossary

Air Traffic Flow

Air Traffic Flow represents the distribution of air traffic over a region of space. Air traffic is undergoing major changes both in developed and developing countries. The demand for air traffic depends on population growth and other economic factors. Air traffic in the United States is expected to grow to 2 or 3 times the baseline levels of traffic in the next few decades. An understanding of the characteristics of the baseline and future flows is essential to design of a good traffic flow management strategy.

Traffic Flow Management

Safety limits the number of aircraft arriving at an airport or in a region of the airspace. Airspace Capacity, the maximum number of aircraft in a region, depends on the technology to keep aircraft separated by a safe distance and weather conditions. Airspace capacity decreases in the presence of severe weather and aircraft may have to be rerouted or delayed on the ground to maintain safety. The imbalance between airspace capacity and traffic flow demand leads to delays. Traffic flow management tries to maintain efficiency of the flows while not exceeding capacity limits.

Complex Networks

A network connects components of a system. The connections and the number of components vary with the function of the network. It is extremely difficult to analyze and visualize the behavior of networks when the number of components in the system becomes large. There has been a major advance in our understanding of the behavior of networks with large number of components. Several theories have been advanced about the evolution of large biological and engineering networks by authors in diversified disciplines like physics, mathematics, biology and computer science.

Scale-Free Networks

Several large biological and engineering networks exhibit a scale-free property in the sense that the probabilistic distribution of their nodes as a function of connections decreases slower than an exponential. These networks are characterized by the fact that a small number of components have a disproportionate influence on the performance of the network. Scale-free networks are tolerant to random failure of components, but are vulnerable to selective attack on components.

Definition of the Subject

Civil Aviation is a vital sector of the U.S. economy. Manufacturing of civil aircraft contributed $59.9 billion to the U.S. trade balance (exports less imports) in 2014. U.S. airports handled 947 million passengers during 2016 [19]. The National Airspace System (NAS) refers to all the hardware, software and people involved in managing air traffic in the United States. More than 42,000 commercial flights operated in the U.S. airspace alone on a typical day at the present time. Although demand for air transportation has decreased from earlier estimates, system traffic expressed in revenue passenger miles (RPMs) is projected to increase by 1.9 percent a year between 2018 and 2038 [17]. This increase in demand will put a further strain on the airports and airspace resulting in delays. Federal Aviation Administration (FAA) estimated the annual costs of delays (direct cost to airlines and passengers, lost demand, and indirect costs) in 2017 to be $26.6 billion [10]. To address the changes required in the air transportation system, FAA and the aviation industry have identified a set of priority capabilities for implementation [18]. Similar activities are being pursued in Europe and Asia [15].

Introduction

Air traffic in the United States has continued to grow at a steady pace since 1980, except for a dip immediately after the tragic events of September 11, 2001. There are different growth scenarios associated both with the magnitude and the composition of the future air traffic. The Terminal Area Forecast (TAF), prepared every year by the FAA, projects the growth of traffic in the United States [17]. Both Boeing [7] and Airbus [1] publish market outlooks for air travel annually. Although predicting the future growth of traffic is difficult, there are two significant trends: (1) heavily congested major airports continue to see an increase in traffic, and (2) the emergence of regional jets and other smaller aircraft with fewer passengers operating directly between non-major airports. The interaction between air traffic demand and the ability of the system to provide the necessary airport and airspace resources can be modeled as a network. The size of the resulting network varies depending on the choice of its nodes. It would be useful to understand the properties of this network to guide future design and development. Many questions, such as the growth of delay with increasing traffic demand and impact of the en route weather on future air traffic, require a systematic understanding of the properties of the air traffic network.

There has been a major advance in the understanding of the behavior of networks with a large number of components. Several theories have been advanced about the evolution of large biological and engineering networks by authors in diversified disciplines like physics, mathematics, biology and computer science [28]. Several networks exhibit a scale-free property in the sense that the probabilistic distribution of their nodes as a function of connections decreases slower than an exponential. These networks are characterized by the fact that a small number of components have a disproportionate influence on the performance of the network. Scale-free networks are tolerant to random failure of components, but are vulnerable to selective attack on components [2, 21].

This paper examines two network representations for the baseline air traffic system. A network defined with the 40 major airports as nodes and with standard flight routes as links has a characteristic scale: all nodes have 60 or more links and no node has more than 460 links. Another network is defined with baseline aircraft routing structure exhibits an exponentially truncated scale-free behavior. Its degree ranges from 2 connections to 2900 connections, and 225 nodes have more than 250 connections. Furthermore, those high-degree nodes are homogeneously distributed in the airspace. A consequence of this scale-free behavior is that the random loss of a single node has little impact, but the loss of multiple high-degree nodes (such as occurs during major storms in busy airspace) can adversely impact the system. Two future scenarios of air traffic growth are used to predict the growth of air traffic in the United States. It is shown that a three-times growth in the overall traffic may result in a ten-times impact on the density of traffic in certain parts of the United States.

The paper is organized as follows. The section on complex network analysis provides a brief overview and terminology of the complex networks useful in the analysis of air traffic. This is followed by an application of the complex network methodology to the baseline air traffic system. The section on Future Air Traffic Scenarios considers different scenarios for the evolution of air traffic in the United States during the next 25 years and looks for changes in the behavior of the network. An analysis of the future air traffic scenarios shows that a three-times growth in overall traffic can result in a tenfold impact on the density of highly-connected nodes in certain parts of the United States. Thus, in addition to bottlenecks at major airports, the risk of airspace congestion calls for route restructuring and the introduction of new procedures and automation to increase airspace capacity. Concluding remarks and possible research in this area are discussed in the last section.

Complex Network Analysis

Complex systems have many agents or components interacting with each other, and their collective behavior is not a simple combination of the individual behavior. The pattern of interaction between agents can be studied as a network of connections between agents. Networks of many types are pervasive in modern society, and scientists from many fields are trying to broaden their understanding of the structure of the networks. A network is made up of basic components called either vertices or nodes. Each node is connected to other nodes in the system. The line connecting two nodes is referred to as a link or an edge. An edge is directed if it runs only in one direction and undirected if it runs in both directions. Degree is the number of edges connected to a node. Figure 1 shows a simple network with nodes A, B, C and D and edges connecting them. The degrees of nodes A, B, C and D are 3, 2, 2 and 1, respectively.

Figure 1. Nodes and edges in a network

The structure of the network strongly influences the functions performed by the network. It is possible to analyze networks of small sizes (less than 100) by drawing the picture of the network and analyzing its properties. The number of nodes in a complex engineering system, such as the worldwide web [11], can easily be as large as a few million nodes. The behavior of Random Graphs, graphs where nodes are connected to other nodes randomly, as the number of nodes becomes large has been studied extensively by mathematicians [14]. The behavior of Regular Networks, idealized systems where each component is identical, has been studied by several authors [21]. Networks describing real systems are neither random nor regular. The ability to model real systems and capture the behavior of key variables is extremely difficult. Recent developments in complex networks examine the statistical properties of large networks and help answer questions about the dynamics and stability of such networks. However, studies on the effects of structure on system behavior are still in their early stages.

A major area of interest is the role played by the distribution of the degree of nodes in a network. Let p_k be the fraction of nodes in the network that has degree **k**. The degree distribution for the network can be computed by generating a histogram of p_k. The degree distribution for large random graphs, where each edge is present or absent with equal probability, can be modeled as a Poisson distribution The distribution tends to peak for a small value of k and decays exponentially for large values of k. When using real data, to reduce the effect of noise in small datasets, the distribution of degree is expressed in terms of the complementary cumulative distribution function (ccdf),, the probability of the number of nodes in the graph with degree greater than **k** . P_k is computed using the expression

$$P_k = \sum_{i=k}^{\infty} p_i .$$

Figure 2 shows the ccdf of the Poisson distribution, $e^{-\lambda}\lambda^k/k!$, for $\lambda = 4$. Figure 3 shows the ccdf for the Poisson distribution on a logarithmic scale.

Figure 2. Poisson distribution

Figure 3. Poisson distribution in logarithmic scale

It has been observed that the degree distributions for some real-world networks, such as the Internet and biological networks, are highly skewed with tails several times longer than the mean. These real networks have a small number of nodes, or hubs, with a high level of connectivity. Hubs play an important role in influencing the properties of the network. Real networks exhibiting a small number of hubs are referred to as "scale-free" networks [5,6]. The distributions of degree for a number of networks, e.g., Internet, World Wide Web, collaboration network of mathematicians, etc., show a power law in their tails: for some constant value of **k**. Figure 4 shows the ccdf for α =2. Power law distributions (Figure 4) appear linear in a logarithmic scale (Figure 5).

Figure 4. Power law distribution

Figure 5. Power law distribution in logarithmic scale

The appearance of hubs in scale-free networks is explained in terms of two behaviors observed both in people and real systems–growth and preferential attachment. There is a tendency for new growth to gravitate towards desirable locations. Generally, all the desirable locations already have some existing nodes. The preferential attachment mechanism leads to the creation of more powerful nodes or hubs. The various hubs compete to attract new nodes and absorb them, resulting in an increase of the number of links in the initial hubs.

Scale-free networks with power law distributions exhibit two important properties: (a) remarkable resistance to random failure of nodes and (b) extreme vulnerability to targeted attacks. The functionality and performance of the network depends on the existence of the edges between pairs of nodes. The distance between the remaining vertices gets longer as nodes are removed from a network and the removal of a certain number of nodes may result in a collapse of the entire system. The tolerance of networks to failures or removal of nodes varies with their level of resilience. The nodes from a network could be removed randomly or in a coordinated approach. Several studies have shown that scale-free networks are generally robust to random removal of nodes. However, they are less tolerant to the selective removal of hubs [28].

The next section will examine the air traffic in the United States to see if it exhibits the properties of a scale-free network and draw analogies from the attack vulnerabilities of other complex networks. The methodology can also be used to understand the properties of the Next Generation Air Transportation System as it evolves over the next few decades [22].

US Air Traffic Network

The National Airspace System (NAS) refers to the collection of hardware, software and people, including runways, radars, networks, FAA systems, airlines, etc., involved in Air Traffic Management (ATM) in the U.S. It has been pointed out that the NAS should be modeled as a complex adaptive system [13]. The NAS can be looked at as a network at several different levels [12]. Some examples of networks involving components of the NAS are the route network of an airline connecting different airports, a network of sectors (geographical region used to monitor safe separation between aircraft) interconnected by geographical proximity, network of airline crew located in different cities and a surface network of ramps, runways and departure gates at an airport. The network components and links vary with the planning interval and the modeling problem. The analysis of baseline traffic uses actual data for a day from July 2006 and constructs two different types of networks for a typical day of operations in the NAS. The traffic data are processed using the Future Air traffic management Concept Evaluation Tool (FACET) simulation software [25] for conducting the network flow analysis.

The major distinctions regarding the two air traffic networks are described in Table 1. The nodes in the Airport Network (AN) correspond to the 40 major airports in the U.S. Today, a set of predefined alternative routes are used for flying between particular city pairs. Each node in network AN is connected to another node through one or more routes. The Airport and Airspace Network (AAN) includes all airports in the U.S. and routes connecting these airports. A route between two airports is defined by a series of geographical positions or fixes in the airspace. Each fix together with the airports represent a node in the AAN network.

Table 1. Different types of Air Traffic Management networks

Computation of the Degree of a Node and the Distribution Function

The computation of the degree of a node and the distribution function is illustrated by an example. The FACET simulation software generates the departure airport, arrival airport and the fixes through which the aircraft travels en route based on air traffic data. Figure 6 shows the intersection of different routes connecting airports through common fixes. In the figure, aircraft traveling from Seattle (SEA) to Atlanta (ATL), aircraft traveling from Oakland (OAK) to Newark (EWR), and aircraft traveling from Los Angeles (LAX) to Boston (BOS) pass through the fix Garden City, Kansas (GCK). The degree of GCK is equal to the total number of aircraft traveling along these three routes during the day. The degree of node GCK is three if a single aircraft travels between each of these three pairs of airports. Similarly, aircraft traveling from Dallas (DFW) to Philadelphia (PHL) and Seattle to Atlanta pass through the fix Memphis, TN (MEM). The degree of fix MEM is two if a single aircraft travels between each of these city pairs. The distribution and the ccdf can be computed easily given the degree associated with all the airports and en route fixes and are described in the next section.

Figure 6. Example of intersection of routes at common fixes

Behavior of the Degree of Nodes in Air Traffic Management Network

The ccdf for the nodes in network AN is shown in Figure 7. The figure shows the probability that an airport in the network has more than a certain number of routes originating or terminating at the airport. The number of nodes at all airports exceeds 60 and Chicago O'Hare airport has the maximum number (460) of connections. The distribution of nodes in the airport network does not show scale-free behavior. The airport connection distribution in the U.S is similar to the distribution of the connections between the networks of world airports [3]. A recent study analyzing global air traffic lists London Heathrow, Chicago O'Hare, Frankfurt, Amsterdam, Toronto, Los Angeles, Atlanta, Singapore, Paris Charles De Gaulle and Jakarta as the top ten airports with most connections [4].

Figure 7. Cumulative distribution function for nodes (40 major airports) in network AN

Figure 8 shows the ccdf of the nodes in network AAN. The ccdf of the nodes in network AAN shows a rapid decay of the percentage of nodes with the degree of the node. However, it has 225 nodes with more than 250 links, indicative of high volumes of traffic through these nodes. Figure 9 shows the logarithmic behavior of the ccdf of the nodes in network AAN.

Figure 8. Distribution of nodes in AAN with baseline traffic

Figure 9. Logarithmic behavior of nodes in network AAN

The nodes of network AAN initially follow the power law curve similar to several scale-free networks [21]. However, towards the end of the tail, the distribution shows a deviation from the power law behavior indicating a limit on the number of nodes that have a high number of connections. The limit on the growth of the large hub nodes, in the distribution of the ATM network, is due to the constraints imposed on traffic demand by the location of the cities, economic development and government policies.

The existence of hub and secondary airports characterizes baseline air traffic operations [8]. The network analysis provides an additional ability to study traffic behavior in the en route airspace. Figure 10 shows the geographical distribution of the nodes with degree higher than 250 in network AAN. These nodes will be referred to as 250G nodes. 250G nodes represent 2.7% of the total nodes in the network. Table 2 shows the number of 250G nodes in different traffic control regions, referred to as Centers. The Centers, Chicago (ZAU), Boston (ZBW), Atlanta (ZTL), Kansas City (ZKC), Washington, DC (ZDC), Indianapolis (ZID), Jacksonville (ZJX), Los Angeles (ZLA), Cleveland (ZOB) and New York (ZNY), each have more than ten of the 250G nodes. The Centers in the western part of the United States have fewer 250G nodes indicative of the lower traffic density in these Centers. It is informative to express the distribution of the 250G nodes in units of number of nodes per 10,000 square nautical miles (10Ksqnm). Using this measure of nodal traffic density, ZNY has the highest nodal density with six 250G nodes per 10Ksqnm. Table 3 shows the nodal traffic density for the 20 Centers in the continental US.

Figure 10. Geographical distribution of 250G nodes in network AAN with baseline traffic and severe weather polygons

The behavior of the degree of the nodes in an ATM network should not be surprising, since the ATM network has evolved to serve population densities in the U.S. Network analysis helps to visualize and quantify the characteristics of the network.

Resilience of Air Traffic Management Networks

The tolerance of complex networks to random and targeted failures depends on their network structure. As observed earlier, a scale-free network is tolerant to random failure, since the hubs are few and the chance of a hub being selected randomly is low. However, the same network may be prone to targeted attacks on a small percentage of vital nodes. In air traffic management networks, weather can be regarded as an agent of attacks on the system.

Convective weather is a major source of uncertainty in ATM networks. One effect of severe weather is to make airspace unavailable for the flow of air traffic. The removal of airspace may result in the failure of hubs and increase the average path length in the network. The impact of weather on ATM system performance appears as delay [26]. The tolerance of the ATM network to weather depends on the geographical distribution of the weather and the coverage of nodes with high degree.

Future Air Traffic Scenarios

National and international projections of traffic growth in 2006 predicted a tripling of passengers by 2025 [7]. There may be increased traffic due to the growing presence of on-demand air taxis and unmanned air vehicles. It is estimated that 5000 micro jets may be operational by 2010 and 13500 by 2022 [29]. The TAF provides forecasts for airports in the NAS. The forecast for the major airports in the United States receives more detailed modeling that takes into account local economic conditions and airline costs. TAF is the basis for most aviation demand forecasts. The TAF data published in March 2006 provides traffic growth rates for the period 2005-2021. The AvDemand model [20] provides three times (3X) baseline traffic scenarios starting with TAF and assuming slightly different conditions for traffic growth beyond 2025. The Transportation System Analysis Model (TSAM) [30] predicts future demand travel based on demographics and population at the county level. It provides a complimentary alternative to the FAA forecast. The results in this study are based on data generated by AvDemand.

Two future scenarios are considered. These two scenarios and the baseline traffic provide a baseline to compare the impact of future traffic changes on the ATM system. The initial values of aircraft routes and schedules used in the extrapolation are based on traffic data for a day in May 2002. Assuming traffic growth from TAF and the nominal traffic schedule, the Fratar algorithm [30] can be used to create future daily total number of flights between each origin and destination pair of the baseline schedule. The traffic growth scenarios using TAF airport growth out to 2025 predict a future NAS-wide traffic growth by a factor of 1.49. To achieve 3-times baseline day traffic (3X) scenarios assumed in future planning [9], consider two different scenarios for post-2025 traffic growth. The compound extrapolation approach grows traffic until it reaches 3X by assuming the TAF airport growth rates for traffic beyond 2025. As an alternative, the homogeneous extrapolation approach assumes the same growth rates at all airports until the traffic level reaches 3X. These two scenarios will be referred to as 3X Compound (3XC) and 3X Homogeneous (3XH) scenarios in the rest of the paper. The scenarios are processed to compute the changes in the network properties of future ATM systems.

Behavior of Future ATM networks

The two scenarios described earlier can be used to study the characteristics of the 3X traffic under the two assumptions. The properties of future ATM networks can be derived similar to the properties of the baseline ATM networks. The computations can be used to compare the geographical distribution of the hubs compared to the distribution today. Figures 11 and 12 show the distribution of the nodes in the AAN network for the 3XC traffic scenario. The results are similar for the 3XH traffic scenario.

Figure 11. Distribution of nodes in NAA using 3X Compound Scenario

Figure 12. Logarithmic behavior of nodes in network NAA under 3X Compound traffic

The future ATM networks, under both scenarios, show exponentially truncated scale-free behavior similar to the baseline ATM network. The distribution of the hubs will have an impact on the growth of delay in future ATM networks subjected to severe weather. The vulnerability of the network to reduction in capacity caused by certain weather patterns will be significant and disruptive to the operation of the system. The impact of the weather on future ATM networks will be described subsequently in the paper.

The geographical distribution of the 250G nodes under 3XC is shown in Figure 13. Table 2 shows the same distribution by Centers for baseline traffic and 3X scenarios. An examination of Table 2 is helpful in drawing distinctions between baseline day traffic and 3X demand traffic. The 3X traffic demand creates close to a six-fold increase in the 250G traffic nodes. Earlier, it was noted that ZNY has the highest 250G traffic nodal density. Under the 3X demand, as can be seen from Table 3, ZNY nodal density of 2006, 5.76, is equaled or exceeded by a majority of the 20 Centers. Even more alarmingly, the nodal density of 250G nodes in ZNY is 6 times the baseline value, and Cleveland and Washington Centers have twice the nodal density of ZNY in 2006. The 3X traffic also gives rise to nodes with even more connections. The hubs, 500G, 750G and 1000G, are defined similarly to the 250G hub. The number of 250G, 500G, 750G and 1000G hubs under different traffic conditions are shown in Table 4.

The actual growth of traffic during the last 10 years has been closer to 2% annually [10], smaller than the 3X growth used in the analysis. Tables 2,3 and 4 provide the distribution of the 250G nodes in different Centers, the nodal density in different centers and the number of 250G, 500G, 750G and 1000G nodes using traffic data for the Year 2017. A comparison of the results between baseline year and 2017 shows that the traffic density is similar and critical regions in the airspace continue to experience congestion and delays.

Figure 13. Geographical distribution of 250G nodes in network N5 with 3X Compound traffic and severe weather polygons

Table 2. Distribution of 250G nodes by Centers under baseline and future traffic scenarios.

Table 3. Nodal density of 250G nodes by Centers under baseline and future traffic scenarios.

Table 4. Total number of nodes for different traffic scenarios.

Impact of Weather on ATM Networks

Another way to view the growth of traffic is to compare how similar weather patterns may affect baseline traffic and 3X traffic. The geographical distribution of the 250G nodes shown in Figure 13 is based on traffic during July 2, 2006. This was a calm weather day with a total NAS aggregate delay of 11997 minutes [16]. The traffic on July 2, 2006 will be assumed as traffic unaffected by weather in this discussion [26].

Whenever there is severe weather in the NAS, airspace capacity is reduced and traffic is rerouted or held on the ground causing delays in the system. The Collaborative Convective Forecast Product (CCFP) is a model of severe weather activity and the areas marked blue in Figure 10 shows the CCFP for July 13, 2006. On July 13, 2006 the NAS experienced a significant total delay of 219350 minutes with ZNY, ZDC and ZTL Centers contributing a delay of 116654, 49400 and 23822 minutes respectively. Next, as shown in Figure 13, the same severe weather is overlaid in blue polygons on the geographical distribution of the 250G nodes under 3XC demand. Table 5 shows hub nodes affected by the weather today and in the future.

Table 5. Total number of nodes affected by severe weather.

A greater number of hubs, between six to ten times, are affected by the same weather pattern under future traffic scenarios than today. If one considers the non-linear growth of delay, in regions such as ZNY, ZDC and ZTL where the demand on the airspace is close to capacity, the increased density of high traffic nodes in these regions will result in much larger delays compared to 2006.

Concluding Remarks

Air traffic in the United States can be modeled as a network to understand the impact of the predicted growth in the demand on the performance of the system. It is demonstrated that the air traffic network with baseline en route flight plan intersections as nodes and with the flight plans as links shows scale-free properties typical of several large engineering and biological networks. A consequence of this property is the non-linear growth of traffic in certain regions of the United States. A preliminary analysis indicates that a three-times growth in the overall traffic may result in a ten-times impact on the density of traffic in certain parts of the United States. The air traffic system currently experiences significant delay during periods of severe weather activity. The impact of weather of the same severity will be magnified several times, especially in the northeastern parts of the United States, leading to lower system performance. Recent research analyzes the vulnerability of ATM networks to computer failures and targeted attacks [23]. The actual growth of traffic during the last 10 years has been closer to 2% annually [10], smaller than the 3X growth used in the analysis. However, the smaller growth rate provides Airlines, FAA and other organizations more time to execute policies to maintain the safety and improve the efficiency of air traffic. Research must be conducted to determine whether this risk to system performance can be mitigated through restructuring routes or by introducing new operational concepts, such as automation assistance to controllers to increase airspace capacity [24,27]. The network analysis described in the paper can be used to guide the development of various traffic flow management concepts to increase the efficiency of air traffic systems.

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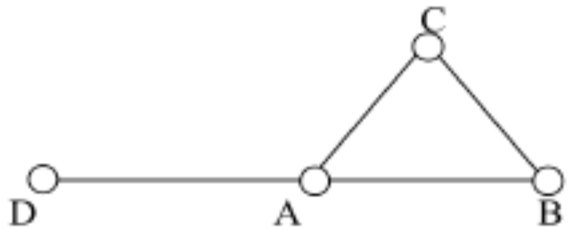

Figure 1. Nodes and edges in a network

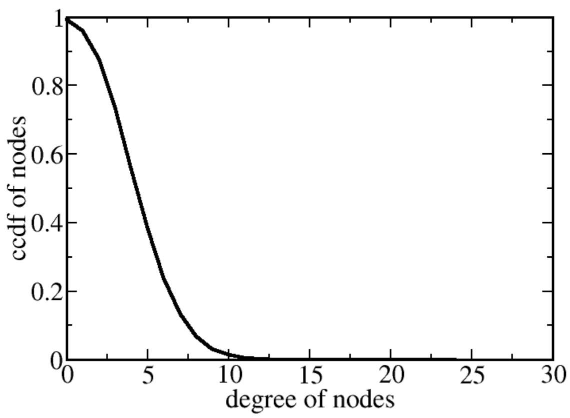

Figure 2. Poisson distribution

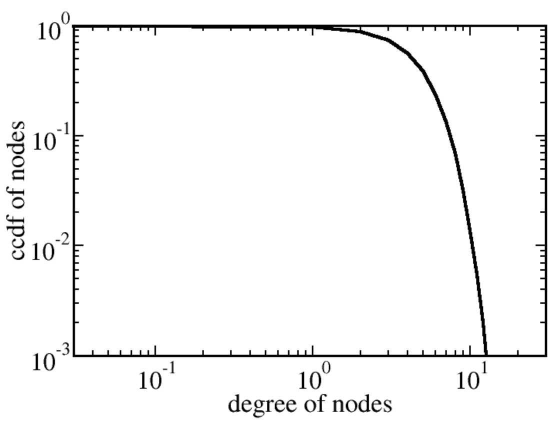

Figure 3. Poisson distribution in logarithmic scale

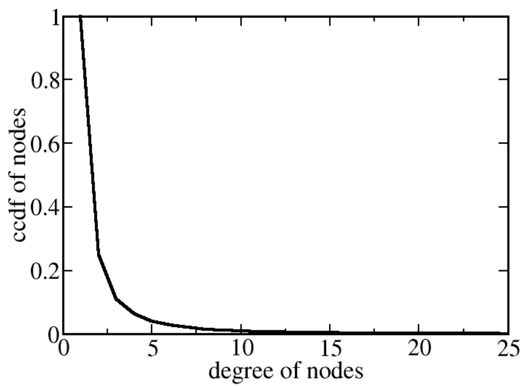

Figure 4. Power law distribution

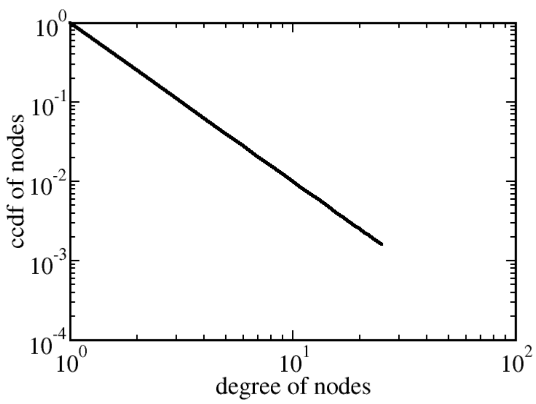

Figure 5. Power law distribution in logarithmic scale

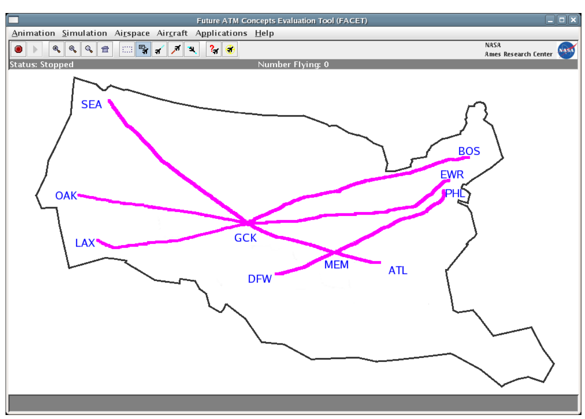

Figure 6. Example of intersection of routes at common fixes

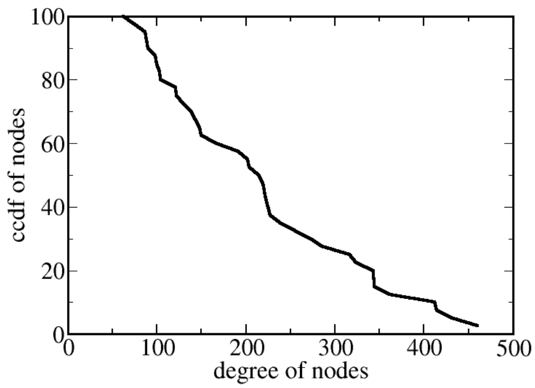

Figure 7. Cumulative distribution function for nodes (40 major airports) in network AN

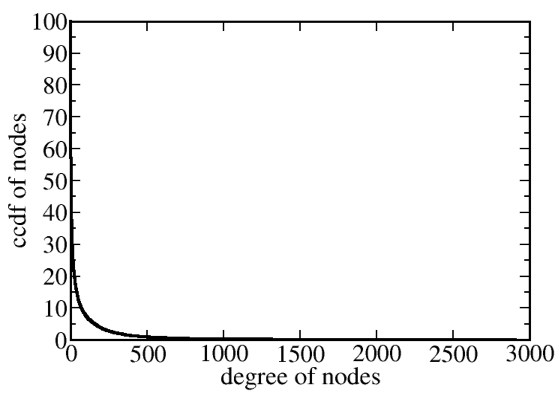

Figure 8. Distribution of nodes in AAN with current traffic

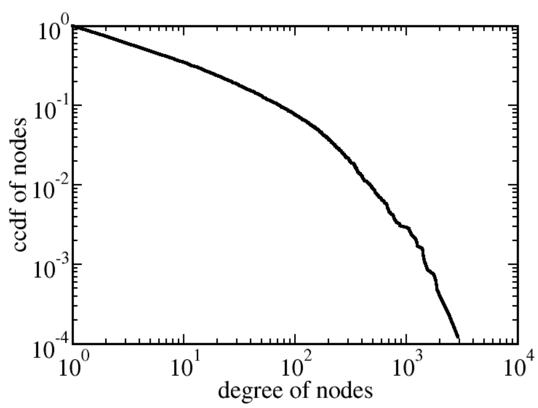

Figure 9. Logarithmic behavior of nodes in network AAN

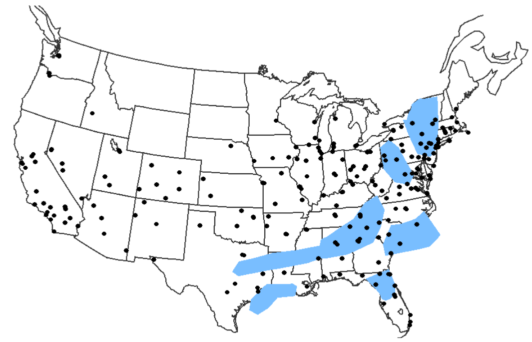

Figure 10. Geographical distribution of 250G nodes in network AAN with current traffic and severe weather polygons

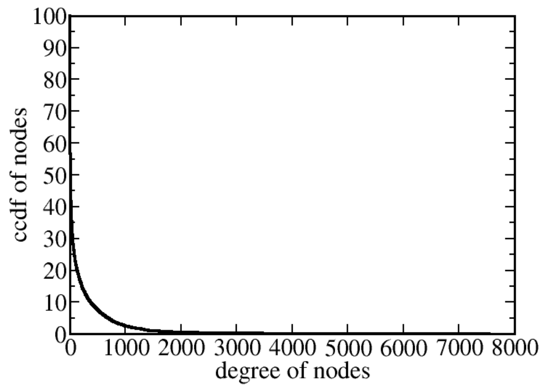

Figure 11. Distribution of nodes in AAN using 3X Compound Scenario

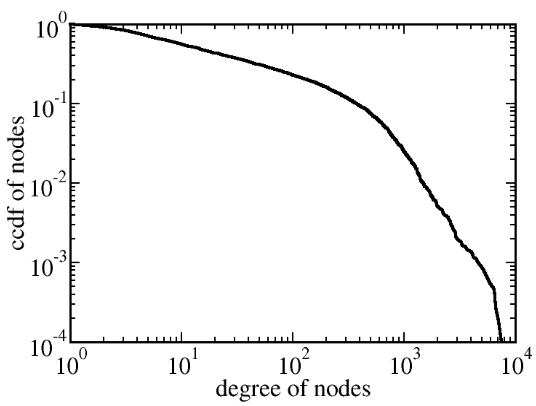

Figure 12. Logarithmic behavior of nodes in network AAN under 3X Compound traffic

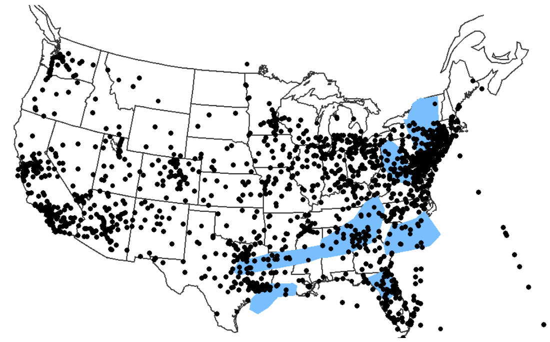

Figure 13. Geographical distribution of 250G nodes in network N5 with 3X Compound traffic and severe weather polygons

Tables

Table 1. Different types of ATM networks.

Network	Nodes	Number of Nodes	Edges
Airport Network (AN)	40 major airports	40	Routes between 40 major airports
Airport and Airspace Network (AAN)	All airports and fixes along routes connecting the airports	8170	Routes between all airports

Table 2. Distribution of 250G nodes by Centers under current and future traffic scenarios.

Center	Current	3XH	3XC
ZAB	7	70	78
ZAU	15	67	70
ZBW	16	77	87
ZDC	22	134	143
ZDV	8	51	68
ZFW	3	59	68
ZHU	8	60	72
ZID	15	71	71
ZJX	14	71	81
ZKC	11	58	50
ZLA	16	102	119
ZLC	5	29	40
ZMA	4	44	54
ZME	10	38	42
ZMP	6	46	53
ZNY	14	80	88
ZOA	10	57	67
ZOB	13	90	89
ZSE	5	35	41
ZTL	15	59	62
Total	217	1298	1443

Table 3. Nodal density of 250G nodes by Centers under current and future traffic scenarios.

Center	Area	ρ1X	ρ3XH	ρ3XC
ZAB	18.04	0.39	3.88	4.32
ZAU	7.60	1.97	8.82	9.21
ZBW	11.62	1.38	6.63	7.49
ZDC	12.69	1.73	10.56	11.27
ZDV	20.18	0.40	2.53	3.37
ZFW	12.32	0.24	4.79	5.52
ZHU	27.64	0.29	2.17	2.61
ZID	7.07	2.12	10.04	10.04
ZJX	14.55	0.96	4.88	5.57
ZKC	13.37	0.82	4.34	3.74
ZLA	13.55	1.18	7.53	8.78
ZLC	31.57	0.16	0.92	1.27
ZMA	28.66	0.14	1.53	1.88
ZME	10.75	0.93	3.53	3.91
ZMP	28.82	0.21	1.60	1.84
ZNY	2.43	5.76	32.92	36.21
ZOA	13.54	0.74	4.21	4.95
ZOB	6.74	1.93	13.36	13.21
ZSE	19.64	0.25	1.78	2.09
ZTL	9.18	1.63	6.43	6.75
Total	309.96	0.70	4.19	4.66

Table 4. Total number of nodes for different traffic scenarios.

Types of nodes	Current	3XH	3XC
250G	225	1312	1468
500G	72	620	806
750G	33	304	452
1000G	22	165	262

Table 5. Total number of nodes affected by severe weather.

Types of Nodes	1X	3XH	3XC
250G	34	191	207
500G	9	96	118
750G	4	49	67
1000G	3	23	41