Spring 2012

Evaluating Network Analysis and Agent Based Modeling for Investigating the Stability of Commercial Air Carrier Schedules

Sheila Ruth Conway
Old Dominion University

EVALUATING NETWORK ANALYSIS AND AGENT BASED MODELING FOR INVESTIGATING THE STABILITY OF COMMERCIAL AIR CARRIER SCHEDULES

Sheila Ruth Conway
B.S. May 1989, Massachusetts Institute of Technology
M.S. May 1989, Massachusetts Institute of Technology

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

ENGINEERING MANAGEMENT

OLD DOMINION UNIVERSITY
May 2012

Approved by:

Dr. Charles Keating, Director

Dr. Resit Unal, Member

Dr. Ghaith Rabadi, Member

Dr. Jeremiah Creedon, Member

ABSTRACT

EVALUATING NETWORK ANALYSIS AND
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THE STABILITY OF COMMERCIAL AIR CARRIER SCHEDULES

Sheila R. Conway
Old Dominion University, 2012
Director: Dr. Charles Keating

For a number of years, the United States Federal Government has been formulating the Next Generation Air Transportation System plans for National Airspace System improvement. These improvements attempt to address air transportation holistically, but often address individual improvements in one arena such as ground or in-flight equipment.

In fact, air transportation system designers have had only limited success using traditional Operations Research and parametric modeling approaches in their analyses of innovative operations. They need a systemic methodology for modeling of safety-critical infrastructure that is comprehensive, objective, and sufficiently concrete, yet simple enough to be deployed with reasonable investment. The methodology must also be amenable to quantitative analysis so issues of system safety and stability can be rigorously addressed.

The literature suggests that both agent-based models and network analysis techniques may be useful for complex system development and analysis. The purpose of this research is to evaluate these two techniques as applied to analysis of commercial air carrier schedule (route) stability in daily operations, an important component of air transportation. Airline-like routing strategies are used to educe essential elements of applying the method. Two main models are developed, one investigating the network properties of the route structure,

the other an Agent-based approach. The two methods are used to predict system properties at a macro-level. These findings are compared to observed route network performance measured by adherence to a schedule to provide validation of the results.

Those interested in complex system modeling are provided some indication as to when either or both of the techniques would be applicable. For aviation policy makers, the results point to a toolset capable of providing insight into the system behavior during the formative phases of development and transformation with relatively low investment. Both Agent-Based Modeling and Network Analysis were found to be useful in this context, particularly when applied with an eye towards the system context, and concentrated effort on capturing the salient features of the system of interest.

ACKNOWLEDGEMENTS

As are many engineering endeavors, the creation of this dissertation began as a solution to a problem; one for which I am most grateful. While working at NASA, I had the pleasure to work with Dr. Bruce Holmes. Unlike so many in our field of Air Transportation System research, Bruce had the ability to take a broad, system-wide view. His interest was in true system modernization, or in his terms, "transformation", as he saw the need for a fundamental change in air traffic management and air transportation as a whole. Not a small feat for a massive, safety-critical system.

However, it seemed that the complex system network theory Bruce thought would help describe and control the future system may not suffice. With this inspiration, I was determined to help derive useful tools for such transformative work. Bruce, you are no doubt my muse for this study, and for this and all your thoughts and wisdom you have shared on system transformation, complexity and other topics over the years, I thank you.

This pursuit would not have begun without my supervisor at NASA, Dr. Kelli Wilshire, who provided encouragement and also endorsed financial support and education leave. There were many others at NASA who helped formulate my thinking in complex systems and modeling. Many of us self-organized a Langley Networkers Working Group to explore such notions, which largely prepared me to tackle such a messy problem. Additionally, Dr. Jeremiah Creedon, then the Langley Center Director, challenged me to create a "little gold making machine" for ATM, demonstrating a small but scalable transformed system and its value. That assignment helped me understand the worth of an appropriate exploratory platform, and the fact that one didn't really yet exist. Thanks all.

I am grateful to The Boeing Company for their generous financial sponsorship. I'd also like to thank my Manager John Olsen who has gently, but consistently, asked for progress reports, and didn't let me lose sight of the value of finishing.

In fact, over the years, many people have encouraged me to complete the project and help move me off "top-dead-center" when I seemed to be stalled: The first real push was from the other graduate students and faculty at the Santa Fe Institute Computational Social Science Modeling and Complexity Workshop. I learned so much there; particularly to focus on capturing the essence of the system in the modeling, and that an old programmer *can* learn new tricks. More recently, an instrumental shove came from Chuck Adler and other colleagues at Boeing who wouldn't let me give up when time was short, and much support and assistance from Maria Consiglio.

I can't sufficiently express my gratitude towards my committee. Fitting with the overall graduate experience in the EMSE Department at Old Dominion, they have been nothing but supportive, not to mention extremely patient. I have learned a lot from this undertaking, and value this wonderful opportunity to return to school with a real purpose. I would particularly like to thank Dr. Charles Keating. Chuck not only co-chaired this dissertation, but also made remote completion of this program possible.

Finally, throughout my education I've been fortunate to have had incredible backing: my parents have always been so encouraging, and for that I will always be indebted. And thankfully my husband Charlie and daughter Anna have been sympathetic and willing to put up with many long nights, not to mention having been a most vocal cheering squad. So nice to have such a wonderful support network right in your own home. With much love.

NOMENCLATURE

Alpha, α	Network Tolerance Parameter: Capacity/Demand
ABM	Agent Based Modeling
ACES	Airspace Concept Evaluation System
ADS-B	Automatic Dependent Surveillance - Broadcast
AGNA	Applied Graph & Network Analysis (software)
ANTs	Active Nonlinear Tests of Complex Simulation Models
ATC	Air Traffic Control
ATCSCC	Air Traffic Control System Command Center
ATM	Air Traffic Management
ATS	Air Transportation System
ATSP	Air Traffic Service Provider
BA	Barabasi-Albert small world network
C, C(p)	Clustering Coefficient, and average for the network
CAASD	Center for Advanced Aviation System Development (@ MITRE)
CDM	Collaborative Decision Making, an FAA Program
CRAF	Civil Reserve Air Fleet
DFW	Dallas-Ft Worth Airport
DOD	Department of Defense
DOT	Department of Transportation
EGlob, ELoc	Network Efficiency- Global (path length), Local (cluster)
EAS	Essential Air Service
EU	European Union
ER	Erdös-Rényi random network
FAA	Federal Aviation Administration (USA)
FAR	Federal Aviation Regulation
GIS	geographic information system
GUI	Graphic User's Interface
HaS	Hub and Spoke
HWP	America West Airline

ICAO	International Civil Aviation Organization
IMPACT	Intelligent agent-based Model for Policy Assessment of Collaborative Traffic flow management
IT	Information Technology
k	Number of links at each node
ℓ, L(p)	Path Length Between Nodes, average or characteristic length
N	Number of Nodes in Network
NA	Network Analysis
NAS	National Airspace System
NASA	National Aeronautics and Space Administration
NextGen	Next Generation Air Transportation System
NGATS	Next Generation Air Transportation System
NRC	National Research Council
OEP	Operational Evaluation Partnership (w/FAA, top 35 airports by commercial flights)
ORD	Chicago O'Hare Airport
FAR Part 121	Operating requirements, Domestic Operations (Transport)
FAR Part 139	Certification of Land Airports Serving Certain Air Carriers
PtP	Point-to-Point
SESAR	Single European Sky ATM Research Program
SFO	San Francisco Airport
SME	Subject Matter Expert
SWA	Southwest Airline
SWIM	System-Wide Information Management
TranSims	TRansportation ANalysis and SIMulation System
TWA	TransWorld Airlines
UA	United Airline
UK	United Kingdom
VAST	Virtual Airspace Simulation Technologies
Zeta, ζ	System dampening coefficient

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CHAPTER 1

INTRODUCTION

For a number of years, the United States Federal Government has been formulating a plan for National Airspace System improvement. These Next Generation Air Transportation System plans, first known as NGATS (NASA, 2006), later became NextGen (JPDO, 2007) as the national initiative to focus on improvements to today's Air Traffic Control systems. Like their European counterpart effort, the Single European Sky ATM Research Program (SESAR), these improvements are aimed at "a comprehensive overhaul" to the system. The FAA says (FAA, 2011):

> *"We're undertaking the largest transformation of air traffic control ever attempted, while thousands of planes and millions of passengers continue to fly safely. The last time this happened we had just fought and won a World War and were on the cusp of the space race."*

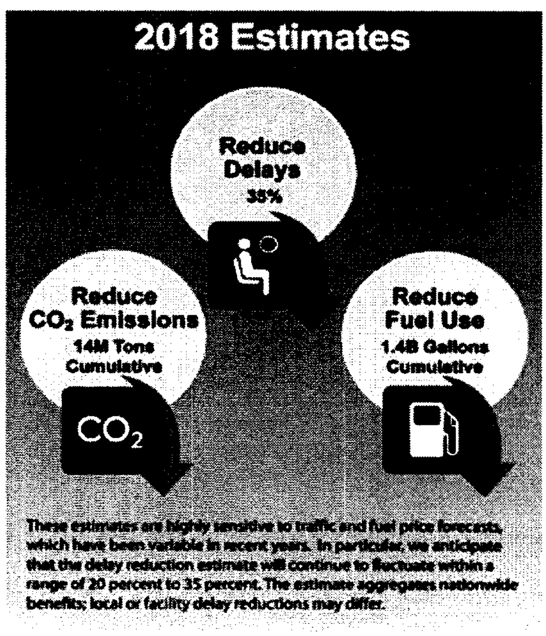


Figure 1: Goals for NextGen (FAA, 2012)

When discussing NextGen, the FAA shows delay as one of the major barriers to improvement (Figure 1). This invokes several questions, such as: Are the root causes for delay understood, and are mechanisms which will positively affect delay reduction being pursued? How will changing demand further confound delay reduction?

Changes in the demand for air transportation are inevitable, and indeed seem to be upon us (Cistone, 2004). NextGen initiatives can hope to achieve incremental improvements in today's Air Transportation System (ATS), but are unlikely to 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." (Shumann, 2001) More dramatically, Secretary of Transportation Norm Minetta called for tripling the air traffic capacity of the United States in a 15 to 20 year timeframe because of growing demand in the airline sector and in additional transportation modes such as jet taxies and unmanned aerial vehicles. He was reported to have said (Wald, 2004), "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."

The economic downturn in recent years has changed the timeframe, but not the basic issues: how to manage traffic for the best result from the myriad of stakeholders' perspectives: the travelers, the community, government, and the for-profit airlines, airports as well as national and international commerce and economics. Though the players have changed over the years, the issues remain largely the same: (Lahr, Robins, & Checchio, 2009) ask the question which is at the heart of this study; "Why is it so difficult to develop federal level policy that would help forward the goals of a safe, effective and efficient air transportation system?" They go on to say that "Differences in political agendas, perspectives towards government roles and diverse vested interests make policy formation a challenge at best, impossible at worst." They describe the recent efforts by Department of Transportation Secretary Ray LaHood to form a committee on the Future of Aviation as a means to stave off an otherwise inevitable relegation of the "U.S. aviation system to second rate status" and that the problems to be solved are "seemingly intractable".

There are other pressures in the forefront in recent years as well. The European Union has imposed strict limitations on emissions based on 2006 levels and strategies of carbon trading for portions of allowable carbon emissions (Ellerman & Buchner, 2007). While not yet universally accepted, such sentiments are gaining traction and beginning to appear in and influence the regulatory world as well as the popular rhetoric (Figure 2, a billboard from *SPURT* (SPURT, 2007), an environmentally-focused campaign to disallow expansion at London Heathrow airport).

Figure 2: Example of Political Influence in ATM

Unfortunately the revolutionary changes required to accommodate a large and rapid increase in capacity while also addressing financial and environmental politics have proven 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 has evolved in response to these powerful social, political, economic and technological pressures. The technological infrastructure, known commonly as the NAS (US DOT, 2000), alone is enormous and represents a substantial investment (Figure 3). Even relatively minor changes can require Congressional intervention.

The National Airspace System (NAS) is a complex collection of facilities, systems, equipment, procedures, and airports. It includes more than 18,770 airports, 21 air route traffic control centers, 194 terminal radar approach control facilities, more than 467 airport traffic control towers, 76 flight service stations, and approximately 4,533 air navigation facilities. More than 34,000 pieces of maintainable equipment, including radars, communications switches, ground-based navigation aids, computer displays, and radios are used in NAS operations. NAS operates nonstop, 24 hours a day, 365 days a year.

Figure 3: The NAS (US DOT, 2000)

There are many factors driving fundamental changes in the air transportation system, some of which are technical, some socially-driven, others political (Pearce, 2008). There are also serious implications to any changes in transportation infrastructure and policy, and many that have interact. There is an immediate need to address these attributes which are common with many complex systems in a transformative effort such as NextGen.

1.1 BACKGROUND

If ATS designers are to provide meaningful alternatives to policy makers regarding this urgent national problem, they need to understand the fundamentals of the system, and develop insight into the dependencies without having to recreate *all* the details. 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. In turn, this suggests that to control development costs, it may be wise to constrain investment necessary for any single iteration, particularly in the early formative phases. Quick-turn simulation of complex systems, like that shown in the inside loop in Figure 4 can allow a designer to explore a number of alternatives with relatively low cost. Then a more elaborate but focused study can follow, which in general will require a larger investment but fewer iterations. Once a system is ready for implementation, substantial investment is required, so it is important to minimize the need for change. Researchers also need a platform to rigorously verify and any suggested changes meet minimum criteria, such as safety and reliability (Odoni, 1997).

Traditional parametric modeling techniques meet the requirement for rigor, but they can be complex and costly to develop (Bonabeau, 2002) (Wieland W. N., 2002). 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 (Jennings, 2001) (Macdonald & Bologna, 2003) (Wolstenholme, 2003) (Parunak, Savit, & Riolo, 1998). Kutaka and Fursova (Kutakh & Fursova, 2003) assert, "The complexity of real systems does not allow one to construct 'absolutely' adequate [traditional] models". Even more importantly, these deterministic models cannot, by themselves, be used for establishing sensitivity to uncertain demand, or generalizing behavior of a yet undefined future system (Schaefer, Wojcik, Berry, & Wanke, 2002) (McLucas, 2001). Given ATS complexity, developing a sufficiently comprehensive model of all higher-order behaviors is unlikely.

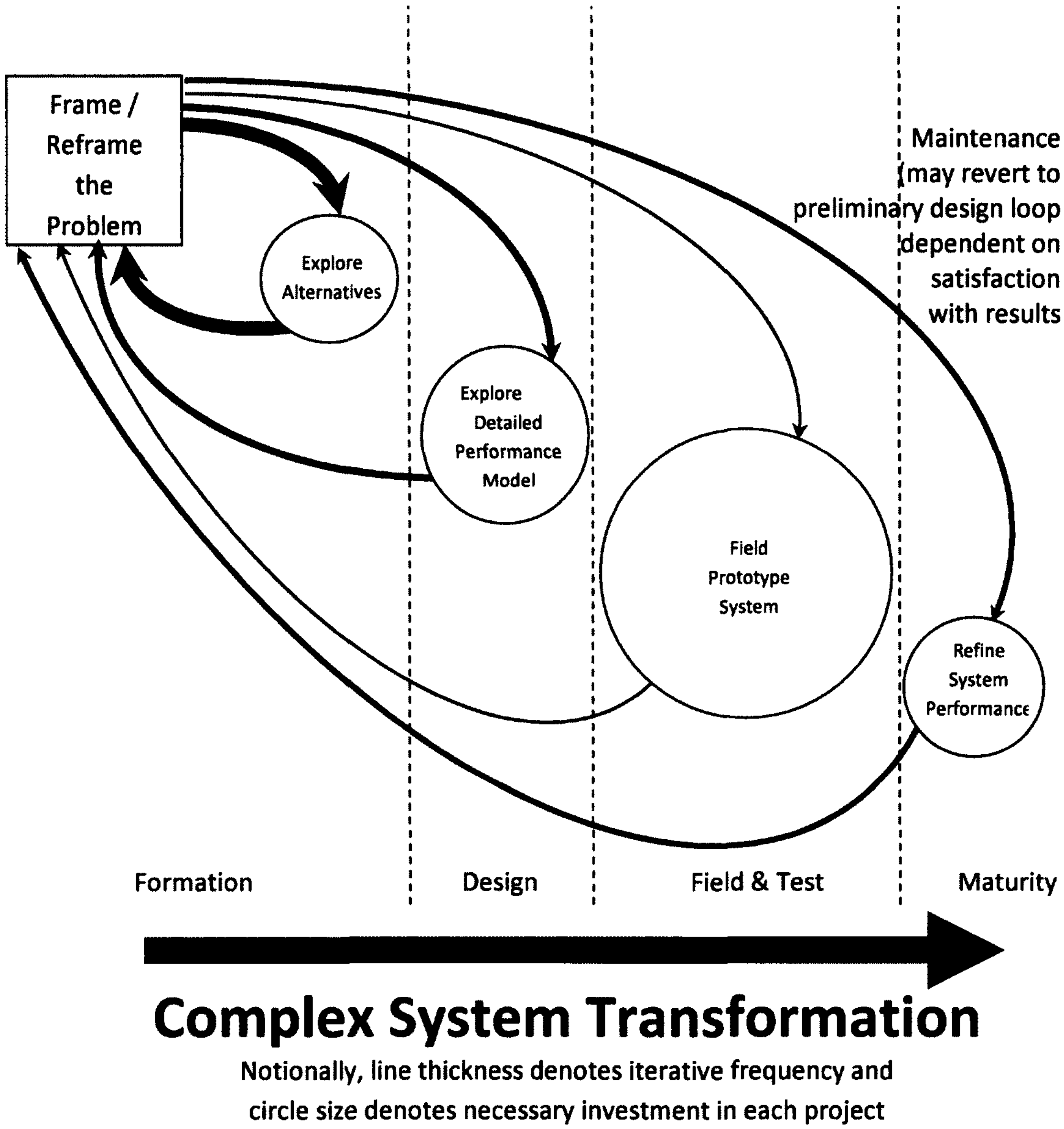


Figure 4: Closed-loop nature of initial transformation phase, suggesting the need for quick, low-investment assessment tools

System engineering methods may be useful in this complex, multi-objective realm. Daniel (Daniel, 1990) 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 cannot be expressed by a single set of objectives (Figure 5). These methods have, however, been criticized for being unverifiable, non-quantifiable, and lacking in rigor (Andrews, 2001).

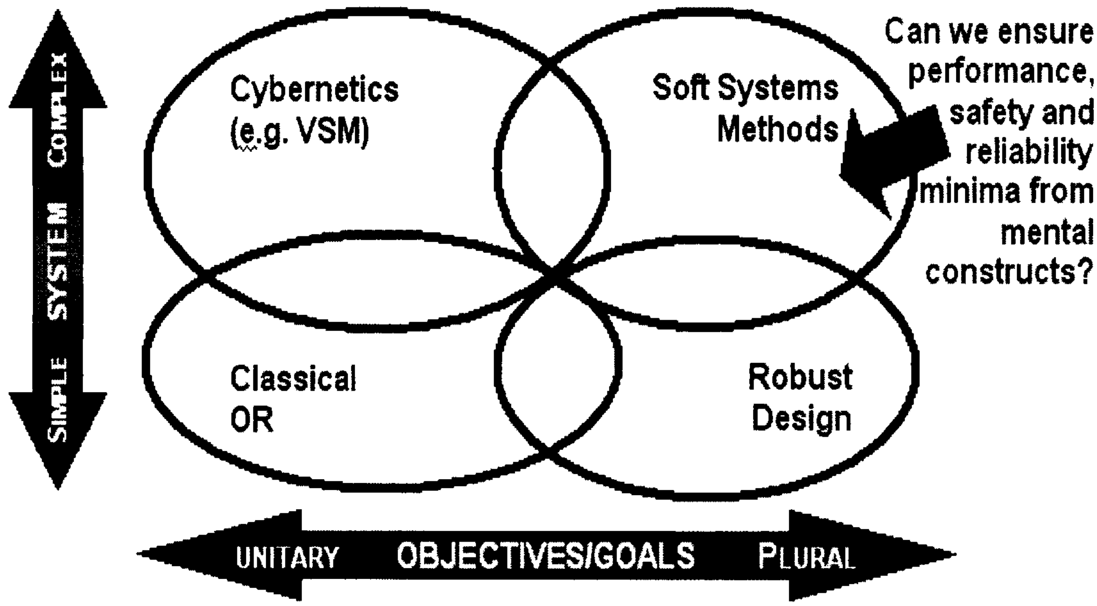


Figure 5: System methods and their application
within problem context (adopted from Daniel1990)

For a safety-critical system with minimum performance criteria, mental constructs (and the flexibility they provide as "controlling" qualities) are not sufficient. Sterman (Sterman, 2002) warns, "Pattern matching often leads to wildly erroneous inferences about system behavior, causes people to dramatically underestimate the inertia of systems, and leads to incorrect policy conclusions." In fact, Moss (Moss, 2002) 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 (Bonabeau, 2002) claims that adaptive agent or 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" models that result.

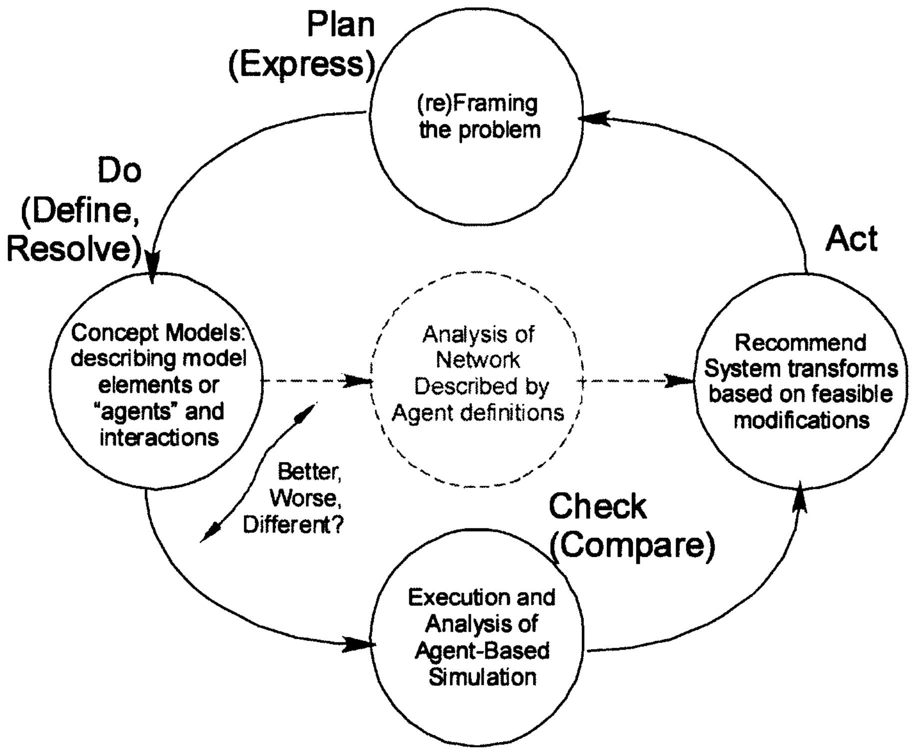


Figure 6: Agent formation: relationship between
network analysis and agent-based simulation

While full-scale ABMs can be as complex and costly to develop as large-scale parametric models (Aronson, Manikonda, Peng, Levy, & Roth, 2003), 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, for example, describe the network of agent communication demands (Figure 6), in turn providing a reasonably simple and reliable means of evaluating the aggregate performance of a proposed ATS.

For some time, network models have been recognized as valuable aids "in the analysis and synthesis of systems. (Whitehouse, 1973)" 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 expose complex system attributes, e.g. system dynamics and emergence without having to develop a full agent-based simulation. It seems this could well serve the quick-turn, iterative nature of the inner discovery loop in Figure 4.

Network science can be used not only for analysis, but for controlling systems as well. The literature implies that behaviors are somewhat predetermined by the structure of the system, or the network(s) that are formed by interactions among subsystem components (Albert & Barabasi, 2002) (Klemm & Eguiluz, 2002). Strogatz, Watts and others have shown that relatively simple rules or constraints on network structure can yield systems with largely similar behaviors. (Strogatz, 2001) (Watts, 2002) (Carlson & Doyle, 1999)

Strategically engineered networks, generated with minimal, but carefully considered operational constraints, could potentially be used to modify and regulate systemic behavior. Of particular interest are "scale-free" networks, as they are well suited to deal with environmental uncertainty and large demand growth. Barabasi and Albert (Barabasi & Albert, 1999) define scale-free networks as those without a single characteristic dimension or degree, but rather a probability distribution of interactions with other vertices that decays as a power law. 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. Because of this ease of formation as well as their utility, they are expected to be ubiquitous (Watts, 2003). It is likely that the future ATS may be, at least in part, a scale-free network. In fact, the route structure of the commercial segment of the ATS is often cited as an example of an existing scale-free network (Jeong, 2003) (Barabasi, 2003) (Watts, 2003).

With pressure for air transportation change and large-scale programs worldwide poised to achieve it, the need to explore various approaches is great. However, traditional methods have proven cumbersome and/or incapable of capturing all the important features without being cost or time prohibitive to develop.

1.2 SCOPE OF STUDY

The ATS is so extensive that creating a comprehensive system model using any method will still demand substantial effort. Before undertaking such an effort, it would be prudent to prove the methodology effective in context on a smaller scale. Looking at a simplified picture of the commercial air transport system (Figure 7), the strategic route management portion and the resultant schedule performance, identified by the lower left feedback loop, is an appealing place to start:

This feedback loop represents the sub-system of airline schedule, or flight demand, on the NAS. Because the NAS has finite capacity to handle air traffic at any given time, policy and business choices can encourage conditions to be created where the airline's scheduled operations exceed capacity. Many studies address maximizing the theoretical usage by efficiently ordering traffic and assigning traffic to specific runways (some flight pairings and landing sequences require more airport resource than others) (Yu, Cao, Hu, Du, & Zhang, 2011) (Rabadi, Hancerliogullari, Kharbeche, & Al-Salem, 2012) (Anagnostakis, 2001) (Bennell & Potts, 2011). Such studies go far to demonstrate possible improvements in air traffic control's ability to maximize the operations through a constrained facility or airspace for given demand. This body of work could be complemented greatly by related work that explored the choices the airlines make and the operating rules air traffic service providers and communities levy upon them which also influence capacity, though more indirectly.

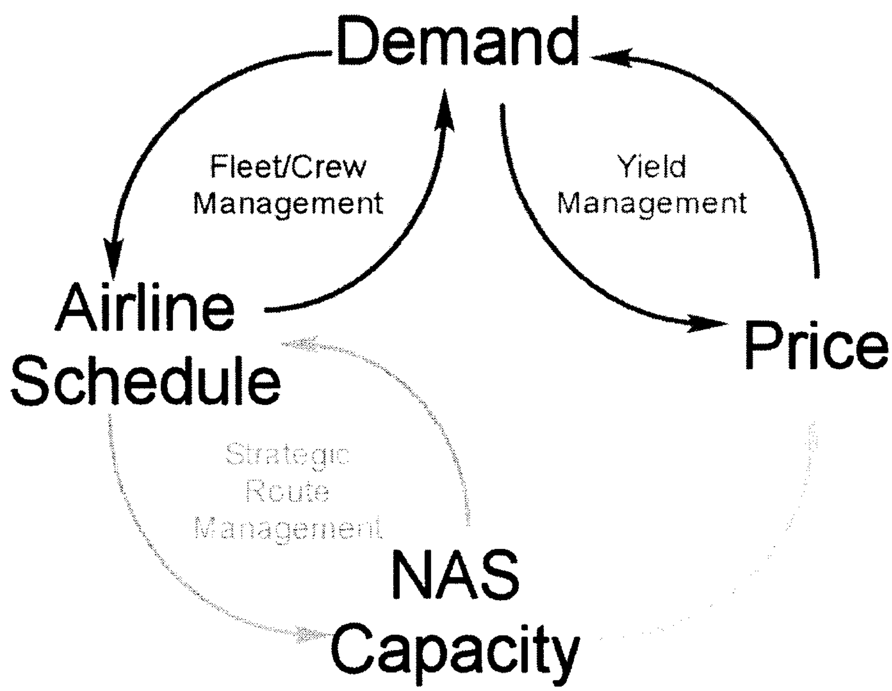


Figure 7: A Simplified Model of Commercial Air Transportation

Along those lines, there are a number of studies that address the airline's primal route choices using network theory to predict which cities are selected and strategies for connecting these to the network of available flights. For example, airline profitability depends on their ability to maintain schedule and operate with planned equipment utilization (Beatty, 1999) (United, dispatch , 2002). In this sense, routing and schedule represents an airline's effort to optimize. Addressing the same notion of a transportation feedback loop for capacity and demand as applied to the road network, Kulash (Kulash, 2001) states traditional "traffic planning, which is little more than applied common sense, is not getting us where we want to go."

Complementary work which could address stability of systems, optimized or not, would help air traffic service providers and other NAS users create policy that could reliably realize such yield and cost objectives. Unscheduled or unexpected delay is a major source of inefficiency and capacity loss (FAA, 2011).

In fact, Narasimhan (Narasimhan, 2001) of United Airline (UA) presented a case for exploring schedule reliability as THE focus of their operational improvements. He was driven by the fact that even back in 1999, the total costs incurred by UA due to delays and cancellations was estimated at $600-700M. He goes on to say that if the airline can maintain its flight schedule, it minimizes all other operational disruptions, such as fleet substitutions, crew scheduling, etc. Even further damage is done to the reputation of the airline when delay exceeds customer's patience: he reports that when delays exceed 30 minutes, the repurchase intent of customers decrease significantly (Figure 8). These are exactly the types of relations that develop into the feedback loops which in turn influence flight schedules. This research seeks methods that could be used to illuminate their influence.

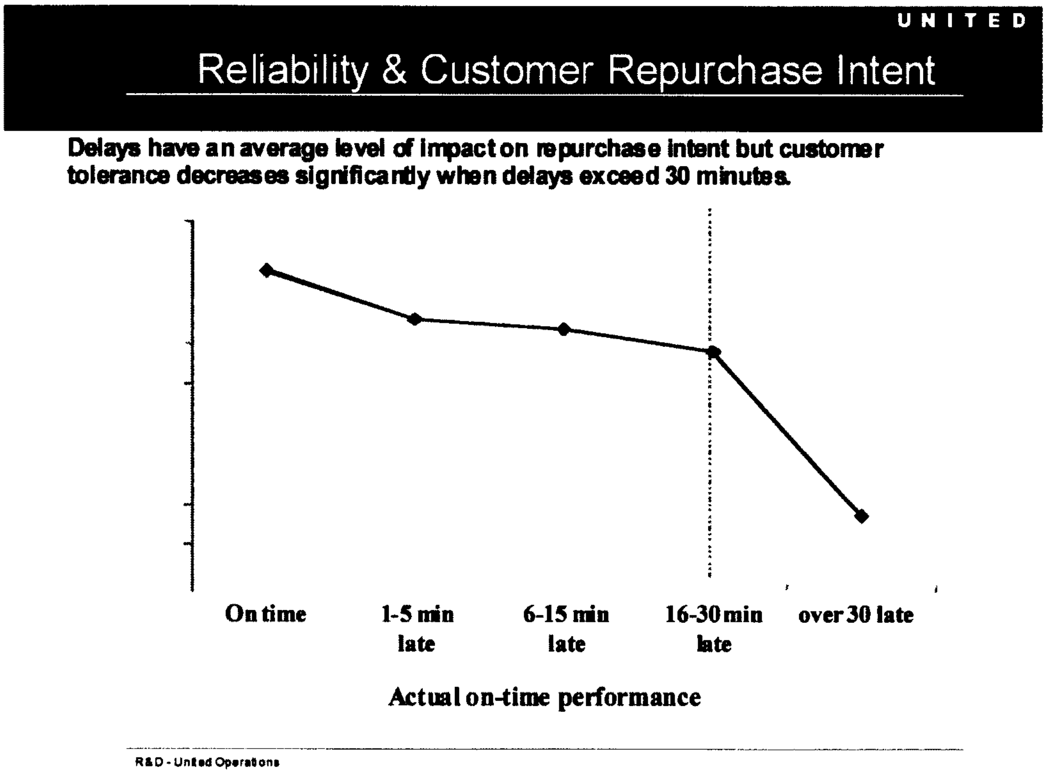


Figure 8: Schedule Integrity Influences Customer Satisfaction (United 2012)

Apparently, systemic analysis of route structure is important for other aviation system participants as well. Sweetman (Sweetman, 2003) reported airframe manufacturers' route performance analysis has yielded critical data regarding the launch of new aircraft. He reported "...But as manufacturer and customers [of the Boeing Sonic Cruiser] looked, with the help of a specially hired team of airline schedule experts, at exactly how the faster airplane would mesh with other aircraft in a real route structure, the benefits evaporated."

The route structures show wide variability, including three dominant modes: Hub-and-Spoke, Point-to-Point, and On-Demand, which these models should be able to characterize and quantify. Both historical and contemporary data are readily available to support investigation of the different route structures based on contrast of NA and ABM methods of modeling.

While route structures are only a portion of this extensive system, they are a key, dynamic operational element as well as one which largely captures the strategic nature of commercial aviation business. To be most useful for transportation research, analytical methods must be able to address both socio- and technical system qualities. Schedule adherence reflects both of these properties.

1.3 RESEARCH SIGNIFICANCE

Much modeling effort in this realm of ATS modernization has been focused on traditional parametric modeling and real-time human-in-the-loop simulations that fall short of addressing systemic issues. Others have tried to build "full-mission", high fidelity simulations, or link existing facilities together at great cost and effort (Adacel, 2012) (NASA, 2012). This makes every new air traffic control concept extremely tedious, costly, and time consuming to explore.

The research and planning community is in need of relatively simple, systemic yet rigorous methodology(ies) for evaluating new operations, their effect on traditional system function, and their ability to support unconventional air transportation models in light of demand uncertainties. Both ABM and NA have been suggested as general approaches to complex system analysis, but there is little discussion of the merits of one over the other as applied to the ATS in the literature.

Low-investment, quick-turn analyses would be useful in addressing many of these issues. In practice, accessing the "real" future-world in critical system design is problematic. Obviously, the NAS can't be changed just to explore "what if" scenarios, but a reasonably simplistic yet operationally significant model of the ATS could be used to explore initial operations prototypes and establish first order effects. As a more robust system emerges, more comprehensive models may be required to address detailed design issues and complete subsequent design cycles. Though there are presently no tools capable of a comprehensive approach to NAS modeling that are inclusive of innovative operations, existing simulations can be expanded to accommodate operations investigations. But because these simulations tend to be difficult and expensive to modify, using relatively simple network and/or agent models in the first iterations could limit the effort required to test new designs. Moreover, even simple adaptive models promise to do something that existing simulations do not reliably do: i.e., predict probable emergent behaviors, both favorable and unfavorable, that are inherent characteristics of such complex systems. In one sense, the establishment of the applicability of these approaches may serve to provide sufficient front end capability to avoid potentially pursuing more resource intensive modeling activities that may be shown early on to be based on faulty system logic.

This research attempted to provide clarity to methods that may be useful in the analysis of airline routes and other complex systems with similar attributes. Two methods, network analysis and agent-based models were explored with the intention to highlight their individual strengths and weaknesses as applied to airline route analysis. In using these methods, two disparate qualitative route strategies that were identified in the popular literature were analyzed, accenting quantifiable attributes and potential performance.

Those interested in complex system modeling are provided some indication as to when either or both of the techniques would be applicable. For aviation policy makers, the results point to a toolset capable of providing insight into the system behavior during the formative phases of development with relatively low investment.

It may be possible to extend their use to other sub-systems, as schedules reflect the effects of both supervening passenger demand as well as the underlying NAS infrastructure (Figure 7). Identifying shortfalls of the methods can also be considered a useful result, as attempts to model the ATS, particularly using agents, is presently consuming substantial effort in the research community.

This research will explore if this utility of agent and network modeling as applied to aviation transportation systems can be improved. It focused on a limited, but carefully-crafted operational system model which is sufficiently detailed to educe performance, but simple enough to be easily developed.

1.4 RESEARCH QUESTIONS

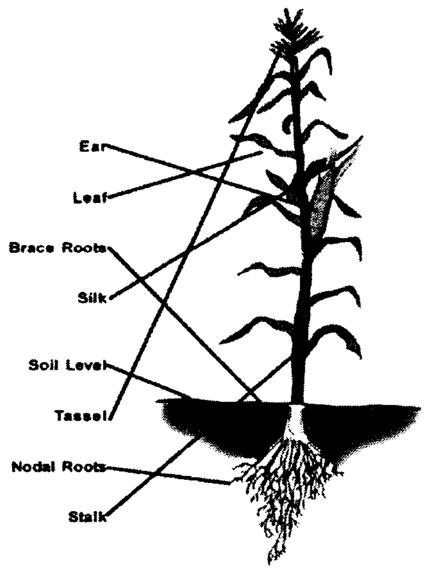
The research hypothesis above raises the following research questions, expanded below:

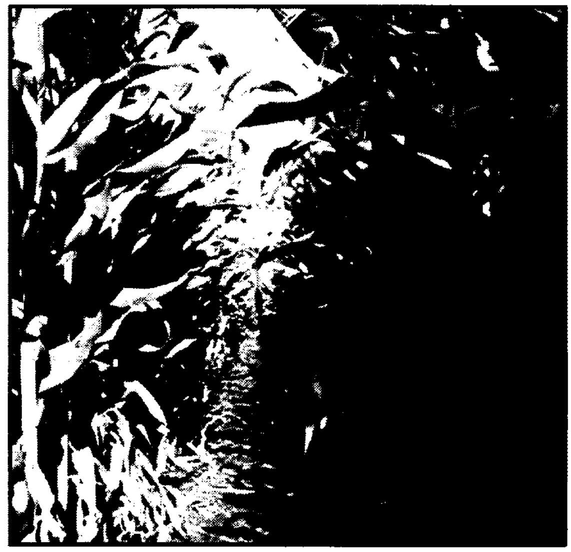
1. What policy, airline operation and environmental attributes should be represented when developing models intended to reveal insight about schedule?
2. What commonality is there between the topology of network models and agent-based models that capture system attributes regarding airline schedule adherence?
3. Do network models and agent-based models of airline operations predict the same static and dynamic schedule adherence responses?

1.4.1 Context and significant details of a route network model

As Albert Einstein once said, "Everything should be made as simple as possible, but not simpler." This caution requires consideration of which aspects of airline routes and schedules are *minimally sufficient* to define agent attributes and their associated communications such that particular systemic behaviors, such as substantial delay propagations, can be uncovered. In the analogy presented in Figure 9, are the detailed elements of the corn plant [identified by (Wagle, 2012)] important? Do you see the path?

Concentrating on the details for every stalk, can you understand the "big picture"? Is there more to see? More about what you're looking at in the conclusion.





What are we looking at?

Figure 9: Models need to be at the right fidelity: too much detail may not be helpful...

Aggregate topology studies are critical to establishing "artificial" problems created by pseudo-hub locations related to politics rather than demand, and establishing their effect on system growth and overall delay. However, it may also be useful to take a more operationally-focused look at schedules to identify dynamic system qualities such as expected nominal delays, forced ground hold programs, or the potential for cascading failures resulting from operational realities. To do so, specific attributes of ATS operations and their associated communications have to be modeled. This study addresses this issue by surveying the technical literature in the field of airspace operations modeling to synthesize issues germane to ATM and flow control.

1.4.2 Relating Network and Agent-Based Model Design

Murthy and Krishnamurthy (Murthy & Krishnamurthy, 2009) and much of the other literature surveyed within this research implies that NA and ABM are somehow related, though no explicit comparisons of them were identified. From the outset, differences in both scope of effort to establish these two models and expectations for their results should be anticipated. NA is focused at systemic-level solutions, much like system dynamics. ABM revolves around the "unit" of the system (the unit being defined by the fidelity of the agent, e.g is the agent an airport, an airplane, or a traveler). Though as these elements interact, systemic emergent behaviors can be demonstrated.

This is not to say that ABM cannot yield similar systemic solutions as well. Qualitative issues regarding a model's ability to impart insight are in play: Is the additional information (at the agent level) necessary or even useful for a transport system study? Is the system so sensitive to assumptions of individual behaviors that ABM predictions are no better, or in fact worse, than network analyses? On the other hand, are NA such aggregated models that the system dynamics are too simplified or too regimented? These questions are certainly within the realm of consideration in the selection and deployment of an appropriate modeling approach to explore the ATS.

Anecdotal evidence of the ability to model system attributes (as defined by the literature in the first portion of this study) using each of the two methods during this study is captured as an essential aspect of the research design. Common sub-structures e.g. networks of related flights, are expected. These operational system attributes are likely the source of behaviors of interest, so if the models cannot easily represent these attributes, the utility of the models is likely limited.

1.4.3 Network and Agent-Based Model Predictive Capabilities

This research ultimately explored the predictive qualities of these two techniques suggested by the literature as appropriate to the air transport system domain: network models and agent-based models. There are clearly comparisons to be made between the outputs from these two different approaches. Additionally, there are likely to be qualitative differences in the system intuition gained in the two modeling experiences. This research addresses this question of model utility and uses qualitative analyses to determine which model better addresses the requirements voiced by the operational design community.

1.5 DELIMITATIONS

The research assessed tools and techniques that can be used to examine proposed air transportation operations, but did not attempt to synthesize new operations that may address system goals. These tools are intended to illuminate capabilities of particular operations and their effect on other sub-system elements, capturing first-order system dynamics. This study concentrated only on tools to evaluate strategic route management, e.g. measuring route networks for attributes that could be expected to exceed NAS capacity and cause disruptions. There was no attempt to comprehensively evaluate all commercial route structures. The tools are not being evaluated for their effectiveness in tactical, real-time operations.

Some airlines use proprietary data and modeling techniques to develop strategic plans. However, because this research is aimed at exploring these two methodologies rather than producing explicit analytical results, only publicly available data was used. This supports dissemination of the results to a broader audience, and provided simplified data handling.

CHAPTER 2

LITERATURE REVIEW

The literature that supports such a study applied to the ATS falls within three broad categories: complex systems science, complex system modeling (including network theory and agent based modeling) and transportation modeling for policy analysis. Each of these categories is expanded upon in the following sections.

2.1 COMPLEX SYSTEMS SCIENCE

Complex systems research is focused on the dynamics of distributed systems: primarily the causal effects of influences between the nodes of a network (Klein, 2002). Uncovering systemic behaviors, such as stability (tending to a single state, condition or value) or periodicity are a central focus. These inquiries are accomplished with the general assumption of incomplete or imperfect system knowledge.

The development of new air transportation policies and their supporting operations are driven by many factors; including capacity, technology, safety, convenience, access, cost, value, competition for resources, politics and the performance of competing transportation sectors. Even this incomplete list suggests that many of the driving issues for future airspace control revolve around "soft" matters of perception, demand and desire.

However, when it comes to ATS improvement initiatives, these issues have traditionally taken a back seat to matters of a more technical nature and avionics development: If we step back and look at the body of ATM research, it becomes clear that the efforts are dominated by technology development. As an example, NASA sponsored a development program for ATM transformation known as the Small Aircraft Transportation System (SATS). The goal of the program was to enable a segment of air transport, general aviation (GA), as a truly viable option for transportation. While formulating the program, a number of barriers which seemed to be impediments to GA's use as a true alternative to commercial air carrier service were identified, and a large, elaborate technology development program was planned. In the end, the 3-day live flight demonstration showcased some new technology, largely developed by NASA (Consiglio, 2005) and other research partners. But the program did not address some of the main barriers such as public policy and economics (NASA, 2012).

Phelan (Phelan, 1999) states though they are related, "Complexity theory differs from systems theory in its agenda (exploratory rather than confirmatory), techniques (agent-based models rather than circular flows) and epistemology (positivist vs. post-positivist)." One could conclude from this statement that complexity science, and the tools that it brings, may be applicable to this ill-defined, non-deterministic problem of ATS improvement. Following the argument of Daniel (Daniel, 1990) above, a systems-based approach is warranted. Application of the principles of *complex* system design is appropriate in this complex systems realm (Keating, 2000). However, for reasons of integrity, robustness and safety, a rigorous approach is also necessary. Avoidance of complex system failure issues such as contextual misalignment, uncompensated emergent patterns, and a dynamic design process are critical.

Because both the disciplines of systems and complexity science are important, applicable principles of both are examined further below.

2.1.1 Systems Science First Principles

Systems theory stresses that framing a problem correctly is essential to effective systemic analysis (Checkland, 2000) (Shekar & Krishnaswamy, 2000). For example, what is the NAS and how does it differ from the ATS? The United States Department of Transportation definition describes the NAS as technical infrastructure and facilities (Figure 3). 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 (a.k.a. "payload") and 14.5 million tons of freight and mail that travel by air (Figure 10). It is important that when considering changes to the NAS, analyses are not restricted to the infrastructure alone. Improvements to the infrastructure for their own sake (e.g. "modernization" of display units) may have a limited or even negative impact on transportation quality. Passengers are likely to have a different perspective of system performance than the FAA or the airlines. In fact, Bratu & Barnhart demonstrated that though the airlines reported performance improvement between 1995 and 2000 as measured by reductions in average flight delays, over the same period passengers experienced a 3-fold increase in total delay minutes (Bratu & Barnhart, 2005).

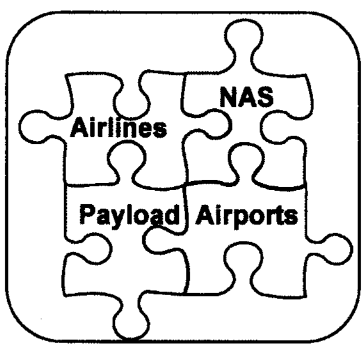


Figure 10: The ATS, A System-of-Systems

Keating et al (Keating, Kauffmann, & Dryer, 2001) define a fundamental system concept of *complementarity* that acknowledges that different perceptions of a single system can exist simultaneously and be correct from each observer's point of view. Gershenson and Heylighen (Gershenson & Heylighen, 2010) say "there is no 'best' model, as different rel-beings are appropriate for different contexts, and different purposes. With a classical way of thinking, we can spend all out efforts in trying to decide what 'is' the system. Complex thinking, on the other hand, allows us to contemplate different representations at the same time in order to have a less-incomplete understanding of the system". Therefore, 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. In fact, grossly different ATS networks descriptions have been indentified (Conway, 2004), stemming from different perspectives, each of which might be correct from their own perspective. With little specific domain literature to back up such an assertion, but much general systems science suggesting that this is a fundamental element of such an extensive system (Keating, Kauffmann, & Dryer, 2001), identifying different operational ATC networks becomes a task for this research.

Acknowledging that Keating's notion of complementarity is an issue due to the broad nature of the ATS, how is a systems analyst or policy maker to determine an optimal state for the system? System science offers a strategy: the theory suggests a range of satisfactory behavior within each perspective may afford sufficient overlap of distinct views to allow for an end state that can be considered successful on many levels. According to Flood and Carson (Flood & Carson, 1993), a system that has to be flexible enough to change over time, operates under many constraints, and needs to meet multiple simultaneous goals, relies on *variety* and minimal constraint. The system must have sufficient variety or capability for multiple configurations. It operates in a manner that Nobel Laureate Herbert Simon (Simon, 1965) says "satisfices" the situation to handle the usage demand in a satisfactory way, as optimization may not be fruitful or even possible due to rapidly changing circumstance. For instance, any one of the myriad of aviation system participants will have *a* way to measure "capacity." But it is unlikely that airline passengers, airports, airlines, and private aircraft operators would choose the same metrics to optimize; some seeing revenue seats, some flights, some airport slots, etc.

System influence can extend beyond arbitrarily created system boundaries: The "Southwest effect" is a prime example of such phenomena. Demonstrative of the influence that Southwest Airlines has when entering a market, after the inception of their Oakland-Burbank route, it became the 25th largest market, growing from 179th, in less than a year (Kelleher, 2003). Southwest's fare structures, typically 65% lower than other airlines, draw other airlines' customers. More unexpectedly, in new markets they also create demand increases on the order of 30%, suggesting that new service not only serves present demand, but also can change the nature of the demand itself. Similar effects have been measured in Europe, where low-cost, simplified fare structures have reportedly stimulated enough new traffic and increased load factors to offset the "dilution" of yield of traditional flagship carriers (Buyak, 2003). In fact, Buyak predicts that without these new route and fare strategies, European carriers will struggle or fail.

2.1.2 Application and Analysis of Complex Systems

The concept of a "system of systems" has arisen in the field of telecommunications amongst other places, and conceptually addresses the need to integrate higher order, complex systems. Onuh (Onuh, 2001) describes a truly integrated system [of systems] necessitating more than sub-systems communications: He suggests "True integration requires that control over a system can be accomplished towards the attainment of global system goals, and furthermore, subsystems must contribute towards the global goals irrespective of what their own local goals may be."

Beyond approaches for analysis, system science also suggests strategies for system transformation and regulation. Bar-Yam (Bar-Yam, 2003) concludes that for a large sub-class of complex systems (which includes air transportation), evolutionary rather than revolutionary strategies are necessary to maintain system operation during grand-scale transformation. This in turn necessitates a means to evaluate and direct multiple interim states as the system is transformed. It also implies that investment in any one state should be kept to a minimum, to free resources for subsequent iterations.

2.1.3 Error Sources in Modeling Complex Systems

Sage (Sage, 1992) suggests that there are many independent sources of error in systems modeling. Some, primarily affecting the accuracy of the model, are related to physical model implementation e.g. poor coding, leading to insufficient data handling in turn causing dropped data or overrun time steps in real time simulations. Others, influencing model integrity, have to do with how results are used or misused. More germane to this discussion are integrity errors that relate to model formation, or what Sage calls abstraction and algorithm errors:

Abstraction error is the difference between a real system and a modeler's internalization of it. Somehow, the modeler must form a context-based "rich picture (Checkland, 1981)" of the system of interest in order to represent it properly. Even with an understanding of the situation, its interpretation can cause problems if not handled carefully. Mitroff (Mitroff,

1998) suggests that a lack of critical, systems thinking can lead to solving the wrong problem by misunderstanding the root causes of issues or *using inappropriate methods.*

In deference to the canons of science, Gulyás (Gulyás, 2002) was compelled to publish a warning to system modelers: Choosing one implementation approach over another "...may have a dramatic effect on the results. It also demonstrates how implementation choices 'guide our hands' and may lead to implicit assumptions about the modeled system." By remodeling a single system using four different techniques, Gulyás was able to demonstrate that four unique solutions were generated. Therefore, it is imperative that the modeling technique itself (as well as the implementation, he argues) be considered in the model design.

Evidence that four verifiable models could yield four different outcomes is indeed disturbing, but brings two points to mind: there can be multiple, complimentary, descriptions of a system dependent on the frame of reference, and that a model can't be absolutely "correct," but rather is itself a system with the inherent attribute of system purpose (Keating, Kauffmann, & Dryer, 2001). While implementation differences are a source of integrity uncertainty, considering different implementations together can create a richer result, as all verified models are assumed to provide useful insights in the context in which they were built. In fact, contrasting both the differences and *similarities* between these results can be considered to improve the external validity, or extensibility, of these models (Yin, 1984).

In summary, the literature points to a number of pitfalls to be avoided when modeling complex systems. In particular it seems imperative that any air transport modeling technique must be applicable from many different vantages, and must be verifiable. Because this study is aimed at a *new* system, the latter is particularly challenging, because by definition there is no historical baseline for comparison. However, other techniques, such as triangulation, can be used to validate results. The use of two complimentary techniques, such as network analysis and agent modeling can address this need.

2.2 COMPLEX SYSTEM MODELING AND POLICY ANALYSIS

Ultimately in the case of air transportation, the federal government is largely responsible for both setting policy, and implementing infrastructure implied therein. To do so necessitates consideration of both the effectiveness of actions and repercussions they may create across the ATS. As Wieland et al (Wieland W. N., 2002) point out, modeling ATM "with all its interrelated components – mechanics, human decision making, and information flow – is a large effort involving multidisciplinary and 'out-of-the-box' thinking. ...The challenge is not only to represent physical NAS dynamics, but also to incorporate the behavioral and relational components of NAS decision making that are an important part of the system. ...A comprehensive model is incomplete and subject to first order errors unless all such interactions are incorporated to some degree."

Wieland et al stress the necessity for ATS modeling at three different time horizons for various purposes: tactical (predictive), strategic planning (investment and policy), and post priori event analysis (also investment and policy). Their claim is that a useful simulation of the ATS intended for setting policy must model the economic, information and mechanics factors of the system *and their interactions*, or gross errors will occur. They go on to recognize that this is a tall order indeed, and that a comprehensive ATS model is a "grand challenge," yet they believe, necessary and obtainable.

Actually, NASA recognized the need for a more systemic study for some time. Credeur et al (Credeur, 1986) reported that "The principal operational improvements desired by commercial aircraft operators in the United States are efficient aircraft operations and delay reductions at the major terminals" NASA later commissioned Krozel (Krozel, 2000) to review all the Free Flight empirical research related to distributed ATM, a widely accepted development concept. He identified not only the existing research, but also the research needs that were not being met more generally. He concluded that:

- Transition between centralized and distributed control is not being addressed (e.g. network structures in ATC for future operations)
- Transition between current and future operations is not being addressed
- Airline Operations are not well represented (e.g. Airline networks in a free flight environment)

In summary, Krozel found that at the time, there were no tools capable of assessing both new and traditional ATS operations simultaneously, and therefore assessing their interactions.

NASA has continued to build upon Krozel's and other's work to develop an entire area of exploration in this subject. During the Airspace Program re-planning effort in 2006, NASA acknowledged the systems engineering problem and created a "System-Level Design and Analysis" task, addressing many of these issues (NASA, 2006). However, in the past five years, summaries of this task area, like (Bardina, 2011) still only discuss very complicated emulations of aircraft and controllers, and do not attend to any other complementary description of or actors in the system. It seems that the policy and alternate system views may continue to be less than holistically addressed by the system-level tools available.

2.2.1 Policy analysis for complex systems

Carley (Carley, 1997) claimed "Social, organizational and policy analysts have long recognized that groups, organizations, institutions, and the societies in which they are imbedded are complex systems." When it comes down to it, he says, policy analysis is generally about complex system design in light of uncertainty. He suggested that analyzing "simple" systems is generally assigned to engineers, or in controlled environments, scientists, implying complexity is left to be studied by those in the social sciences.

Certainly, complexity and uncertainly abound in ATS transformation. Influencing ATS performance is complicated enough, but ATS policy reaches outside often-arbitrary system boundaries. Sheate (Sheate, 1995) complains that standard ATS policy decisions have lead to a business market that decides "where capacity is needed and therefore fails both to maximize the use of existing airport resources and to recognize the importance of environmental capacity constraints." He argues for policy analyses that consider the interplay of system capacity, demand, and aircraft capability.

Unfortunately, policy analysts in the ATM arena have continued to use methods more suited to regularly-behaved systems to develop strategy (Lahr, Robins, & Checchio, 2009). Apparently, this is a pervasive problem throughout the policy community. Bankes (Bankes, 2002) laments that there are "few good examples of the classical policy analysis tools being successfully used for a complete policy analysis of a problem where complexity and adaptation are central." He continues to say that policy analysis in the face of "deep uncertainty" must focus on *robustness* rather than single-point optimization. This reinforces the notion of developing many different plausible environmental scenarios, and recommending policy that is viable across their range. Addressing this same concern, Iyer

(Iyer, 2000) offered that the "basic contribution of complexity theory [to planning] is its focus on systemic interactions at various scales…" that can address uncertainty.

Moss (Moss, 2002) expresses the view that "policy analysis has to start with observation and the specification of a problem to be solved." While this may seem obvious, he points out that often insufficient effort is spent on understanding the essence of a problem before jumping into an effort to emulate it. With this base understanding of root causes, he suggests appropriate analysis tools can be defined. Moss, Iyer, and others suggest that deterministic and even stochastic approaches to complex policy development are incompatible, though ABM may be applicable.

Borshev and Filippov (Borshchev & Filippov, 2004) suggest that systems modeling is a useful a way of solving problems that occur in the real world, particularly when prototyping or experimenting with the real system is expensive or impossible. They state that "for complex problems where time dynamics is important, simulation modeling is a better answer" then an analytical or static model. In comparing system dynamics modeling to ABM, they conclude that there is a place for both: ABM is well suited to systems where most knowledge is at the local level (e.g. agent-level) and little or nothing is known about global interdependencies. However, they state that System Dynamics may be a more *efficient* approach, particularly if agents are uniform and/or have little true "active" or autonomous behavior.

Fundamentally, they suggest matching modeling techniques to the "nature of the problem," and that any one technique will almost surely not be most appropriate for all systems. They call for modeling techniques that "would allow for integration and efficient cooperation between different modeling paradigms."

Borshev and Filippov's sentiment regarding matching models to the system they are intended to explore rings true for this application. However, the use of system dynamics in early stages of investigation can be challenging due to the difficulty in acquiring a level of system knowledge necessary for its proper implementation.

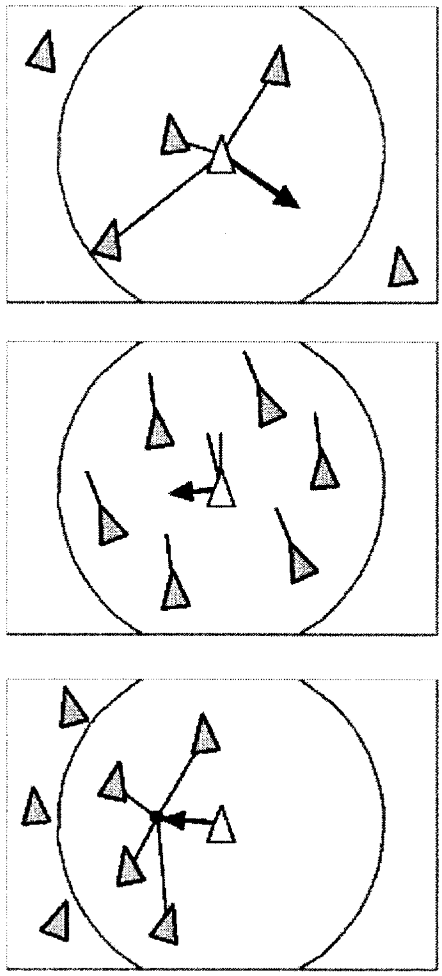
2.2.2 Agent-Based Modeling

Agent-based modeling techniques have been proposed as an alternative to traditional parametric models because they can exhibit higher-order behaviors based on a relatively simple rule set. Agents are interactive entities that capture salient but generally localized behavior of system elements. Typically, agents are implemented as multiple replications of software which interact and respond within a fixed set of rules. Agent-based modeling is a software environment with multiple agents and sometimes an environment imposed as restrictions on the agents and their interactions.

When these agents are modeled using system science methods within an appropriate environment, using even simple rules systemic higher-order behaviors can emerge, as Reynolds (Reynolds, 1987) shows in the examples in Figure 11.

Jennings (Jennings, 2000) and Jennings and Wooldridge (Jennings & Wooldridge, 1996) offer further clarification, saying agents:

- are entities with well-defined boundaries and interfaces
- are situated in a particular environment
- strive for specific objectives
- are autonomous (distinguishing them from objects)
- can be both reactive and proactive in achievement of their objectives.



Separation: steer to avoid crowding local flockmates

Alignment: steer towards the average heading of local flockmates

Cohesion: steer to move toward the average position of local flockmates

Figure 11: Some Agent Attributes (Reynolds, 1987)

Jennings outlines his argument in favor of agent-based modeling of complex systems, saying the requirements of complex system development and notions of ABM are highly compatible. He argues that agent-based models are particularly well suited to modeling certain complex systems because they are:

- an effective way of partitioning the problem space of a complex system
- abstractions that are a natural means of modeling complex systems
- appropriate for dealing with the dependencies and interactions that exist in complex systems

However, he also admits that these same properties can lead to issues of unpredictability. Unpredictability is a problem to the simulation world, because it makes verification very difficult, as one cannot repeat exact results consistently. The lack of deterministic behavior is also problematic for validation. Jennings also warns that by its nature, ABM only allows for control at the agent level and is poor for emulating centralized control. In this sense, the model is too similar to the complex system it tries to emulate. Jennings and others claim that these difficulties can be circumvented by formally analyzed interaction protocols, limiting the nature of agent interaction, and adopting rigid organizational structure among the agents.

Much hope is laid at the feet of ABM, particularly in the social science realm where complexity and uncertainty are significant issues. Bankes (Bankes, 2002) summarizes three reasons why ABMs are potentially important: *1*) the unsuitability of competing modeling formalisms to address the problems of social science, 2) the ability to use agents as a natural analogy for many social problems, and 3) the ability to capture emergent behavior. While the latter two arguments are similar to those of Jennings, Bankes claims that dissatisfaction with the restrictions imposed by alternative modeling formalisms is driving modelers to agent-based solutions. In his opinion, the most widely used alternatives, such as systems of differential equations and statistical modeling, are viewed as imposing restrictive or unrealistic assumptions that limit their use for many problems. He says, "...the list of assumptions that have been objected to is lengthy, but it includes linearity, homogeneity, normality, and stationarity."

What Bankes fails to mention is that these shortcomings are not necessarily avoided just by deploying ABM methods. Rather, a model still has to be appropriately defined to describe salient features for the system served. Additionally, addressing issues such as homogeneity, or the consistency of system elements, requires not only more effort in model specificity, but also more information related to distributions of variables or behaviors that may not be available. A homogeneous population model might be of sufficient fidelity for describing some systems, while an assumed (but erroneous) normally-distributed one, for example, would likely also yield misleading results. A more complex or detailed model is not necessarily more precise: What is important is that model is accurate *enough*.

Arthur (Arthur, 1994) suggests agents are a natural way to deal with ill-defined or complicated "reasoning" within a system, often induced by inclusion of humans in a system. He argues, "…beyond a certain level of complexity human logical capacity ceases to cope – human rationality is bounded." Agents can be designed to mimic the *inductive* behavior of people when placed in unfamiliar or complicated environments. However, the example he provides, a problem of deciding whether or not to frequent a bar based on the expected crowd, exemplifies a prime concern with assuming agent "intelligence" (which has to be present to differentiate the agent from a mere object in Jennings and Wooldridge's terms). In his example, the agents select from a pre-determined set of schemata based on some outcome metric (actual number of bar patrons). Can this be considered true inductive behavior? The "induction" was accomplished [by the modeler] in the generation of the options, not by the agent in their selection later on.

If appropriate strategies were not included in the agent's definition, Arthur's agents would have never succeeded. Recognizing this, he does acknowledge that people's ability to induce [emulated by agents using lists, genetic algorithms, etc.] is a "deep question in psychology" and thus can only be marginally imitated. Generally speaking, agent "intelligence" at best will be limited by the degrees of freedom their internal models are allowed to explore, and may be further limited by methods of exploration.

Agent modeling appears to address many of shortcomings of other modeling techniques, and the large-scale efforts in ATM today. Caution is offered by many practitioners of agent application: it seems just as easy to fall into emulation vs. simulation approach with agents: they must be given sufficient, but not more than necessary, behaviors. When modeling human elements like pilots, controllers, dispatchers, and travelling public, defining useful, economical agent behaviors will clearly be a challenge, but one that may well be worthwhile.

2.2.3 Network Structure and Distributed Networks

From the description above, it is clear that interaction among agents could be described by network structure: there are well-defined nodes (agents) and links (interfaces, interaction protocols). It remains to be seen if in a highly autonomous environment, network descriptions of systems could be sufficient to capture the rich, non-linear, time variant behavior of agent-based systems' network structure. With the added constraints that verification and validation necessitate in the ATS, this is even more important.

Network science may be useful in the ATS simulation/design task in analysis of mean expected system performance. Network science is an extension of graph theory, whose roots are often credited to Euler's *Konigsberg Bridges* problem of 1736. In a definition that has persisted, Euler described networks as mathematical and/or graphical descriptions of systems using nodes (e.g. airports) and links to connect the nodes (e.g. routes).

By definition, nodes that constitute a network are interconnected in some way or another, and can therefore be 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 (Albert & Barabasi, 2002).

Wuchty et al (Wuchty, 2003) state that all networks can be classified by some basic, quantifiable measures. These include the average number of links or interactions at each node, k, degree distribution or function of number of connections across the network, P(k), average path length $<\ell>$, and the average clustering coefficient, C(k) related to click-ness which is described as the connection to strings of connected, nearby neighbors (Figure 12).

- Degree (Connectivity)
  - # of links (interactions) at each N node (elementary constituents): k
  - Mean: $<k>$
  - Degree Distribution: P(k), to capture potential variation
- Path length
  - Shortest path from node i to node j: ij
  - Mean: $<\ell>$
- Clustering Coefficient
  - Degree of click-ness for each neighbor: Ci
  - Mean for each node: $<C>$
  - Average clustering coefficient, denoting structure: C(k)

Figure 12: Basic Network Features (derived from (Wuchty, 2003))

The ability of these metrics to differentiate operationally unique airline route strategies and their resultant distinctive structures is yet to be shown. Braha and Bar-Yam (Braha & Bar-Yam, 2004) suggest that functional classes of networks might be expected to have differences in their topologies, such as directedness.

Stemming from these basic metrics, networks often exhibit higher-order dynamic functions, thought to be associated with their unique structures. These include robustness or a network's resilience to the removal of links or nodes (Dekker & Colbert, 2004), fragility or fragmentation due to loss of links (Brah, Minai, & Bar-Yam, 2006), percolation or the likelihood of points in one portion of a network to be connected and accessible to others (Schwartz, 2002) and searchability or the ability to extract information from or locations on a network (Glakkoupis, 2010). 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.

Operational experience, the literature, and comments from airline operational centers have all pointed to uncertainty in flight schedule performance (e.g. unanticipated delay or earliness) as a prime factor in system performance problems. Some, like (Jaillet, Song, & Yu, 1996) have claimed that system topology alone can provide mechanisms for system instabilities in ATM, manifesting themselves as schedule uncertainty, as discussed in section 2.3. The question arises whether these topologies can be determined a-priori by network features, and if so, whether they can be shown to indeed exhibit instable behaviors. Therefore, various network structures must first be identified, and then their different behaviors assessed. The following sections briefly describe five different network structures and some of their structurally-derived inherent attributes:

2.2.3.1 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 probability $p(k)$.

In his popular work *Linked*, Barabasi (Barabasi, Linked, 2003) 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.

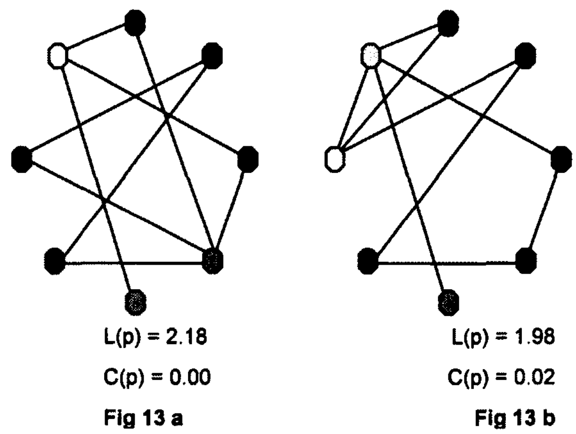


Figure 13: Random Networks

Figure 13 shows two examples of very simple random networks, the circles being nodes, and the lines between them network connections or graph edges. Network b is derived from random "rewiring" of a. Though b looks somewhat more organized, it still exhibits properties of a random network.

2.2.3.2 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 have few or no direct connections (e.g. Figure 14).

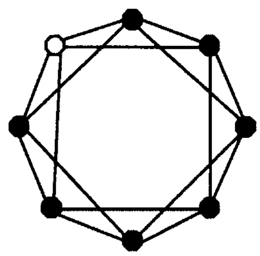


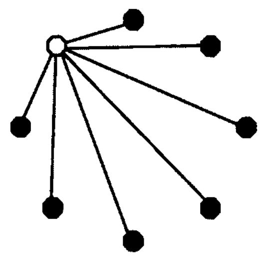
Figure 14: Regular Network

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 direct paths or "short cuts" to far-off system areas.

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

2.2.3.3 Centralized Networks

Centrally-design networks have very easily recognizable structure. They have a single node which serves as collection and distribution center (as in, Figure 15), with all other peripheral nodes attached to this "hub" creating "spokes" of links, not unlike a bicycle wheel. When small, these networks are highly efficient related to their link-per-node served connectivity, as a single link connects the new peripheral node to any other on the network with only 2 or 1 degrees of separation. However, the connection efficiency is limited, as the average link length between any two nodes tends toward 2 as the network grows. Perhaps more limiting is the obvious congestion issues at the hub node. Because of the key, central function of the hub, such networks are generally extremely vulnerable to both targeted attack and single-point random failure.

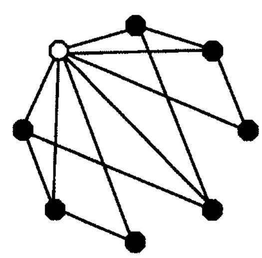


L(p) = 1.75 C(p) = 0.0

Figure 15: Centralized Network

2.2.3.4 Hierarchical Networks

Somewhere between a regular network and a centralized network is a semi-regular or hierarchical network. These exhibit regularly-repeating patterns of connections, but are not fully connected nor necessarily connected to the same number of nodes as its neighbors, but is rather similar to another connection of another node. Such connection regularity will create "fractal" geometries, where small sections of the network will have similar mathematical properties of larger portions of the same network. These networks are generally robust to random failure, though a targeted attack can still dramatically reduce the system performance. In the very simple illustration (Figure 16), one can see that decommissioning the yellow node, while not completely breaking the network (like a central node would), does create a very long path between the green nodes.



L(p) = 1.54 C(p) = 0.58

Figure 16: Hierarchical Network

This type of structured network does have a signature feature: The clustering coefficient is proportionate to average number of links, though it exhibits scale-free attributes, defined below:

2.2.3.5 Decentralized, "Hub& Spoke" Networks

Father along the spectrum to a naturally-predicted structure is a decentralized hub& spoke network (Figure 17). These also exhibit repeating patterns of connections, but not necessarily regularly-repeating ones. Such connection can emerge from randomness with the application of a simple rule-set, such as preference to connect to a highly-connected neighboring node. These networks are also generally robust to random failure, though a targeted attack can still dramatically reduce the system performance, and they can also be vulnerable to cascading effects throughout the network. This type of networks have a signature features of typical path lengths proportional to log of the number of nodes and become very similar to scale-free networks.

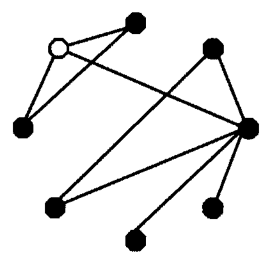


Figure 17: Decentralized Hub-and-Spoke Network

2.2.4 Network Properties and their inherent attributes

2.2.4.1 Scale-Free Properties

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 manmade 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 rewiring or adding only a small fraction of connections that comply with simple but contextually-relevant rules. Unlike hierarchical networks, the connections are not necessarily found in regular patterns by design, but rather are generally formed by some operational or functional rule-base, and in this sense are "organically" derived.

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 (Barabasi, 2003).

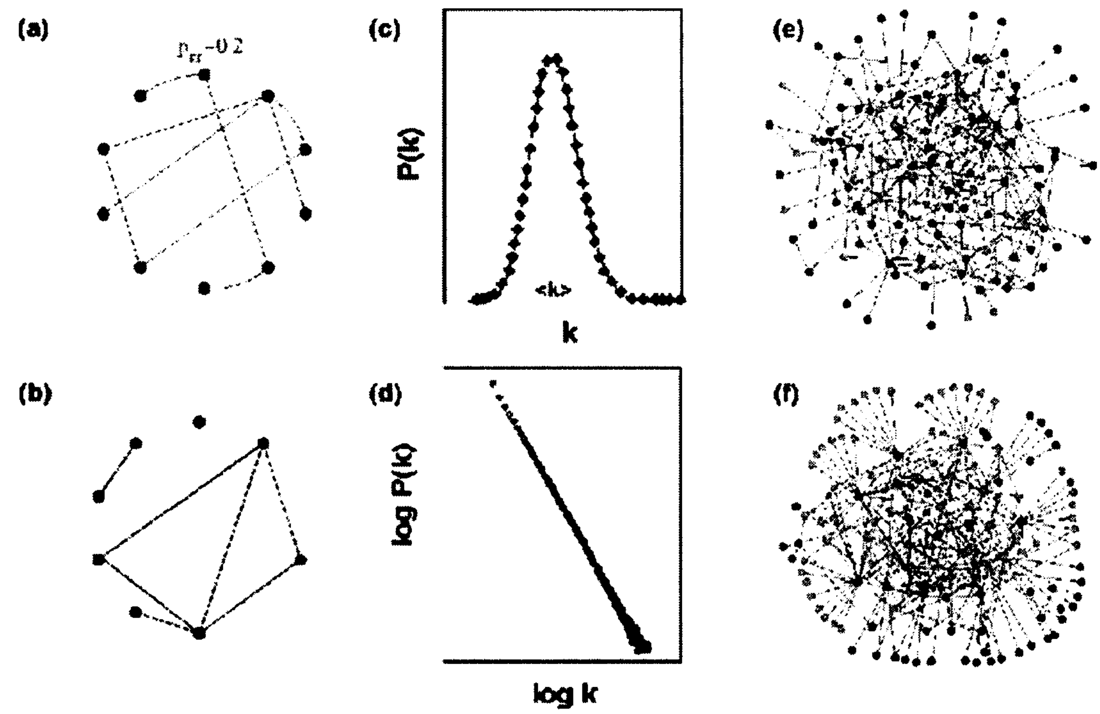


Figure 18: Random and Scale-free Structure (Barabasi, 2003)

In other words, scale-free networks have a unique trait that N(k), the number of nodes with k links, follows ~k-γ as shown in Figure 18 a comparison of random (a,c,e) and scale-free structure (b,d,f) from Barabasi (Barabasi & Albert, 1999). Carlson & Doyle (Carlson & Doyle, 1999) suggest that in a system engineered for robust design in light of uncertain environments, this power law structure will naturally occur due to "tradeoffs between yield, cost of resources, and tolerance to risk"

Multi-scale is a meta-structural property that has been characterized in many natural and man-made systems. Dodds et al (Dodds, 2003) described its importance in susceptibility to cascading failures and congestion robustness. Callaway et al (Callaway, 2000) express caution due to potential network fragility and percolation mechanisms (non-linear growth). Watts and Strogatz (Watts & Strogatz, 1998), 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. Searching through seemingly unrelated data sets, they find evidence of small-world network topology and imply it is a naturally-occurring (such as in Caenorhabditis elegans, a.k.a. roundworm, neurology) as well as man-made systems, such as power grids (Table 1). They move to show that such high clustering coefficients make these networks different than those that might form through a random process.

	L_{Actual}	L_{Random}	C_{Actual}	C_{Random}
Movie Actors	3.65	2.99	0.79	0.00027
Power Grid	18.7	12.4	0.08	0.005
C. elegans	2.65	2.25	0.28	0.05

Table 1: Network Attributes of Some Typical Networks (Watts & Strogatz, 1998)

Operationally speaking, many natural networks are extensive (large and complex) and exhibit emergent behavior in complicated patterns without the existence of a central control. They are referred to as *decentralized spatially extended systems.* As reported by Hordijk (Hordijk, 1999), the emergent patterns "give rise to some form of globally coordinated behavior…used by the system to sustain itself or make certain decisions." He gives the example of an ant colony that *decides* the shortest path to its' food source. Though the behavioral effect may be one of decision, it is not clear that the emergent behavior is an expression of collective reasoning (thinking) or collaboration. Rather, in this example, the ant that returns to the colony earlier than the others may be setting precedent while other scouts are still on their journey. Though a "decision" is made for the colony, reason did not enter into it. On the other hand, the optimization effect is one that could not have been realized without the network dynamic.

There is no doubt that emergent pattern formation, regardless of is origin being decision or systemic consequence, in Hordijk's words often provides, an "important functionality for the system as a whole." However, airlines, and more generally NAS networks, have centralized control functions and are highly regulated. In such environments, potential emergent behavior may be suppressed.[a]

Scale-free networks, as expressions of decentralized spatially extended systems, can support emergent behavior. Hordijk summarizes several potential advantageous attributes of such a network's emergent behavior, including efficiency, flexibility and robustness. But like many other authors, these claims are made somewhat abstractly: scale-free networks may tend to show particular classes of behavior, but it is not clear that they actually evolve in practice. There is little in the literature on the effect of mitigating strategies such as regulation on network behavior.

2.2.4.2 Network Efficiency

Latora and Marchiori (Latora & Marchiori, 2001) call for the measurement of average path length, clustering coefficient, average degree, and degree distribution as do Strogatz, Watts, and others, but also suggest the use of efficiency and cost. They define efficiency at both the local (E_{loc}) and global (network-wide, E_{Glob}) level as "the measure of how efficiently it [the network] exchanges information."

In mathematical terms, they report that the global efficiency of network G is:

$$E_{Glob}(G) = 1/N(N-1) \Sigma_{i \neq j \in G} 1/d_{ij} \qquad \text{(Equation 1)}$$

---

[a] Validating interference with preference of scale-free network structure in air traffic schedules by regulations – see 4.1.2.5.4 Deregulation and Essential Air Service

and the local efficiency is the average efficiency of the local subgraphs of i:

$$E_{LOC} = 1/N \, \Sigma_{I \in G} E(G_I) \qquad \text{(Equation 2)}$$

They suggest that E_{loc} and E_{Glob} are really more general measures for path length and clustering metrics, and therefore are more naturally applicable to the majority of networks, though are sometimes more difficult to calculate.

In a later work (Latora & Marchiori, 2002), the authors argue that the Watts/Strogatz measures are only effective in quantifying a network in the "topological abstraction, where the only information retained is about the existence or absence of a link." Following the above arguments that quality/cost of the links are paramount to describing operational functionality, it appears unlikely then that path length and clustering metrics alone will be useful abstractions for describing air transport networks. Latora and Marchiori, using the Boston Subway for an example, suggest that substituting efficiency measurements resolves difficulties in general application of topologic analyses to weighted and directed systems.

Once measured, Crucitti, Latora and Marchiori (Crucitti, 2003) show that efficiency measures can be used as indicators of potential cascading failure, and can be used as a "measure of performance" of the network. They define an additional metric of the *load* of a node to be the total number of most efficient paths passing through it at a particular time. The load is limited by the capacity of the node. They adjust the efficiency (E) of a node *and connected nodes* proportionally to its load factor, the percentage of its total capacity. Though the authors developed this rule for rerouting information around congested nodes, the same principles can be applied to delay propagation measures.

Using E, Latora and Marchiori showed marked differences in the non-linear behavior (onset of cascading failure) of two different, well-documented network topologies: the

Barabasi-Albert small world model (BA) and the Erdös-Rényi random model (ER). As shown in Figure 19, a reprint of some of their work, they show the efficiency of the networks (average number of links necessary to connect nodes) under either random (squares) or targeted (sold circles) removal of nodes for ER graphs are nearly the same, regardless of the node capacity. They further show the proportional relation to the "tolerance parameter" or α, the ratio of theoretical capacity to actual demand (Figure 19a). However, E for the BA model system was very sensitive to the node failure being either random or specifically targeted to central nodes. In Figure 19b, the large value of α, or high over-capacity or under-utilized resource, required to protect against global network efficiency loss is evident. This dramatic change in efficiency can cause complete network failure or a cascade effect, quite rapidly with little pre-cursory indication of efficiency loss.

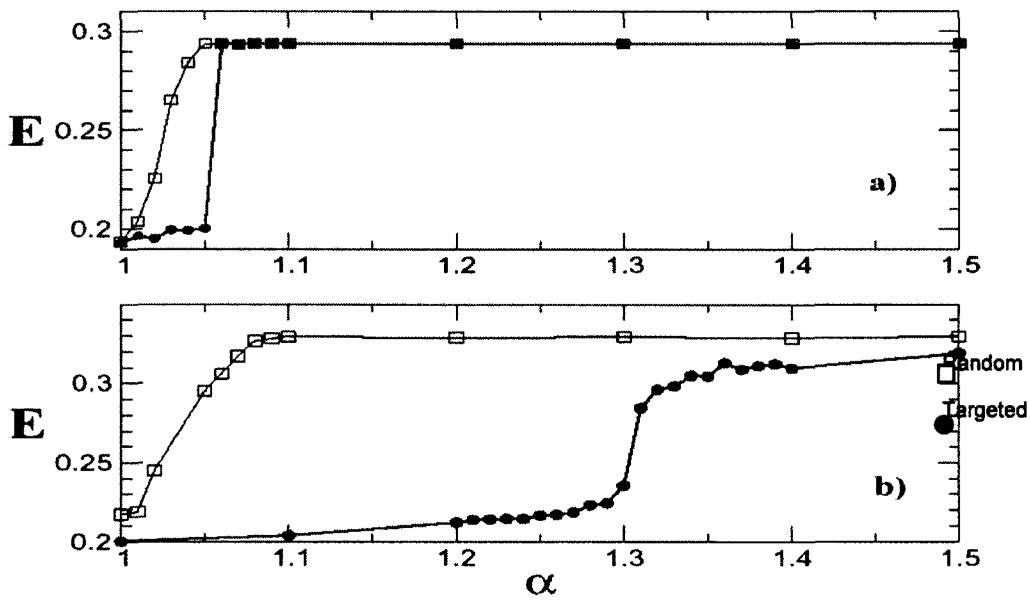


Figure 19: Cascading Failure in a)ER (random) and b)BA (scale-free) networks (Crucitti, 2003)

2.3 TRANSPORTATION NETWORK MODELING

There are many applications of network modeling of transportation systems, but they are mostly applied to automotive issues. (Hoogendoorn & Bovy, 2001), (Wu & Miller, 2001) and (Cominetti & Correa, 2001) have all explored various aspects of automotive networks that may be pertinent to a distributed airborne network. Unfortunately, their applications tend to be very focused on squeezing more capacity out of very rigidly defined roadway or train networks. These approaches seem sensible as applied to the nation's highways, but may be too prescriptive for aviation, where the networks are vastly more flexible. Interestingly, though Helbing (Helbing, 2001) was also studying rigidly constrained automobile and pedestrian traffic in a similar study, he still identified power law phenomena.

In the air carrier realm, Teodorovic has published many papers on the specific subject of airline routing optimization (Teodorović, 1994) (Teodorović & Stojkovic, 1995), but does not account for external consequences of routing changes, such as congestion at hubs or lost passenger revenue, that could more than counteract the optimal solution's benefit. Brueckner (Brueckner, 2001) and Bogulslaski et al (Boguslaski, 2003) compared routing strategies in the single dimension of economic optimization. Though this latter study was more comprehensive in that it did address the bottom line business case for the airlines in question, it still did not capture all the influential forces of the NAS, particularly when investigating new operations. Levinson et al (Levinson, Gillen, & Kanafani, 1998) studied the social costs of air transportation in today's system, a dimension not often considered in NAS infrastructure modeling.

Dobson and Lederer (Dobson & Lederer, 1993)focused on economics, but from a demand/service-price perspective, excluding operational constraints and other possibly limiting systemic considerations such as regulations. Lederer and Nambimadom (Lederer & Nambimadom, 1998) also explore the economics of different route structures. They conclude that no one network is optimal, but rather that each of four strategies they considered could maximize profit under some conditions. Also, they state that "congestion at the hub has relatively small effect on the optimal network design. This implies that even with increasingly congested hub airports, hub networks will continue to operate." However, their simplifying assumptions, particularly regarding uniformity of demand and a continuum of airline capacity, preclude its extensibility to operational evaluation.

Jaillet et al (Jaillet, Song, & Yu, 1996) 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

Still other studies continue to investigate the raw, inherent nature of transportation networks from their topology, as if they were nodes on an Information Technology (IT) network. Zanin et al (Zanin, Cea, & Cristobal, 2009) used a familiar IT network metric of PageRank or nodal centrality to note that indeed, larger airports are more connected and therefore would contribute more proportionally to delay propagation. However, their research goes no deeper: how could this sensitivity to delay be reduced? Why are airlines exposing themselves to such delay when alternate network topology would be more robust? It seems much of the work continues to be uni-dimensional. Even when such studies attempt to address dynamic capacity, such as Lacasa (Lacasa, 2009) they often miss inherent complexities in the inbound/outflow of flights. Without investigating these schedule features, their assumptions of flight count in and out of a hub being representative of potential delay may not capture key features of the network at hand, and certainly do not from the multi-network-perspective that is inherent in hub-and–spoke air transportation.

An examination of an airline route/schedule reveals many subtleties and complexities. Some previous studies have taken an aggregated "route-map" approach. They considered the network to be comprised of nodes representing cities served, and links, representing (any) service between these nodes irrespective of volume or frequency. Guimera et al (Guiemera, 2003) did this, characterizing 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 links 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, 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."

Recognizing that there is more at play than simple network topography explained by geographic centrality, Guimera at al (Guimera, 2005) later measures of the world-wide scheduled air transport network recognize that factors beyond those that simple network topology optimization must be al play. They report that "the most connected cities are not necessarily the most central, resulting in anomalous values of the centrality." They go on to propose such topology may arise from political influence, though they do not go as far as to test their hypothesis nor address the political mechanism, even by a simple model. Their observations demonstrate that there are forces other than theoretical optimization at foot, but they do not explain or even suggest an explanation for the network attributes they observe. With some simple modeling, they could test their hypothesis to demonstrate which political influence would indeed yield a network with attributes they observe.

Generally, these studies and others like them may be useful for the purposes of affirming a reasonably well understood ATS with respect to a single (or some of) dimension(s) available to the airlines. However, there are few studies looking at infrastructure and regulatory changes necessary to facilitate operations outside the scope to today's environment.

Towards that effort, researchers at NASA Langley (Peters, 2002) have been developing an agent-based simulation environment designed to be modular for flexibility, and expandable with an eye towards systemic evaluations. However, to date, their effort has been concentrated on human-in-the-loop feasibility and concept definition studies, so systemic analysis extensions to the simulations (such as batch capability and pilot-operator models) have been left for the future. They have found development of comprehensive, ATS simulation beyond the scope of their architecture at this time, though in a related effort, an agent-based tool capable of multi-scenario, fast-time (batch) evaluation is under development (Williams, 2004).

In a parallel effort at NASA, the Virtual Airspace Modeling and Simulation Project spawned the Virtual Airspace Simulation Technologies (VAST) sub-project. VAST is described as "modeling and simulation capabilities to assess both the individual and integrated behavior of the current and future ATS at the NAS-wide level and at the detailed human-in-the-loop level." (NASA, 2012) VAST is a collection of modeling facilities, from a virtual air traffic control tower to a systemic model. According to the National Research Council (NRC, 2003), the committee responsible for the independent review of NASA's aeronautic technology programs, VAST is fighting an uphill battle: trying to develop a comprehensive model without complete knowledge of the system of interest. The NRC reports that the models lack input from operations designers. The council's report leaves the impression that VAST is not the designer's tool that is necessary for systemic planning or alternative synthesis, but rather is too large and inflexible to be used for an iterative design process.

In response to some of these criticisms, a portion of VAST is developing as an agent-based rendition of legacy ATC models (Aronson, Manikonda, Peng, Levy, & Roth, 2003) known as the *Airspace Concept Evaluation System (ACES)*. The power of such a tool is that through a common interface, the agent-based architecture affords flexibility to modify either all or parts of the simulation to investigate innovative operations. ACES en total appears to be a tool both more comprehensive and more cumbersome than the NRC report called for. However, small incremental modifications to this comprehensive model, though requiring substantial familiarity with the code, should be manageable. Unfortunately, the project is experiencing problems that may be considered typical of such efforts (Sweet, 2002): validation is difficult because of the extent of the system, and verification is problematic due to simulation scope, complexity, and run-time event timing.

MITRE's Center for Advanced Aviation System Development, CAASD, has also been developing simulations for investigating advanced aviation concepts. (Schaefer, Wojcik, Berry, & Wanke, 2002) They divided the effort into four realms, based on the time horizon to implementation of change, and the nature of the change, to either operational decisions (tactical) or infrastructure and regulatory (strategic). They have concluded that together these issues necessitate four distinct tools, as shown in Table 2.

Table 2: MITRE/CASSD Research toward Advanced Aviation Concepts [adapted from Schaefer et al (2002)]

	Near-term Projects: Decision-making		**Long-term research: Advanced concepts**	
Tactical	Traffic Flow Management	CRCT	Probabilistic Flow Management	IMPACT
Strategic	Infrastructure Changes	DPAT	Institutional Change	JETWISE

The Intelligent agent-based Model for Policy Assessment of Collaborative Traffic flow management (IMPACT) is their solution in the long-term tactical realm or operational considerations in the future ATS. However, in their description of the tool, it appears that uncertainty in the future under consideration is largely due only to "imperfect weather" information. This tool affords the opportunity to "change decision-making policies to reflect information uncertainty." IMPACT is an agent-based model based on a "well-understood framework for assessment of decision-making." The authors state that the actions of agents, representing individual airlines and FAA entities, are probabilistic.

However, they also report that because airline information and action models are heavily abstracted, they have had difficulty validating results against actual events. Also, the authors have only published results pertaining to single-facility events, such as reduction of acceptance rate at a single airport. They make no mention of using the tool to investigate cascade effects of such imperfect weather events across the airline or ATS networks.

MITRE researchers are also developing Jet:Wise, an object-oriented approach to the more strategic issues of supply/demand for airline seats. A spin-off of IMPACT, Jet:Wise is CAASD's first attempt to model "the entire air traffic system on a long-term scale." From this model, they expect to see route/schedule behavior such as hubbing change in response to an imposed objective function. They state that the primary focus of this effort is not in operational viability, but rather in defining likely areas of demand for future research consideration. To date, they have apparently not used the tool to assess validity of new operational concepts, but rather only explore options within the existing system. It is not clear if Jet:Wise would be extensible to such application.

While CAASD also continues to explore more traditional modeling capabilities (Schaefer & Millner, 2001), they state that agent-based models will be needed to fulfill many long-term modeling needs. ABMs of ATS operations are better suited to demonstrate unexpected, emergent behavior due, for example, to business model changes. These sentiments are echoed by Lee et al (Lee, 2001), who add that not only are ABMs necessary, within them hybridization of the handling of time (discrete v. continuous) must be flexible within a simulation to afford computationally tractable models of large, complex systems such as the NAS.

Building off previous conflict detection and resolution operational concepts, Hoekstra (Hoekstra, 2001) puts forth the hypothesis that "Free Flight with Airborne Separation Assurance is feasible." He and other researchers (Ballin, Wing, Hughes, & Conway, 1999) (Conway & Consiglio, 2001) have attempted to prove the feasibility of a NAS operating radically differently than today: with no roll for air traffic controllers in local traffic management, but rather a strategic or global goal. Hoeksta was not the first to develop such an idea: The concept of Free Flight is often credited to Bill Cotton, who first suggested distributed separation tasking in his Master's thesis in 1965 (Cotton, 1965). Hoekstra et al set out to develop the concept and prove it viable (Hoekstra, Ruigrok, & vanGent, 2000).

Hoekstra and his research team implemented a free-flight concept in discrete-event simulation. They attacked operational practicality, running a number of interesting yet mathematically non-rigorous examples of what appear to be extremely challenging scenarios (e.g. one aircraft self-separating while flying through a "wall" of oncoming traffic). They also attacked acceptability, granting a limited number of pilots an opportunity to fly simulated scenarios and then soliciting opinions regarding workload, safety etc from their perspective.

Interestingly, Hoekstra reports that the pilots overwhelmingly were satisfied that free flight was feasible based on exposure to traffic in excess of 3 times the current European density under free flight rules. Air traffic controllers on the other hand, not only were unable to cope with the seemingly unstructured traffic, they couldn't handle those same traffic densities under today's route-structured operating rules. From these results, Hoekstra concludes that 1) *radical* changes in the manner in which traffic is controlled are necessary if substantial gains in system capacity are to be realized, and 2) that free flight operations were plausible.

2.4 LITERATURE SUMMARY

Hoekstra addresses not only areas of technical feasibility but also economics and politics. This body of free-flight work, though repeatedly cited, is often discounted as "wild," "dangerous" or just plain crazy (Grundmann, 2000). Why is this? Hoekstra himself is quick to point out that the system he suggests is complex in nature, and is likely to exhibit emergent or unpredicted behavior. Another issue may be absence of operational constraints that many in the air transport community have grown accustom to. Perhaps the uncertainty related to potential emergence alone is enough to scare away all but the morbidly curious from application of distributed control to safety critical systems such as ATM. However, in light of growing demand uncertainty, the adaptability of a distributed ATS with emergent tendencies may also be its most salient feature.

Though the ATM research community has attempted to model particular attributes of the ATS, there hasn't yet been a method capable of answering questions regarding the systemic response to substantive changes in operations as summarized in Table 3. To date, agent-based, elemental simulations have proven too expensive and unwieldy to complete. Parametric simulations have proven too inflexible to be used as design tools.

Table 3: Transportation Network Modeling Literature Summary

Author	Application		Sufficiently Expandable	Technique Applied		
	NAS only	ATS		Parametric	Agent-Based	Network
Hoogendoorn & Bovy 01			no			X
Wu and Miller 01			no			X
Cominetti 01			no			X
Helbing 01			no			X
Teodorovic et al 02	X		??			X
Brueckner 01			no			X
Bogulslaski et al 03			no			X
Dobson and Lederer 93			no	X		
Levinson 98		X	no	X		X
Jaillet et al 96		X	??			X
Peters et al 02	X		**$$**		X	
Williams et al 04	X		**$$**		X	
NASA VAST 12	X		no		X	
Schaefer et al 01	X	X	**$$**		X	
Hoekstra 01		X	Possibly, $	Partially	Partially	

The complex science literature suggests that fundamental attributes of complex systems include extensivity, non-linearity and incomplete or imperfect system knowledge. These in turn make modeling and/or purposeful systemic change difficult. The research and transportation policy literature has demonstrated that these attributes are indeed problematic in the realm of the air transportation.

From these three bodies of knowledge, ATS goals from a complex systems science perspective can be summarized as to:

- Meet/exceed minimum performance and safety criteria
- Accommodate a wide variety of operational models
- Avoid unnecessary constraints
- Afford adaptability to changing demand
- Ensure stability in the face of schedule disruption (robustness)

It follows then that the models of such systems need complementary attributes. For example, a model that is specific to a single operational model (e.g. today's procedures) cannot satisfy the system designer's requisite variety regarding operations.

This complex system modeling literature survey suggested that for complex systems in general, most traditional systemic modeling approaches fail to capture dynamic behaviors and the changing nature of large interconnected systems. However, there are a limited number of approaches, including NA and ABM, which may. Additionally, it is possible to modify these models quickly to test system innovations with reasonable investment, making these methods viable candidates for a system designer's toolbox.

Either NA or ABM, or perhaps both in combination, may provide clues for uncovering lurking problems, provide confidence regarding systemic performance, and contribute to developing mitigation strategies for systemic ATS issues. The question is then which technique(s) to employ.

While both techniques have seen limited application to ATS, there is no study in the literature that addresses their joint use as applied to this system, or one that would be expandable to do so with reasonable effort. This research serves to fill this void. Moreover, these techniques have been typically been applied from a single context in exquisite detail, but often with little operational context of other, important external influences. The use of emulated systems, recreating all the detail of the real ATS, seems to prohibit investigators from creating such a context-rich study. Much attention is given to recreating the world in simulation (emulation), but substantially less in *modeling* the essence of the ATS from operational perspectives. This research seeks to show the complementary nature of careful, contextual modeling to well-established system analytics.

CHAPTER 3

RESEARCH METHODOLOGY

This study examines two methods for analyzing operational consequences of commercial air carrier routing: agent-based modeling and network science, or study of the network topologies. The purpose of these analytical tools is to gain insight regarding the operational viability of such systems under uncertain conditions. These tools can provide a means to explore the effect of transformation mechanisms, e.g. policy changes and technology development, on system operations.

Building on the general notion of natural inquiry, both methods were evaluated for their utility by their application to this real system problem. Publicly available objective data in the form of historical and recent flight records and trend statistics represented stakeholder interests and objective comparative data respectively. Analytical metrics were secured from the literature. Airline routes were initially determined by using actual common-carrier published flight schedules, and subsequent experienced performance obtained from DOT-required airline self-reporting statistics. The validity of these data is established by FAA/DOT oversight and strict reporting regulation (US DOT, 2002).

3.1 RESEARCH DESIGN

The research began in the qualitative realm with the compilation of system parameters from the literature to be used as performance metrics for the test cases. These metrics came from two sources, one being the ATS community calling for such tools, and the other from the complex system community that specifies system attributes such as the ability to connect any two cities reflected in path length distributions, and stability, demonstrated by local and global efficiencies.

Next, route models reflecting actual route data attributes were generated so results could be compared across route strategies. The test cases themselves were chosen to represent the two dominant routing strategies operating in today's ATS, namely point-to-point and hub-and-spoke. Then the two systems were modeled using network techniques. The researcher noted the common features of these models, e.g. topology. The results from the two models, e.g. their ability to explain or demonstrate schedule anomalies, were then compared, as were the qualitative attributes of each model such as the ability to identify local issues rather than systemic trends.

The steps are summarized in the next five subsections:

3.2 DEDUCING VIABILITY AND PERFORMANCE METRICS

Select systemic parameters were identified as representative of NAS system operational characteristics and performance from the subject-expert literature, including Odoni, Greene, Hoekstra, Kostiuk, Wojcik, and Wing. They then were mapped to quantitative network variables described in the literature by Crucitti, Latora, Marchiori & Rapisarda, Strogatz, Barabasi, Boguna, and Pastor-Satorras & Vespignani. The investigator also assessed other qualitative features of future ATS analytical tools identified by Bonabeau, Weiland (Wieland, 1997), Wojik (Pepper, Wojcik, & Mills, 2003), and Kutaka, such as the natural mapping of the real system to the simulation.

Additionally, operational concerns collected during past visits to two airline operational centers and various FAA facilities including the National Air Traffic Control System

Command Center in Herndon, VA were incorporated into the design. The primary concern of these parties was reducing the uncertainty in operations timing. Given a known schedule, these airline representatives felt they could manage to modify their schedules to best fulfill their goals. But when their schedule uncertainty is large, as during a major widespread weather event or even less predictably, an ATC facility closure (National Air Traffic Controllers Association, 2000) (BBC News, 2004), they reported that reworking the schedule becomes a "logistic nightmare." From these statements as well as the literature above, it seems that delay due to system congestion as well as systemic response to discrete events that could trigger delay are primary concerns of the community.

The selected network parameters were further validated by a number of subject experts with differing stakeholder positions. The parameter list and the basis for selection of the items were reviewed in semi-structured interviews, details of which can be found in Appendix D.

The basis for 'subject expert' designation will be publication in refereed research forums related to air traffic operations development or five or more years of experience in the field. Additionally, the expertise of the research community selected was authenticated by involvement in an international ATM standards committee (e.g. an RTCA working group), or as a reviewer for a refereed forum.

3.3 DEVELOPING STUDY DATA

Two dominant airline-scheduling strategies are identified in the literature: "direct" or point-to-point routing, and Hub-and-Spoke (Beatty, 1999) (Guiemera, 2003) (Teodorović & Stojkovic, 1995) (Barla & Constantatos, 1999) (Jaillet, Song, & Yu, 1996). For experimental purposes, actual, aggregated route data are not necessarily optimal, and are extensive. Rather, city pairs and routes were generated that best exemplified these two primary commercial routing models.

A published airline flight schedule was used as the basis for each model as suggested by multiple references in the literature: Southwest Airlines representing point-to-point routing and United Airlines representing the Hub-and-Spoke model. These data will be used to build representative profiles of on the order of 60 nodes for each strategy.

In each case, a functionally based picture of each airline's route structure was developed. Aggregation of route data was only allowed where it represents a reasonable approximation of actual flight operations. For example, though United Airlines has 650 destinations on their route map (nodes), only 104 of these are served by United itself, while the rest are accessible through either their code-share partners or their contract commuter links. In this instance, either the 650- or the 104-node version of the United "network" could be valid, dependent on the observer.

Each airline was analyzed for its basic network attributes. Publicly published schedule data was measured for correlation to various known network types discussed in the literature by measuring characteristic path length, clustering coefficients and degree distribution. Consideration of operational constraints such as the time-based availability of links was modeled using network-modeling techniques such as link weighting and persistence. Multi-partite structures were employed to represent sub-structures within the routes (e.g. banks of flights that rely on connectivity). These data were also used to levy constraint on agent behavior and therefore link capacities.

Based on these findings, a generalized route model representing the hubbing strategy was constructed for comparison to agent modeling. The developed schedules and systemic considerations were used to build a synthetic route network for study. The synthetic network was validated against actual route profile attributes of flight frequency, clustering and degree distribution. Also, many different synthetic routes were used in an attempt to understand performance sensitivity to these network features.

3.4 NETWORK ANALYSIS

The systemic parameters developed in 3.2were mapped to quantitative network variables described by Crucitti, Latora, Marchiori & Rapisarda, Strogatz, Barabasi, Boguna, Pastor-Satorras, and Vespignani. Using these metrics, the resulting synthetic route structures were characterized, and the essential characteristics of the networks identified (e.g. operational limitations, expected non-linearities, etc)

Nominally, the nodes represented cities connected by scheduled service of an airline. The links represented opportunity to pass data between these nodes, predicated on scheduled flights. The "data" traveling on this network was delay, or the positive difference between scheduled length and actual possible length of service. The links served to propagate delay across the network.

No attempt was made to model aircraft or flight performance. The total equipment leaving an airport facility may not equate to the equipment departing a station due to dead-heading (the practice of repositioning crews or equipment on non-revenue missions) and maintenance. Crews (both flight and cabin) are often swapped, as are aircraft. Therefore, the influence of an individual flight is difficult to model simply. Rather a network of potential for delay propagation was constructed by assigned interdependencies amongst the flight operations. The simplifying assumption is then of a localized "delay phenomenon" at an airport, rather than a flight-specific cause of operational delay.

One concern with modeling these networks was how to handle time. These networks change over time as different cities are served different times of the day. To create a single static picture (or series of discrete pictures), this continuously changing representation of an airline's operation was discretized in time. A first step was to determine the discrete time interval's influence.

Profile of the network performance, represented by local and global efficiencies, was plotted against varying values of node capacity. This analysis established the propensity for the designated networks to show non-linear behavior, and the threshold value of capacity that could allow such behavior to arise.

Nodal capacity, related to node delay, was nominally related to a change in airport capacity (number of operations per hour) relative to typical operational rates[b]. The simulated airport facility had a capacity of operations/discrete period: any exceedance of this implied delays.

The purpose of the network model was to measure potential for delay propagation rather than predict specific operational delay. The study explored a route structure's predicted (theoretical) ability to perform without delays based on stability criteria, complexity measures (E_{loc} and E_{global}, etc.). These results were compared to historical performance for validation. For example, the criteria for delay specified on the FAA's command center real-

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[b] Typical operational rates range dramatically, from 43-270 operations per hour in fair weather, and 38-185 per hour in reduced weather as reported by the FAA *Airport Capacity Benchmark Report* (FAA, 2001).

time airport status page is <15, 16-45 min, ground holds, >45 min, closure. These values were represented as deferred flights and capacity limitations.

Since the net effect of facility operations was the focus of this study (e.g. can flights arriving at this airport meet their schedules), detailed modeling of flight operations (e.g. aircraft) was not necessary. Different delay distributions were applied to flights to test network robustness.

Aircraft modeling may be prove important in the future for determining cause of delay other than network structure and exploring mitigation strategies (beyond the scope of this dissertation). The focus of the network model was: Because departures from an airport were delayed, the other flights in the network are expected to either also be delayed or that the system will recover the schedule.

3.5 AGENT-BASED ANALYSIS

Corresponding agent-based models were constructed in *Repast* (Collier, 2004)as the environment for flight agents. As in the network analysis above, capacities for each node were modified to educe non-linear system behaviors in predicted operation time for flight schedules.

The agents represent flights traveling on a fixed network of airports. The flight agents had attributes of scheduled service demand time and actual departure time. The airport nodes had attributes of service capacity and general probability of random delays for service. The flight agents could also experience flight-specific enroute delays, affecting their availability at their scheduled service time.

3.6 USING THE TWO METHODS

For the purpose of this study, delay was considered to be the amount of time flights arrive beyond their nominal schedule. Delay could only be positive: no credit was granted for early arrival of flights, since this provided no operational benefit to the network assuming nominal turn times are sufficient. Generally, turn-based resources (e.g. gate space, the next crew, catering, etc) cannot oblige early arrival, so no operational benefit is realized. Delay propagation was defined as the spread of delay to a node that is not experiencing its own operational delay, but rather was affected by delay elsewhere on the network. Stability was determined by a network's ability to mitigate the propagation of delay. If delay was found to dissipate quickly (for example in <5 discrete cycles after a disturbing event has passed), the system was defined as stable. If delay grew and spread, the system was defined as unstable. Finally, if delays remained but did not grow, the system was considered marginally stable.

The challenging feature of the data from this study was that they were both quantitative and qualitative in nature. Certainly, these two methods could be used in a "bake off" design: the use of each method compared directly against the other in controlled scenarios. This information could useful to establish a basis for agreement or disagreement with the general hypothesis of the two yielding equivalent results. In fact, some numerical results were used to demonstrate their degree of sameness or differentness. However, an experiment of this type does not paint the whole picture.

To enrich the result of the proposed effort, these two methods were also held against the expectations of experts who desire such tools, as reflected in the academic modeling, policy literature, and identified in structured interviews. They outline desired traits for models (Wieland W. N., 2002) (Wald, 2004) (McLucas, 2001).

No single well-established research design was identified that could capture the essence of "Is a model useful for a particular complex system analysis?" Maxwell (Maxwell, 1996) suggests, in agreement with Leedy and Ormrod (Leedy & Ormrod, 2001) and Yin (Yin, 2003), that a qualitative study is an appropriate base for this kind of theory building. He offers promise for a content analysis design, saying that the goal of coding data for qualitative analysis is not to count things, but to "fracture" the data and rearrange it in categories. These in turn aid the researcher in developing theoretical concepts.

Acknowledging that a qualitative research approach may be better suited to interpreting some of the issues at hand (Leedy & Ormrod, 2001), a content analysis is considered as the basis of the research design. Leedy and Ormrod define content analysis as a "detailed and systematic examination of the contents of a particular body of material for the purpose of identifying patterns, themes or biases." The approach is reportedly often used in combination with others, also appealing for this application because the body of material includes quantitative models. Unfortunately, the approach, as are most qualitative approaches, is not often applied to engineered systems, even those where humans play major roles. The specifics of coding data and its analysis described were not directly applicable to the proposed study, but rather were used in an analogous fashion.

This research took Maxwell to heart, beginning with developing the categories of interest to the ATS community as expressed through the literature which helped formulate the structured interviews, and analysis of the outcomes of their modeling efforts. There was no pretension of objectivity here: an experientially based framework developed by the researcher. By application to the route/schedule adherence of models of two ATS network strategies, data was accumulated within each category, building a case that supports or refutes the hypothesis that either (or both) of these modeling techniques is sufficient. The quality of the models – their ease of formation and their ability to lead, be understood, explain, etc. - was judged by the researcher against the standards described in the literature and defined in the framework developed in first part of the study.

CHAPTER 4

RESULTS

4.1 AIR TRANSPORTATION SYSTEM ANALYSIS

As travelers, perhaps the most familiar ATS structural element is airlines' static, overall route structures. These routes are frequently (and almost exclusively) cited as an example of network structure within the ATS. With some relatively simple analysis, it is possible to uncover fundamental mathematical differences in airline routing strategies. They are a good starting point for investigating airline strategy and service coverage, but have determined that they have some severe limitations from an operational sense.

4.1.1 Airline Routes - Context and System Network Extent

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 generally, the city pairs that are connected via their network of flight offerings. America West (federal airline identifier HWP) connected nearly all flights to Las Vegas or Phoenix as depicted on its' route map, Figure 20. The airline's strategy, consistent with that suggested by (Teodorović, 1994), to efficiently collect passengers at a central hub location and redistribute them to the "spoke" cities in the rest of their network is evident.

Just by inspection, it appears that Southwest Airlines (SWA) has a different strategy, as evident by their destination map (Figure 21). Indeed, SWA has such a "messy" route structure, they do not publish the city-pair connections, though they were added to this figure to aid visual inspection of the different route offering strategy. SWA and HWP were vying for the same market segment, i.e. low-cost travel consumers, but appear to have chosen clearly measureable different strategies in their route networks. Indeed, route maps alone may reveal different market strategies, though without further knowledge, what these route maps imply can be misinterpreted:

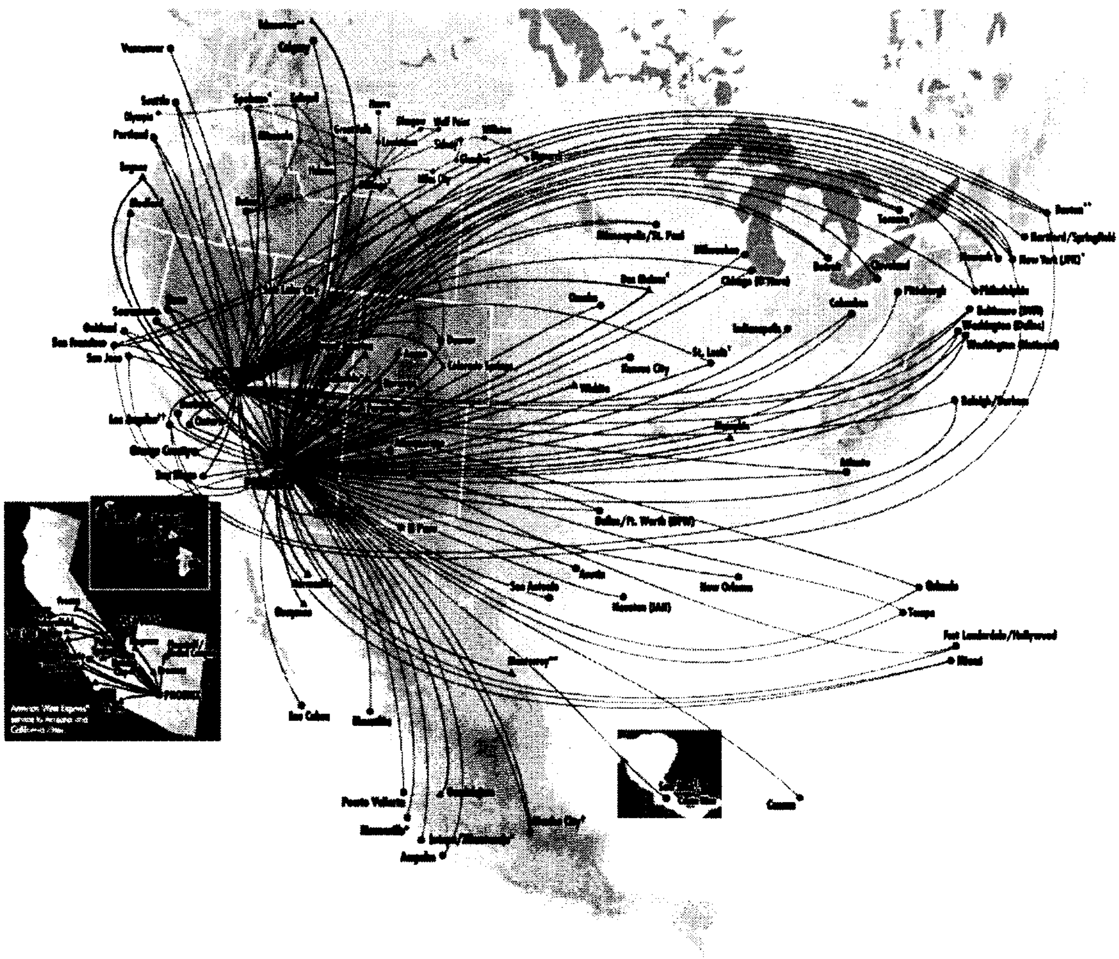


Figure 20: America West Airlines: Non-stop Routings Showing Substantial Hubbing and Reflecting Centrality (2003)

An analytical model, even ones like above - 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

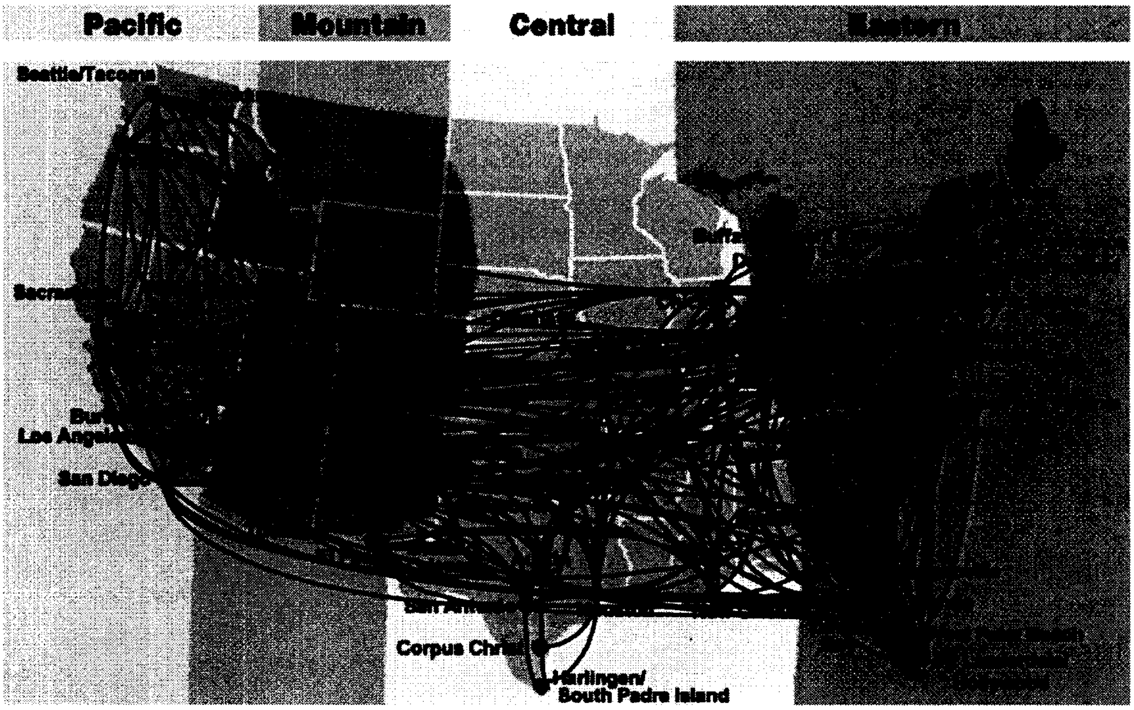


Figure 21: Southwest Airlines Non-stop Routings
Showing A Unique Strategy in Their City-Pair Selections (2003)

Figure 22 shows the route map of Mesa Air Group in 2003. From some perspective, this is a realistic depiction of the airline's operations. However, passengers didn't ever fly "Mesa", but rather the livery of the major airline they were contracted to serve as the regional (e.g. United Express). So while the route map makes sense from a strategic (or perhaps investor's) perspective of the airline, they may have no relevant context from the passenger or even the parent company's daily operations. Without understanding the operational context, such network mappings are of very limited use and can actually cloud understanding.

In Figure 22, the different "operations" run by Mesa are evident. While one might assume that Mesa's fleet is a hybrid of the two strategies above with multiple mini-hubs, that is not the case: Each shade-coded grouping of city pairs is a actually a feeder to a different client major airline, flying under different livery, and presumably, is structured to best serve the parent airline it is feeding passengers to.

While Mesa may have been United Express on the east coast at the time this map was published, their west-coast operations were extensions of another major carrier's route system: United Express western regional operations were contracted to Sky West at the time, then an independent regional contract house (later bought by Delta). So while there is certainly corporate strategy in multiple operations, this map is more a collection of airline sub-maps than a good representation of a single airline as far as schedule for equipment, crew, or even passengers.

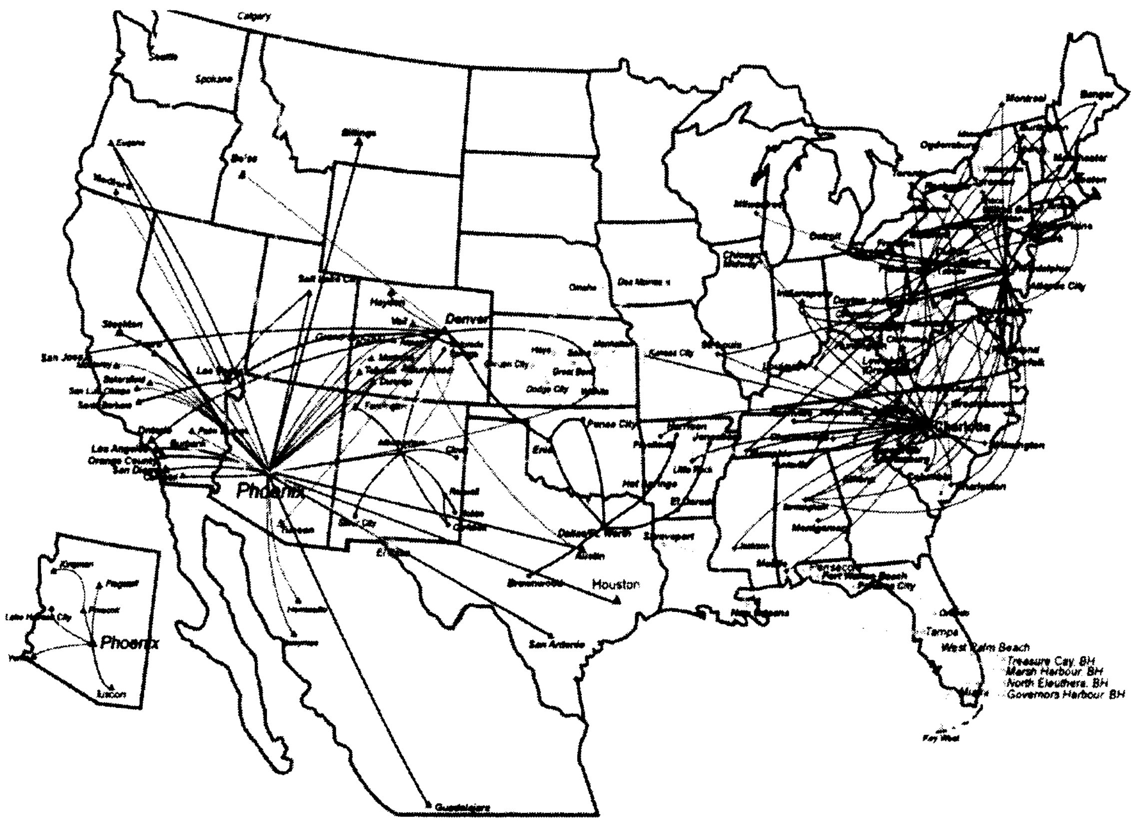


Figure 22: Mesa Air Group Non-Stop routings (2003)

Another example of the importance of contextual domain knowledge and model application of such airline route networks is the United Airlines (UA) route map (Figure 23). It shows over 650 destinations worldwide, though UA *themselves* fly non-stop between only 104 cities (United, 2003). The "appropriate" nodes for analysis are dependent on the vantage point of the network user and the purpose for the model: 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 (Atlantic Coastal Airline, 2007) 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 their own.

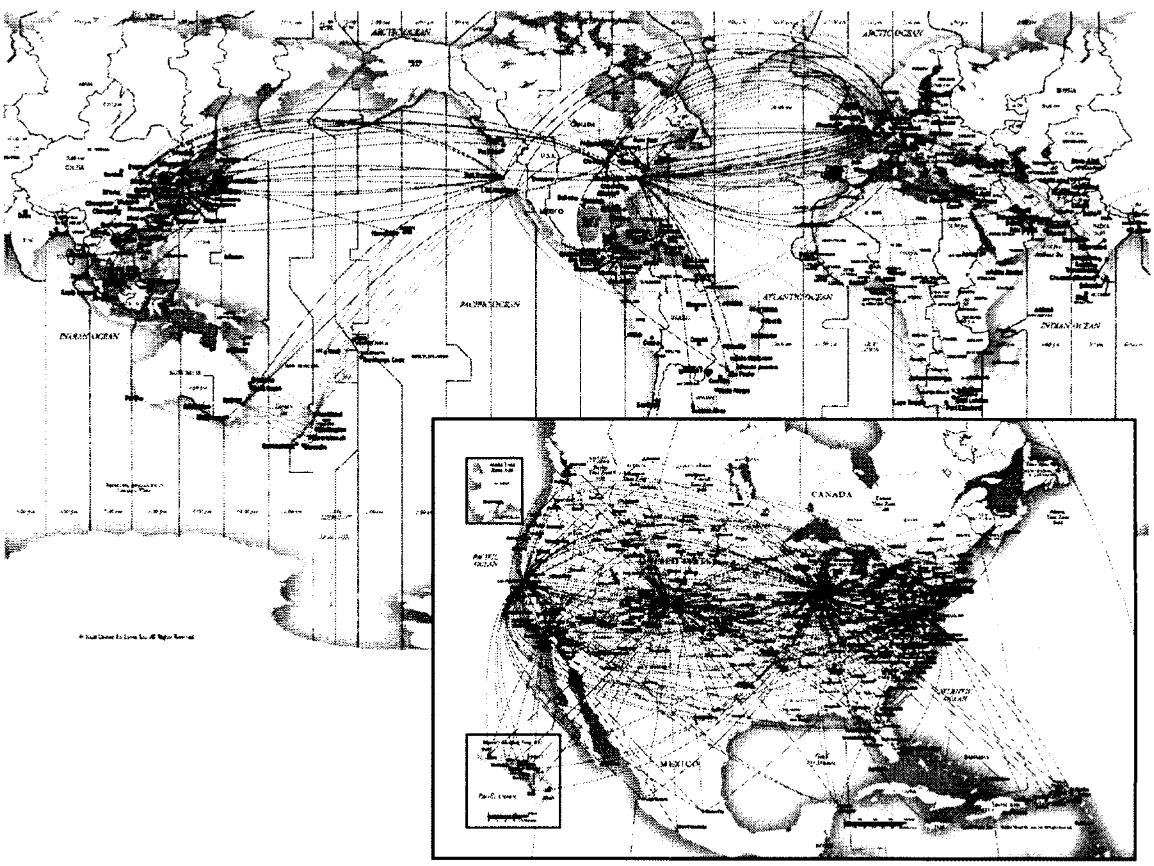


Figure 23: United Airlines Domestic and Worldwide Routings (2011)

4.1.2 Quantifying Strategies for Certain Airline Route Networks

An airline has many factors in creating its city-pair offerings, and strategic and competitive reasons to build a specific network. Are these airline operation and environmental considerations reflected in their network structures? Are their structures indicators of their schedule stability, and does this stability factor into their city-pairing selection? To answer these questions, a few different route maps were explored within the context of the potential for schedule adherence: Case studies of differing network connection strategies were developed to identify strengths and weaknesses in each.

4.1.2.1 Point-to-Point

Point-to-point (PtP) routing is one example of a strategy an airline can take in developing its' route map. Using this method, sufficient passenger demand for city-pairs creates a link between those nodes, or cities. When demand exceeds a single flight, more flights are added. Since some airlines have fleets of aircraft that vary in passenger count, they can match seat availability with demand at multiple times of day and also meet demand by selecting larger or smaller aircraft. For the passenger, this affords a high quality, efficient (non-stop) product if the flight meets their expectation for exact city pairing and time of day. On the other hand, if a traveler's city pair is not represented, or the time is not when desired due to limited demand between a pair, such as might be the case from a smaller community to another small community, this type of service may be less desirable. This can also cause complication from the airline perspective, as swapping equipment or scheduled service is not something that can be easily done, as different crew, maintenance, and service requirements for various aircraft limit flexibility and the ability to tactically adjust seat offerings to demand.

Often offered as an example of a PtP route structure, a large portion of the cities in the Southwest Airline (SWA) route structure connect to many other cities (Figure 21). Southwest flies to 59 destinations, and has an average of 11.5 links per node <k>. SWA degree distribution doesn't follow a random connection pattern, and does exhibit certain 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 flight schedule shows the clustering coefficient, C(p), a measure of the connectedness of a node's neighbors (or other destination city in this case), is predictably high at 0.641. This is compared to a predicted C(p) = 0.195 for a similar-scale random network, leading us away from a random network model of their operations as we'd expect.

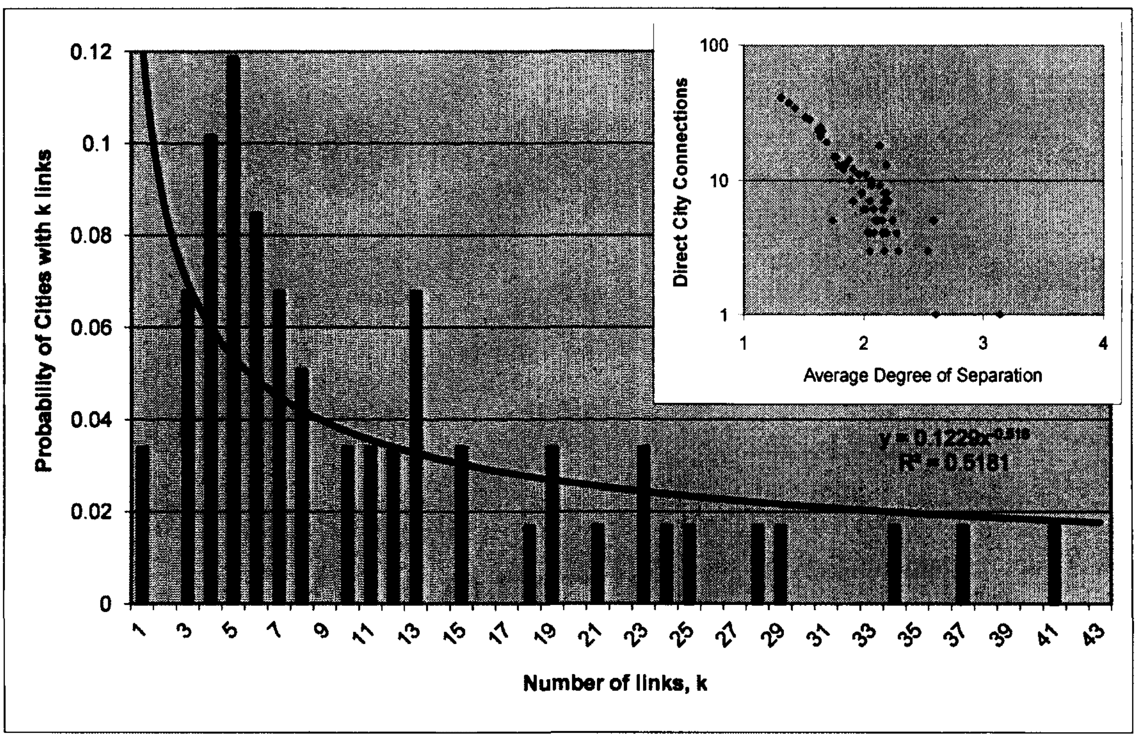


Figure 24: Degree Distribution, SWA 2003

However, SWA does not have nearly as many singularly connected cities as a power-law model predicts, as shown by Figure 24, SWA's degree distribution. Perhaps other operational influences are dominant over those that drive a system to a purely scale-free network. This lack of direct connections causes a relatively higher number of connections between cities than would be true if the network were randomly connected (L(p)=1.994 vs. L(rand)=1.670). Try to catch a non-stop flight from Buffalo on SWA and you will experience the relevance of this statistic, unless your destination was LasVegas or Chicago. The lack of lightly connected cities as would be suggested by a scale-free SWA network begs inquiry into other network influences than the city-pair structure and geographical position alone.

4.1.2.2 Hub-and Spoke

Another network type, often found in airline route maps by inspection, is a centralized or pure hub-and spoke. Following the description in the network section above, a hub-and spoke airline network is one in which the carrier has all their flights either originate or terminate at a single city or hub as shown in the HWP map above (Figure 20). For very large networks, airlines often have "local" hubs, serving a specific region. These are connected with regular service, creating a decentralized hub-and-spoke network.

It seems that America West (HWP) took (Jaillet, Song, & Yu, 1996) optimality considerations to heart: The airline served 61 destinations, and nearly all of their flights connected through either of their two hubs, Las Vegas and Phoenix. Interestingly, with a relatively small total network and the number of cities they chose to serve, a network with such strongly centralized characteristics make sense - *if* - you can keep your hubs operating smoothly: The hubbing shows in the HWP network statistics, Figure 25: C(p)=0.533 while

C(rand)=0.052. The result; an average distance between any two cities gave customers great connectivity with only one stop L(p)=1.972 while L(rand)=3.622. Such a high random expected journey is reflective of the limited service between cities, and lends more to the reasoning of such an airline to use a strongly-centralized approach to passenger collection and re-distribution.

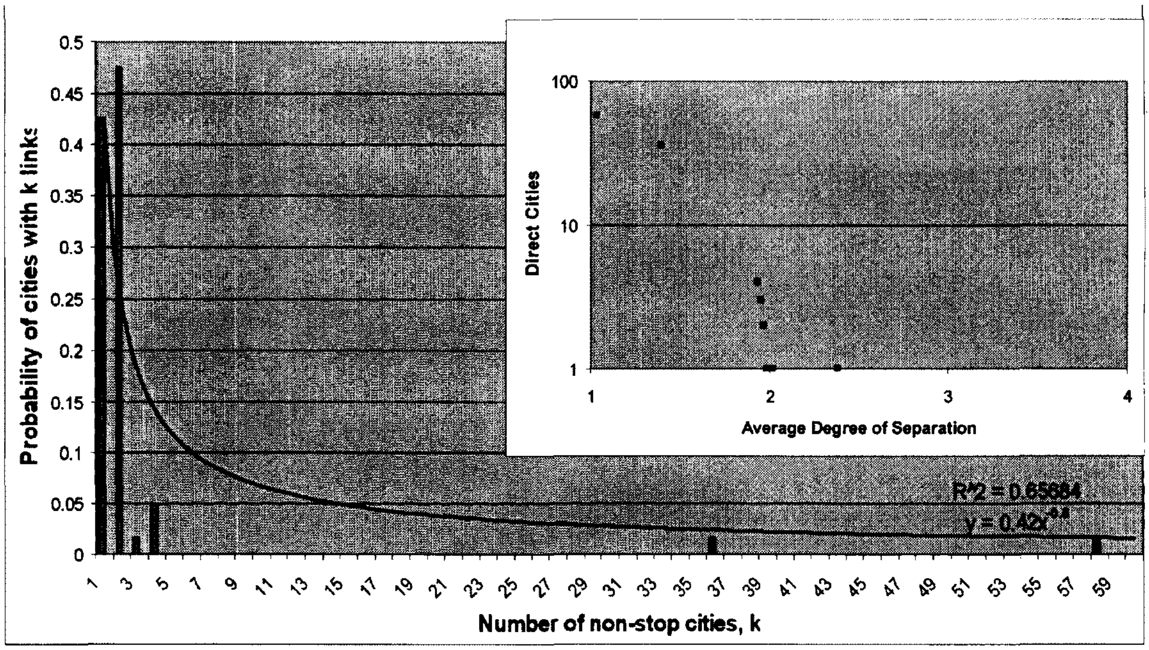


Figure 25: America West City-Pair Degree Distribution

Results from (Jaillet, Song, & Yu, 1996) also support UA hubs at SFO and ORD despite their continuous weather and congestion problems (FIGURE 26). However, unlike SWA, little if any of UA's degree distribution is well explained by a power law function. UA has a large number of cities that are singularly connected, in fact, more than would be predicted by a scale-free network. The UA network is more bimodal like America West, with cities either modestly or highly connected, shown at its five dominant hubs.

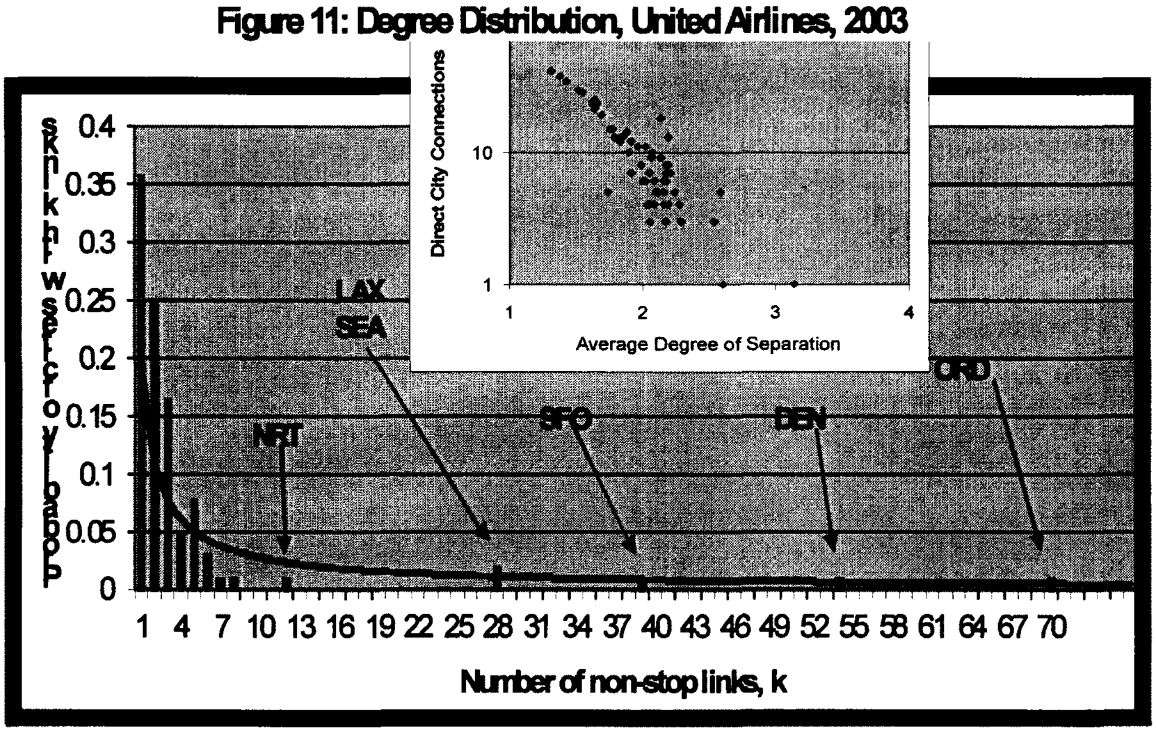


Figure 26: United Airlines City-Pair Degree Distribution

4.1.2.3 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, 2001) and others imply.

4.1.2.4 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 (Barlow, 2002) (Barlow, 2002) 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 (Sharkey, 2002) (Leonhardt & Markels, 2002). 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. (Mann, 2002)" 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 (Schepp, 2002) (Grossman, 2003). In fact, Brancatelli (Brancatelli, 2003) 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 (Barnhart, Kniker, & Lohatepanont, 2002).

4.1.2.5 Exogenous Factors for Airline Route Selection

Profit, not revenue is the goal of any industry. Airlines, with extremely thin profit margins, large gross receipts, and very high operating costs (VanWijk, 2003), are especially sensitive to government intervention: regulation and subsidy. Perhaps these are factors of route structure which tend to divert structures from more naturally-derived scale-free forms:

4.1.2.5.1 Mail Contracts

A source of financial guarantees available to the nation's largest air carriers are the U.S. mail contracts. Since commercial aviation came to be, one of the very first commercial services was carrying the U.S. Mail. Over time, the mail contracts and other freight have become very important influences on US carrier routes. Airlines are paid subsidies in the form of guaranteed freight contracts for mail. In 2001, commercial carriers were paid to carry 4,000,000+ tons of mail (US DOT Bureau of Transportation Statistics, 2002)on existing but specific revenue flights. In the past, this has influenced airlines' route selection, frequency of service, and even which cities themselves are served. As the US Postal service declines, this previously substantial factor may become moot.

4.1.2.5.2 Civil Reserve Air Fleet (CRAF)

An additional source of guaranteed airline income is participation in the (CRAF). 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 (GAO, 2006), 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.

4.1.2.5.3 Regulations & Environmental Caps

EU reports that though only 3% of total human-caused carbon emissions come from aircraft, aviation is the fastest-growing source of carbon pollution (BBC News, 2006). In a recent move to force global response to this issue, the EU has initiated a forced carbon emission trading program on all international flights to/from European airspace after Jan1 2012. The measure requires airlines to "cap" their carbon emissions at their historical output. To exceed this value, they are permitted to buy "permits" from other airlines that have reduced their emissions, thus freeing up some of their allotment for resale. Recent attempts to flight this measure in the European Court of Justice by North American airline advocacy groups have failed (Associated Press, 2011).

Caps on aviation-related carbon emissions have become serious political battlegrounds, as have similar discussions on community noise exposure caused by changes in airline schedules and airport growth: In September 2011, the same court ruled EU states can "establish maximum noise levels, as measured on the ground, to be complied with by airlines over-flying areas near an airport" (Agence France-Presse, 2011). One of the major issues in the 2010 National election in the UK was strategies for limiting or growing operations at London's Heathrow Airport due to community concerns with noise and emissions from growth and flight scheduling practice (BBC, 2010). As it is, the Heathrow operation is heavily constrained by noise agreements with the community (British Airports Authority, 2011) causing the flights to be divided between their two runways to share the noise burden across the community. This is done at the serious but perhaps more insidious cost of extra emissions due to the noise-constrained operational limitations: In Figure 27 we see the excess noise exposure to Central London, due east of the airport, by flights forced to align with a specific runway (more efficient, parallel approach procedures are allowed only by exception). The net effects of such environmental concerns have already influenced airline scheduling, limiting flights and reducing profitability for others. In the future, noise constraints may become one of, if not *the* dominant influence at key airports.

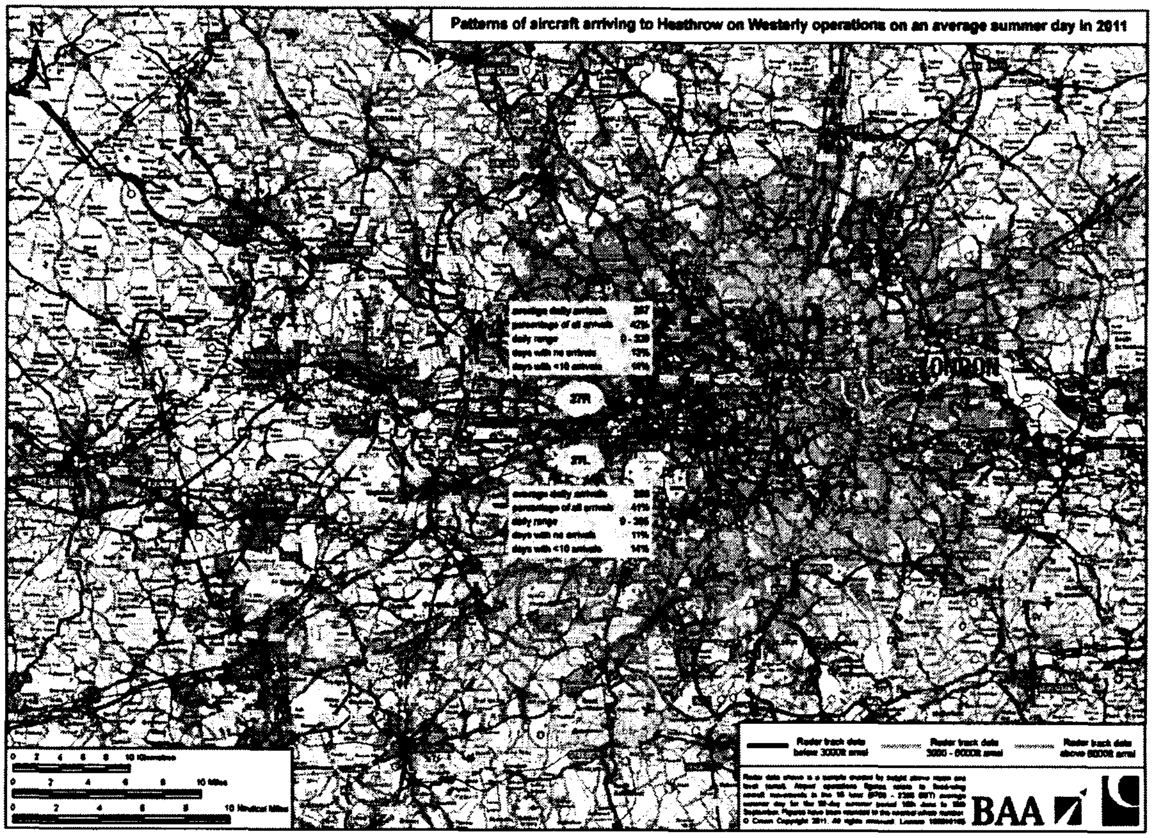


Figure 27: London Over-flights – Heathrow Approaches (British Airports Authority, 2012)

4.1.2.5.4 Deregulation and Essential Air Service

Deregulation and subsequent legislation apparently has had a measurable effect on airline network structure. As the early airlines formed, they built their route structures to maximize their potential profit, including the government contracts mentioned above. Before the airlines had autonomy to serve only the markets they deemed profitable, U.S. Government intervention dictated much about the required provision of service to specific communities for reasons other than the mail, such as access. The government also set ticket prices, and limited competition on many routes. All of these rules changes in the 1978, when "deregulation" allowed the airlines to make many of these choices for themselves...many, but not all.

The US DOT (Office of Aviation Analysis, 2009) 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. As of 2009, the airlines were guaranteed payment (in part) to fly to 105 otherwise presumably non-profitable communities.

To better understand if industry regulation has a measurable effect on the route network, data from the U.S. National archive from the period prior to deregulation was explored. Shown in Figure 28, Trans-World Airways (TWA) March/April 1976 route system is a representative sample, and was analyzed for its network properties. As demonstrated in the company route map, TWA was both a domestic major airline and a major competitor for Pan American Airways international routes in this period before deregulation. Interestingly, even in the heavily regulated environment of the time, analysis shows that this PtP schedule's probability distribution function was highly correlated to a scale-free, power law model (R^2=0.926, Figure 28). 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. In fact, no current airline city-pair model shows such clear power-law connectivity.

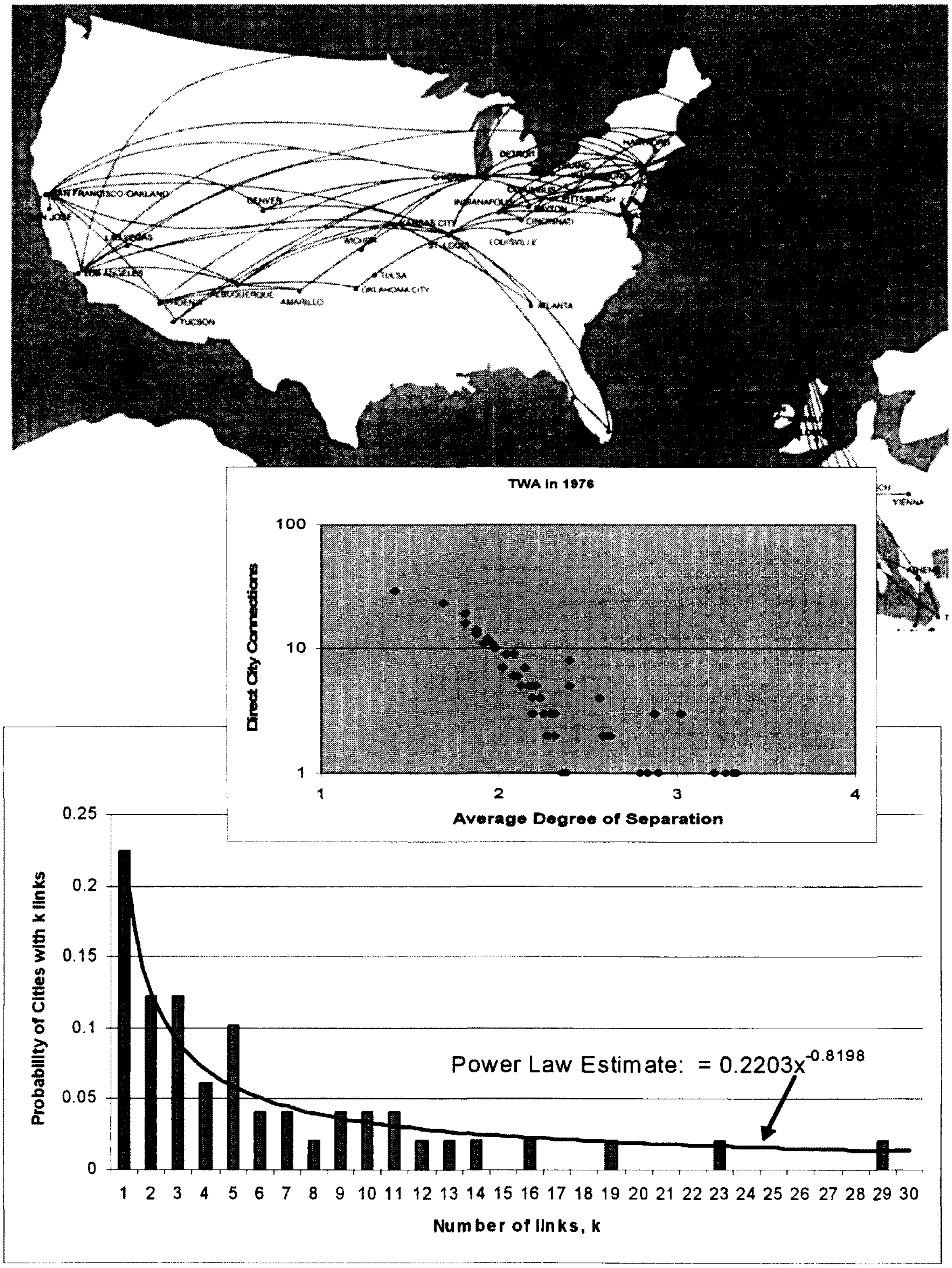


Figure 28: TransWorld Airlines City-Pairs (Routes) and Degree Distribution (1976)

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).

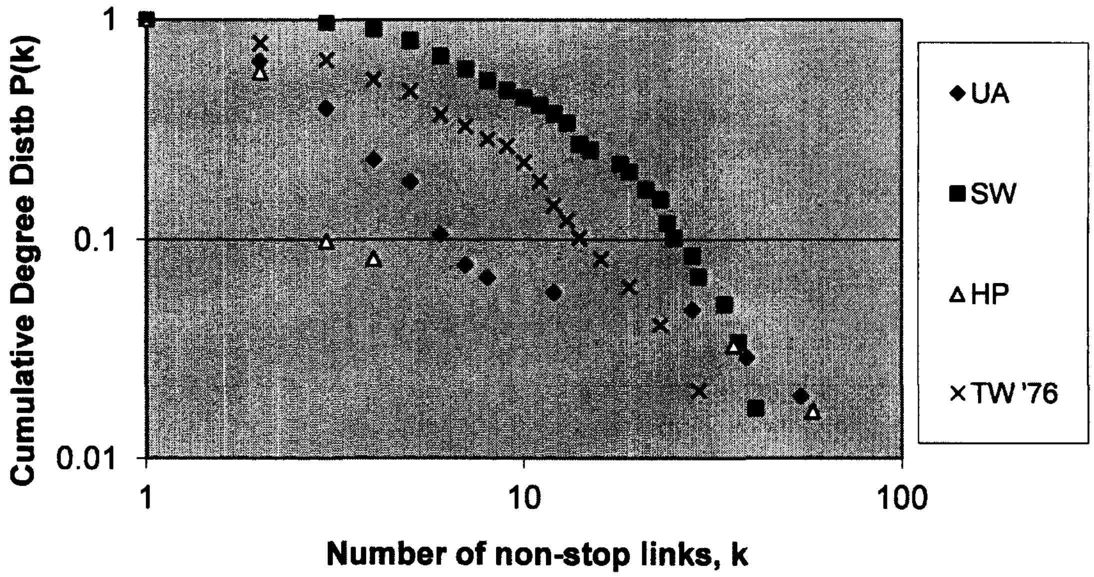


Figure 29: Different Airline Routing Strategies and Their Degree Distributions

When plotted together as in Figure 29, the different strategies the airlines have used to formulate their route structures is reflected in the varying shape of the degree distributions. As discussed above, three of these four distributions are from contemporary airlines, while the fourth, plotted in Xs (TWA) is legacy data from the period when these routes were largely constrained by federal regulation. The triangles are representative of a highly-centralized airline network (HWP). The diamonds are from a modern, multi-hub airline (UA), while the squares show an airline that has chosen to plan with the most distributed strategy (SWA), and has indeed reduced clustering below that expected of a scale-free network.

These different strategies are clearly evident in these network metrics, but what drives them? TWA was and UA continues to be an international carrier with both business and holiday traveler customers. The difference between these two networks might be explained by changes in the regulatory environments in which they operate. However this may not be the only external factor at play: HWP and SWA were contemporary domestic-only carriers who catered to a similar clientele, yet also have chosen dramatically different, demonstrable differences in their city-pair networks. Perhaps the fact that HWP is no longer operating, and SWA continues to be a strong competitor in this tight market points to real, fundamental (and superior in SWA's case) differences in their strategies which are captured nicely by evaluating these degree distributions.

4.1.3 Complementarity

Of course, not all attributes of a particular scheduling strategy are equally beneficial from all vantages. The routes mentioned above were also analyzed for their degree of separation, or the number of "legs" a passenger would have to take to connect from one city to another. This graph is also very different for the TWA system than the others analyzed: a passenger on this network may be required to make one or even two connections, while most itineraries today are supported by either non-stop or one change of flight. This type of service difference is not so evident from the airline's perspective, but is very much apparent from the travelers'. Similarly, airline passengers on carriers like SWA experience some of the same issues...trading lower cost for longer total travel times due to multiple connections.

Keating and Varela (Keating & Varela, 2002) 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. They say 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. Similarly, the same network and performance could be seen differently be different stakeholders. Therefore, the first challenge for network analysis is to identify which networks must be described, and if there are many different networks from various stakeholder perspectives which influence the system of interest, how they might interact.

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. 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.

To illustrate the variety and breadth of complementary network structures within the ATS, a selection of observational points of view are addressed in the following sections.

4.1.3.1 Airline Persepctive

Beyond the route structure, there are many other networks in the airline's business. These create dramatically-influential network structures for the airlines to navigate. Some of the key ones directly related to flight schedules are the flight crew schedules (Barnhart, Belobaba, & Odon1, 2003), the cabin crew schedules, and equipment networks. Flight and cabin crew scheduling are based on different elements of regulation, and are governed by different union agreements with individual airlines. These different resource networks behave differently than the flight schedule network itself, but of course, have to harmonize together. Otherwise, the dreaded experience: "Sorry, but our crew has timed out. Please disembark and wait in the gate area until the new crew arrives."

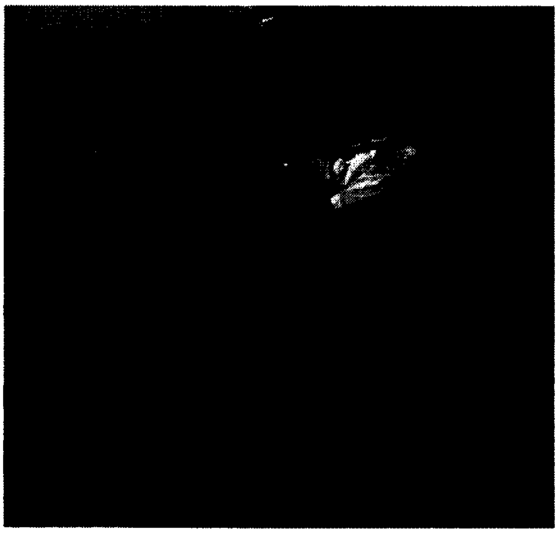


Figure 30: Crew "Rest?"

Both cabin and flight crews have mandated rest periods, limited on-duty times, and required rest periods (to avoid scenes like Figure 30). Recent safety concerns have demanded more stringent restrictions on pilot duty time, and longer rest periods. (FAA News, 2012) Within required restrictions, the airline pilot's schedule, or "line", is determined by their Preferential Bidding System, or their "line bid" (Figure 31). These can be complicated systems of seniority-based selection which also factor qualifications for specific equipment and operations, home airport, etc.

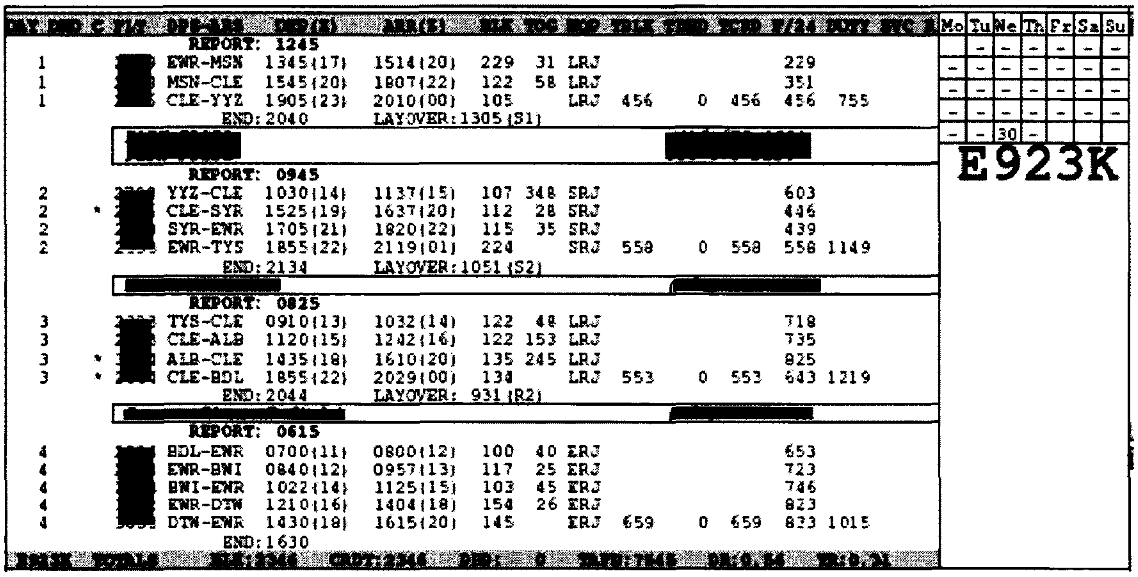


Figure 31: Crew Bid Sheet

Crew schedules must be arranged such that their previous flight completes where there next one is to begin. This sounds trivial, but many times the crews do not depart on the same equipment they flew in with. Additionally, there can be crew pairing restrictions for certain crew members due to required experience, on-the-job training, etc. All of these factors have to be satisfied to provide a crew for flight. In turn, from the airline's perspective, the flight connections in a line create dependencies amongst flights in their service network, as a flight cannot operate if the crew is delayed from a previous leg on their line. The same is true for the cabin crews, though of course, their lines can create completely different dependency networks due to duty and labor practice restrictions.

Beyond the crews, the equipment itself forms another dependency network. A "flight" is really an abstraction of a business practice until crews, equipment, and payload (passengers and freight) are all matched in a viable flight plan (assuming amenable weather and traffic). If the equipment is delayed from a previous leg, that delay will propagate to any flight using that equipment. Scheduled equipage outages of which there are many with aircraft for maintenance, can be scheduled. Other maintenance items can delay or cancel a flight, as can a weather divergence.

4.1.3.2 Air Traffic Control Persepctive

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 (FAA, 2012)." 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 (Figure 32). What might models 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 themselves recognize the "diversity and challenge" they have in improving this complex "collection of systems (FAA SAIA, 2003)."

A portion of the ATC system is of course the NAS: The technical infrastructure and facilities which connect air traffic control facilities to each other, aircraft, navigation satellites, etc. create a very large number of networks themselves. Some of these are integrated as a single system and can communicate with each other; others are not (Figure 33). Of course, this figure is not intended to be read in detail in this paper, but is rather included here to show the breadth and extent of the NAS infrastructure. Details of the NAS architecture can be found at the source web site (FAA, 2012).

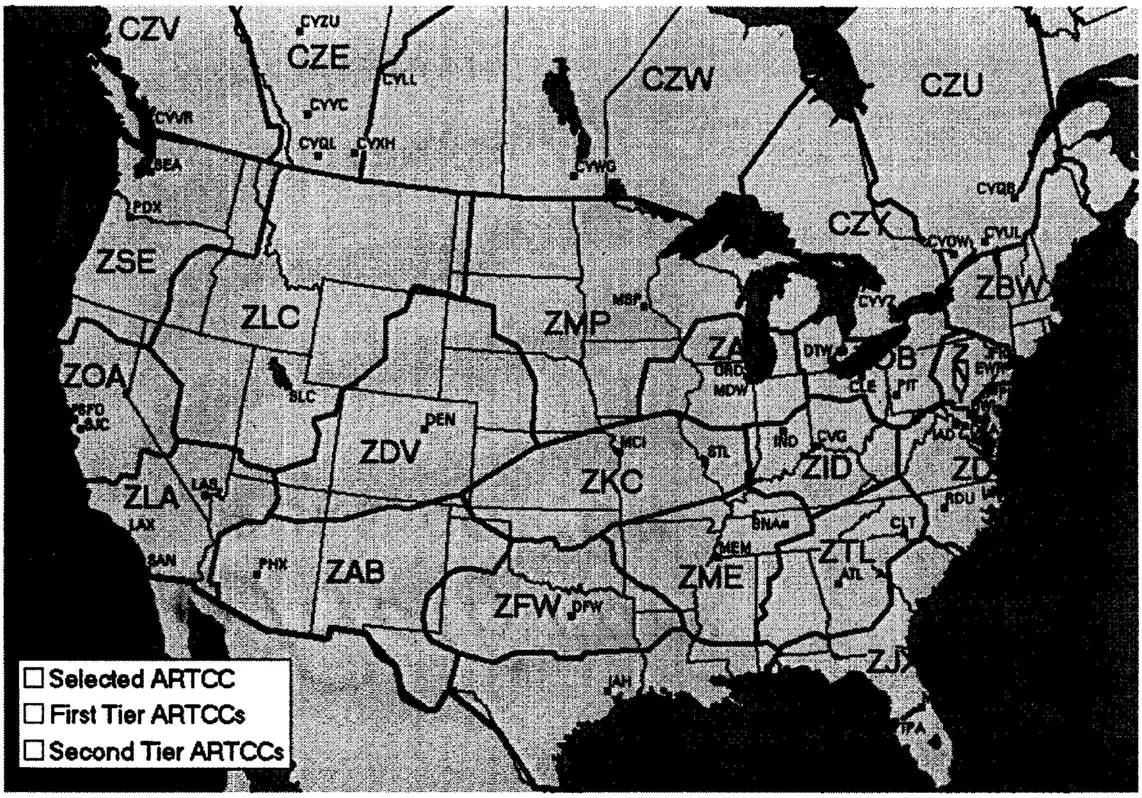


Figure 32: U.S. ATC Centers – One of the Many Facility Networks

There is a major effort for the communications portion of this infrastructure to become more integrated. As a portion of the NAS infrastructure, the System-Wide Information Management (SWIM) project aims to orchestrate new emerging technologies with requirements and existing infrastructure to make information within the ATS more available (FAA ATC Service, 2012). 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 delay or other attributes of the system.

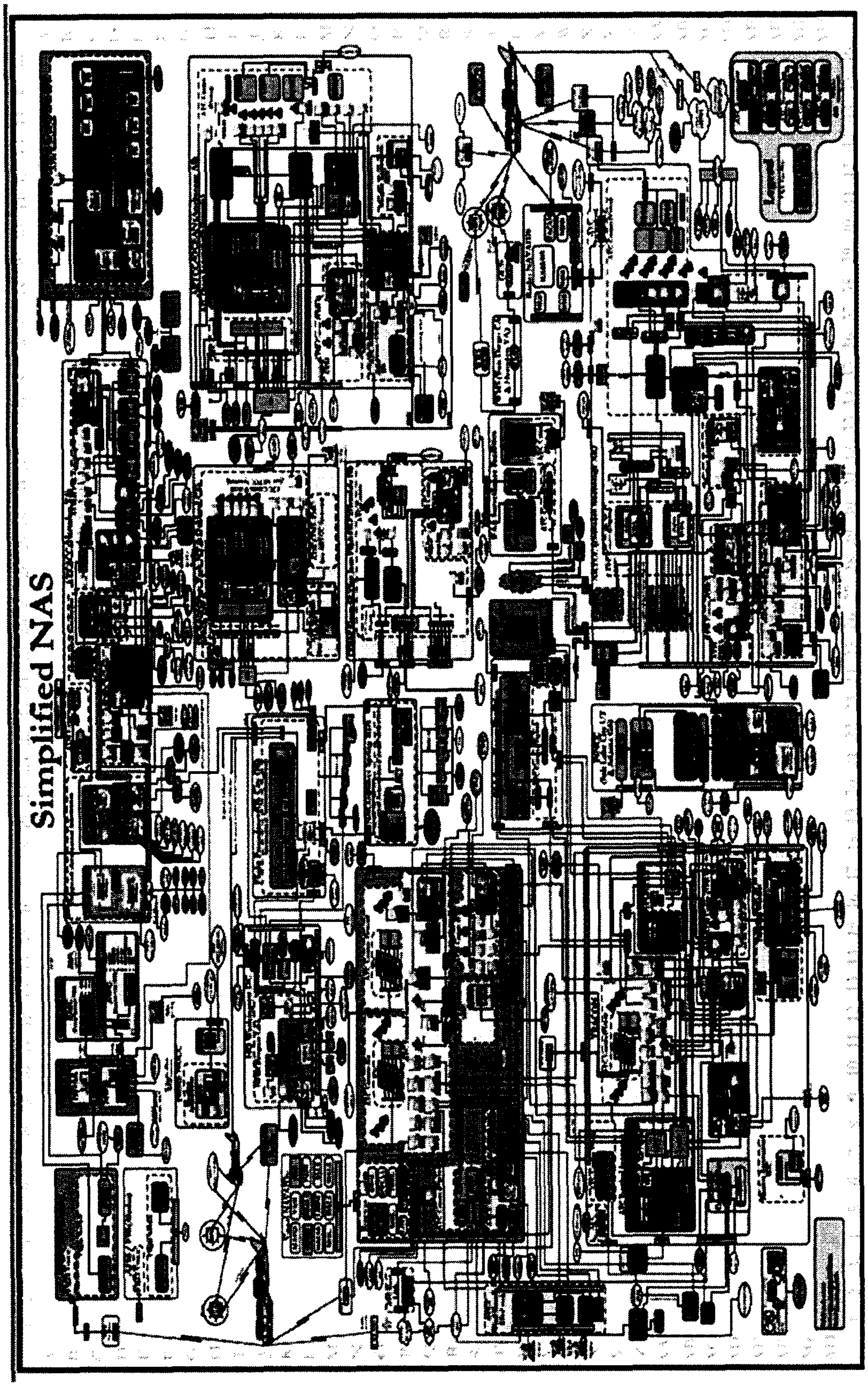


Figure 33: "Simplified" NAS Infrastructure (FAA, 2012)

For yet another perspective, a functional rather than physical network model of the ATS 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 34 is offered as a model for flight operations within the ATC domain. Differing from either a facilities network or an infrastructure network, it represents a functional network for ATC operational control. The shaded node 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 (Metron, 2012), 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.

This initial ATC functional model indeed exhibits small world characteristics: It has $L(p)=2.0$ 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).

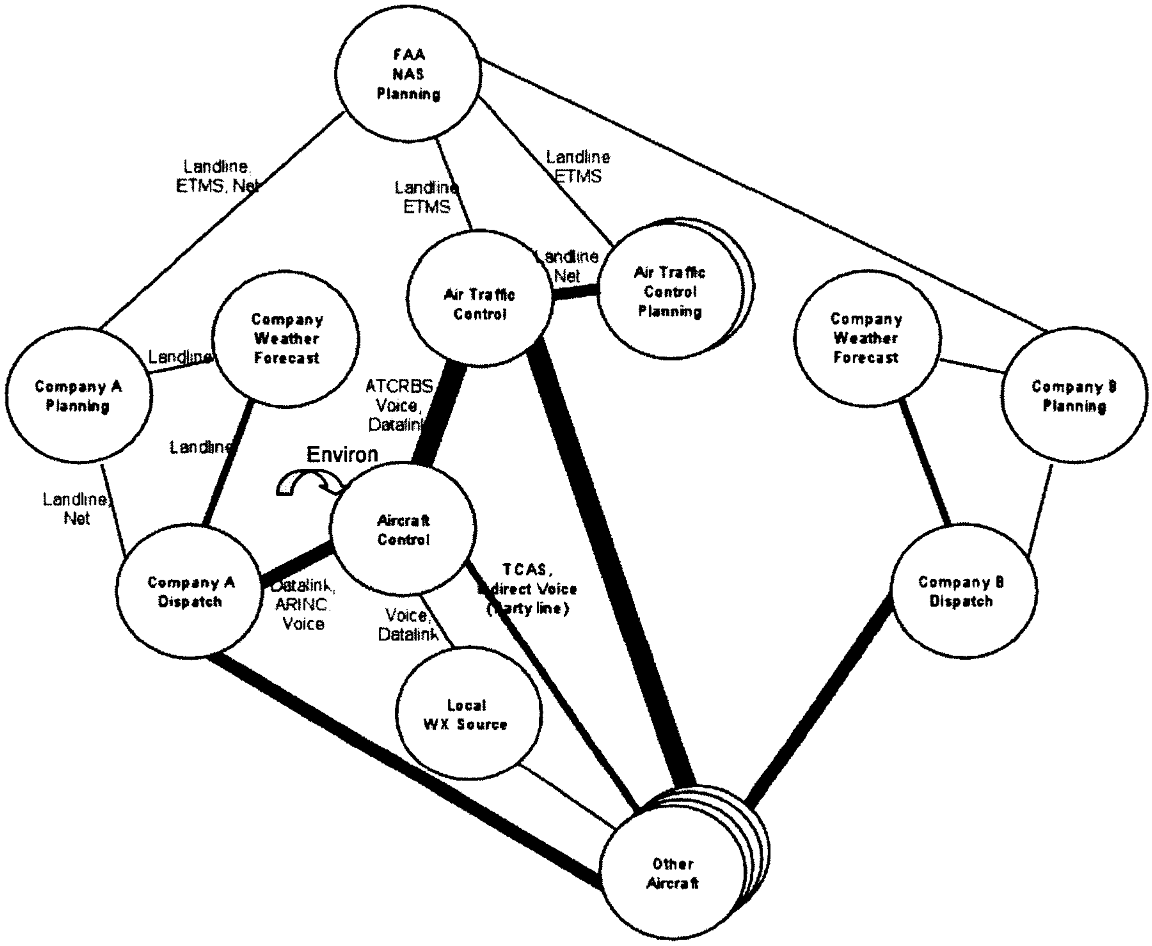


Figure 34: ATC Network of Functions Supporting a Flight

4.1.3.3 Payload: Passengers and Freight Persepctive

For passengers, individual 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 & Bratu, 2001) 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. Their data shows the reason for their warning. In Figure 35, they show that though the number of delayed flights went down in the six year period between 1995 and 2000, the total delay minutes the *passengers* experienced went up substantially.

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.

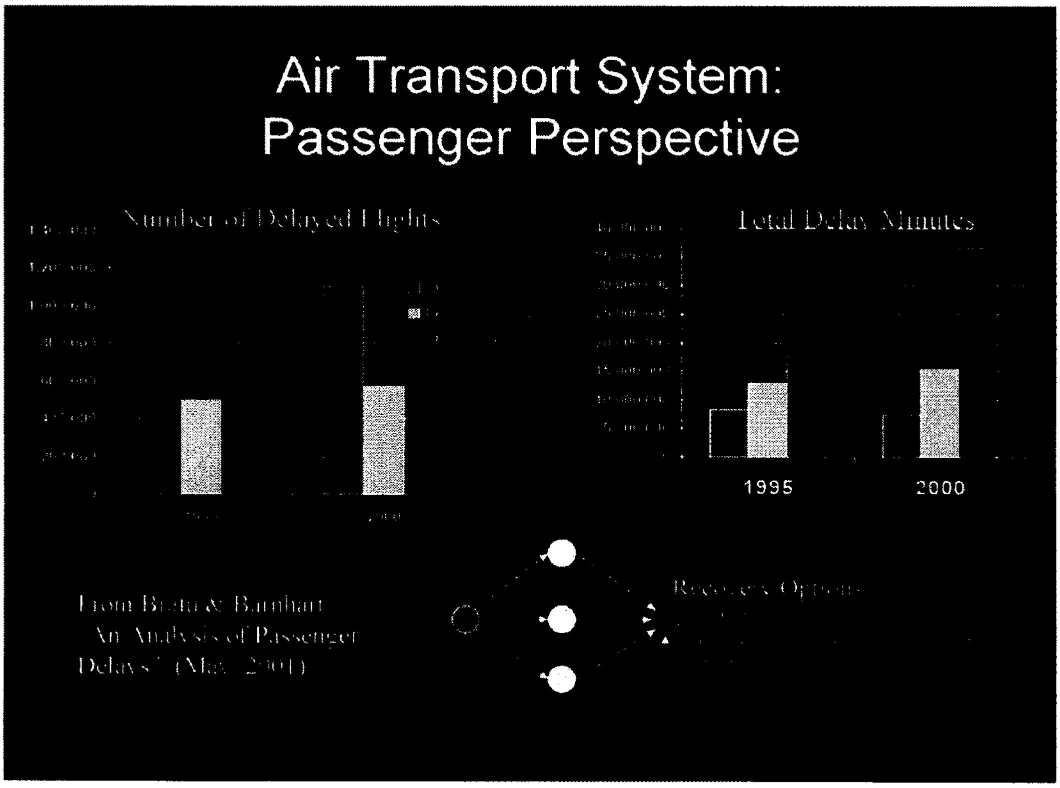


Figure 35: Air Transportation from the Passenger Perspective

4.1.3.4 Airports / Communities Persepctive

An analysis of a local network, even from a small, local commuter hub like Norfolk, Virginia (ORF), reveals that, even restricting the network to non-stop and one-stop

Figure 36: Non-stop and One-stop Cities from ORF, Norfolk VA

destinations, surprisingly good connectivity is possible (Figure 36). 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 (Norfolk Airport Authority, 2003). 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. This is important 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 community 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. In effect, this creates a situation where although the ORF clustering coefficient is high and implies good connectivity, the typical passenger cannot cost effectively travel throughout this network.

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 (GAO, 1999). 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.

4.1.3.5 Complimentarity in ATS: Summary

All of these different perspectives, and the network descriptions that result, point to the importance of complementarity in ATS modeling, and highlight some difficulties as well. Network models can certainly be created which will adequately describe most of the dimensions of a system. However, interactions between such extensive and diverse networks appear to be difficult to model, as matching between nodes of one description will not be 1:1 for another dimension. Some techniques for multi-modal network modeling are further explored below in section 4.2.

These results suggest if interactions of multiple networks are likely to be instrumental in analyzing the extent of the system of interest, such methods may be cumbersome to implement or simply intractable. The onus is on the modeler to estimate the importance of the complimentary. Clearly, the purpose, client, data available, etc will all weigh on such a determination.

4.2 ATS NETWORK MODELS: TOOLS AND TECHNIQUES

One of the key elements in modeling the ATM network for operational analyses was not to get distracted by creating yet another suite of network analytical software, but rather to focus effort on the *modeling*: i.e. how to capture salient attributes of the system with a network description: nodes and links.

4.2.1 Network Modeling Tools

The functions necessary to maximize utility of a tool for this purpose were: 1) Import of large datasets, 2) Statistical computation, 3) Visualization 4) Optimization, and 5) utility by subject matter experts in *transportation*, not software (i.e. dirt-simple).

Some ubiquitous tools, such as Microsoft Excel, provided some necessary function, but fall short in other areas without a substantial effort in tool development. Computing these metrics, even in a spreadsheet, is relatively straightforward once the network is captured mathematically in the software of choice. However, once network data is captured in a simple database or spreadsheet, there are a number of software packages created explicitly for network analysis and visualization that become quite useful.

Most network-oriented analytical software is oriented towards social networks, however a few of these software packages were generic enough to apply to any modeled network. It seemed that a socio-metric analysis tool should be able to be re-purposed: The literature suggests that basic network attributes such as degree and link-length distributions could be used at a system level to describe likely behavior, such as a propensity to cascading disruption or propagation of delay.

Table 4: Complex System Analysis Tools by Function (CASOS, 2011)

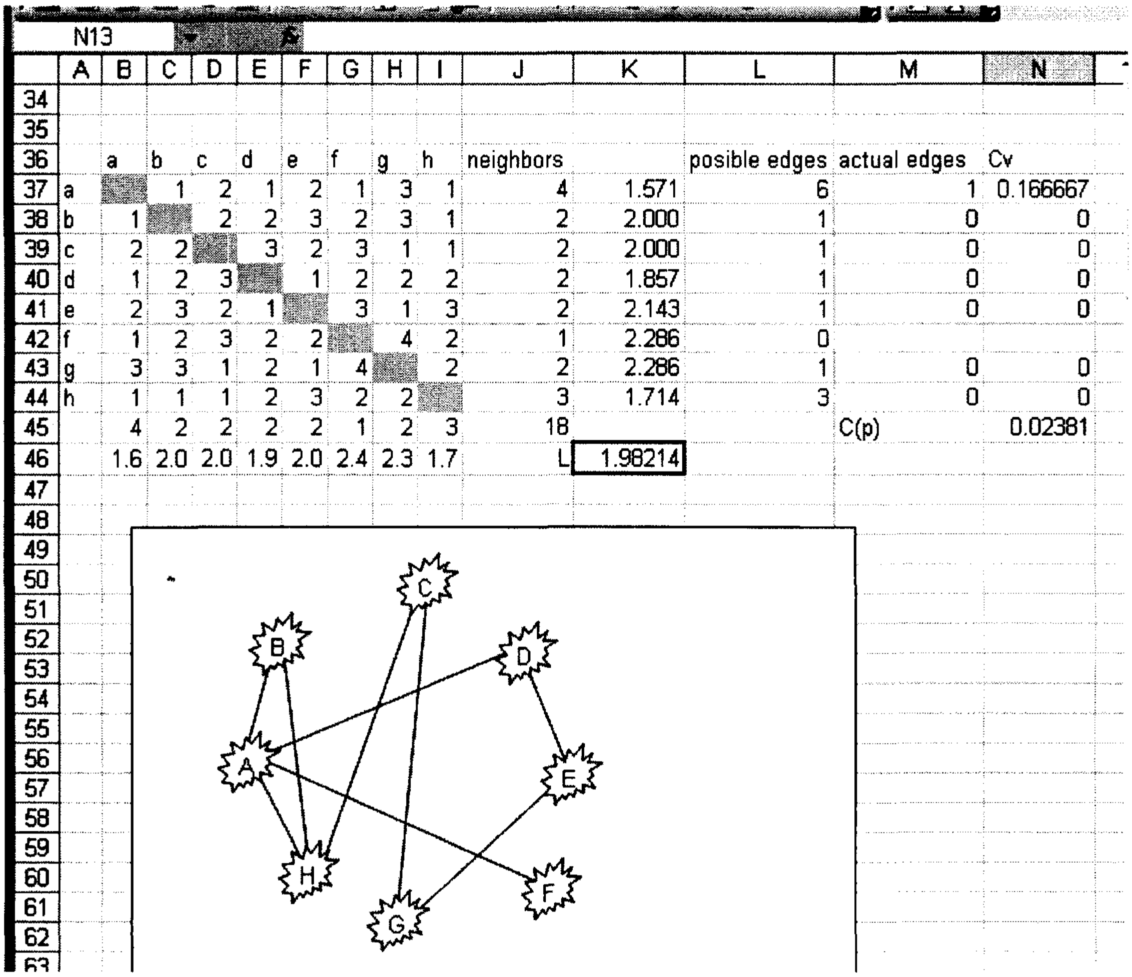
Primary Function	Complex System Analysis Tools
Dynamic Network Analysis and Social Network Analysis	• AGNA • BLANCHE • Construct • COSIN • DyNet • EgoNet • FATCAT • ICKN • IKNOW • InFlow • KeyPlayer • MatMan • Multinet • Negopy • NetForm • NetMiner • NetStat • NetStatPlus • NodeXL • Optimizer • ORA • Pajek • PermNet • Proximity • SIENA • SNA • Socilyzer • SocioMetrica • Stocnet • UCINET • visone • VisuaLyzer
Network Document Analysis and Data Entry	• AutoMap • CEMAPII • iNet • KEDS • ORA • PileSort
Network Visualization	• aiSee • breve • CamStudio • daVinci • GraphViz • Krackplot • Mage • MatView • NetDraw • NetMiner • ORA • ORA Flash Network Visualizer • ORA-GIS • ORA-LOOM • Pajek • SoNIA • TouchGraph • VGJ • visone • VisuaLyzer • WilmaScope • yEd • Zoomgraph
Multi-Agent Modeling	• ACT-R • BioWar • BLANCHE • Brahms • Construct • CORES • DyNet • INDIGO • NetLogo • NetWatch • OrgAhead • OrgCon • OrgSim • RePast • RTE • Semiophore • Sim Vision • Soar • SoarDoc • StarLogo • Swarm • TrustMe • VISTA
Representation Formats, markup languages and ontologies	• GraphML • DyNetML

A number of software tools were explored, though none were found that were purpose-built for air transportation system (perhaps demonstrating the lack of such analytical application to the ATM network practice). Table 4, from the Computational Analysis of Social Organizational Systems (CASOS) lab at Carnegie Mellon University (CMU), summarizes many of the tools available for related applications. The highlighted products are ones they identified that were used/considered in this research. The plethora of tools brought the burden to determine if any of these tools would meet the requirements for this study, or if a purpose-built tool would be necessary.

In addition to the four practical requirements discussed above, it was clear that much of the software available was "freeware", with no cost to use, and some was "open", which afforded full access to source code. The latter condition, while useful if modification would be necessary, was not deemed a requirement for this research effort if the results of the analytical portions could be verified, and the software provided the necessary analytical elements.

Clearly there is a large body of work developing purpose-built tools. Though even with the Social-network tools outlined by CASOS and all the purpose-built tools aimed at the aviation system, a toolset derived principally for use by system designers to gain insight is lacking. .

Digging deeper in the literature for transportation regional -focused tools led to TRANSIMS, "an integrated set of tools developed to conduct transportation system analyses (USFHA, 2011)" This large software suite has been under continuous development since at least 1995. It is a cellular automata model, a specialized agent variant, comprised of 4 major modules, and uses road and transit networks as well as transit schedules as *inputs*. It is clearly specialized to road traffic behavior, and does not at all meet the requirements, particularly in the utility/ease of use area. However, its use of networks as *inputs* to an *agent* environment is very much germane to this study. While the actual software was found to be far too cumbersome and specialized to roadway use to be of use in air transport studies, (Appendix C details the experience of using TRANSIMS)the general notion of the four modules was applicable: population synthesis, trip planner, route planner, and simulation.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
34														
35														
36		a	b	c	d	e	f	g	h	neighbors		posible edges	actual edges	Cv
37	a		1	2	1	2	1	3	1	4	1.571	6	1	0.166667
38	b	1		2	2	3	2	3	1	2	2.000	1	0	0
39	c	2	2		3	2	3	1	1	2	2.000	1	0	0
40	d	1	2	3		1	2	2	2	2	1.857	1	0	0
41	e	2	3	2	1		3	1	3	2	2.143	1	0	0
42	f	1	2	3	2	2		4	2	1	2.286	0		
43	g	3	3	1	2	1	4		2	2	2.286	1	0	0
44	h	1	1	1	2	3	2	2		3	1.714	3	0	0
45		4	2	2	2	2	1	2	3	18			C(p)	0.02381
46		1.6	2.0	2.0	1.9	2.0	2.4	2.3	1.7	L	1.98214			

Figure 37: Using Excel to Prepare Data for Agna

For this study, a combination of Microsoft Excel and Applied Graph & Network Analysis (AGNA) (Cognitie, 2005) were used. Excel is a portion of the Microsoft Office

Suite of products, is widely available, and can accept datasets of sufficient size to model airline city-pair offerings quite easily. In this case, it was used principally to create files in a format compatible with AGNA, and to do some simple analyses and plots of airline schedule structure. An example of such use is shown in Figure 37.

The AGNA platform was chosen because it met the basic functional requirements while also being intuitive to use. It is also free to use and distribute, making the results of this study easy to disseminate and share with subject-matter experts in the field. From their website, AGNA is described as "...a platform-independent application designed for social network analysis, sociometry and sequential analysis."

Basic city-pair information for an airline can be pulled from the OAG schedule data (OAG) or the airline's own published schedule. In matrix form, the schedule might look something like Figure 38, where there are entries in the matrix if a route (i.e. link) exists between two cities. In turn, such a matrix can be formatted as input to other analytical tools such as AGNA, or used as the basis for further analysis such as degree of separation throughout the network, as shown in Figure 39.

4.2.2 Using AGNA

AGNA installation is simple, but requires installation of a JAVA-compatible engine[c] on any platform supporting Java.

Once installed, AGNA has a decent set of GUIs, including both a spreadsheet and visual network editor interface, generically shown in Figure 40. Data in tabular form can be

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[c] JAVA Virtual Machine from SUN is available for free at www.java.com/en/download/index.jsp

imported into the spreadsheet GUI for use. Standard spreadsheet editing is also available within AGNA, though not as full-functioned as products sole-purposed for data manipulation. Standard network statistics are provided, and is also user configurable. The visualization GUI is also user configurable, and contains some tools for automating the placement of nodes based on network attributes such as centrality.

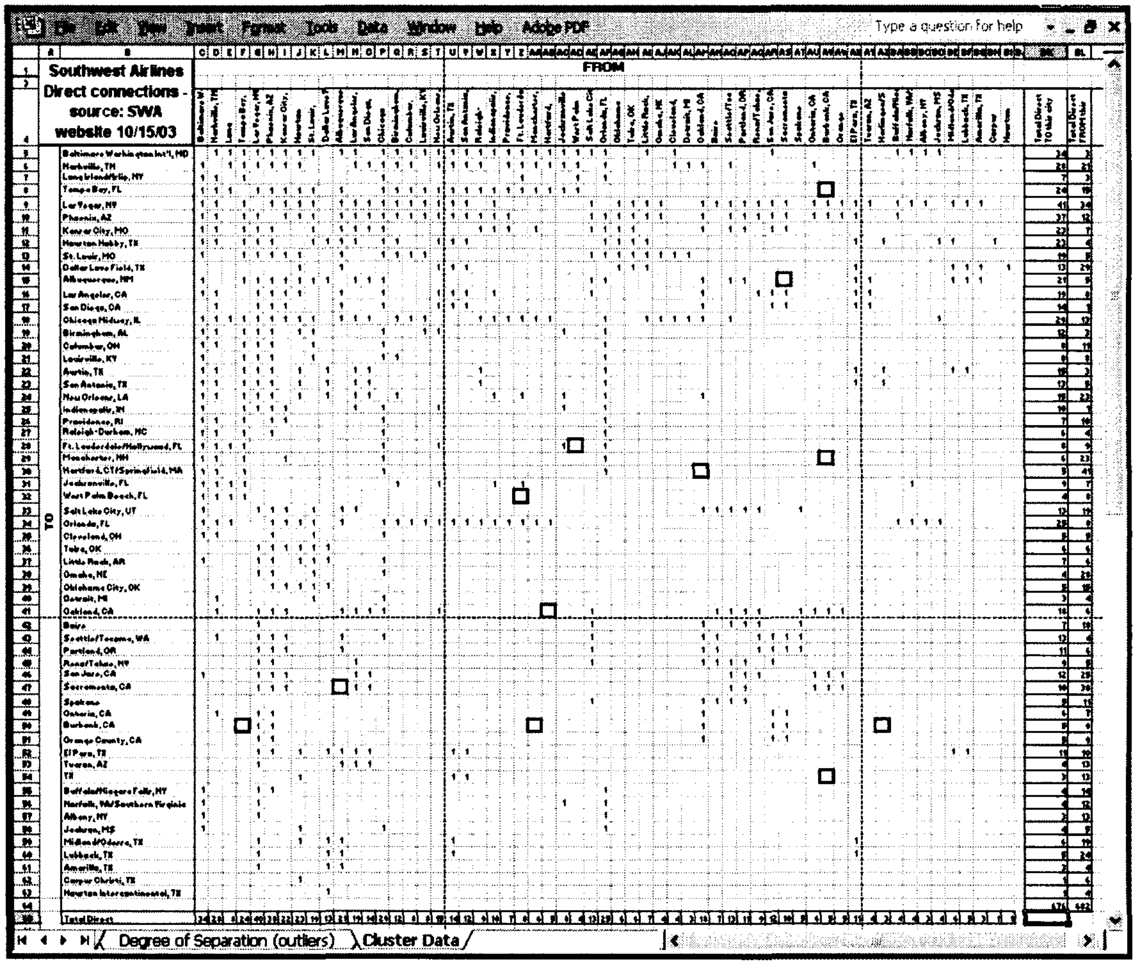


Figure 38: Southwest Airline Direct Connection Matrix

The AGNA visualization tools are user configurable as well, making it possible to manipulate the nodes to better explain the network at hand. In Figure 41 the cities were arranged roughly by their relative East/West and North/South to one another, making the larger traffic flows more clear, particularly as time was later considered (as exemplified by

Figure 71 through Figure 94 in Appendix A, a depiction of a day's worth of city-pairings in the UA network, discretized in 1 hr time-slices). Other similar tools have additional capabilities for network layouts based on statistics such as centrality, or strategies such as cyclic, tree, force-directed, or edge-weight (Smoot, Ono, Ruscheinski, Wang, & Ideker, 2011) (Batagelj & Mrvar, 2003).

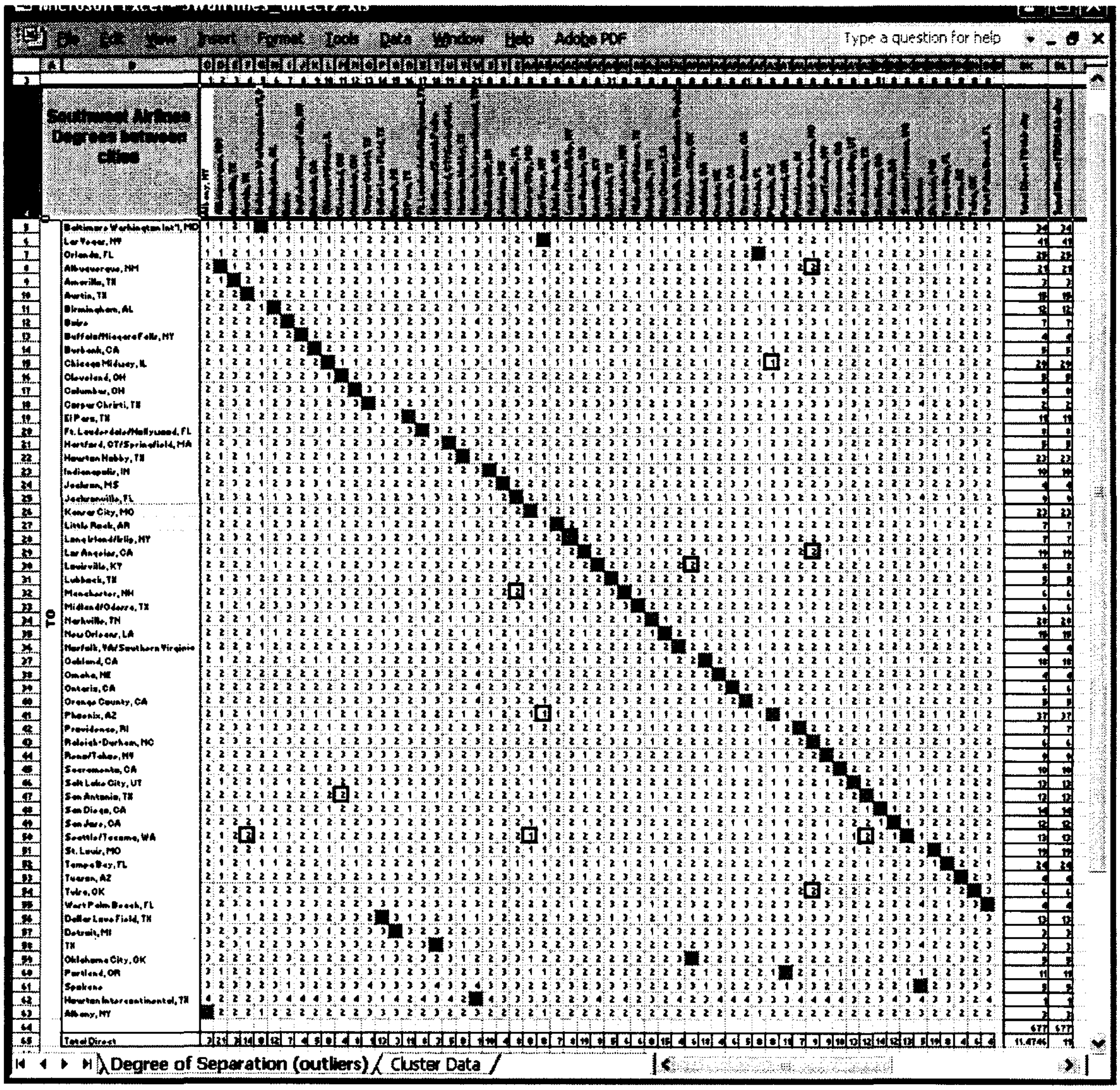


Figure 39: Southwest Airline Degrees Between Cities

4.2.3 ATS Network Models: Strengths and Weaknesses

One clear strength network models have is an ability to make large datasets easily understandable. Since ATM transformation is as least as much political as technical, such tools are essential for messaging and advocacy to constituents.

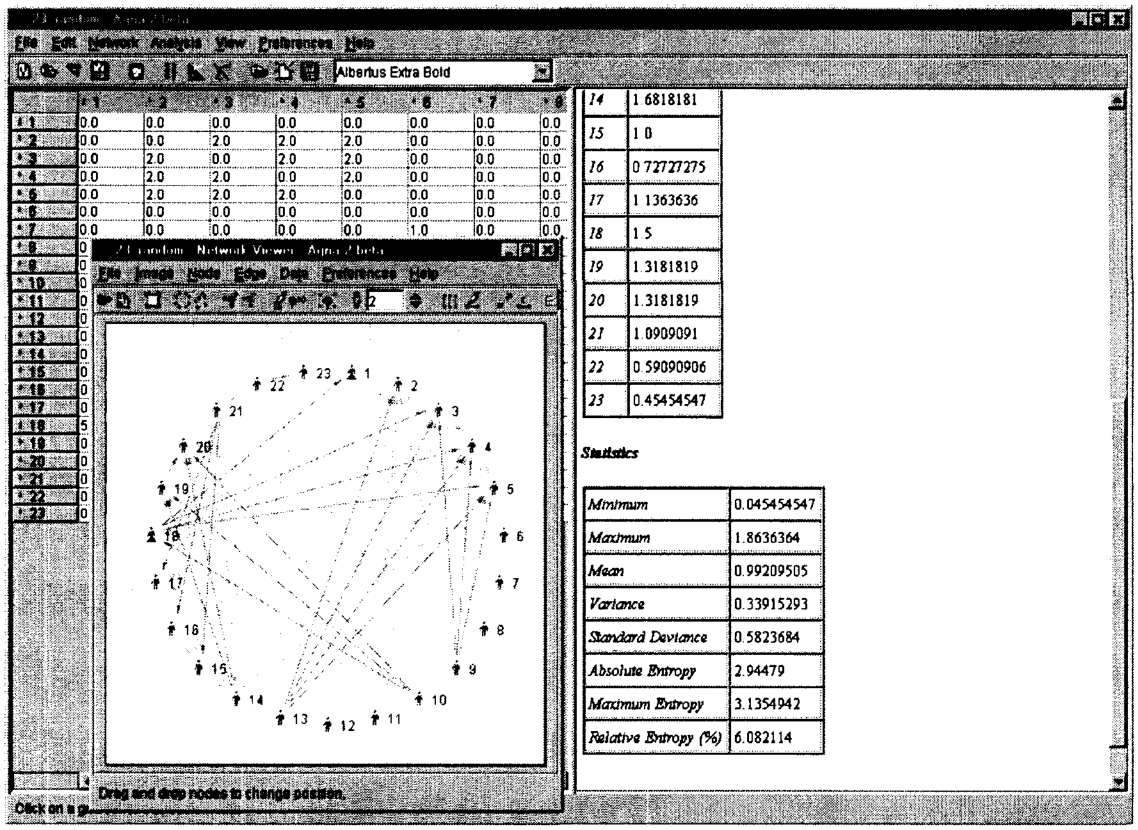


Figure 40: AGNA and Its Graphic User Interfaces

However, even network models themselves sometimes need context to make them visually compelling. Take for example the next two figures (Figure 42, Figure 43), depictions of the Southwest Airline city-pair routing. They have the identical number of links and nodes: The geographical context provides organization for the observer, simplifying their view of the network. It is an important feature of network depiction as it can provide organization to complex and/or extensive systems, making them more easily understood.

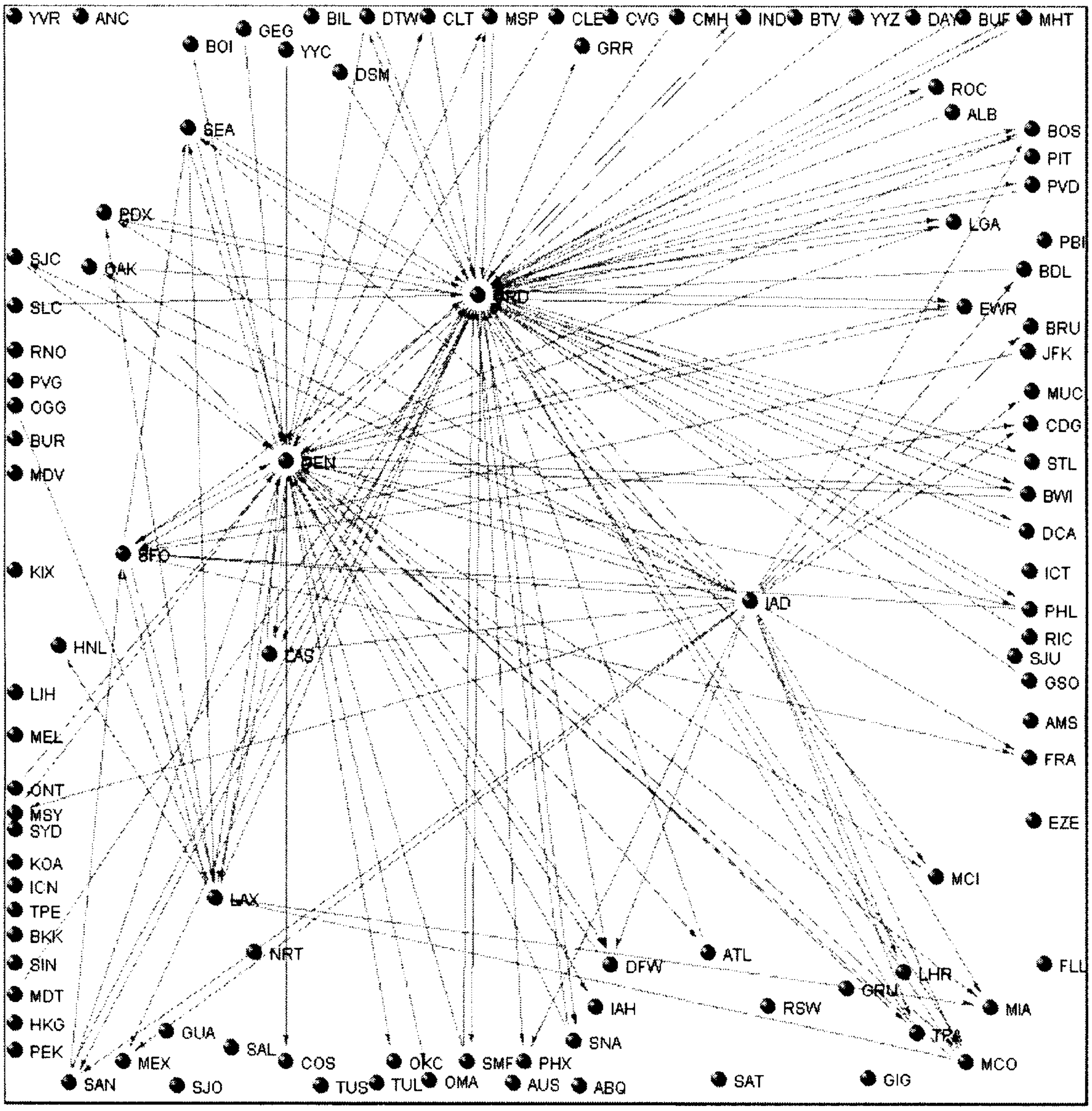


Figure 41: Typical AGNA Network Visualization output

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.

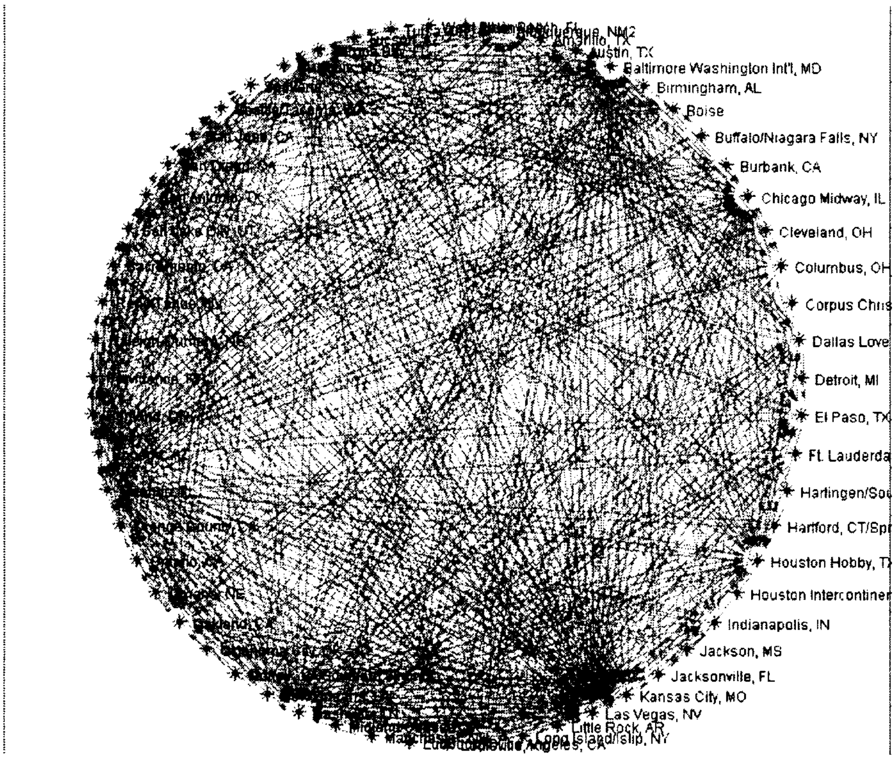


Figure 42: Southwest Airlines City-Pair Network

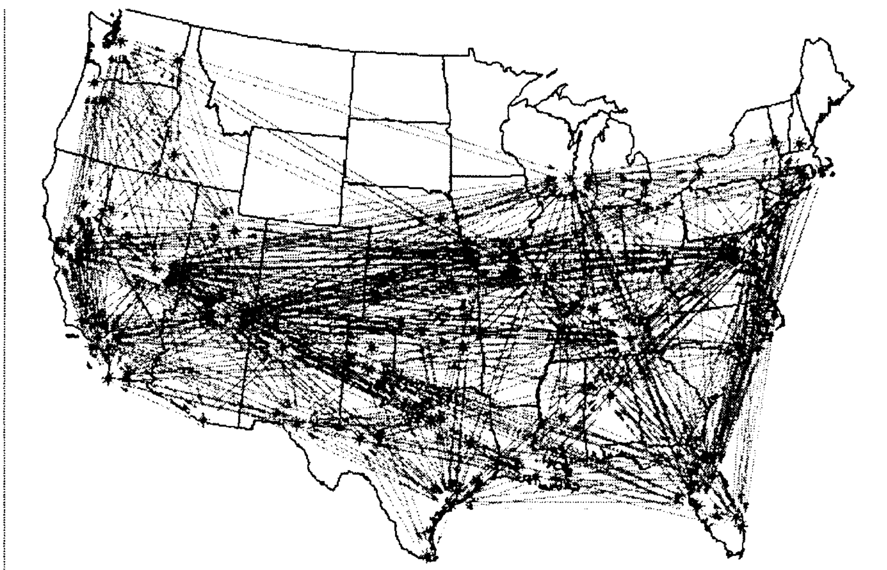


Figure 43: Southwest Airlines City-Pair Network in Context

Addressing the network route structure vs. yield problem, Brueckner et al (Brueckner, Dyer, & Spiller, 1992) 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. Congestion at the hub is clearly a limiting factor to a single-hub operation.

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 (Nicholson & Burns, 1997)and others (Conmy, 2002) 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 network model methods can apparently help determine margin from full capacity in a rigorous manner to help generalize a network's ability to gracefully respond to partial failures.

The downside to such multi-hub constructions is vulnerability to disruption. Networks with hubs that have a high probability of experiencing problems are also likely to proliferate 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 disruption (Hoekstra, 2001). Again, network analysis methods can help educe these system attributes quite quickly.

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 (Strogatz, 2001). 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 cannot properly capture the dynamics of the system.

Perhaps the most serious issue in air transport network modeling is the treatment of time: Time must be accounted for because the most of air transport-related networks change during the course of the day as a result of the intermittent nature of flights. Unlike a network of pipes or wires, or even roads, city pairs in air transport networks are not continuously connected. In fact, they are very sparsely connected with only a few opportunities a day to be linked (Figure 44, a segment of United's schedule). This is also true for many of the network structures identified in air transportation.

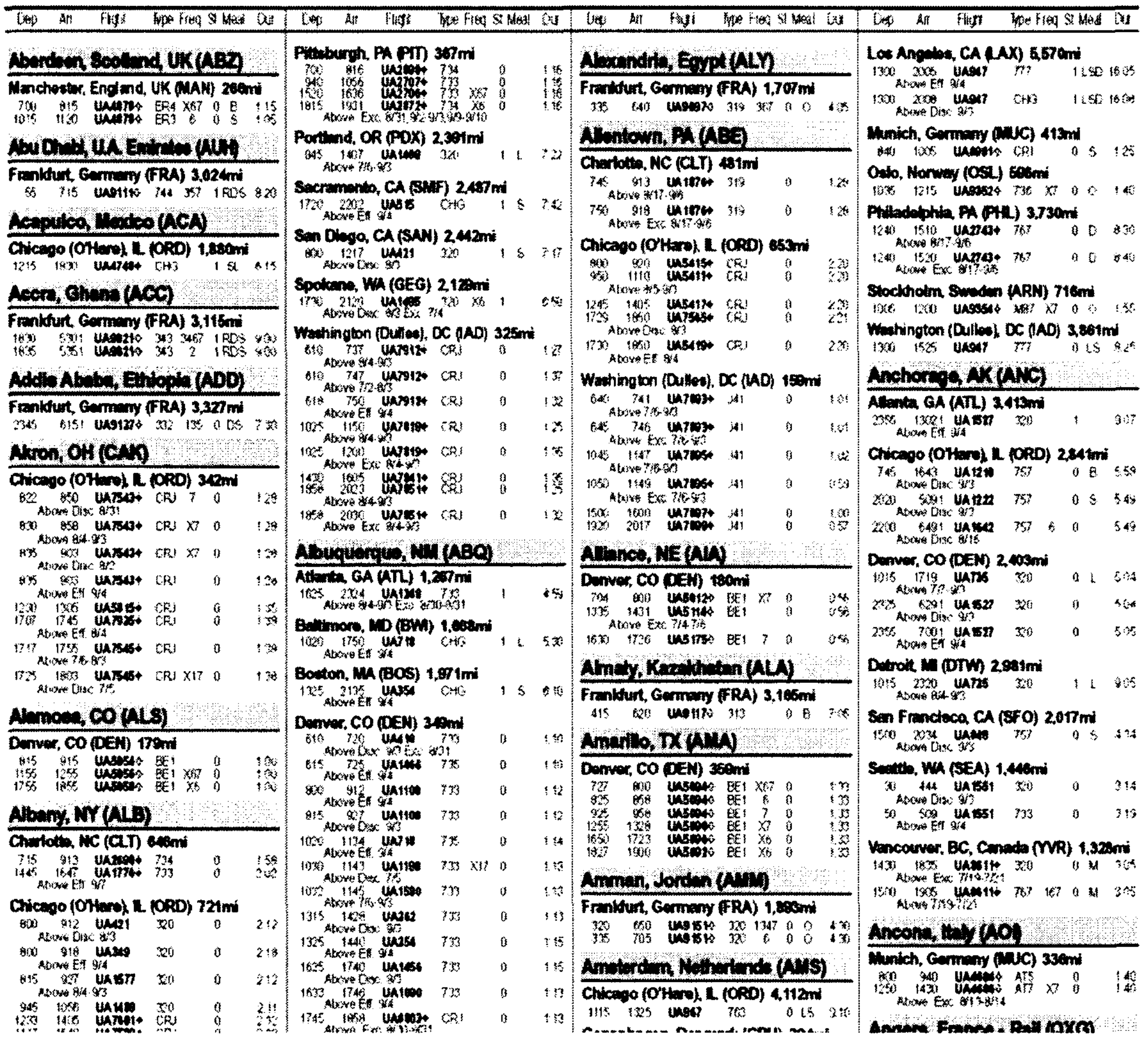


Figure 44: United Airline Flight Schedule Segment

Of course, it is also important to look at this dimension within context itself. For example, Figure 45 shows all the flights operated by UA at a particular time of day, organized by originating city name (alphabetically). Each square and X symbol represent a departure or arrival respectively. At any time of day, read across a row, the chart depicts the operations scheduled for that hour. In this figure, you can clearly see busy times of day per city, and if/when they operate a "rush" or concentrated period of operations for a hub.

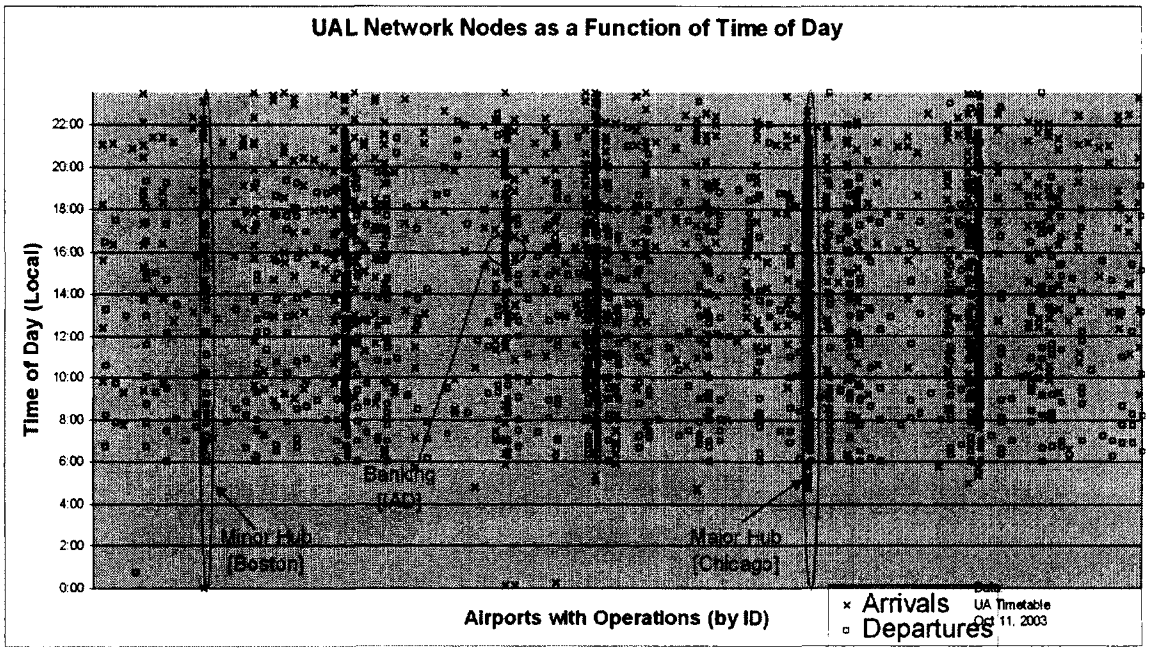


Figure 45: UAL Networks as a Function of Time of Day by City

However, different organization of the same data can reveal systemic behaviors. Figure 46 is the same city-pair data, but it shows the operations by their time of arrival/departure, organized across the chart by the airport's time zone, moving westerly to the left. The movement of the fleet across the country and internationally to Europe and Asia can be seen, as well as the relatively quite period in the middle of the night in North America. Also evident is banking of flights at the hubs during a number of peak times. The boxed areas show two different effective network structures in the same airline, dependent on the time of day considered.

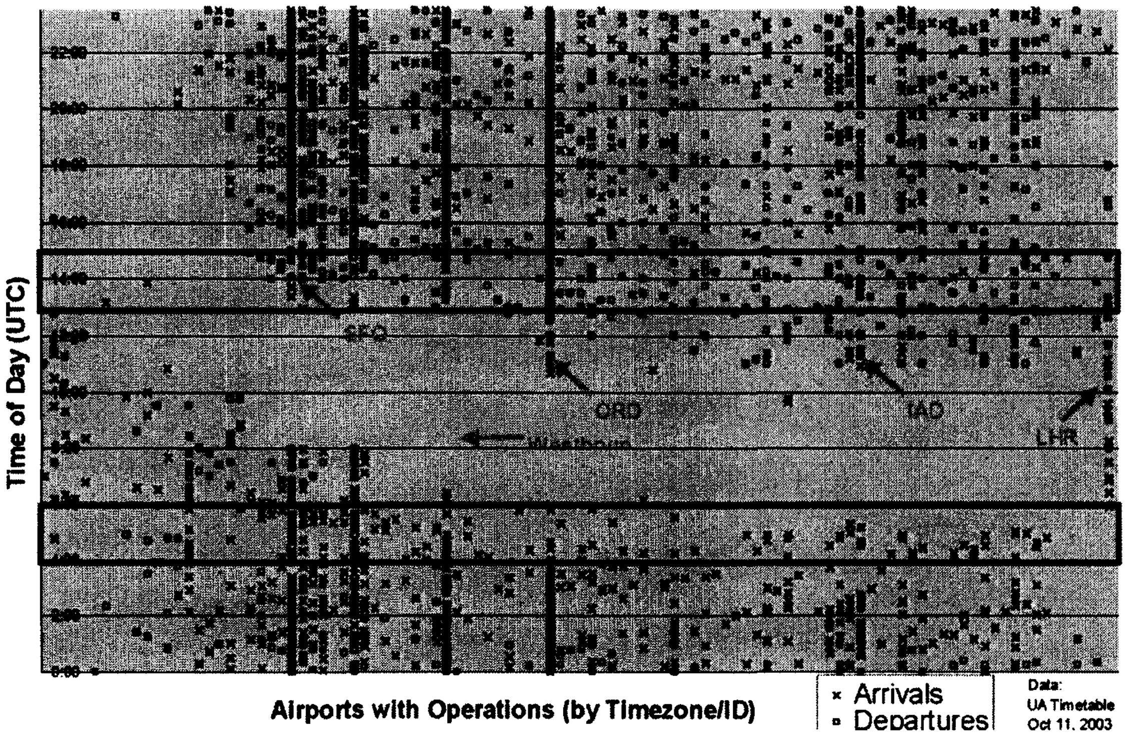


Figure 46: UAL Network as a Function of Time of Day By UTC

Pictures of these two different arrival networks might look something like those in Figure 47, plotted with AGNA's network visualization tool. As you might imagine, the numerical network attributes of these two networks are very different indeed. For network analysis to be useful operationally, the changing nature of the network over time has to be captured. In an attempt to characterize the changing nature of the United network in time, hourly depiction of city-pairs with arrivals in that time period were created and analyzed. The networks themselves are shown in appendix A. When put in motion as a cartoon or flip chart, these figures really show the flow of traffic through United's network of city offerings, and their intermittent nature.

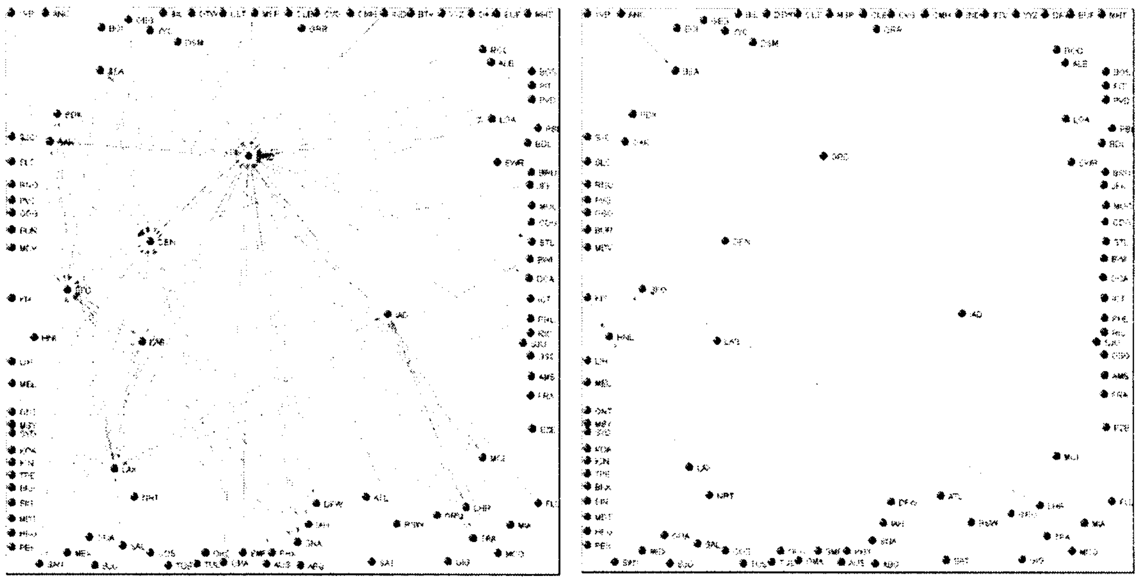
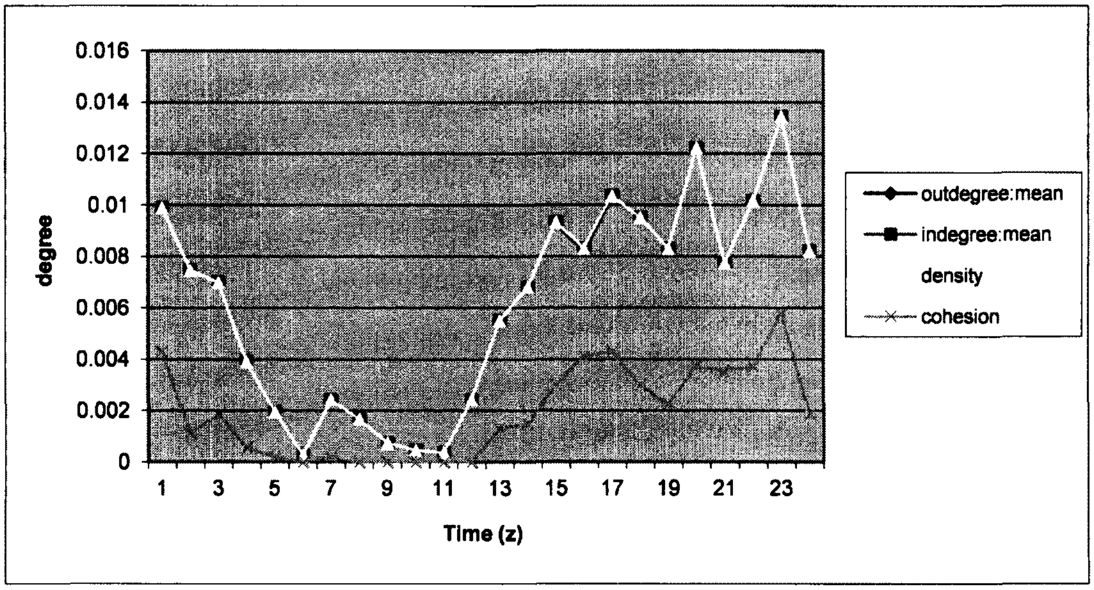


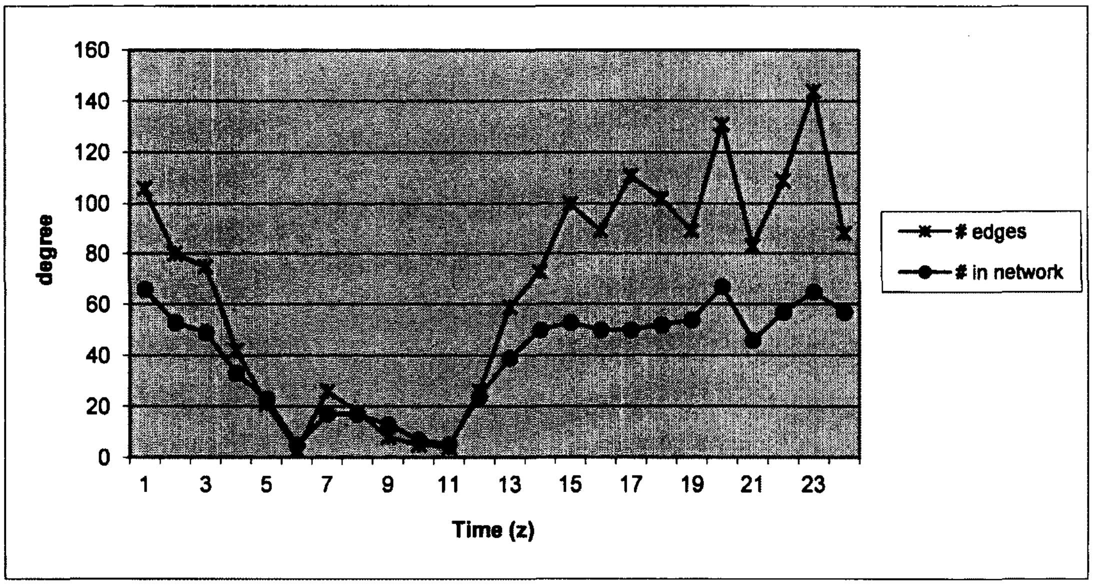
Figure 47 a&b: Different Time Slices of United City-Pair Network

These networks can also be shown to have significant differences in the measurable attributes. In Figure 48, plots of these hour-wise UAL city-pair networks clearly change as a function of time. These measures, common to network thwory, suggest periods of reduced network efficiency and susceptibility to delay. The two measures of degree, "in" and "out" make a distinction between inflow and outflow from a node, or in this case, arriving and departing flights. Closely related is density, defined for such a binary network as the proportion of all possible node connections that are actually present. Also shown is a measure of cohesion, or the number o f mutual connections in the network divided by the maximum possible number of such connections. It may not be intuitive that if you are to consider discrete time slices over the course of the day, arrivals and departures are not matched evenly, but rather follow such patterns. These trends are important for many different aspects of an airport operation, from air traffic management to how many attendants are working at a particular time at the parking garage.

In the third plot in Figure 48, the Freeman Coefficients (Benta, 2003) (Benta, 2005) are shown as a function of time. The Bavelas-Leavitt or B-L centrality coefficient measures the distribution of information within a network by characterizing how many nodes are connected to others, or which cities are accessible by non-stop flights and perhaps how many. Other measures of centrality are closeness- the inverse sum of the distance of each node to all others, and betweenness-the sum of the ratios of the number of paths between all pairs of nodes and paths that connect these pairs through another node. The plot shows substantial changes in these metrics over the course of the day when the city-pairings served within hour time-divisions are considered to be representative of this transport network.

It is clear from these data that aggregating the behavior of airline networks as a single daily snapshot may be misleading: Such analyses will allow us to manage this issue more carefully: some strategies include tactically applying schedule controls at times when the networks have statistics of concern like extreme nodal centrality, or more strategically creating a means to level the network and presumably improve performance. Rolling hubbing (Wu, 2010), a practice of spreading the peak demand to off-peak hours partially addresses this operationally. If these network statistics were correlated with performance metrics for delay, such a time-based analysis of the schedule could help plan effective rolling hubbing to ensure that threshold values were not scheduled to be exceeded. Of course, the airlines must trade reducing hub congestion with increased connection time for passengers.





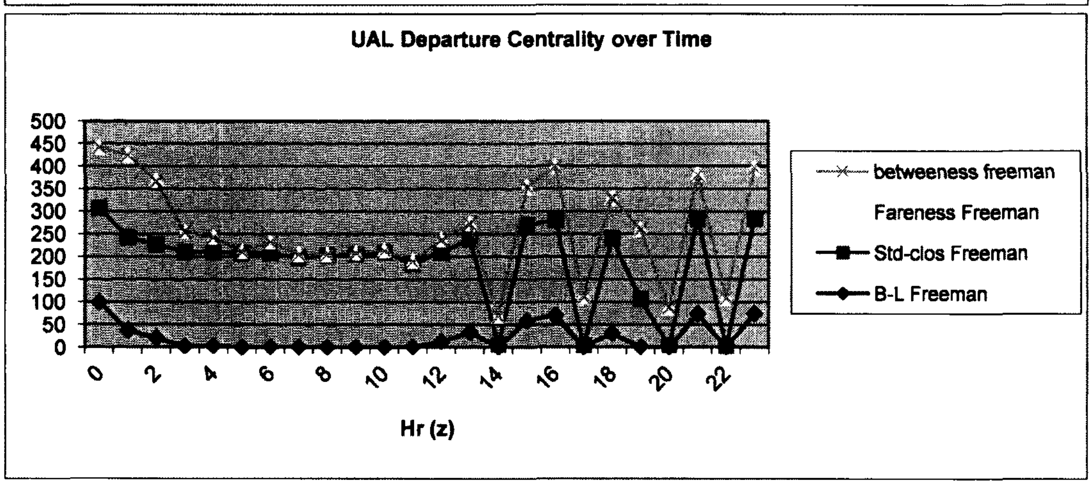


Figure 48: UAL Network Attributes as a Function of Time

4.3 AGENT-BASED MODELS: TOOLS AND TECHNIQUES

Just like in network modeling, a key requirement in developing the agent model was to focus effort on how to capture salient attributes of the system, this time with an agent-based description of actors and communication links between them.

The basic agent-based model includes primitive versions of all the principal air traffic system attributes alluded to in the literature, namely system capacity, demand, and aircraft capability, and affords a venue to explore their interdependence in a time-dependent, dynamic system simulation.

4.3.1 Agent-Based Models

There are many agent-based platforms aimed at a wide array of modeling audiences. One of the fundamental requirements for platform selection was ease of use. As discussed in Section 0, one objective of this research is to make modeling accessible to operational experts so they themselves can explore alternate traffic control schemas against various environmental and other exogenous factors. Since agent modeling requires "programming" or assigning behaviors to elements of the model, the language should be as familiar as possible to those subject experts asked to define the behavior. Additionally, open source and/or freeware make this software more portable and easier to disseminate to a wide audience of experts.

Purpose-built agent models of transportation systems tend to focus on emulation of "real-world" issues. For specific applications, such as road improvements or aircraft gate reassignments, software suites such as *TranSims* and *VAST* can be useful. However, they can also quickly get very cumbersome to use, and a system designer can quickly get lost in the details. Without insight into how these models are constructed, it is hard to tease out first order effects from minor ones, and which elements of the models are truly limiting and/or controlling.

One of the key elements of modeling is the exercise of *building* the model. Agent models considered for this study were oriented to the modeling portion of discovery.

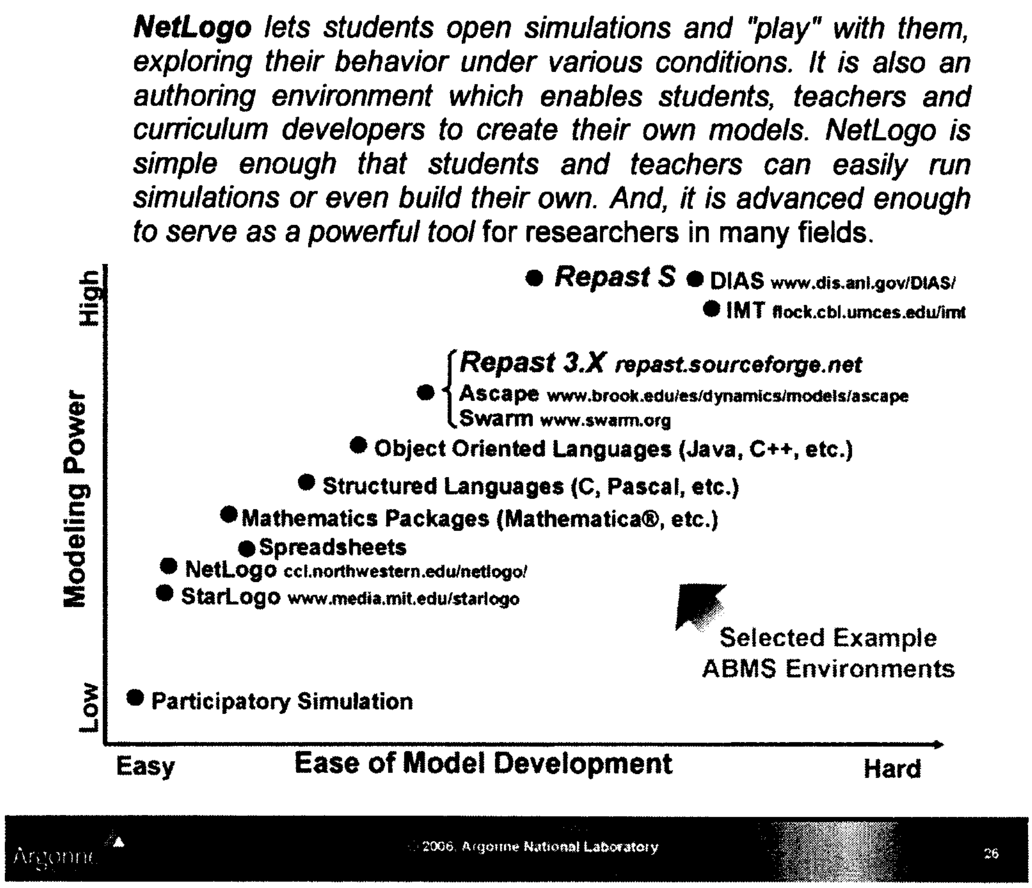


Figure 49: NetLogo and other Agent-Based Tools (Macal & North, 2006)

Table 4 showed a wide array of general agent models as well as some specialized for social interaction research. Of the general ones, there are some, like NetLogo and StarLogo that fit the bill for ease of use. NetLogo is intended to be easy enough for kids (should be easy enough for Parents maybe) to learn computing and agent modeling, and has a relatively intuitive Graphic User Interface (GUI). It seems Macal and North (Macal & North, 2006) agree, as they rate NetLogo as easy to use, but limited in power as shown in Figure 49. However, they had limited analytical capabilities in their standard tool set. In recent years, this limitation has been alleviated by a link to Mathematica (Wolfram, 2012), a very powerful commercial analytics package. Netlogo has improved recently, and may prove to be a very useful tool in ATC development. Their web site indicates that the intent of the software is to address the need to explore systems (NWU, 2011):

An appealing alternate to NetLogo was the Recursive Porous Agent Simulation Toolkit (RePast, 2011). The Repast Suite is a family of advanced, free, and open source agent-based modeling and simulation platforms. One of the attractive elements of RePast is that the basic functions have been hosted in a variety of platforms. One of the more simple languages, Python, met the requirements for access and ease of use to non-hacker types. As a partially graphical front-end to the more powerful C++ based version, RePast Py affords a serious analytical tool and access to C++ libraries of scientific utilities without having to spend a tremendous time writing basic simulation code. It exploits a "lite" version of Python which is intended to be a "natural" programming language in that it supposedly resembles English language commands. RePast is well documented and training courses and support are available (RePast, 2011).

4.3.2 Modeling the System

Before any coding could begin, the system was modeled to capture its salient elements without adding unnecessary complexity. A simplified version of the system of interest was determined to be a series of arriving and departing flight agents at a capacity-constrained airport, and exploring any queuing that occurs because of an imbalance between demand

and capacity. Schedule uncertainty caused by such elements as weather diversions, winds, baggage, etc must be accounted for. This is a reasonable, yet still simple model of airport flight operations, as there is an intrinsic capacity limitation caused by wake turbulence separation and collision avoidance requirements.

The first step was to develop a "schedule" for these flight agents from which to measure delay. Like actual flights, the simulated flights must be operating to a scheduled time, or in this case, a slot. Rather than attempt to recreate demand profiles from actual schedules, or from first principles of traveler preference (like TranSims), the demand on the airport is a generated by use of a series of simple variables, as is the airport's modeled intrinsic capacity to manage flights. This allows the designer an opportunity to test their control strategies against a variety of demand and capacity profiles, ensuring a robust solution and reducing errors associated with solving the wrong demand problem. Of course, actual schedules and airport capacities can also be used as input to the model for validation purposes.

The model simulates commercial airline demand at a busy airport with a simplified hub-and-spoke route structure. It is comprised of a series of 'rushes' or 'banks' of flight agents[d] operating in or out of a hub airport facility (Figure 50). Both the demand (average number of agents or flights per unit time, e.g. nominal bank size, n) and the facility capacity, C_{max} are controllable.

At each time slice in this discretized model, agents with a scheduled use time matching that time slice will "request" service at the facility, representing a bank of flights for that time t. Nominally, the flight will "operate" or pass through the queue as long as the capacity of the facility has not been exceeded. If for some reason demand at that rush (time) exceeds

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[d] Emulating either arrivals or departures, but regardless, consume 1 unit of facility capacity in the model.

capacity, the flight is rescheduled to a later time and is put in a holding queue. The difference in the originally scheduled time and the actual service time, when it is pulled from the holding queue and sent on its way, is captured as delay.

Flights could also be delayed for other reasons. This model makes no attempt to reason why a flight was delayed, but only to address the consequence, so delay can be captured by a simple probability. The purpose is to demonstrate how much schedule uncertainty the airport can tolerate before it begins to build substantial delays.

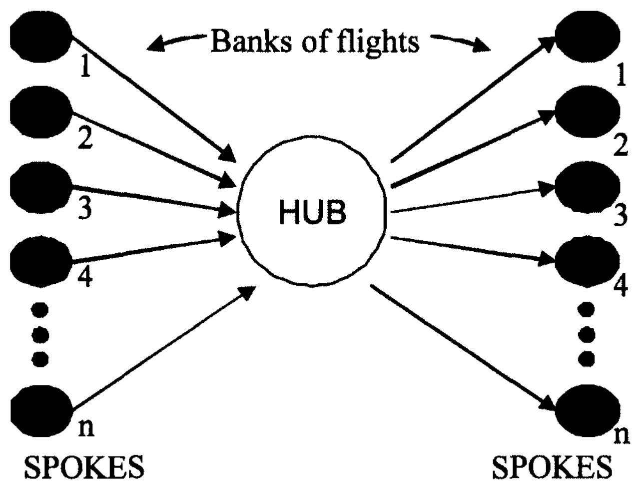

Figure 50: The Agent Hubbing Model

After an initial round of modeling, the behavior of the simulated system was observed to be more stable than that of a real hub-and-spoke operation: Delays were absolutely predictable based on a linear ratio of demand and capacity, even with the inclusion of random missed slots. It seemed some major effect was missing in the model.

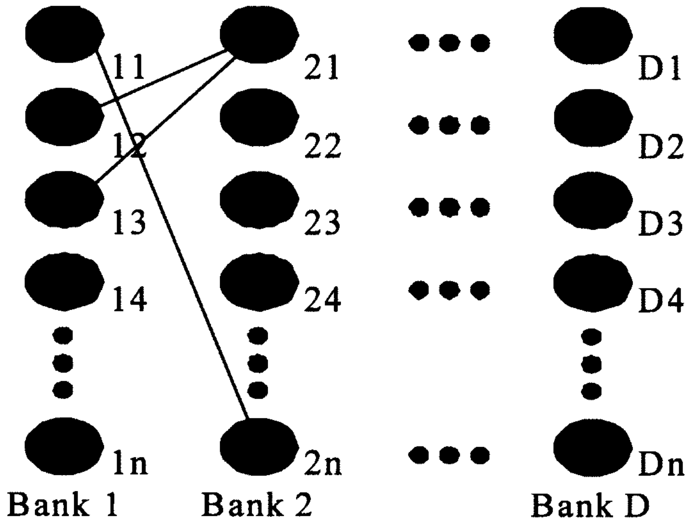

Figure 51: Flight Dependencies

A potential contributor to the dynamic behavior seemed to be an airline's linking of one flight to another in a previous bank (by crew, equipment, connecting passengers, etc.). To capture this effect, flights in banks 2 through D were assigned an average of k dependencies with flights in a previous bank. For example in Figure 51, a hypothetical model schedule, the first flight in the second bank (t=2) would not operate until the second and third flights scheduled for the first bank (t=1) have been served. This simulates actual dependencies such as equipment that must be used for a stop-over, gates that must be cleared before another flight can operate, or crews or passengers transferring from one flight to another. In fact, with all these factors taken into account, a flight is likely to have many dependencies. The model allows the capture of the most important three, and could be randomly or heuristically assigned.

The ability for individual flights to operate on schedule could also influence a scheduled system's behavior. In practice, there are many reasons why a flight may not operate on schedule beyond those caused by air traffic service delay. Regardless of the cause (e.g. late "push" from a gate on departure or weather causing a late arrival), the net effect is that the flight misses its slot. The next slot becomes the earliest this flight can then operate. This model emulates the effects of these schedule anomalies by sliding a flight's schedule with probability P.

4.3.3 Using RePast

With these abstractions of the system in hand, coding the simulation was relatively straightforward. REPAST PY (North, Collier, & Vos, 2006) was selected as an appropriate platform, providing a quick way to create the simulation environment with minimal coding overhead (including batch capability, data logging and visualization).

Using Repast PYrequired becoming familiar with an object-oriented C++ compiler, the RePast Libraries of subroutines, and a simplified version of the programming language Python, Not Quite Python (NQP) which is used to give the agents in the simulation behaviors. More details on the software, platform, and using RePast in Appendix B.

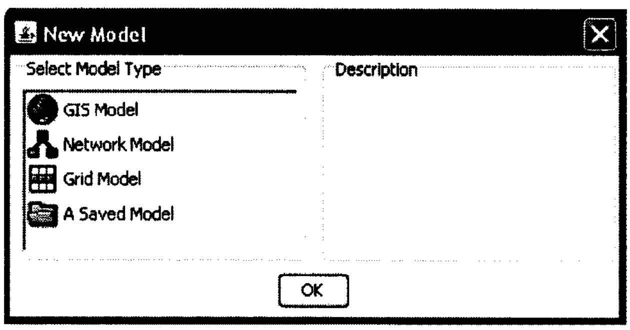

Figure 52: RePast New Model GUI

RePast Py provides three types of pre-defined models, either GIS (map-oriented) models a network model or a grid model (Figure 52). The first decision was the form of the model: with the relationship between networks and agent models for ATC, it might seem logical that a network model form was chosen. However, the graph model provided a means to capture the system-of-study, a queue of scheduled flights in discretized time, and visually demonstrate how these demands were met . Though it doesn't have the physical appearance of flights traveling across a network, it best represented and captured the behavior at this single airport very well, and served as a historical record of service and efficiency. The grid was set up to depict the demand for service at each time slice: Each column was sized to represent the maximum service capacity of the facility. Then flight agents were scheduled against this capacity constraint and queued in the column. In this research, no time slice was allowed to have an original schedule that exceeded capacity. However, as this is common practice at some facilities, this condition could also be easily considered.

Once the model type is selected, the basic development environment appears (Figure 53), where actors are created, simulation elements such as graphs and grid displays can be added, and links to other windows where actor behavior can be defined are found. This window also provides controls for model storage, compilation and run commands.

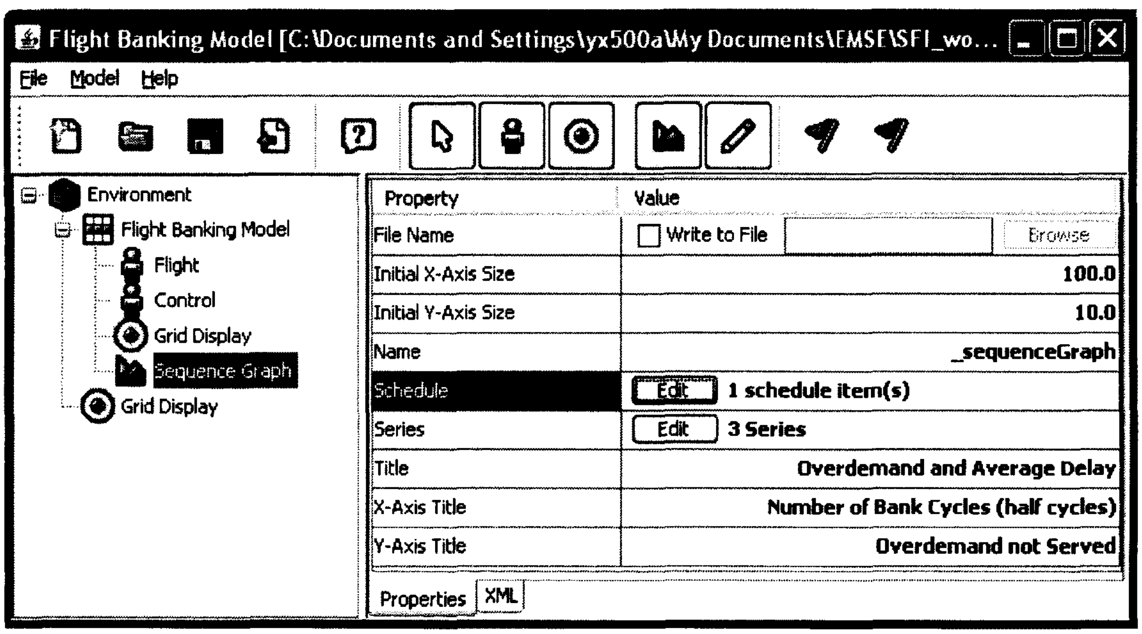

Figure 53: RePast Main Gui

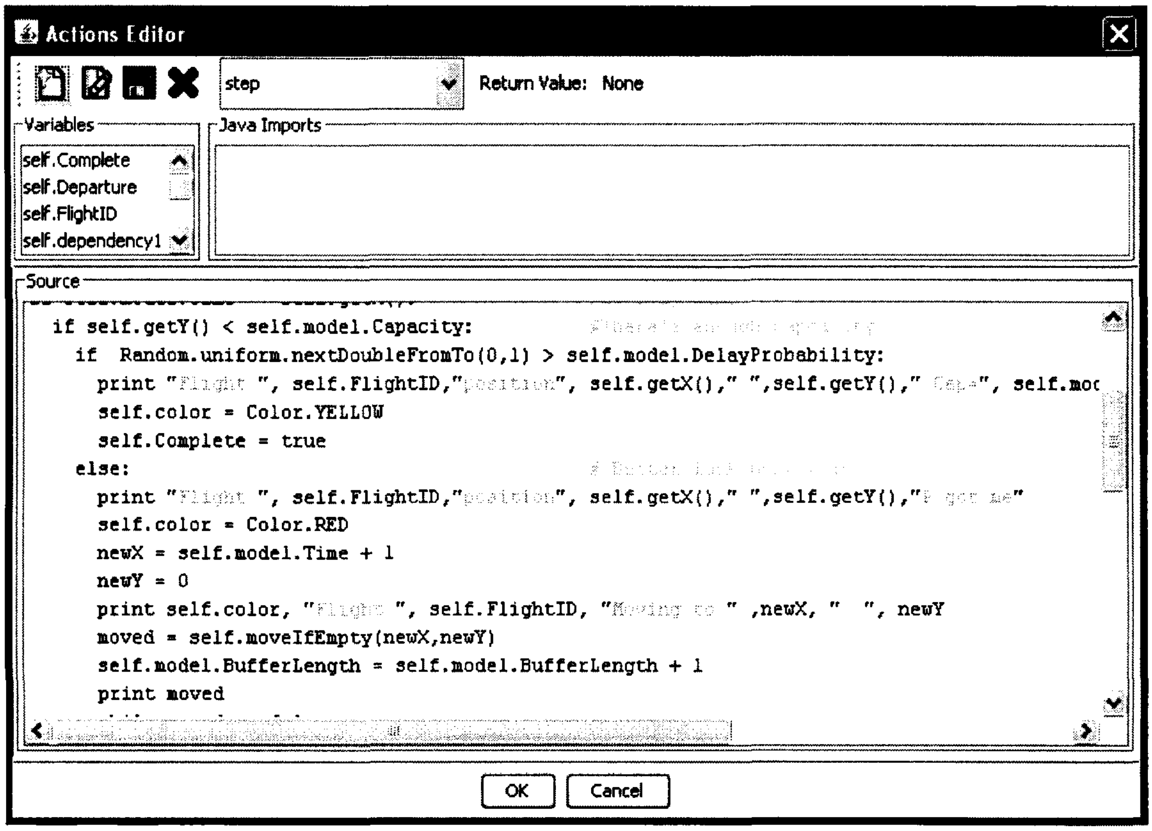

Figure 54: RePast Actions Editor for Agent Behaviors

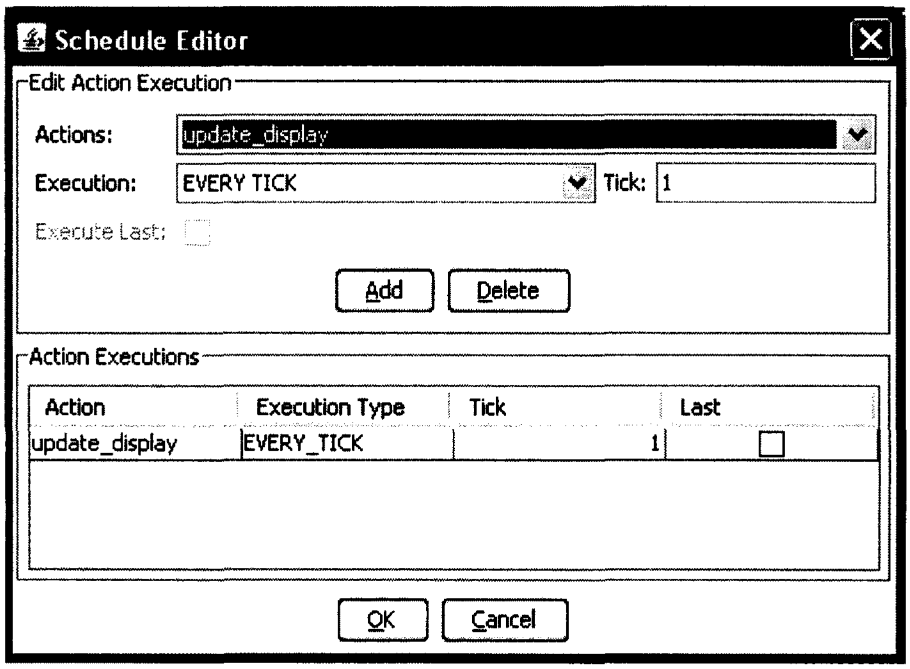

Figure 55: RePast Schedule Editor

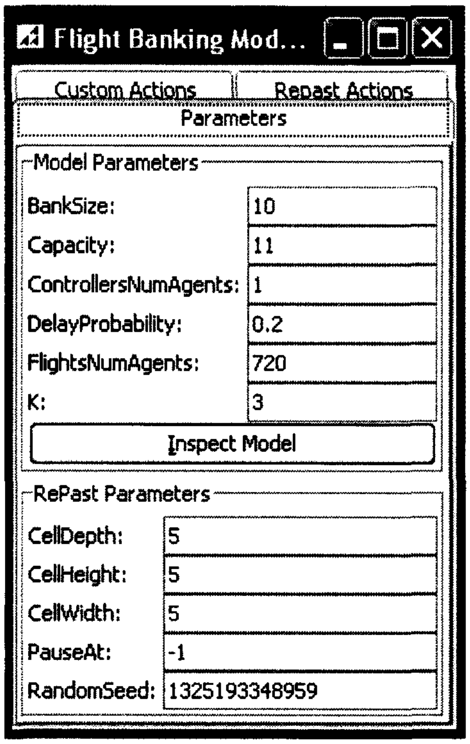

Figure 56: model Input GUI

Each actor's actions are created in an Actions Editor which is accessed from the main window (Figure 54). In the Schedule Editor (Figure 55), Grids and graphs are also assigned actions dependent on the modeler's needs for event-sequenced or regular capture of movement and data recording.

A selectable number of flight agents per bank, were initiated according to their nominal scheduled (time slot for operation). Using k, dependencies to operations in the previous bank were also assigned at initiation using the Input GUI (Figure 56). In this manner, the network of flights and their relation to each other was created a priori.

Before running the simulation, the grid representing the planned flights and their schedule look like Figure 57. In this example, each time slice has 10 flights, while the facility capacity is 11 operations per time segment. To distinguish the banks visually, each other one is colored differently.

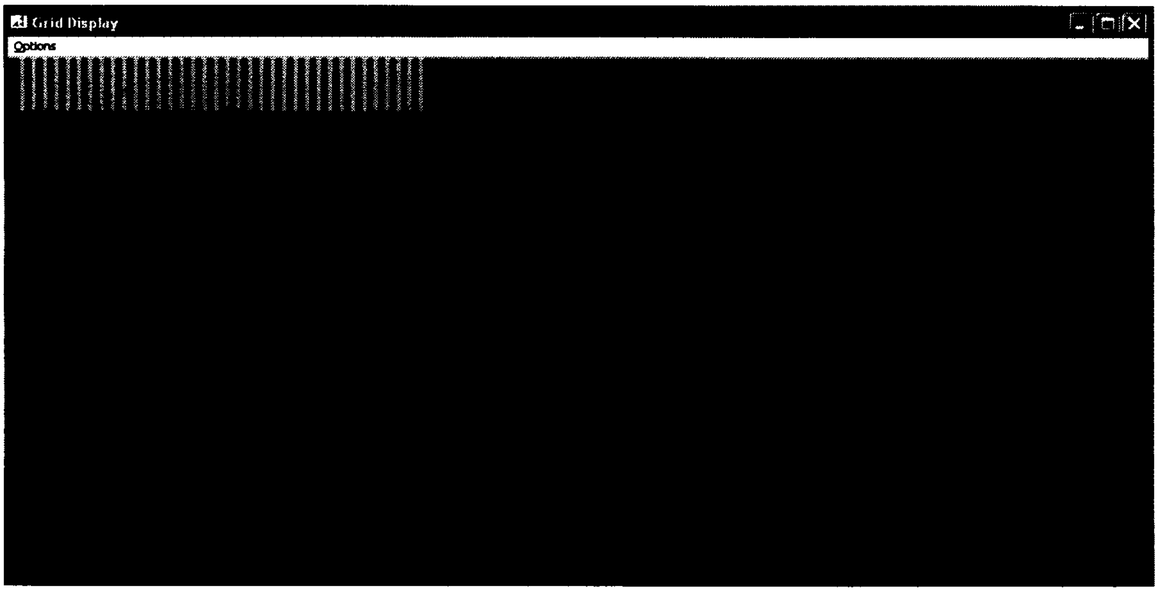

Figure 57: Planned Banks of Flights – At Initiation

During the simulation, advancing time was represented by servicing of the next bank or block of flights, i.e. indexing *t*. Each flight agent checked its scheduled operations time vs. the current bank as well as the disposition of its dependencies (if any). Assuming all dependencies had been previously served and they weren't randomly selected to miss their slot (*P*), flights 'operated' (dropped off the service queue for that rush and were marked yellow as "operated") until the capacity of the airport was met. Any remaining flights in the bank were rescheduled for the next bank and their color changed to highlight them visually as shown in Figure 58, a snapshot at time slice 9.

Also depicted in Figure 58 is a record of which flights in the previous bank were served (in yellow) and holes where flights were either randomly selected to be delayed or were held back because their dependent flight in a previous bank had not yet been served. Also shown is the building queue well exceeding the capacity for the next time slice, made of the currently-scheduled flights as well as delayed flights (in red). Figure 59, is a snapshot, later in the same run, of the queue length (red circles), average delay time (blue X), and max delay (aqua squares) metrics as they are being recorded by the RePast data logger.

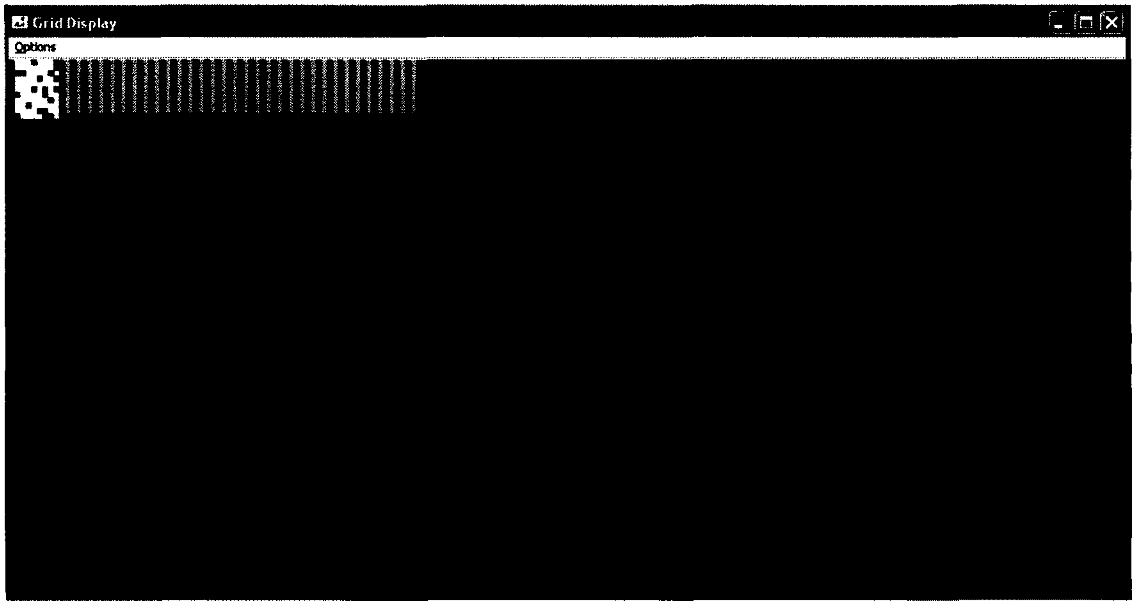

Figure 58: Service Record of Simulated Flights

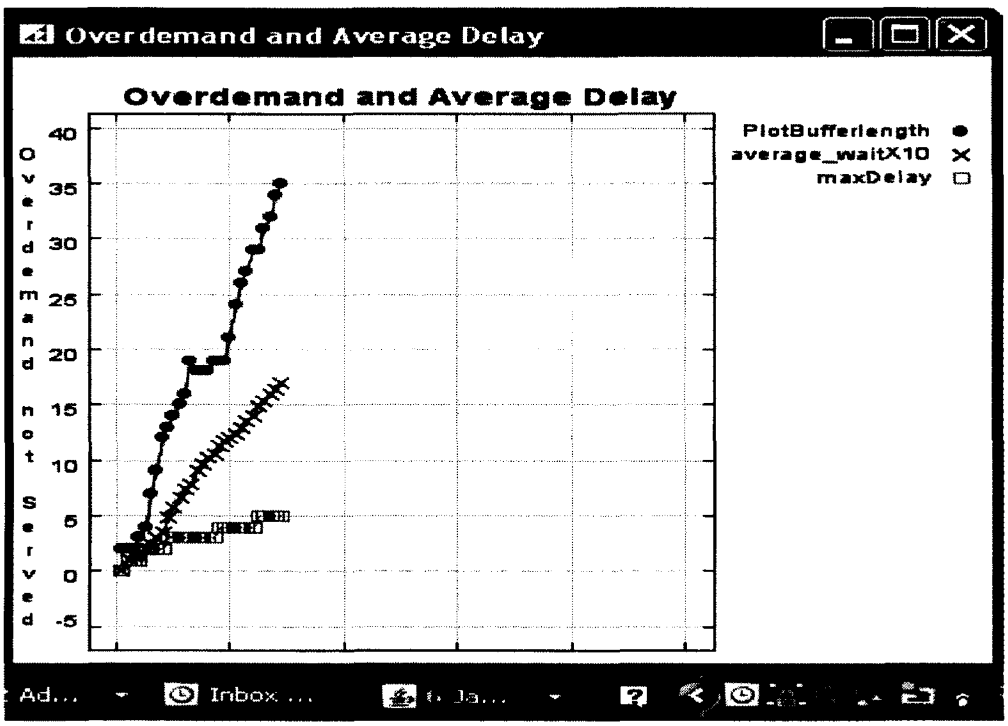

Figure 59: System Performance Metrics

4.3.3.1 Experiment Design

To test the utility of such a model to gain insight on control strategies and their dynamic effect on queuing, three different strategies to clear flights within the queues were created; original schedule followed by rescheduled or delayed flights, earliest scheduled flights first, or random draw. The agent behavior was modified to reflect each of the strategies, and the results judged for the change in system behavior.

A full-factorial designed experiment was conducted to explore the effects of the user-defined variables and their interactions. Results consisted of metrics related to service quality; average time in queue, max time in queue, and the max number of aircraft waiting for service.

4.3.3.2 RePast Modeling Results

The model yielded both expected and some surprising results. In some configurations, delays grew to a certain level and then remained relatively constant: it seemed that in these scenarios the system had the ability to manage temporary, small spikes in demand In other instances, delays grew seemingly unbounded: once a flight with substantial "centrality" was delayed, the dependent flight also became delayed, and the system had insufficient bandwidth in capacity in any time period to recover. Interestingly, even without inter-flight dependencies, the inclusion of delays of certain flights could cause instabilities: instances where delays seemed stable, but then would suddenly grow quickly. For example, in Figure 60, compare the first 15 cycles in figure 3 with the subsequent response: the change implying a delay threshold condition was exceeded from which stability was not recoverable. Even without flight dependencies, note k=0 in this run, this non-linear behavior is witnessed. The importance of flight dependencies as well as the heuristics used to clear the queue became obvious, as discussed below:

An important goal of this research was to demonstrate the ability to investigate the system from different perspectives. Network modeling required building new networks. Agent modeling required using different parameters, and metrics, though the actors can be the same. For example, from a facility perspective, where flight dependency is less of a factor, the model can simulate their interests by simply zeroing the flight dependency parameter. In this way, service of each flight at the facility is basically independent of the other. This allows the investigator to consider capacity vs. demand from the ATSP perspective. From the airline perspective, schedule integrity, not average schedule adherence is paramount: if an outbound flight is otherwise ready to leave, but it's flight crew is on a delayed inbound flight, their operation is disrupted or stalled.

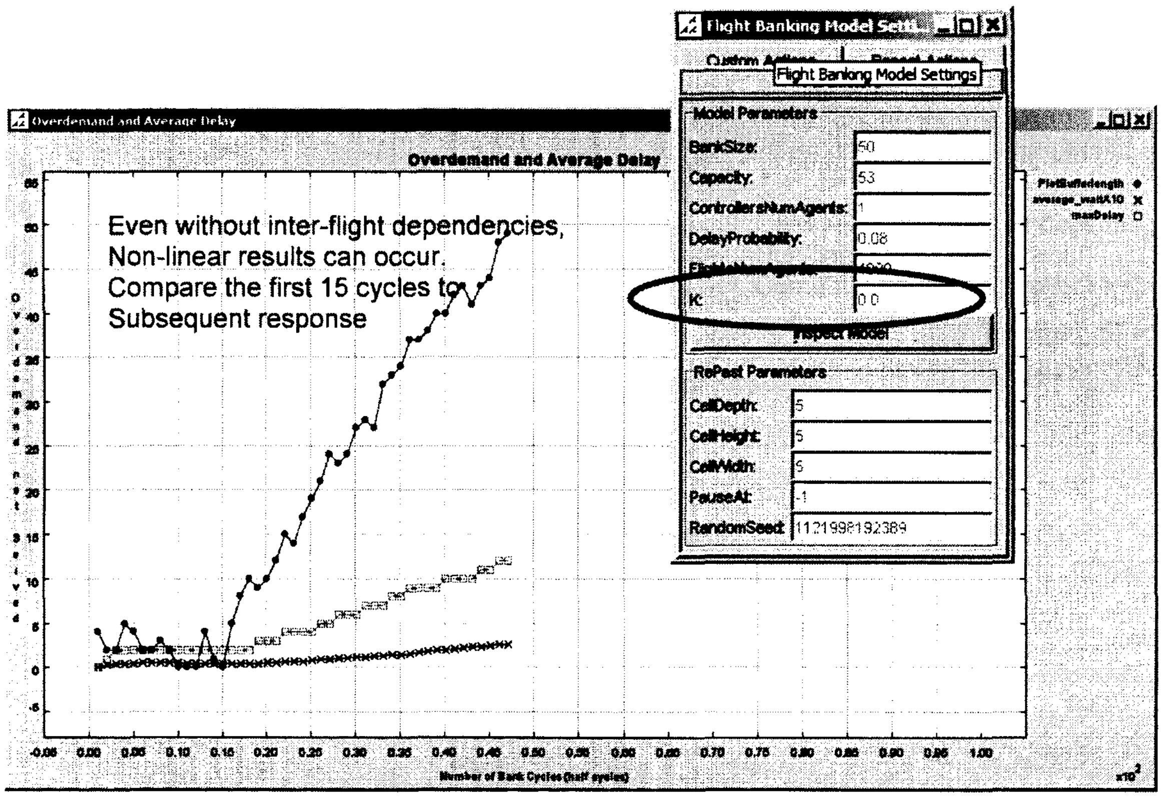

Figure 60: An Example of Non-Linear System Behavior

Using these simple modifications to the model, it seems possible to build some rules-of-thumb about service provision: When flight dependency (k) is zero, such as it is from the ATSP perspective, observing a number of runs showed that the model predicted reasonable stability (queue lengths not growing unbounded) as long as there is approximately 10% greater capacity than demand. Interestingly, looking back at Figure 19, the authors predict this same stability point for random graph and network capacity.

In their paper, they discuss a phase transition point where lack of capacitance in the system causes propagation across a network quite rapidly. They claim that dependent on the topography of the network, these transition points sensitive to "tolerance ratios" (inherent nodal capacity over demand) will behave differently. They show certain topographies, particularly randomly-connected networks, show a dramatic, steep or nearly binary transition from a stable to an instable condition, but that this does not happen until demand is with ~90% of capacity. Other systems, such as those with scale-free structure, degrade a bit more slowly, but begin to show signs of network failure with fewer dysfunctional links.

In the scenario which generated Figure 60, without flight dependencies included in the model, the queue-clearing heuristic (e.g. either first-come-first-served or scheduled-first) was less important that the unfortunate event that began a major, run-away delay. Looking closely at the non-served queue metric, it becomes evident that though the average bank size was well below the system capacity, the 8% probability of flights not using their scheduled service slot caused a problem. In the 16th time slot, even though the queue had been previously cleared, there were apparently 5 aircraft not served. With only 3 unscheduled slots on average, the "capacitance" of the system was insufficient to deal with this serge in demand immediately. In the next time slot, this happened again to a lesser degree, and the queue began to grow. Without sufficient buffer in ability to handle serge demand, the system could not recover, and the queue grew.

For airlines, particularly at their hub, such behaviors could have dire consequences: if an airline chose and was allowed to do so, they could schedule a block of flights effectively delaying an entire downstream bank of operations. Various versions of schedule gamesmanship of sorts have been documented (Belobaba, Odoni, & Barnhart, 2009), and can easily be demonstrated with models such as the one developed in this study. Also influential was the ability of flights to meet their scheduled slot (non ATC related, reflected in the delay probability). With these parameters bounded and flight dependencies unaccounted, the model predicts stability regardless of the ATC strategy used to clear aircraft in a service queue as demonstrated in Figure 61.

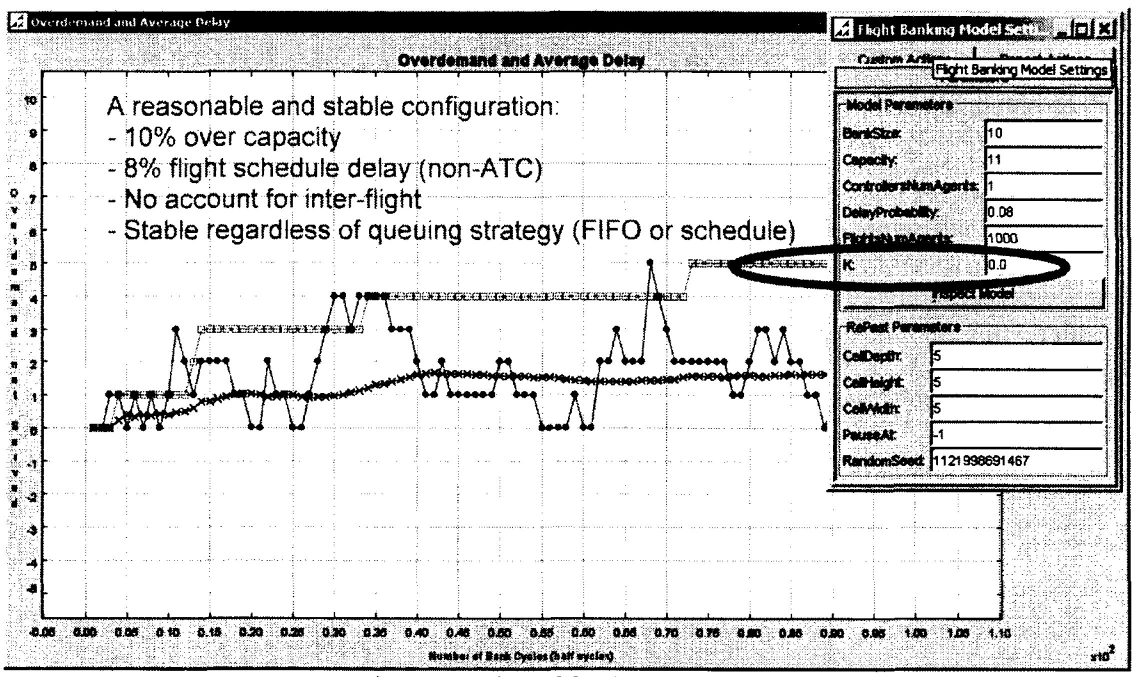

Figure 61: A Stable Configuration

However, flight dependencies are critical to airline business models and practical operational considerations. With an assumption of total dependence between flights (k=n) to simulate the system from the airline's perspective, ATC strategies are even more critical to system performance: for example, for certain system parameters, a strategy of the scheduled flights served first demonstrated run away delay (Figure 62) while an alternative strategy of serving the aircraft (with the same on-average demand and system capacity) who had been waiting the longest proved more stable (Figure 63).

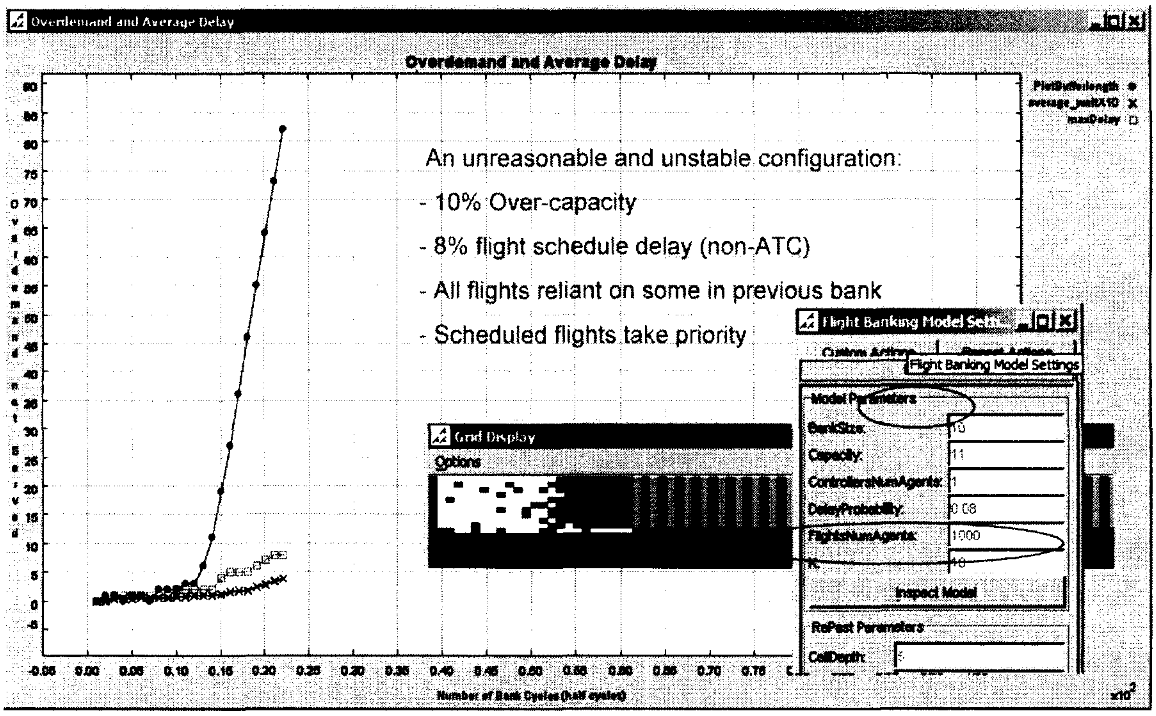

Figure 62: An Unreasonable and Unstable Configuration

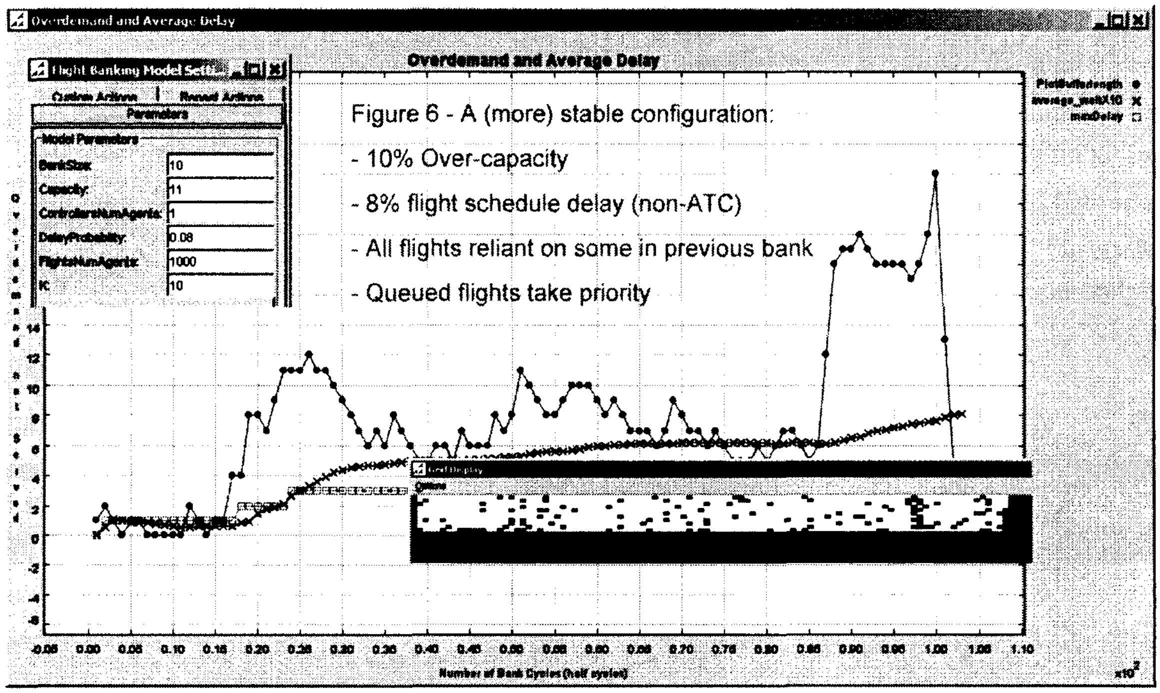

Figure 63: A More Stable Configuration

Such results can point to system performance differences stemming from the different queuing heuristics, and be explored very quickly, albeit in a non-statistically-rigorous fashion. The results in Figure 64and Figure 65 were generated with a series of runs, automated through RePast initiation scripts. These meta-routines recompile and run the model and log data from model variables in a specified range. These routines were used until predicable behavior of the system as a function of queuing heuristic was evident to the researcher, though the demonstrated differences were not validated for statistical significance. The strategy, along with the modeled uncertainty in slot meet-time (ability to adhere to scheduled slot time), appeared strongly correlated to both the maximum buffer length and average delay in these simulations. It was also clear from observation that the heuristic which first served scheduled flights was much more sensitive to uncertainty than the other strategy. Note the variation in these data vs. the consistency in the data which represent a first-come-first-served strategy. This simple simulation proved to be a powerful tool to observe the influence such heuristic changes could have on system performance very quickly and efficiently, and provided feedback to areas of inquiry worthy of further effort.

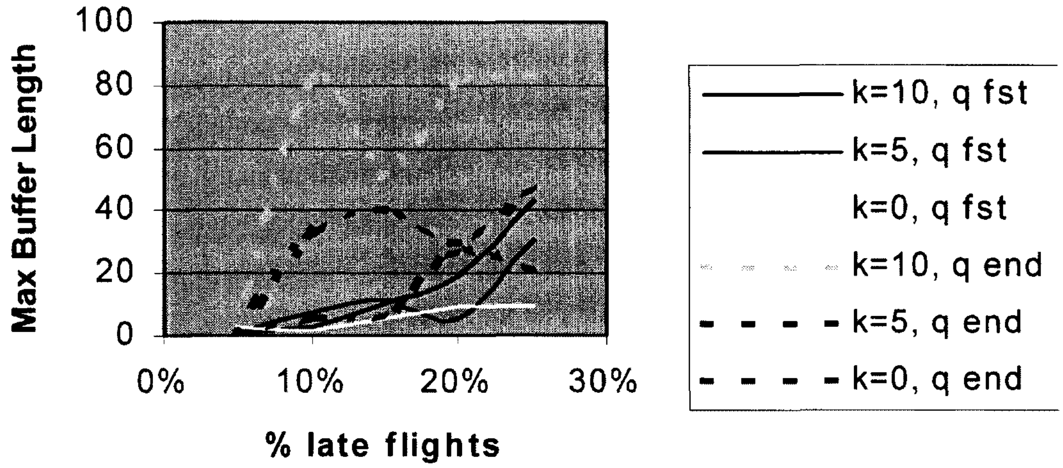

Figure 64: Queue Strategy and Flight Uncertainty vs. Max Buffer

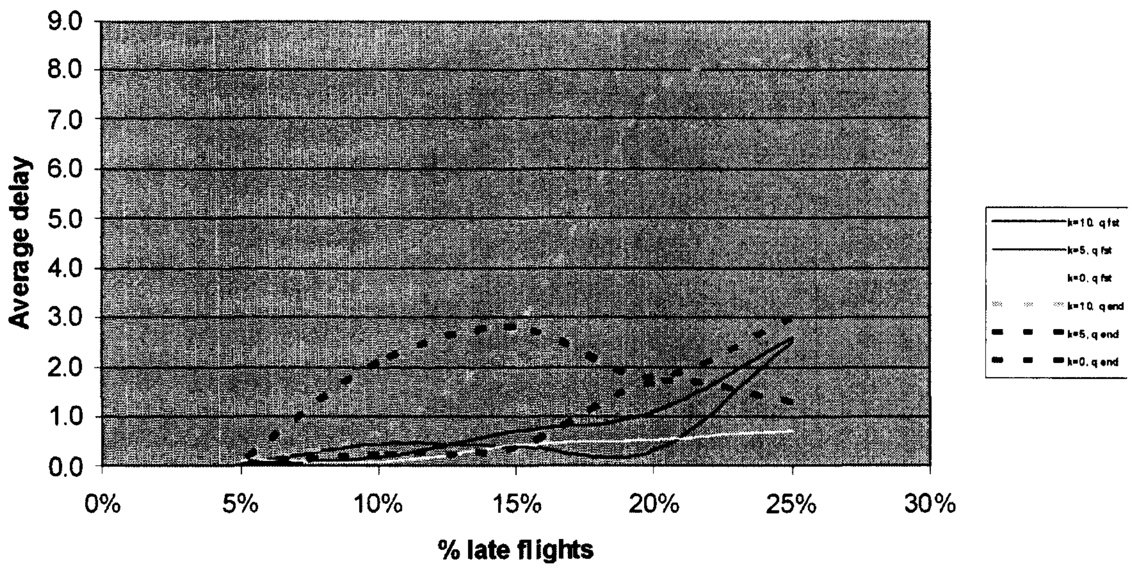

Figure 65: Queue Strategy and Uncertainty vs. average Delay

These results, if they were to hold true under a more rigorous study, substantiate the long-standing "first-come, first served" rule of ATM (FAA ARO, 2012), and demonstrate its stabilizing influence on delay. They suggest the system may be more susceptible to unstable behavior using a scheduled-flight priority heuristic rather than a first-come heuristic. This study implies that this is even more evident as k increases, suggesting that while it is important for clearing the *ATC* queues, it may be vital for the *airline's* operational integrity. Such results point to the need for more careful, statistical study.

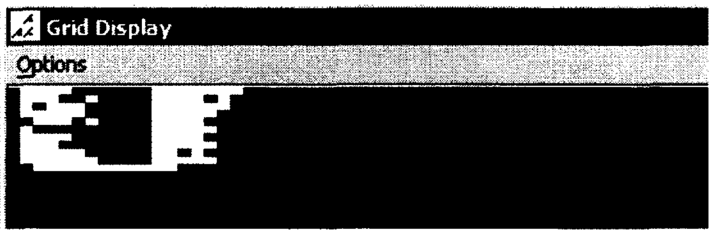

Figure 66: Histogram of flight activity - 10/bank 11cap 15% 100flights 10/bankDep

Another result was the dramatic effect of flight dependency from the airline perspective. In the run whose results are shown in Figure 66, flights in every bank were linked to at least one previous flight, not unlike actual airline scheduling. As evident from this histogram of service, despite available capacity, the "wrong" flight, one perhaps with a high clustering coefficient in its network of connections, became delayed. For many cycles, though the slots went unused, the queue kept building until the "log-jam" cleared, and that pivotal flight was released. This is a clear call for optimizing the trade between the effects of these types of delay mechanisms and the cost of idle resources such as crew, gates and aircraft. The implication is that perhaps more than airport capacity, airlines can help themselves by decoupling dependencies between close connections as much as practical, such as limiting dependencies to multiple inbound flights to obtain crew from one, equipment from another, and passengers/payload from a third when scheduling a departure. This result also suggests the airlines may want to explore if first-come is in their best interest to continue to support, or if they should work to expand the FAA's Collaborative Decision Making (CDM) program (FAA ATCSCC, 2012) to negotiate for preferential handling of key, strategic flights[e].

One surprising result was the demonstrated positive correlation between demand and actual capacity from the facility perspective. While the best scenario for an airline is to get service exactly on demand without wait, it turns out that unless perfectly orchestrated, such an operation is sub-optimal from an ATSP perspective. This will feed back to the airline eventually, creating delays for them. This non-intuitive result can be demonstrated with a simple model such as the one developed:

The minimal interval between flights cannot drop below specific thresholds for safety reasons related to wake vortex separation[f], and thus sets a maximum throughput threshold for any arrival stream, and a target theoretical maximum arrival spacing[g]. An air traffic controller's goal is to make the spacing between aircraft be as close to the target as practical without dropping below the required minimum. If spacing becomes greater than this prescribed minimum, landing capacity is "lost", as the arrival rate will be less than theoretically allowable.

The demand on the airport is a key factor in a controller's ability to maintain this minimal spacing interval and maintain airport throughput: It's obvious that if demand is

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[e] CDM is a philosophy on how to conduct business between the various components of aviation transportation, both government and industry. There are 24 airlines currently participating in this initiative. It consists of tools and procedures to enable the FAA Air Traffic Control System Command Center (ATCSCC) and the NAS users to more easily respond to dynamic ATS conditions.

[f] Aircraft wakes are severe but local areas of turbulence that trail behind aircraft. They are a by-product of their lift generation and aerodynamics. Every pairing of sized aircraft, such as a heavy leading a small, have distance-in-trail restrictions based on the wake generation of the lead, and the penetration or upset likelihood of the trailing aircraft. These vary from 3nm to 10nm, dependent on the relative size of the aircraft. If aircraft spacing begins to drop below such thresholds, controllers must pull an aircraft out of the landing sequence and reroute them for another approach due to safety concerns.

[g] Theoretical arrival rates can be further reduced if the geometry and location of the runways and taxiways demand high runway occupancy times.

substantially less than capacity, that maximum throughput will not be achieved: there simply will not be enough traffic to fill the landing slots. However, less intuitively, the model showed that while wait times increased as demand built, there was a positive effect on airport throughput. If the traffic is spaced very irregularly, or is nearly regularly spaced but the flow is close to or even just above the maximum acceptance rate, a controller cannot create a consistent enough stream to close gaps as well as open wake-related ones. With more traffic at hand, controllers were better at creating an appropriately-spaced traffic stream.

Holding, or at least some delay maneuvering, creates a ready supply of aircraft to be pulled from to create the landing sequence, and acts as a capacitor or dashpot does, to smooth out the available supply for the airport system. Of course, a "buffer" or capacitor full of traffic meant extra maneuvering (vectoring) or waiting (holding, or "spins" in ATC vernacular), reducing flight efficiency. However, in many circumstances, this loss of efficiency is still far less than the lost opportunity cost of reducing the overall demand to a level which could be operated without delay.

So while holding is generally thought of as undesirable, this simple model suggests that a system whose demand does not require delay will likely have reduced throughput, and demands a proper balance of over-demand-caused delay vs. landing slot value. This insight was an interesting demonstration of how specific optimizations within such a complicated system can have very different consequences for different stakeholders.

So holding/vectoring can be a good strategy for controllers *and airports* since they are generally targeting maximized throughput. What is not clear is the *net* benefit to an airline: is the improved throughput at a key airport, by itself a good thing, a big enough benefit to offset the cost of a sub-optimal flight profile to the airport? Is the same airline that is flying extra miles in vectoring or holding to maintain pressure on the airport arrival stream also the one who is using the "extra" landing slot that is or not wasted? That might depend on other circumstances, such as the carrier's dominance at the airport, dependencies on that equipment, the crew, or passenger connect times. The considerations quickly become complicated.

4.3.4 Agent-Based Models: Strengths and Weaknesses

In many cases, the researcher observed that plots of the average delay demonstrated a dynamic "ringing" behavior, typical of a second order oscillator model from system dynamics theory. In such a system, the response to an input can be described mathematically by a second-order differential equitation. This type of behavior is seen frequently in systems that have feedback mechanisms as well as some regulation and some capacitance to respond, absorb, and nullify changes. As the relative dominance of these system dampening qualities change, the fundamental response of the system changes too.

Figure 67 shows a traditional view of the propensity of a system to return to a steady state value in light of a disturbance as a function of an inherent system quality. This feature, ζ (zeta) or damping coefficient in engineering terms, will influence the response of a dynamic system. With $\zeta<1$, the system is considered under-damped, meaning when perturbed, it will "overshoot" its targeted recovery value, and then "undershoot" etc. until finally settling to a stable value. This over/under performance is the typical "ringing" of a second-order oscillator. If $\zeta>1$, the system is over-damped: the response will return to the stable condition without overshoot. However, the time to get to the stable condition is slowed. If $\zeta = 1$, a second-order system is considered "critically-damped". This represents a system that will reach its stable configuration (stop ringing) in the shortest time, with a single dynamic cycle or overshoot.

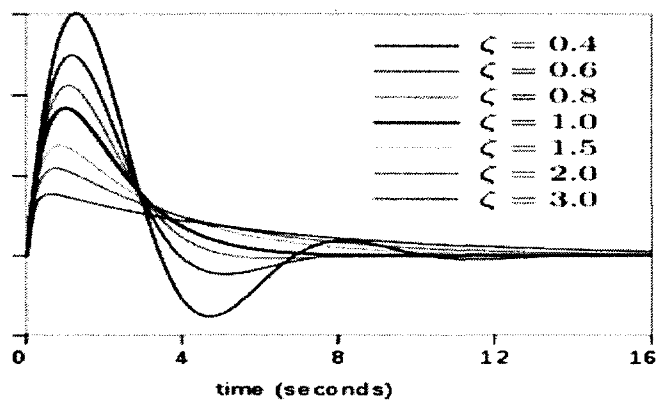

Figure 67: Second-Order Oscillator response to disruption (Irwin, 2006)

After using the model to collect experimental data, it appeared that the average wait parameter in time often showed qualities of a second-order oscillator. Further observation and analyses revealed what appeared to be a relationship between overcapacity (capacity-bank size divided by the bank size) and the probability of a flight missing its expected slot, as the over-capacity behaves as a capacitor, influencing dymanic response to a delay perturbation. Dimensionless analytical technique (Sonin, 2001), borrowed from fluid systems engineering, implied that these dynamic properties should be able to be described by a term akin to a damping coefficient. Upon inspection of the data, this term, ζ, was estimated as:

$$\frac{Cmax - N}{Cmax} \bullet \frac{1}{P} \sim \zeta \qquad \text{(Equation 3)}$$

Using this concept, the data from what was observed to be a near-critically damped case was used to estimate a value for ζ. This was then used to successfully predict a *stable* tolerance for delay or value for P given a 50% overcapacity and an *unstable* or under-damped overcapacity threshold for a different value of P (Figure 68).

Such relations could be critical to planning and system investment. Understand the trade between extra capacity at a facility and the uncertainty of the demand on that facility could afford decision makers an important tool. Though never easy, adding capacity at some ATM facilities can be less onerous than others. On the other hand, some facilities experience much more uncertainty in their demand, due to factors such as weather or proximity to other airports. With some rules of thumb and simple models demonstrating trade-offs, the interplay of both of these system attributes against required performance can be explored. It seems agent modeling can quickly help discover such relations, assuming the model sufficiently captures realistic features.

Agent modeling is particularly well suited for addressing the service delay issues of a capacity-constrained air traffic facility. Abstraction of the system of interest was straightforward, and the relative ease of building an ABM made capturing all the influential elements of the system easier: Initial attempts to model the system could be quickly explored and expanded. Adding behaviors to existing agents was uncomplicated. With this relatively simple model, the efficacy of ATM three different control strategies as well as their interactions with airline usage was demonstrated.

With additional research into user behaviors, the model could easily be extended to explore "gaming" that is known to occur in airline scheduling and its influence on operational delay in general or specifically for rival airlines. Additionally this is a natural platform for investigating distributed responsibility for control, e.g. ordering operations, and other peer-to-peer interactions. It is also particularly suited for the engineering of local and global control strategies simultaneously as is occurring in ATM.

While the experiment used a fixed demand with some random noise to build the nominal schedule, using actual demand profiles, origin and destinations, schedules, and even passenger loading data would only require using these data to supplant the nominal values in flight agent initiation. These historical data as well as travel forecasts could be used to determine the demand profiles most difficult to control, and provide a means to test strategies designed for their mitigation.

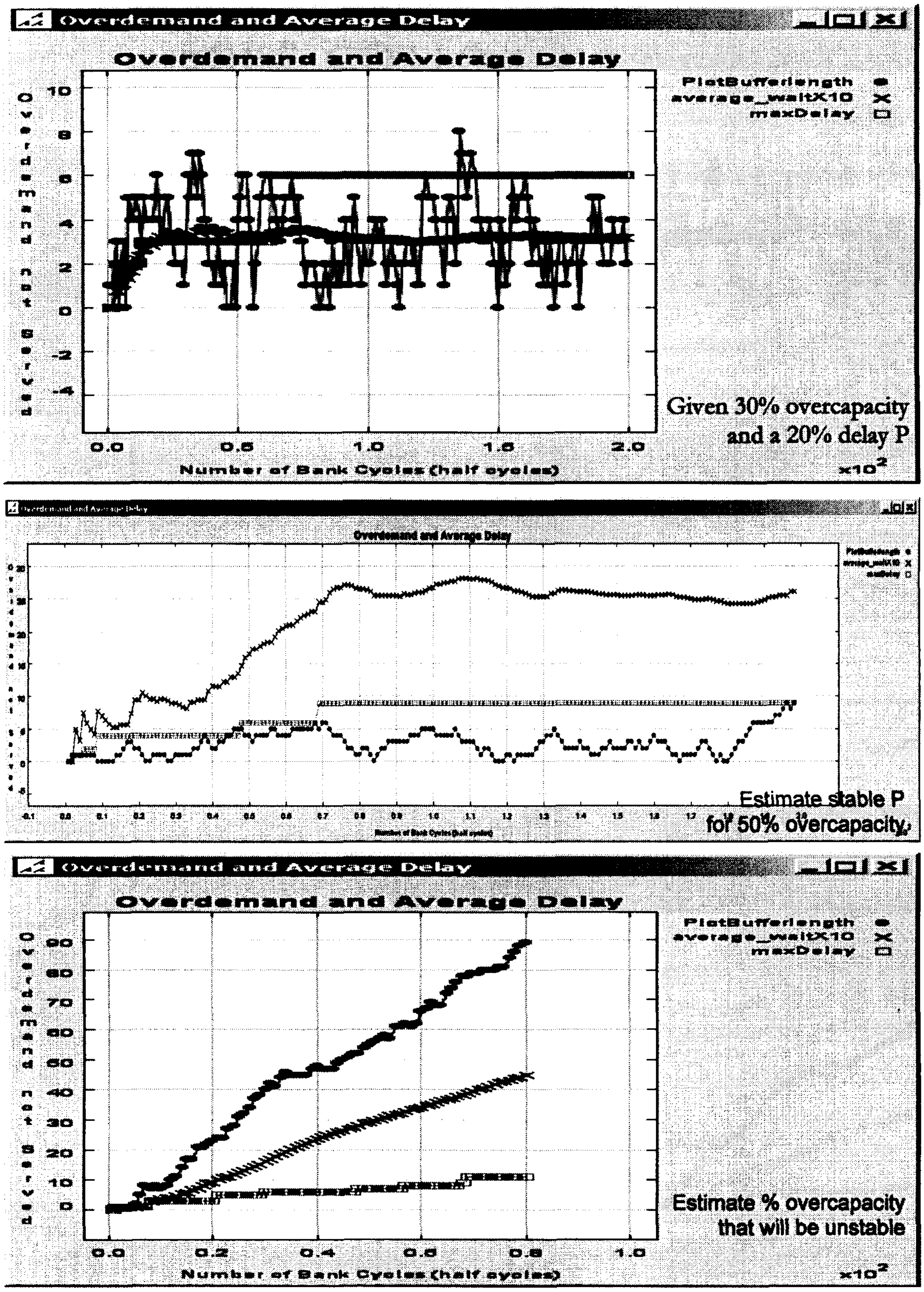

Figure 68: Using Estimated ζ for Anticipating Stability

Finally, these models could serve as the bridge between full-mission operational modeling used for detailed system design/safety analyses and more coarse models often used for cost benefit analyses. For example, with the addition of passenger agents having some simple mode choice behaviors and the airlines adjusting their scheduled service to this demand, such a model could be used to address the dynamics of demand rebalancing, travel time, etc. in light of operational delay. The influence of these potential feedback effects would be otherwise difficult to capture in parametric models.

As billed, an agent model of air traffic service delay, if built with sufficient domain integrity, does indeed seem capable of offering insight to the intrinsic schedule adherence qualities of this complex, dynamic system.

4.4 SUMMARY

This research addressed the use of network analysis and agent-based modeling techniques for investigating the stability of commercial air carrier schedules. The research questions were addressed by developing models using both methods, and looking across the two resultant models.

Firstly, it was clear that the two models, though different, can be related. Network analysis relies principally on constructing the relations between system elements. Agent modeling, as the name implies, focuses on the active system elements which in turn have relationships with other agents that form networks. In many familiar descriptions of airport and flight systems, the network of flights, connecting airports, seems to fit naturally with either technique: airports as nodes or constrained agent resources, flights as links or system agents. However, the dynamic properties of these networks presented a challenge. Unlike a road or pipe transport network, airlines do not fly to the same destinations continuously. In fact, over the course of a day, the networks created by airline routes vary dramatically. While this is naturally captured by agent models, it can pose a real challenge to network modeling.

Interestingly, when the dependencies between flights, not the cities they served, were modeled as the links in a network of flights, the loss of stability in the flight schedule predicted by network characteristics matched very well with experimental results from an agent simulation. This highlighted the need for careful consideration of the elements in either model.

It was also challenging to identify which elements needed to be captured, and which ones did not. Before flight dependencies were added to the agent model, for example, not only was the model behavior not very realistic, the underlying network of flight dependencies was not even recognized. In fact, this network could be useful in estimating thresholds of capacity and when excess would cause fight delay. Once such realizations were made, either method is capable of representing transitions to a degraded performance state.

With the right network model, general schedule stability indicators were identifiable. The challenge was to define the correct network. The city-pair service map was not sufficient: While there are clear route constructions that could yield static instabilities and limits to service growth due to capacity (such as HaS), the dymanic behavior of such networks was not obvious. However, with different network depictions of the same system, i.e. which flight connected to another, and which crew and passengers were hubbing, a more useful dynamic model was created.

Interestingly, in the end, the two very different approaches served to validate each other: The (Crucitti, 2003) theoretical approach to network stability showed there were "break points" of over-capacity. Their work argues that when network capacity exceeds demand by a particular value, the system can be shown to be robust against delay and become more efficient. They showed for all but targeted overloading of critical nodes on a scale-free network, this break-point was about 10% overcapacity. In other words, one would calculate a theoretical capacity, but to maintain good performance, only plan to ever use about 90% of this capacity. In this way, the system is more efficient, being robust to surges in demand, unexpected delays on the network, etc. The agent model showed the *same break-point.* With just 10% over-capacity at the service node, it was possible to maintain a schedule and recover from surges and unpredicted schedule disruptions with all but the most interdependent, unpredictable systems.

In fact, the two methods are perhaps not two totally distinct methods, but rather are emphasis on different portions of a single approach. Macal & North's model summary (Macal & North, 2006) implied this, and after the modeling exercise it became clear why: The agents' communications, whether representing proximity, data exchange, or the like, create a clear network structure for transmission. In this study's model, this network was formed by the service schedule, and later augmented by the assigned dependencies between flights. Without running the simulation, this network itself would afford insight into expected system behavior.

CHAPTER 5

DISCUSSION

There are many different approaches to modeling systems, but few that are suitable for capturing the complex behavior of large, interconnected ones. The brightest of minds challenge us to think simply about complex topics in order to gain insight. They do so, they say, because simply emulating everything experienced at best will only bring you back to the understanding you could have gleaned from the actual system without a model. Models are purposeful abstractions that draw their essence from the systems they address.

Much of the ATS planning community has come to realize, either through their own formal approach to research or by experience, that traditional models are not servicing their needs. The numerous ATS models in development attest to the demand for system models, but also the failure of many of these efforts to yield meaningful insight.

The modeling of a complex system like air transport is in itself a complex system endeavor. Substantial constraints confound research efforts, some technical, some political (National Research Council, 2003). Nevertheless, a groundswell of complex system modeling practitioners, both applied and theoretical, has recognized the need for new methods and tools that are better suited to their work. While some are happy to apply the tool du jour, or are heavily constrained to specific methods by legacy technology or software, others have come to realize that a systemic approach to design of their research *methods* (including tool development to support them) is necessary.

In 1999 Eric Scigliano stated (Scigliano, 1999), "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.

In May of 2003, Marion C. Blakey, then the FAA Administrator, stated (Blakey, 2003) "We must be nimble, because we cannot precisely predict the future shape of aviation. Already, we're seeing more business jets traveling to small airports; and changes in the hub-and-spoke schedules. We expect more complex demands on airspace and air traffic facilities. We don't know what the future will look like. We do know the future will require nothing less than the transformation of the U.S. air system." The FAA and other controlling entities of our precious transport system resource seem to acknowledge that we need to make changes to our systems, but rarely can articulate the means to do so.

In 2000, Hogge, the Director of Operations & Infrastructure for the International Air Transport Association (IATA) suggested one key element of change. He summarized the necessity for systemic development of the NAS, saying "Gone are the days when the ground deployed 'navaids' and control centers while it was enough to equip aircraft with compatible avionics to create a workable system. ATM is fast becoming a complicated network in which each node is connected to others, exerting influence and being influenced at the same time. …Airborne and ground capabilities must be such that they complement each other, interacting as needed to achieve the efficient operation of the network." (Hogge, 2000) He seemed to be identifying the need for a system-wide, rather than piecemeal approach.

Though there has been progress in setting some technology standards in recent years, we are not much closer to implementing truly new operations than when any of these speakers expressed themselves. Evidence of aviation policy development from as early as the 1970's e.g. (Fraser, 1970) shows we have possibly habitually taken, and continue to take, a non-contextual or too narrow a view of research and development in air transport.

5.1 NETWORK MODELING

A 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 model that can capture operational, dynamic effects? 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.

Barabasi et al (Barabasi, Dezso, Ravasz, Yook, & Oltvaif, 2004) ask "Are real networks behind diverse complex systems fundamentally random? Our intuition offers a clear answer: complex systems must display some organizing principles which should be at some level encoded in their topology as well...We need to develop tools and measures to capture in quantitative terms their underlying organizing principles."

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 structure 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.

This research clearly demonstrated value for network modeling techniques in capturing the essence of various elements of the ATS. The results point to benefit of going through the modeling exercise, and forcing the investigator to find the key elements of the system in question. The exercise of capturing the networked properties, i.e. interdependencies, flows, nodal degrees, is in itself useful in gaining insight in addressing the inherent nature of the system-at-large. It is also useful in limiting the scope of study, as it begins to shed light on which connections are truly important, and if there are multiple types of networks inherent.

The airline schedule city-pair flight database has been used and studied by many, and for many different purposes. Often, its' network attributes are measured and reported: Airports often describe the number of locations accessible with direct or non-stop flights. Airlines also use this same data to describe the extent of their reach globally. However, these static descriptors of the schedule data are often not the whole picture. Without the notion of *time*, or the relative order of flights to and from an airport, the static route map is a poor reckoning of a passenger's ability to get from city A to B at any time. Though some had attempted to address the changing nature of the topographic network over time (Zanin & Lacasa, Jamming Transition in Air Transportation Networks, 2009) their work is intended for strategic planning rather than influencing dynamic, operational decisions.

Are network features, such as centrality, operationally valuable to understand? Zanin, Cea and Cristobal think so (Zanin, Cea, & Cristobal, 2009). They discuss the measure of centrality of an airport as directly proportional to the influence an airport's operation would have on propagating delay throughout the system. While they don't account for the time variability of the network as the day progresses, they do manage to capture this feature abstractly. They use a weighted network where the weight of each link is proportional to the number of flights between the airports it connects.

Clearly the issue of capturing time in the network description needs to be resolved. Good work on dynamic properties of agents on transportation networks, a likely extension of this research, has been thwarted by repeated use of a static depiction of an otherwise dynamic model. Lacasa, Cea and Zanin (Lacasa, 2009) fell into this trap, using the network of 858 airports as nodes and the 11170 flights connecting them as links on a scale-free mega-network. They discussed a phase transition where saturation of the network takes place: A great approach, but if traffic management is the subject at hand, one which would be substantially strengthened by treating the time-variant nature of the system properly.

Indeed, one must dive into additional data to get a functionally-relevant understanding of the schedule as a transport network since many if not most of the links are actually non-persistent from the traveler's point of view: arrive after your flight has left, there may not be another "link" until tomorrow, or Tuesday. On the other hand, the fundamental city-pairings, when viewed at the macro-level, do create a network with inherent characteristics that can be valuable to study and understand. For example, historical route data demonstrated a clear, fundamental strategy shift in the airlines as the market matured. A network analysis of the data demonstrates that political forces, such as subsidies for rural air service and US mail contracts further influenced the markets and frequency of service which airlines choose to operate.

What is yet to be shown is use of network analysis as a predictive tool relative to such public policy. Interestingly, we may have such an opportunity on the very near horizon. In fact, these two entrenched policies, mail carriage and rural air service, are under tremendous political pressure to either dramatically shrink or go away all together[h]. In fact, according to Wyatt (Wyatt, 2011), the 2011 FAA was held hostage because of a disagreement on policy: Congress shut down the agency by allowing the FAA's funding to expire due to "disagreements between Republicans and Democrats over a program that subsidizes commercial air service to rural airports".

Particularly when combined with additional policy change that may be forthcoming, such as carbon capping at major airports, the route maps of pre-de-regulation, more oriented towards scale-free and "naturally-derived" structures, may become more appealing than the 80's and 90's dominant hub-and-spoke connectivity. These static models may be poor at predicting dynamic behavior of air transport system delay due to their limited ability to capture the salient elements of air traffic control, e.g. time. But they may prove valuable as predictors for more strategic decisions, such as which cities will have ANY scheduled service

[h] Many communities that used to receive mail by small contract-carrier air service (which in turn subsidizes that route link) have moved to other land or boat transport with reduction in mail volume and service frequency, i.e. West Isle Air's daily mail route in the 1990's to Decatur Island, WA which is now served by Water Taxi service 2 times a week.

in the future, and which airports are likely to have strong pressure for continued growth due to their centrality in the network or other strategic net-centric attribute.

From this observation, it follows that Network Science indeed has a place in Air Carrier Schedule assessment, but perhaps by itself is not as useful for some inquiries as it may be for others. Such models have proven useful for answering more strategic questions such as efficiency in connection to other network locations (i.e. number of stops in general to other cities/airports). They were also demonstrated to show vulnerabilities to disruption and node failures (i.e. a snowstorm that shuts down a hub disrupting ALL flights vs. a schedule that might only cause disruption to a portion of the network).

5.2 AGENT-BASED MODELING

Agent modeling proved to be a natural extension of subject-matter expertise. The myriad of agent-based simulation platforms and the ever-improving interfaces to these models are making these techniques available to a wide audience of modelers. With a small investment in learning one or more of these tools, a true subject-matter expert can build a model to explore a relatively complicated, dynamic system in short order. With a simple interface to the agent behaviors, it was easy to change management strategies.

Agent modeling helps to understand the system at hand, and helps the modeler bound the system. In creating agents, one must consider how many there are, if there are more than one type of actor in the system, and whom with and how they interact. In creating their environment, a modeler is forced to think about limitations to communications, what data is available, and other true-to-life restrictions *if* they expect they will influence an agent's ability to perform. This draws a modeler down a path of extracting the key elements of the system without emulating all data flows and features.

Surprisingly, even with this substantial domain knowledge, a relatively short list of model elements and "simple" relational attributes proved to yield insight into otherwise unobserved and unexpected behavior. As touted by many in the literature, the potential for such results from models that are sufficiently simple that the underlying mechanisms for specific behaviors can be understood are exactly what makes them extremely valuable. This proved true for this simple experiment with scheduled flight service as well. With simple modifications to the relational rules which can be changed very quickly in such models, both pre-identified systemic attributes of interest and some unexpected consequences were quickly explored.

In both NextGen and SESAR, there is an international movement for fundamental change to the long-standing service policy of "first-come, first served", one of the scenarios tested in this study. As "best equipped-best served" is considered, and before equipage-based priority systems are touted as improvements, such simple agent-based models could afford exploration into this new control policy's effect on delay and service quality. By design, these new policies are largely purposed to incentivize airlines to higher-performing equipage, in turn affording an overall system improvement. However, realities of airline equipment maintenance and scheduling and crew training make it impossible for an airline to instantly equip. In the interim, while an airline is improving their fleet (it could take years to fully upgrade some NextGen systems fleet-wide), such a equipage-based policy could wreak absolute havoc on schedules. Simple agent models could help explore appropriate policy which could both incentivize equipage and maintain a viable operation.

5.3 ADDRESSING THE RESEARCH QUESTIONS

There is clearly a need to explore potential changes to ATS that will evolve from programs such as NextGen and SESAR and the operational policy that they bring. However, there are many issues that follow such changes, three of which were addressed by methods explored in this work.

Firstly, when exploring delay in the ATS, a detailed literature search and expertise of practitioners in the field, in the form of structured interviews, pointed towards a specific but limited set of parameter to explore. This both helped scope the work, and pointed to the "essence" of what was necessary for capture.

During the development of the network and agent models, it was noted that commonly-held network models of airline operations did not address some underlying network structure. Demand of flights on an airport or ATSP facility is often referenced in network studies, but the operational dependencies between flights are data held private by airlines. Though these data would be useful to prioritize flight management and service, ATSPs have little access to such information for to influence their tactical traffic management. Similarly, these dependency networks are rarely studied in the ATSP community. In light of changing policy on flight management from first-come-first-served to a more "optimized" solution, this research has demonstrated that these dependency networks will substantially complicate system response, and may cause unexpected consequences for many stakeholders. While these dependencies ultimately create "networks" of dependencies, it seems that modeling of flight agents and all the applicable attributes from a particular stakeholder's vantage really helped to illuminate these ties.

Fortunately, a combination of agent modeling and network analysis can be used for analysis. Both methods can be used for quantitative analysis of air traffic systems. With proper contextual description, they can predict similar system response. Their combined use helped this researcher both describe clearly defined system interaction, like communication links, as well as more nebulous system structure created by phenomena such as the use of flight assets on a route and reuse on another, not typically captured in route studies.

5.4 CONTRIBUTIONS

This research contributes to the practice of ATS modeling by investigating the appropriateness of two generally-recognized complex system modeling techniques. Firstly, this research contributes practical application of both of these techniques in a contextually rich environment. Though there are a number of published models, detailed discussion of the models and the systemic features that drove their formation are still limited. However, the use guidelines distinguished herein may prove useful when applied to a broader range of air-transportation policy analyses.

Finally, modelers are often encouraged to begin with published work and then customize it, therefore limiting their modeling overhead. (North, 2001) This research has added to the growing body of both network and agent-based contextually-formulated models.

The key contributions are summarized in Table 5:

TABLE 5: KEY RESEARCH CONTRIBUTIONS

	Key Contributions
Theoretical	Agent and Network modeling can be used in ATC development when applied in a framework of substantial domain knowledge. These methods can be used to parsimoniously explore rare, unusual, or hazardous situations and the effect of mitigating strategies with consideration of system-of system attributes such as complementarity . Insight into the influence of uncertainty in ATM can be improved with non-deterministic approaches to system modeling.
Methodological	Issues of validation can be mitigated using both methods to triangulate to similar results and system transition thresholds. Combination with other engineering techniques such as non-dimensional analysis affords quick development of useful rules-of-thumb for system development
Practice	Identified schedule stability criteria: relationship between theoretical airport facility maximum capacity, flight dependencies, and external flight delay sources. Identified positive influence of queues for airport throughput.

5.5 RECOMMENDATIONS FOR FUTURE RESEARCH

This research determined the potential utility for these methods. While they have both proven useful, there are areas in which they could benefit from further development. These largely revolve around the specialization of such methods for application to ATM. One of the key findings of this research was that both numerically-based and soft-system methods must be made accessible to domain experts.

A first-order improvement in the field would be to develop a package or library extensions to an agent-based platform that could collect and define networks which grow out of agent interaction. As explored above, the physical connection between ATC entities is not always the "network" of most interest. For example, this research on schedule adherence suggested the importance of the network of flight dependencies. While some of these are related to using the same airport "node," other dependencies were related to other elements, such as crew or passenger connections between specific flights in the schedule. An augmentation to an agent model would be to these dependencies to build a network which itself could be analyzed for stability, robustness, efficiency, etc. *a priori.* In this way, potential problems the agents may face in future operations could be mitigated, like forecasted communication congestion, tight connections without sufficient time buffer, or problems from scheduled service disruptions.

Another improvement would be to develop a simulation environment *for domain experts,* specialized to enable their substantive participation without the necessity for the rare additional expertise in simulation. Between the recently-funded United States NextGen effort (Lowy, 2012) and similar scale efforts in Europe, tens of *billions* of dollars will be spent on research and development over the next five years. However, the basic trajectory-based control concept and ensuing improved system performance hasn't been demonstrated, as there is no appropriate system-wide simulation available. But the promised benefits are so compelling that many people are backing NextGen and SESAR. Relatively simple platforms for system-wide testing of new operational procedures, particular with the widespread, high-level concepts of trajectory management, could explore the true potential for achievement of the claimed benefits of NextGen. These will only be useful if done early, quickly, and simply, but they must capture the essence of the proposed changes.

Little is really understood about the ramifications of this transformation operationally, but there is little opportunity for experts in ATC to "play" with new system concepts. A specialized agent/network platform could afford the opportunity to test these grand ideas with the necessary domain expertise before jumping into the billion-dollar implementation plan. Such a simulation platform could allow the experts in the current system as well as experts from other fields, such as transportation, IT, etc to work together to build a simple but dynamically-relevant, and elegant model

One specific issue that needs attention when using an agent-based simulation approach to analysis, particularly in light of the safety-critical nature of traffic systems, is the issue of validation. Agent-based simulation appears to be a very useful method to gain insight into the non-linear interactions within the air traffic system driven by political, economic and policy issues. However, according to Miller (Miller, 1998), "these same characteristics make understanding such models using traditional testing techniques extremely difficult." How to validate a non-deterministic model-based analysis of a critical system? Miller suggests the use of ANTs (Active Nonlinear Tests of Complex Simulation Models).

The basic premise of ANTs is to use an optimization algorithm to search through a model's states in an attempt to create a "broken" one....This differs from Monte Carlo treatment, though also useful for validation, which statistically seeks to find the likelihood of a particular scenario. It also differs from traditional sensitivity analysis, or designed experimentation, which could have a similar role in analyzing a better-behaved, linear system. Miller's ANTs are rather seeking "maximum error", or model states that are out of acceptable parameters. He suggests the use of non-linear search techniques (such as Genetic Algorithms or Simulated Annealing) that use heuristics to modify parameters in model execution to further the result in a particular direction: in this case, to destabilize the airline flight schedule.

Clearly the model used to explore the agent modeling in this study is not sufficiently detailed to catch all the important influences in flight schedules. Even as is, and certainly as detail was added, ANTs could be deployed to delve into corner cases and non-expected behaviors. As the model become more complicated, and less tractable, the ability to test its robustness will grow.

5.6 CONCLUSIONS

What became evident in the assessment of applicability of both techniques to the ATC domain was that understanding the mechanisms at play, and therefore those that needed to be included in the model, was fundamental to both. Prior to building either model type, it was absolutely necessary to spend substantial effort to identify the likely influences and first-order driving variables. Additionally, it is evident from the modeling efforts in this study that the potential interactions between such variables yielded valuable and sometimes non-intuitive results. Clearly, substantial domain knowledge of the system-of-inquiry is necessary to select a cogent but limited set of variables and their relations for any model. Both approaches afforded the opportunity to focus on the abstraction of the system, rather than the "coding" or mechanics of producing s simulation.

Sometimes the network structure is obvious, particularly in context, and sometimes not. The act of creating both the agents and the networks on which they interact in it self seems to lead to a better level of system understanding. For example, creating the "network" of interaction within ATC, figure "ATC Network of Functions Supporting a Flight" was relatively difficult. While SWIM is designed to address the ATC communications network, the system's functionality is not usually thought of as a network. Data flows and functional control in such a network are different than the communication links between functions, though communication is a vital required element.

In retrospect, the figure represents a picture muddled with commutation processes and control. A truly functional diagram would begin to explore the shared nature of responsibilities between flight crews, ATC, and airline dispatchers. Depending on the defined system extent, it could even go as far as to include the cabin crew and the passengers, as everyone has some responsibility for function during a flight (do *you* read your emergency card provided in the seat back?!). The details of network and agent models both require this kind of careful, domain-specific consideration of the system of interest, infusing operational relevance.

In closing, these tools did indeed provide insights. Beyond experience with the modeling itself, and the application of these methods to ATM, three key takeaways from the models related to delay propagation in airline schedules were uncovered:

- 10% over-capacity– an indicator for a potential rule of thumb
- Positive influence on throughput from queuing…who would have thought delays were good from any perspective?
- Stability criteria derived from a simple study – points to a means for exploring trade-offs between additional theoretical runway capacity and more predicable flows provided by new air traffic control operations

The process of modeling using either of these methods helped to force recognition of details, and helped to select the most relevant ones with major influence in system performance. The act of creating these models by experts in their fields that are not encumbered by irrelevant details or complicated coding can truly lead to unexpected insights. It can allow practitioners to advance knowledge and understanding of the system without excessive risk while expending minimal resources for the degree of understanding attained….

. . . . and see system patterns to help understand the big picture.

Figure 69: Liberty Ridge Farm Corn Maze, Schaghticoke, NY October 2011

Figure 70: Stocker Farms Corn Maze, Snohomish, WA September 2006

Thanks to NASA and Boeing for sponsoring this research

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APPENDIX A:

TIME VARIATION IN THE UA CITY-PAIR NETWORK

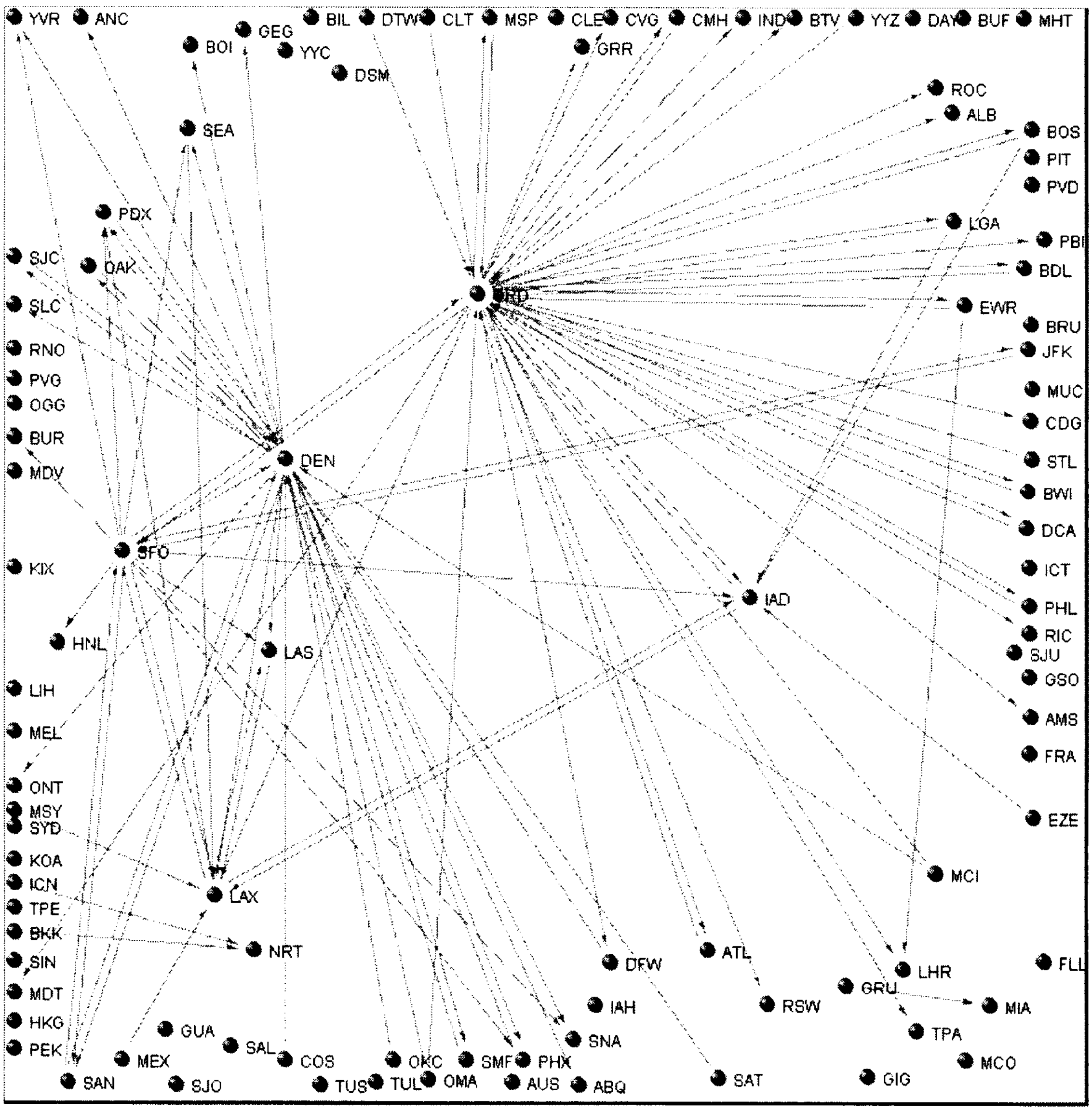


Figure 71: UAL City-Pair Network as of 00z

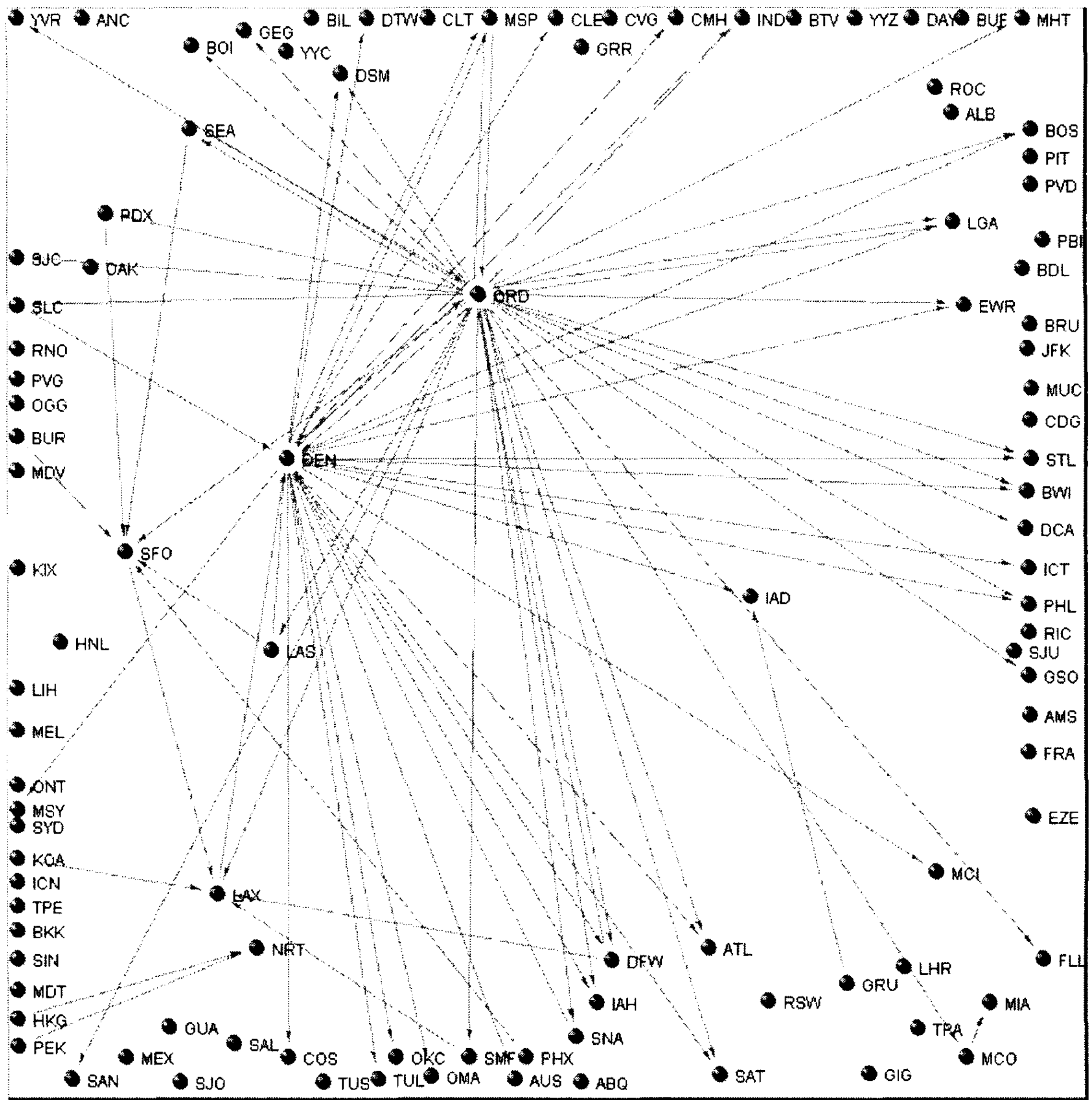


Figure 72: UAL City-Pair Network as of 01z

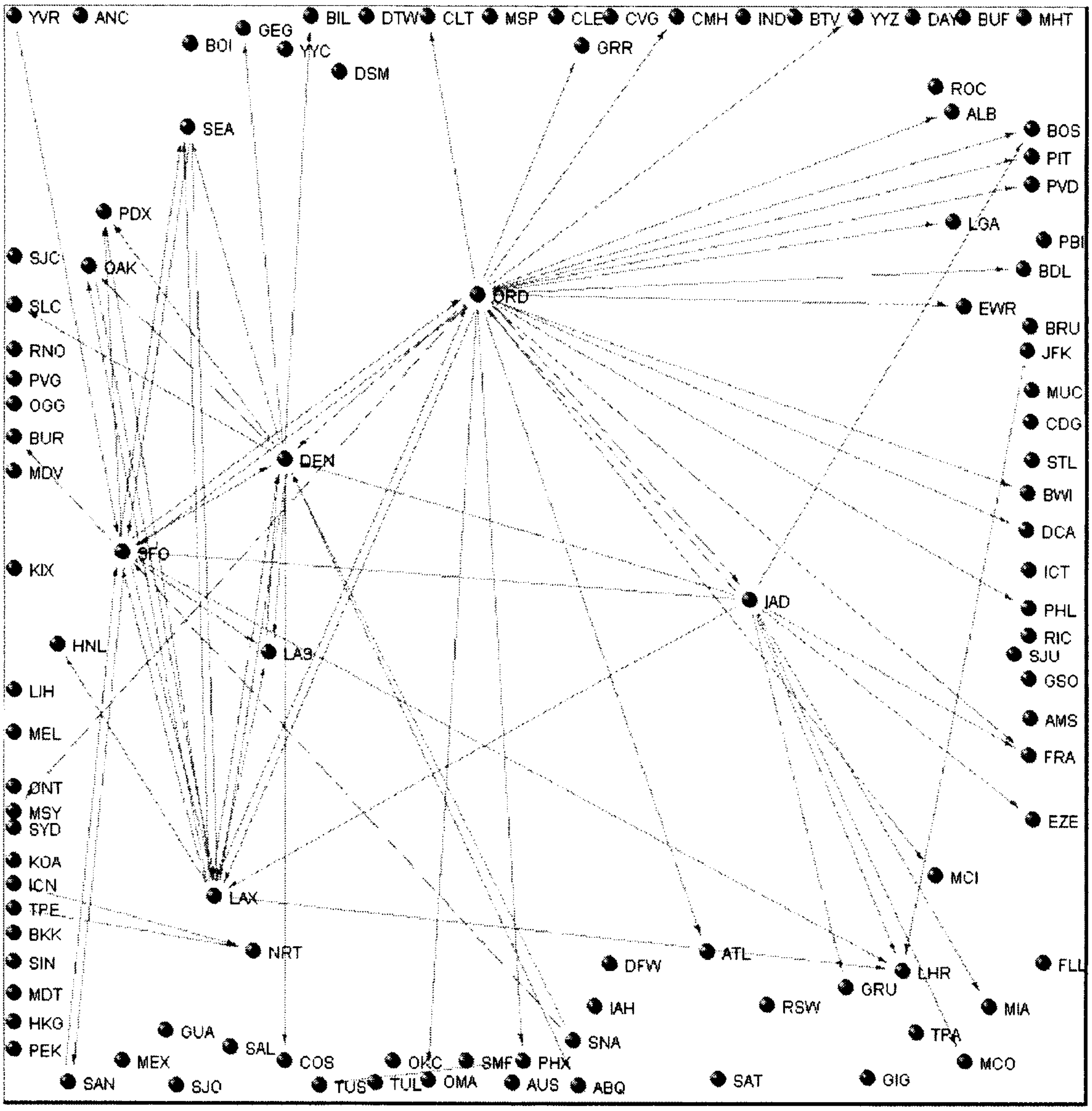


Figure 73: UAL City-Pair Network as of 02z

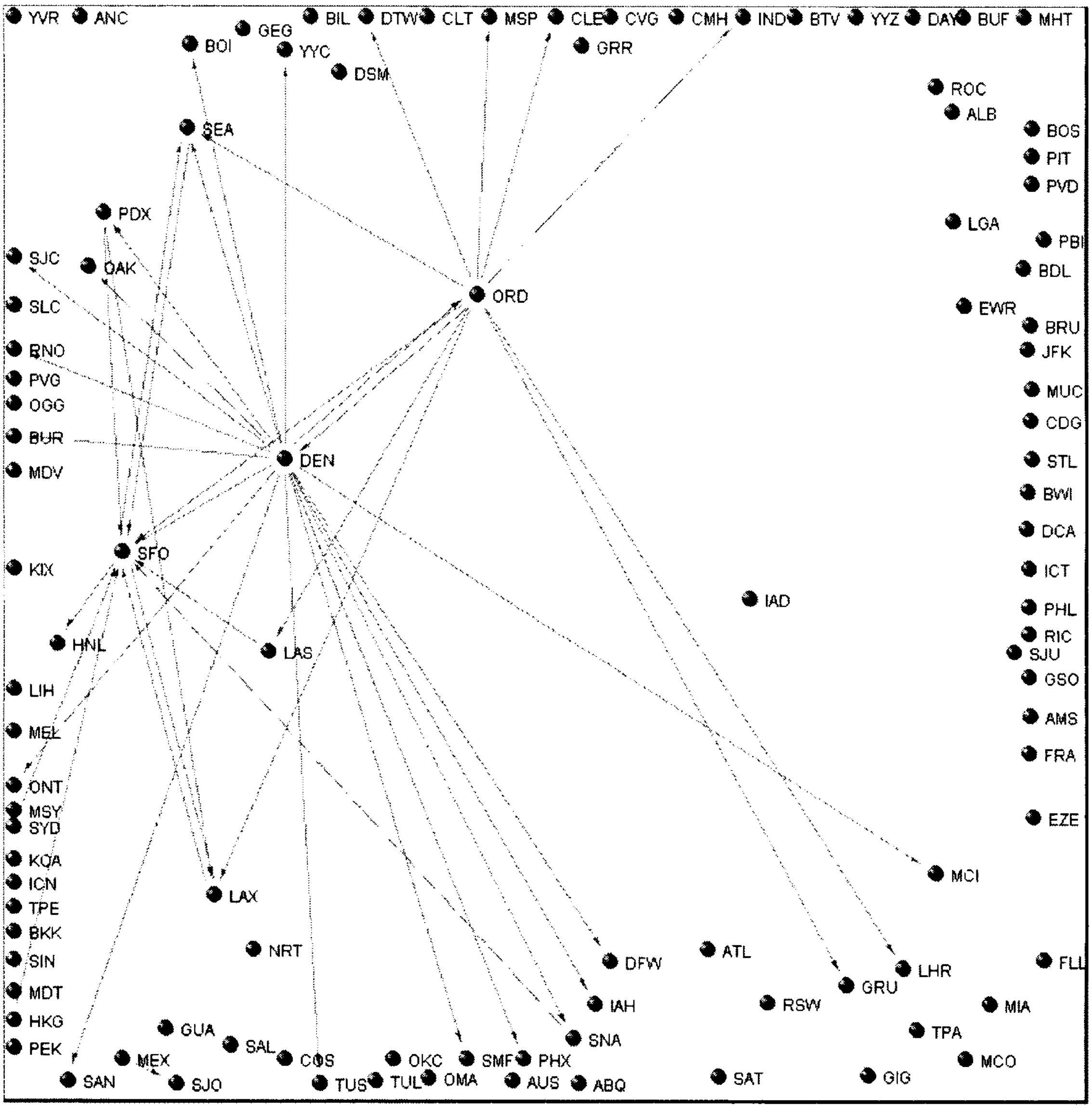


Figure 74: UAL City-Pair Network as of 03z

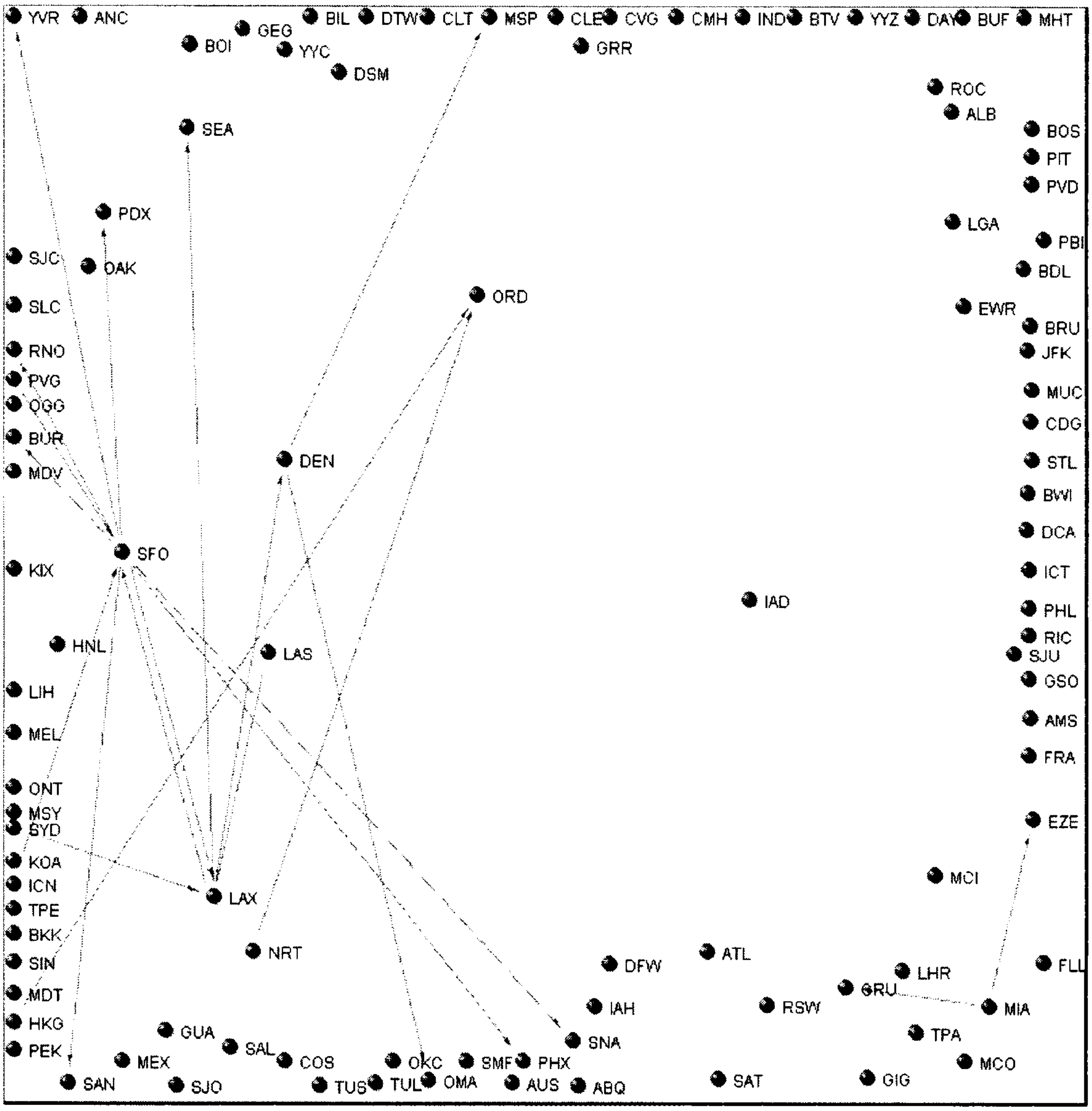


Figure 75: UAL City-Pair Network as of 04z

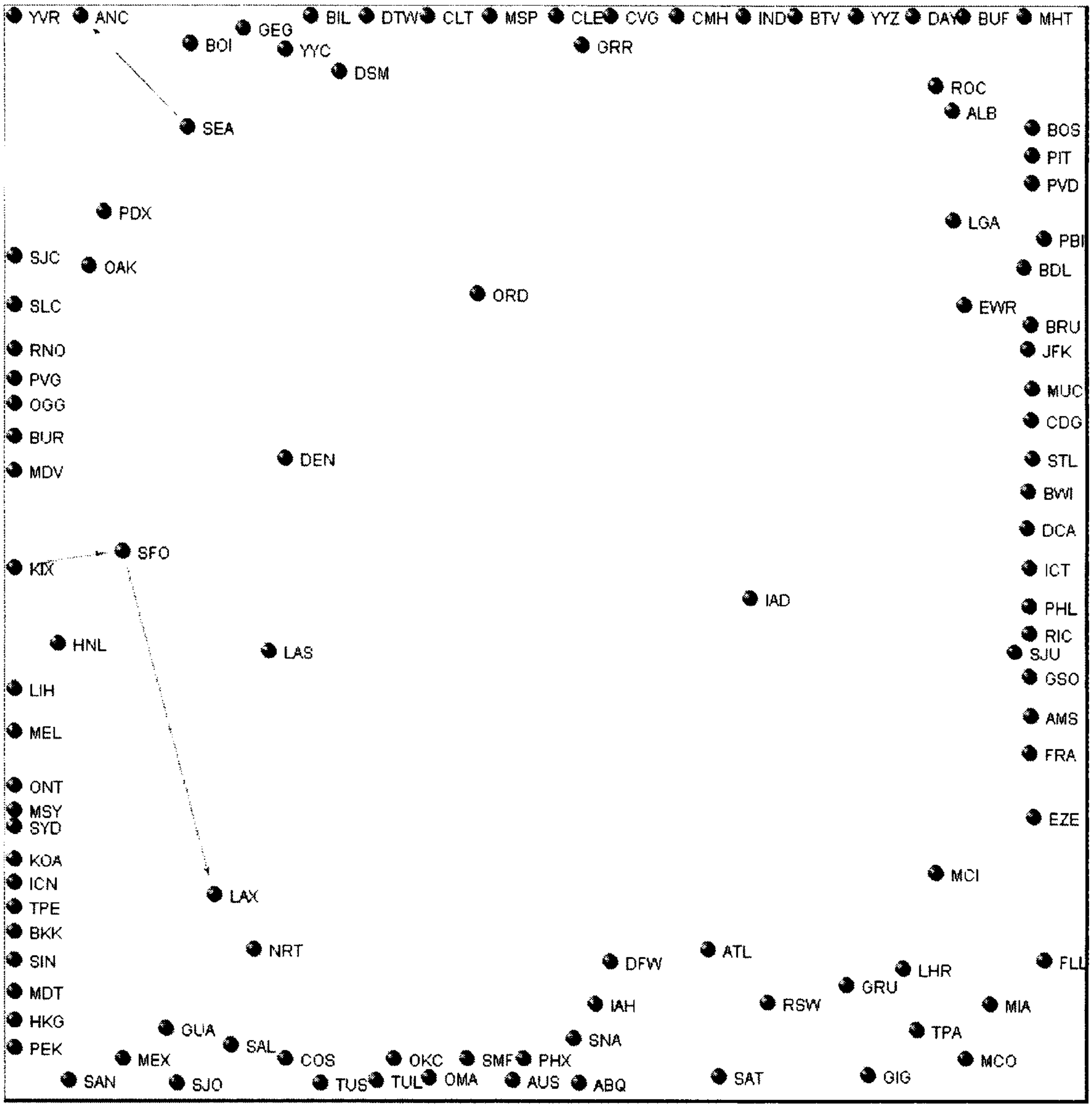


Figure 76: UAL City-Pair Network as of 05z

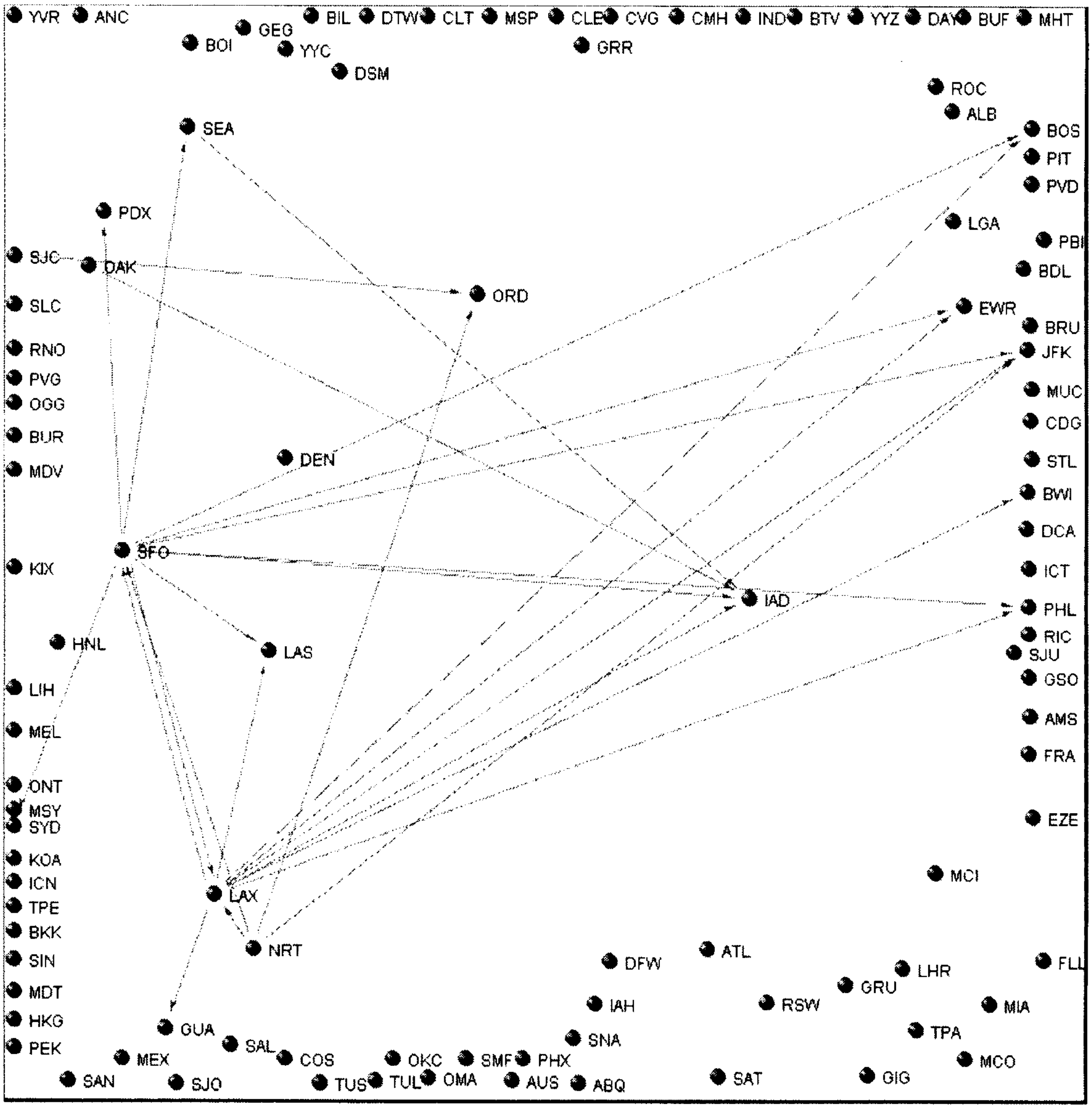


Figure 77: UAL City-Pair Network as of 06z

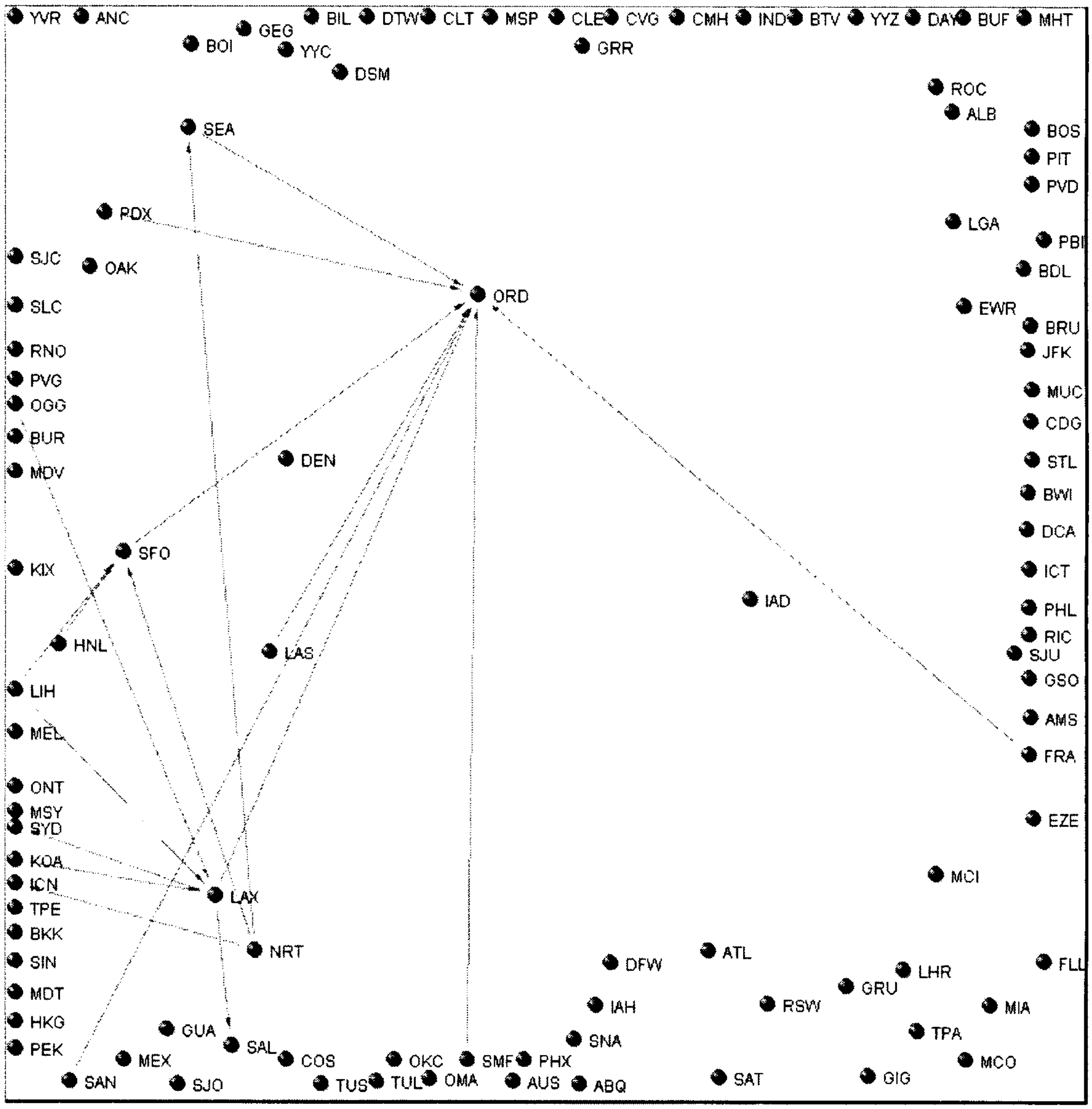


Figure 78: UAL City-Pair Network as of 07z

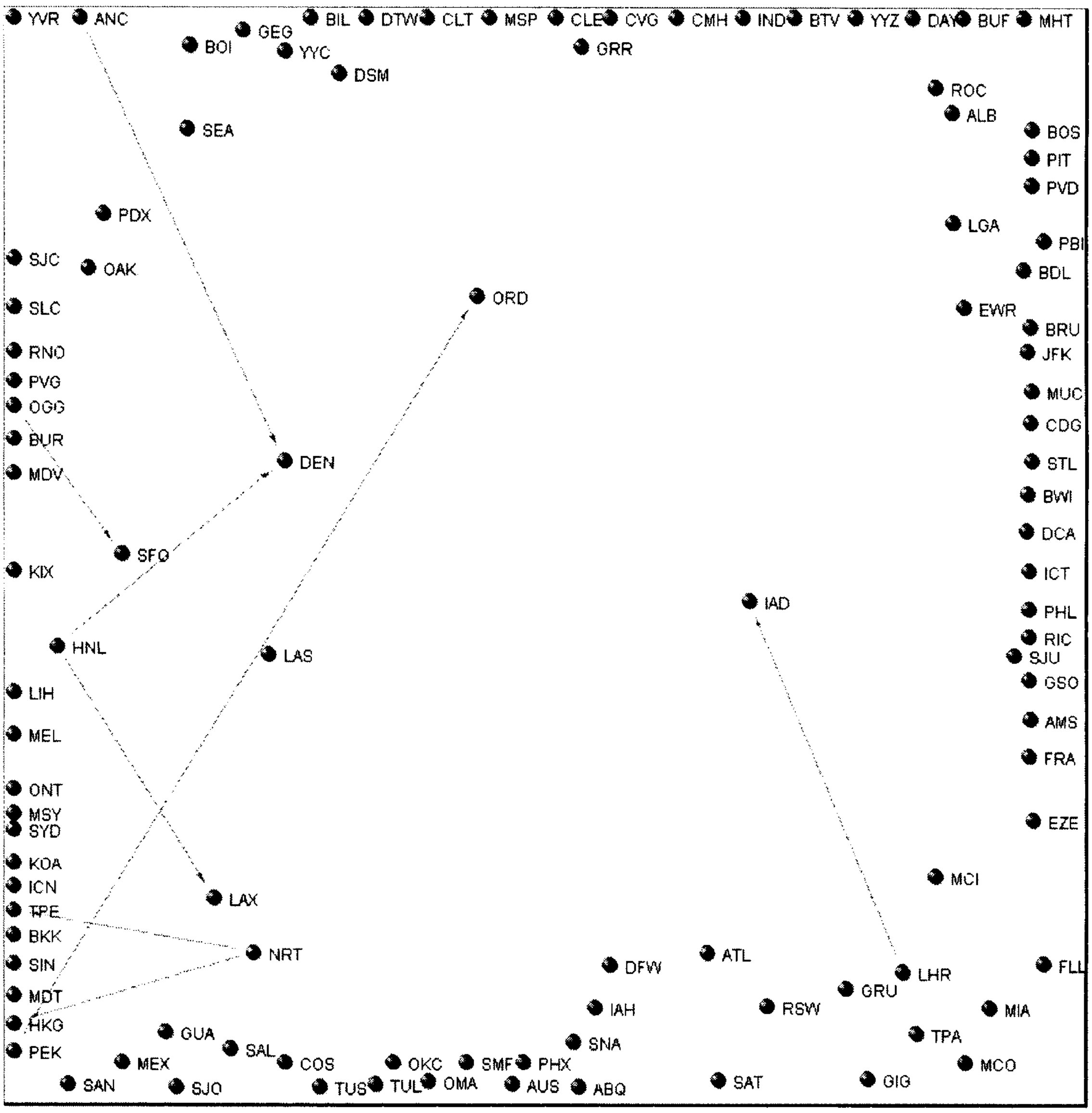


Figure 79: UAL City-Pair Network as of 08z

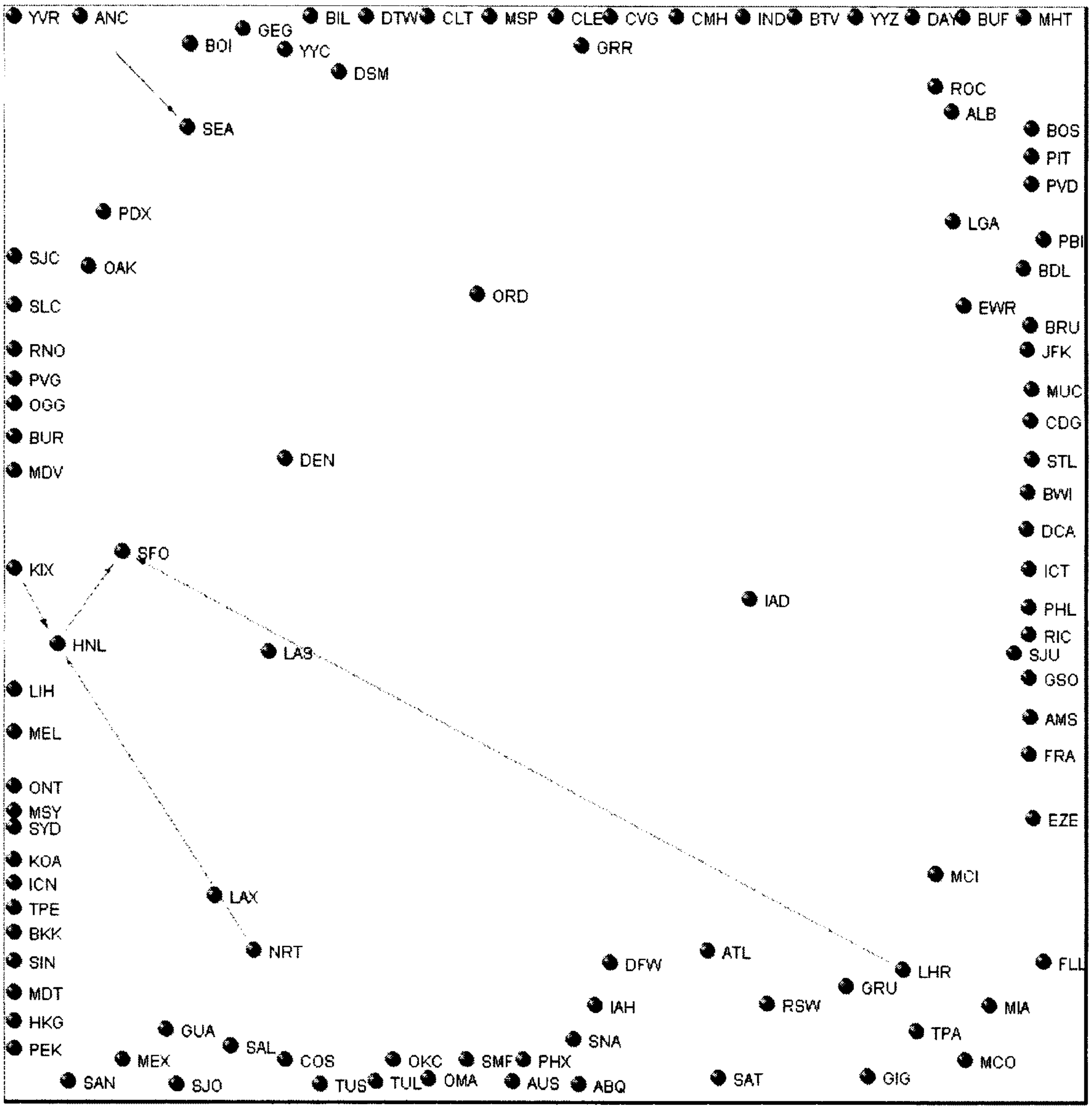


Figure 80: UAL City-Pair Network as of 09z

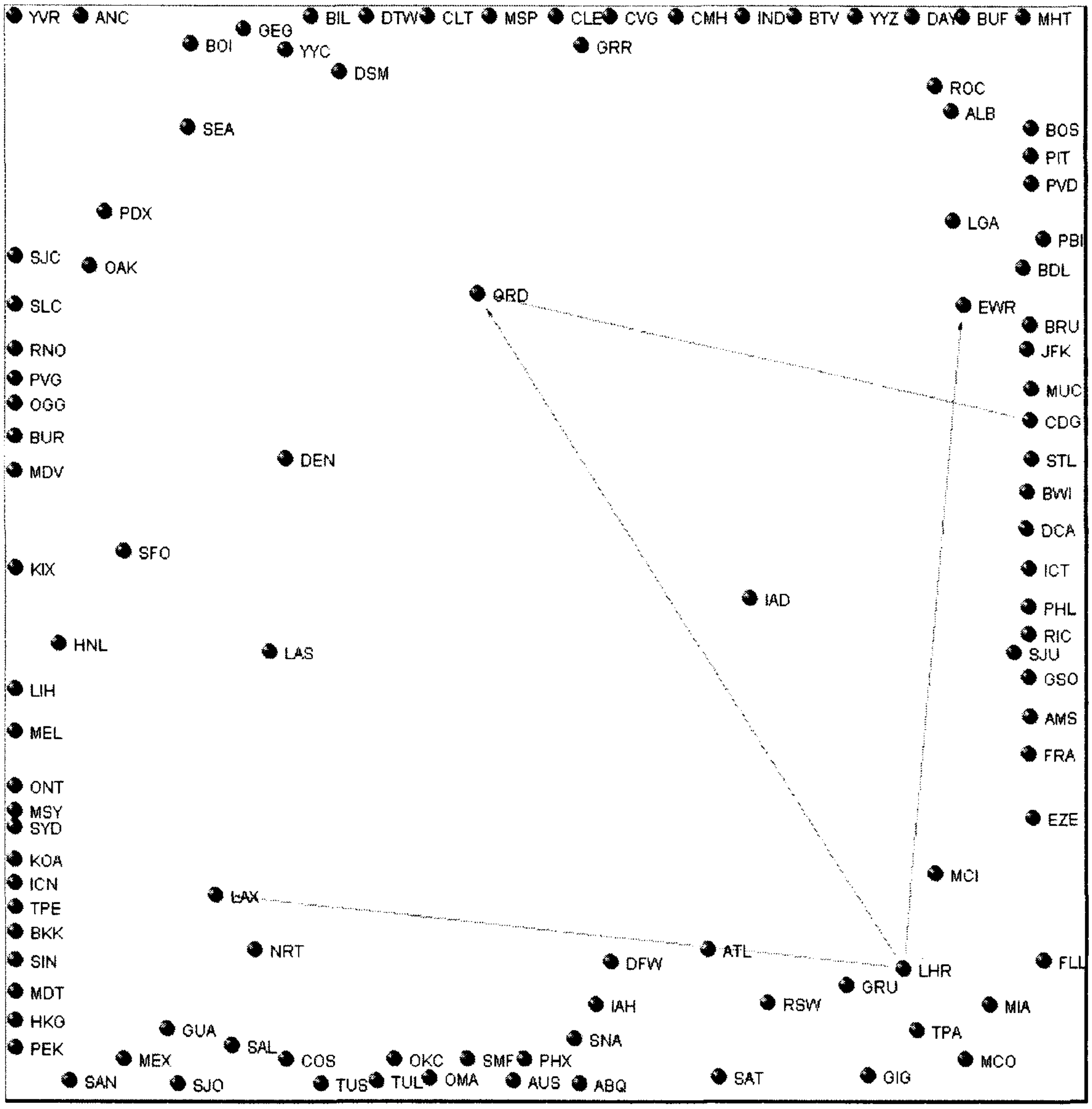


Figure 81: UAL City-Pair Network as of 10z

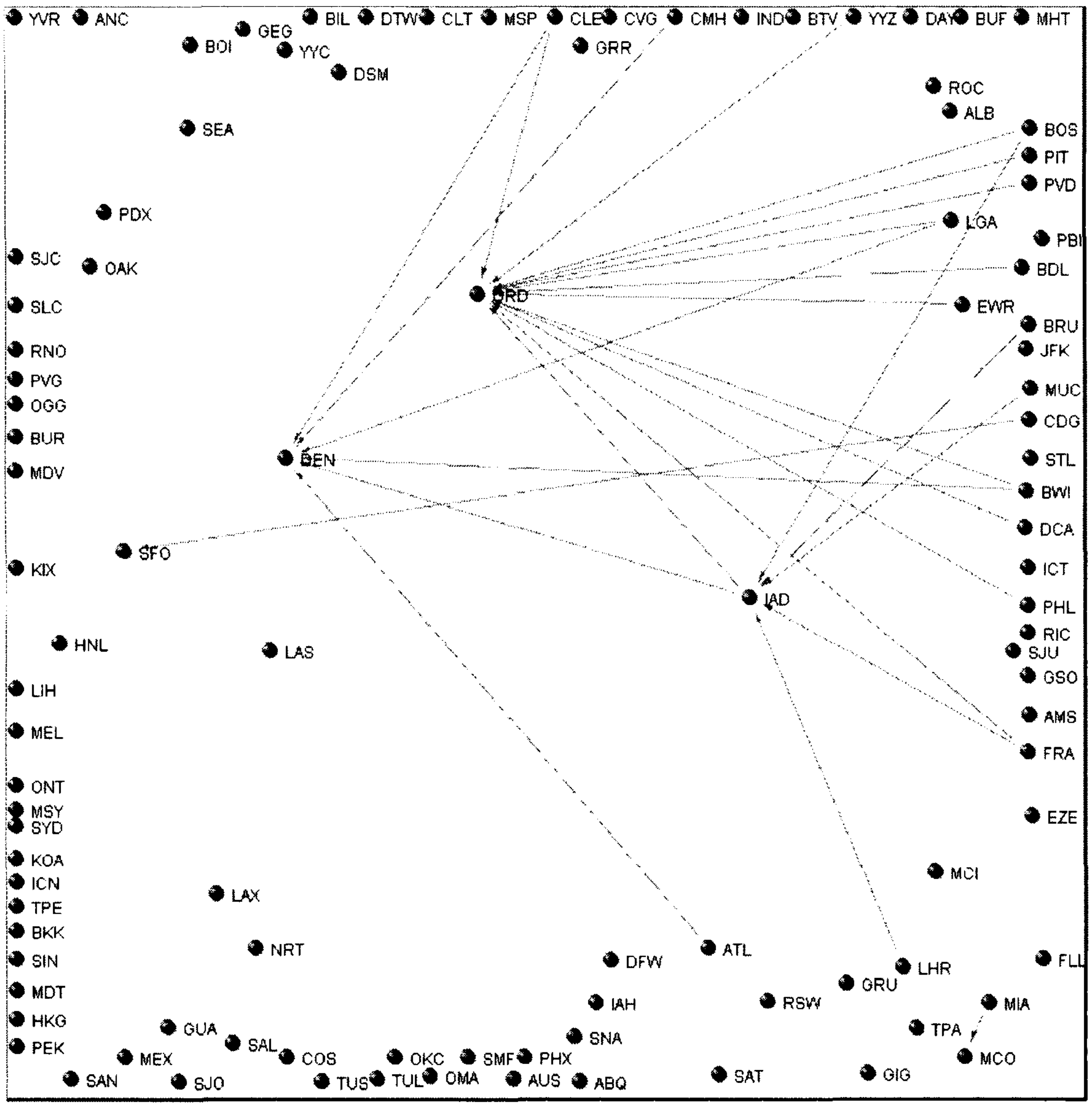


Figure 82: UAL City-Pair Network as of 11z

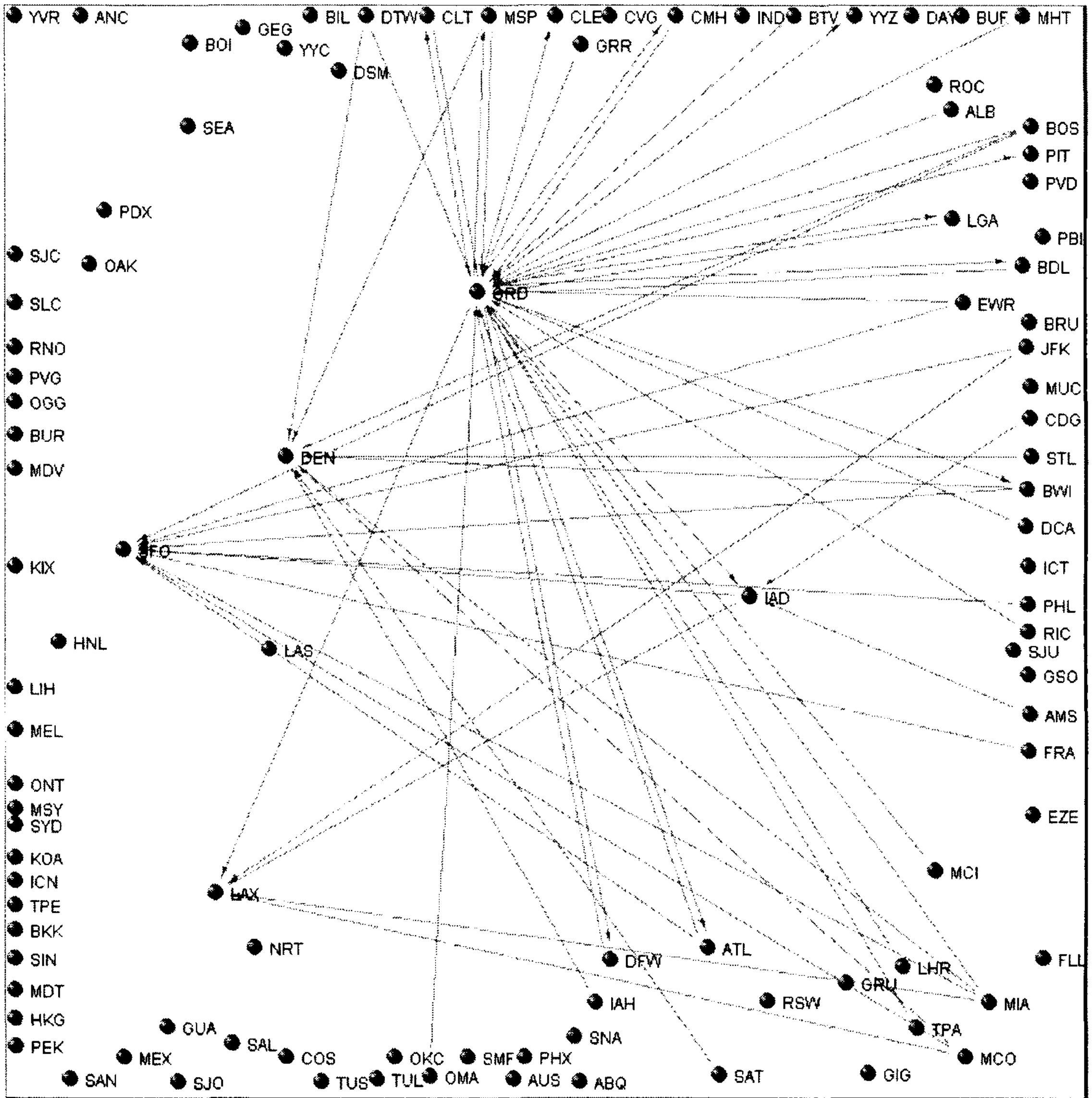


Figure 83: UAL City-Pair Network as of 12z

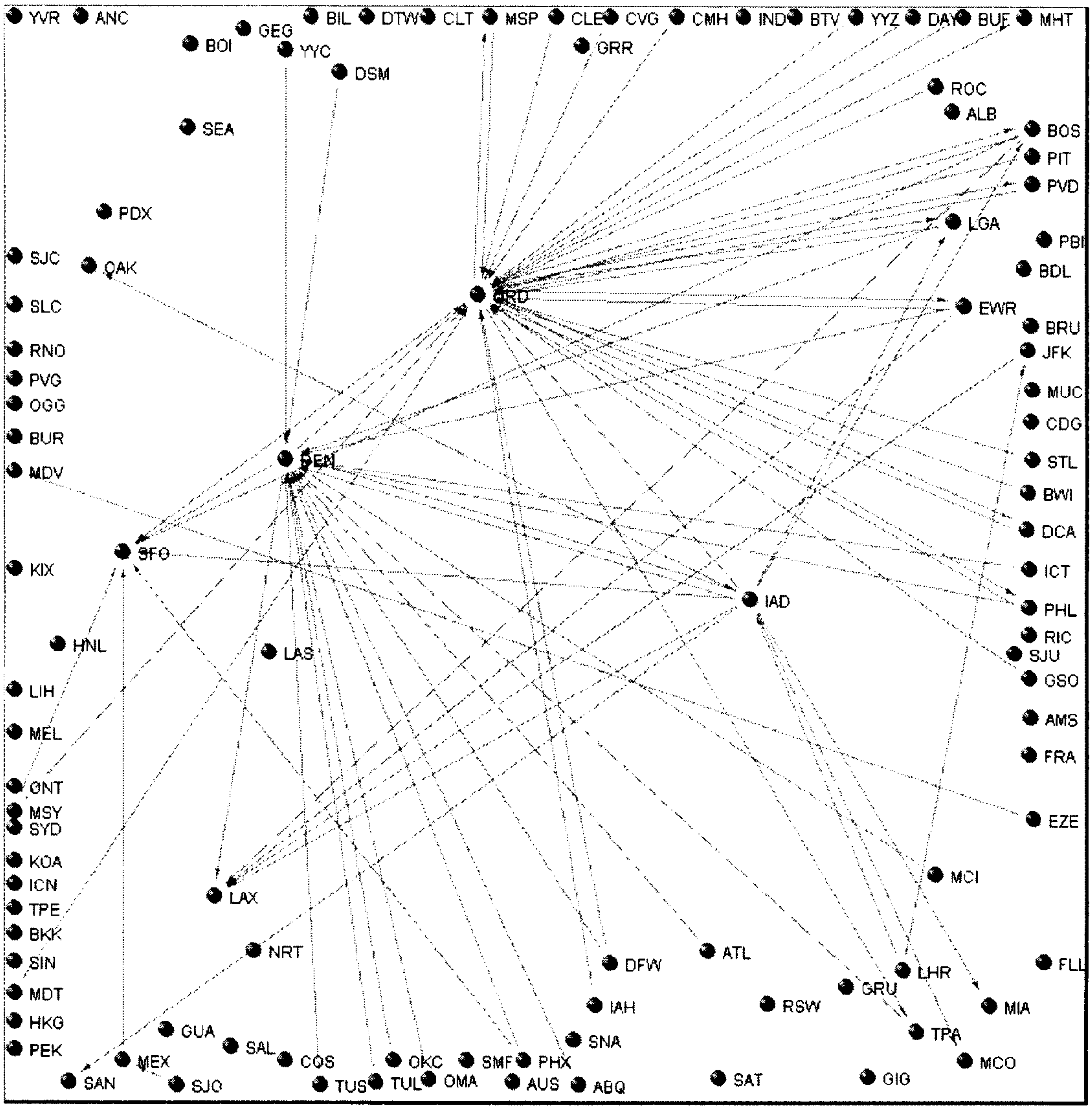


Figure 84: UAL City-Pair Network as of 13z

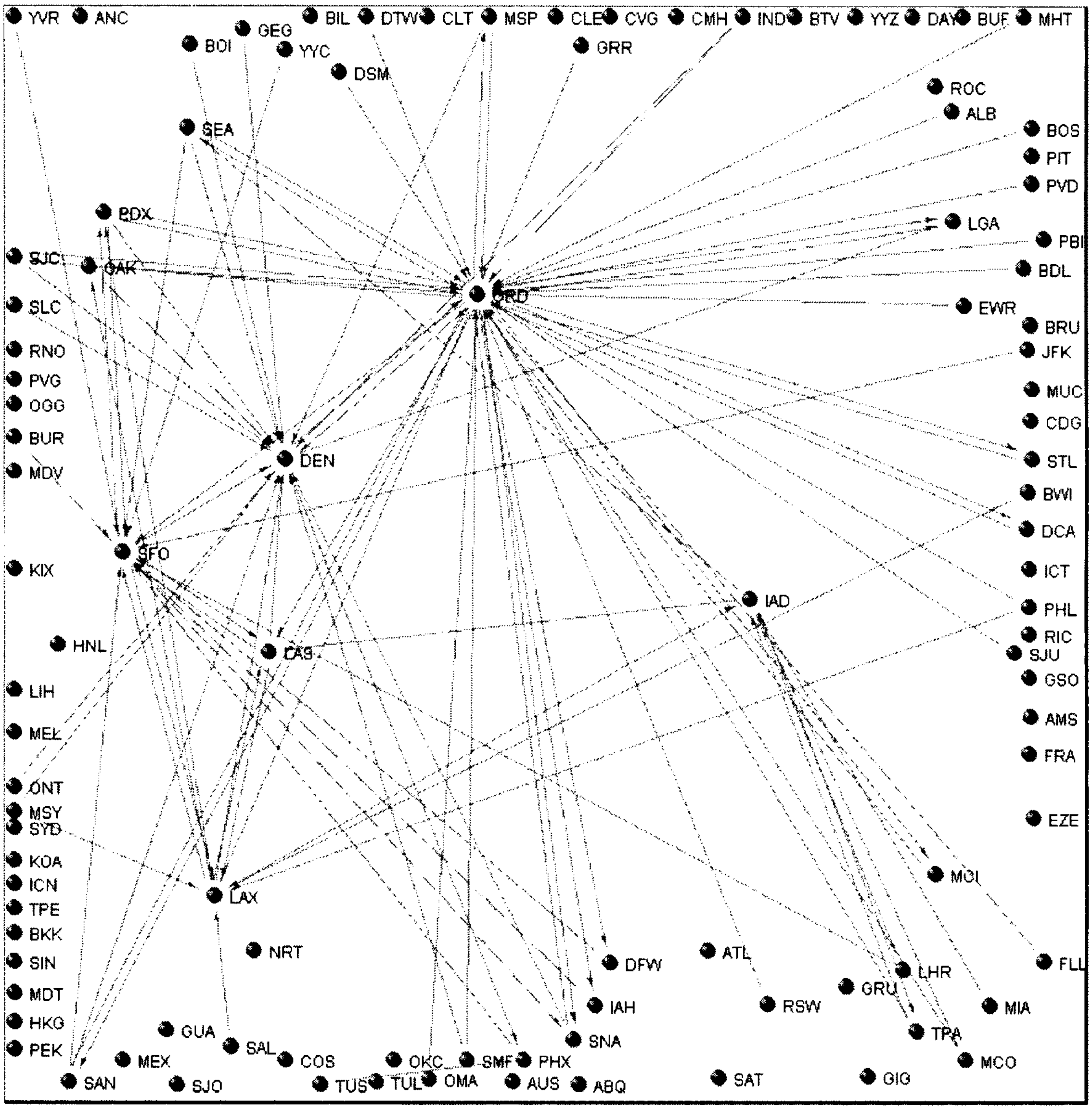


Figure 85: UAL City-Pair Network as of 14z

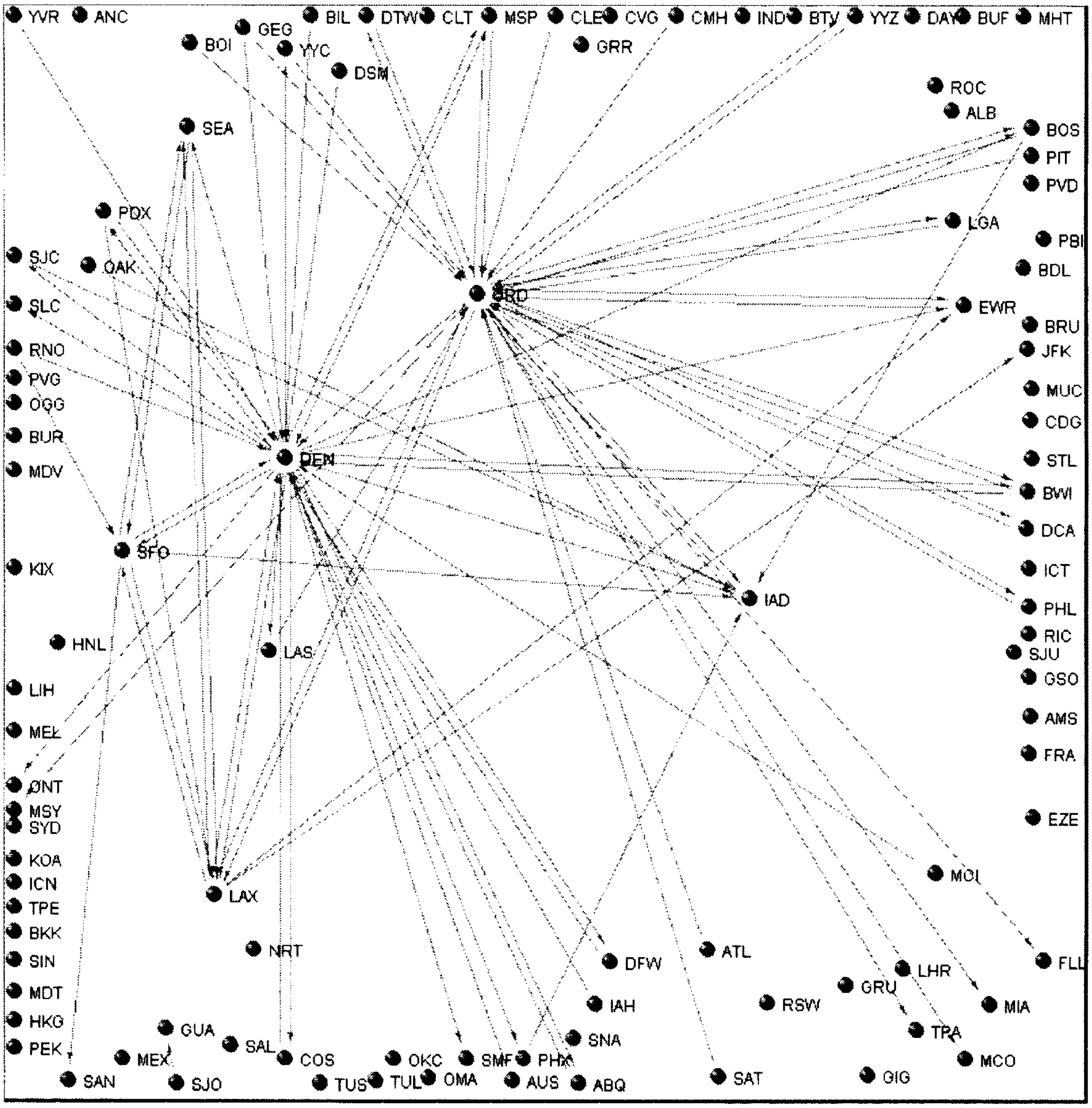


Figure 86: UAL City-Pair Network as of 15z

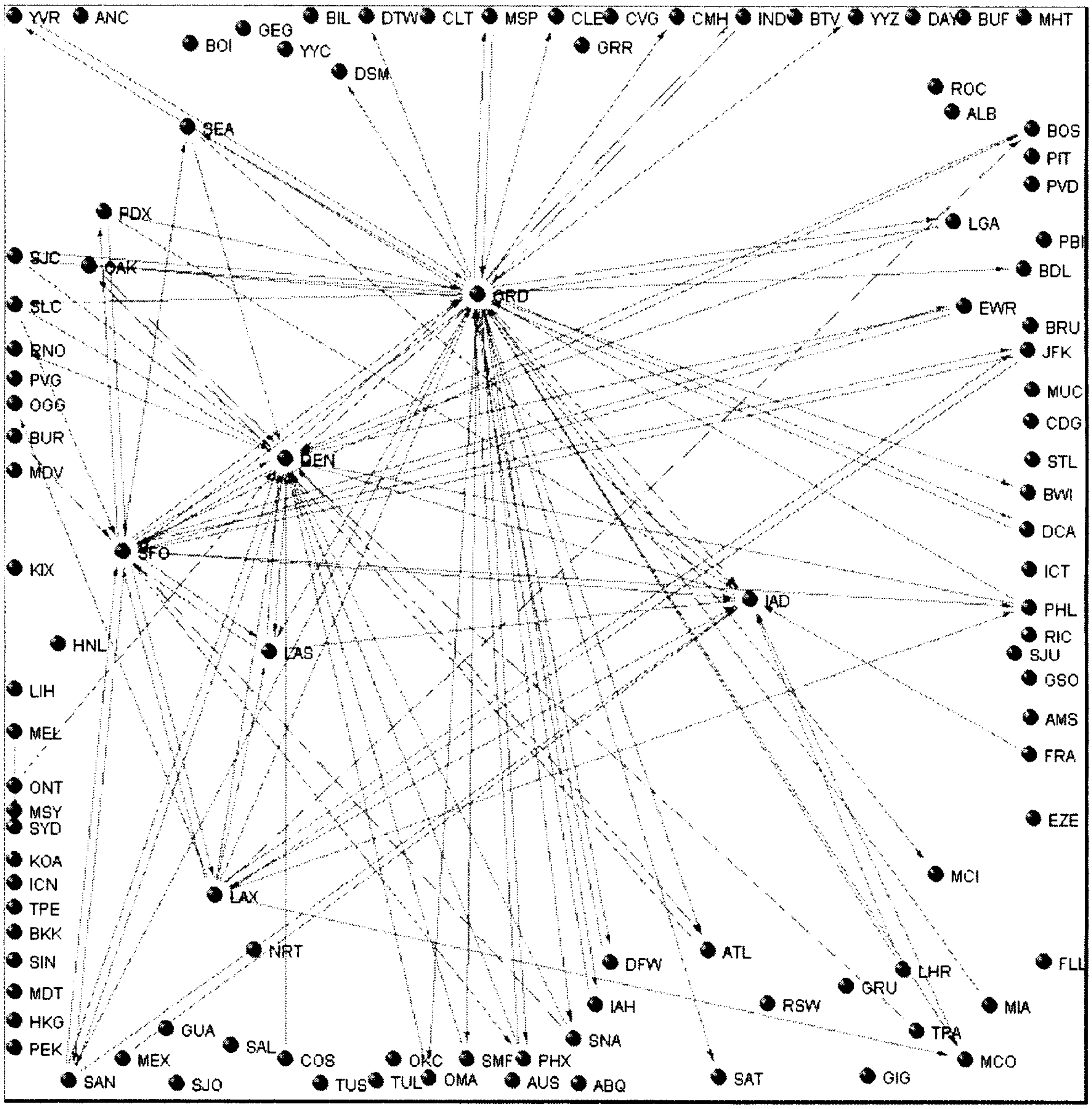


Figure 87: UAL City-Pair Network as of 16z

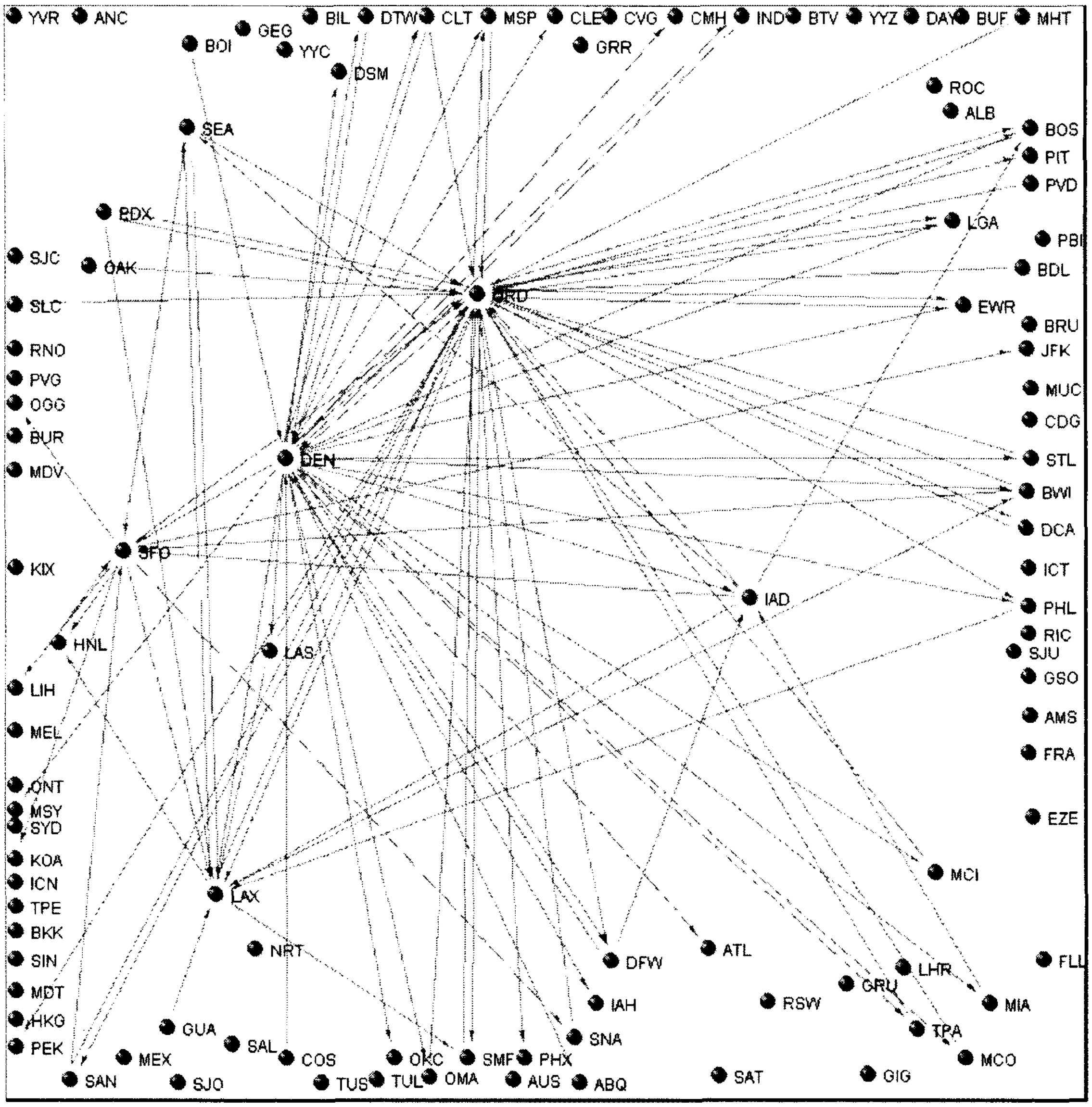


Figure 88: UAL City-Pair Network as of 17z

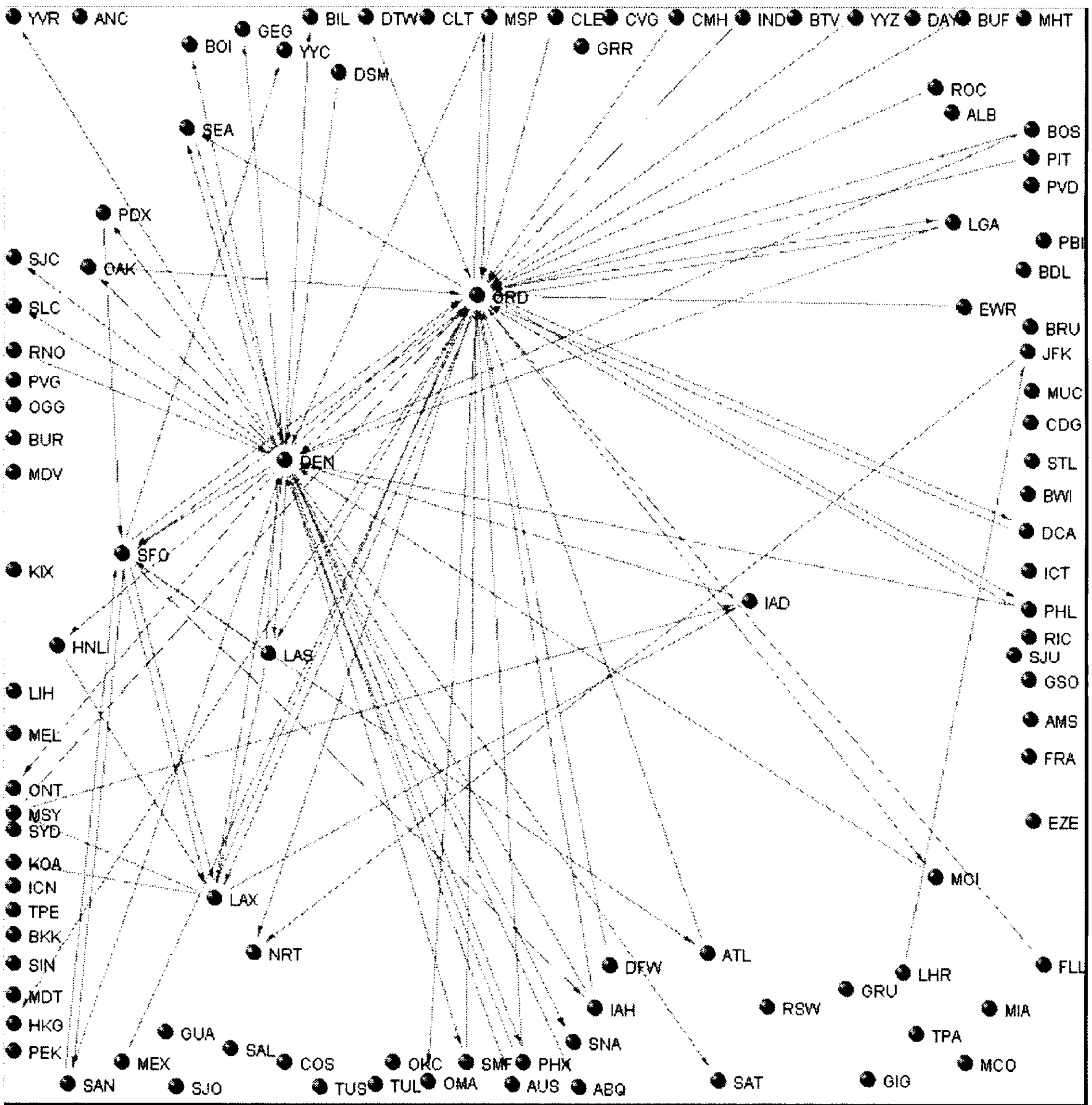


Figure 89: UAL City-Pair Network as of 18z

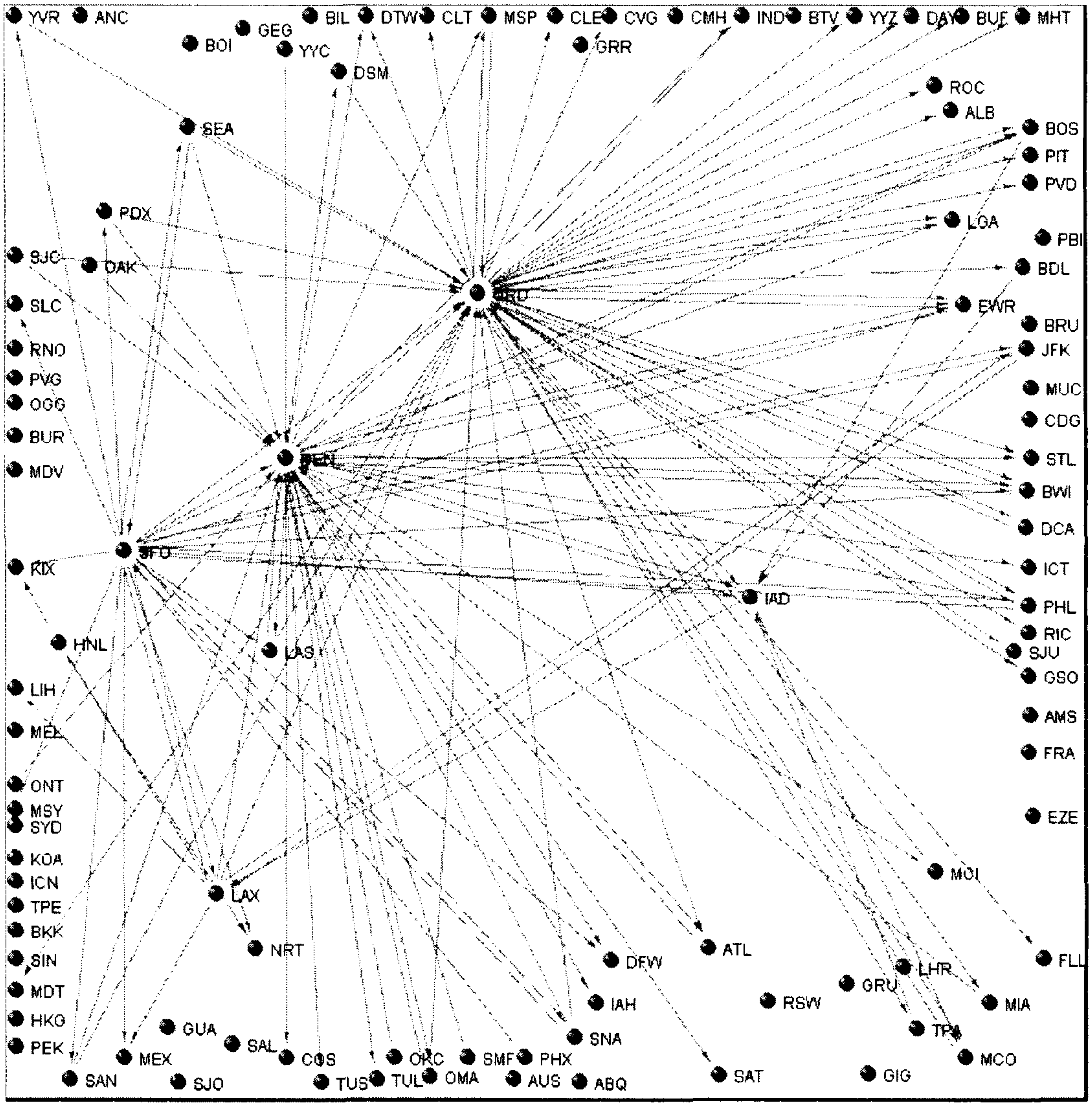


Figure 90: UAL City-Pair Network as of 19z

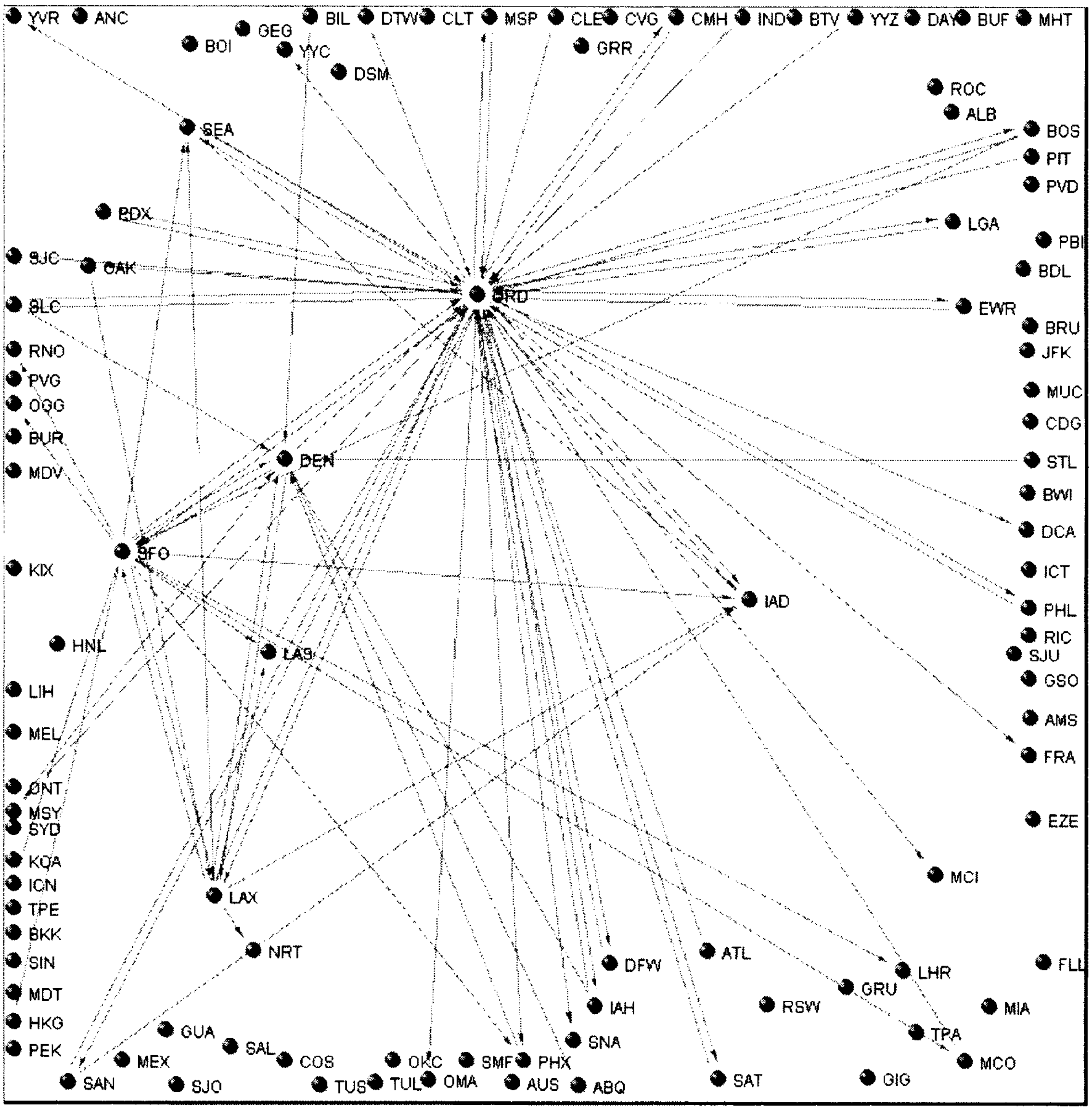


Figure 91: UAL City-Pair Network as of 20z

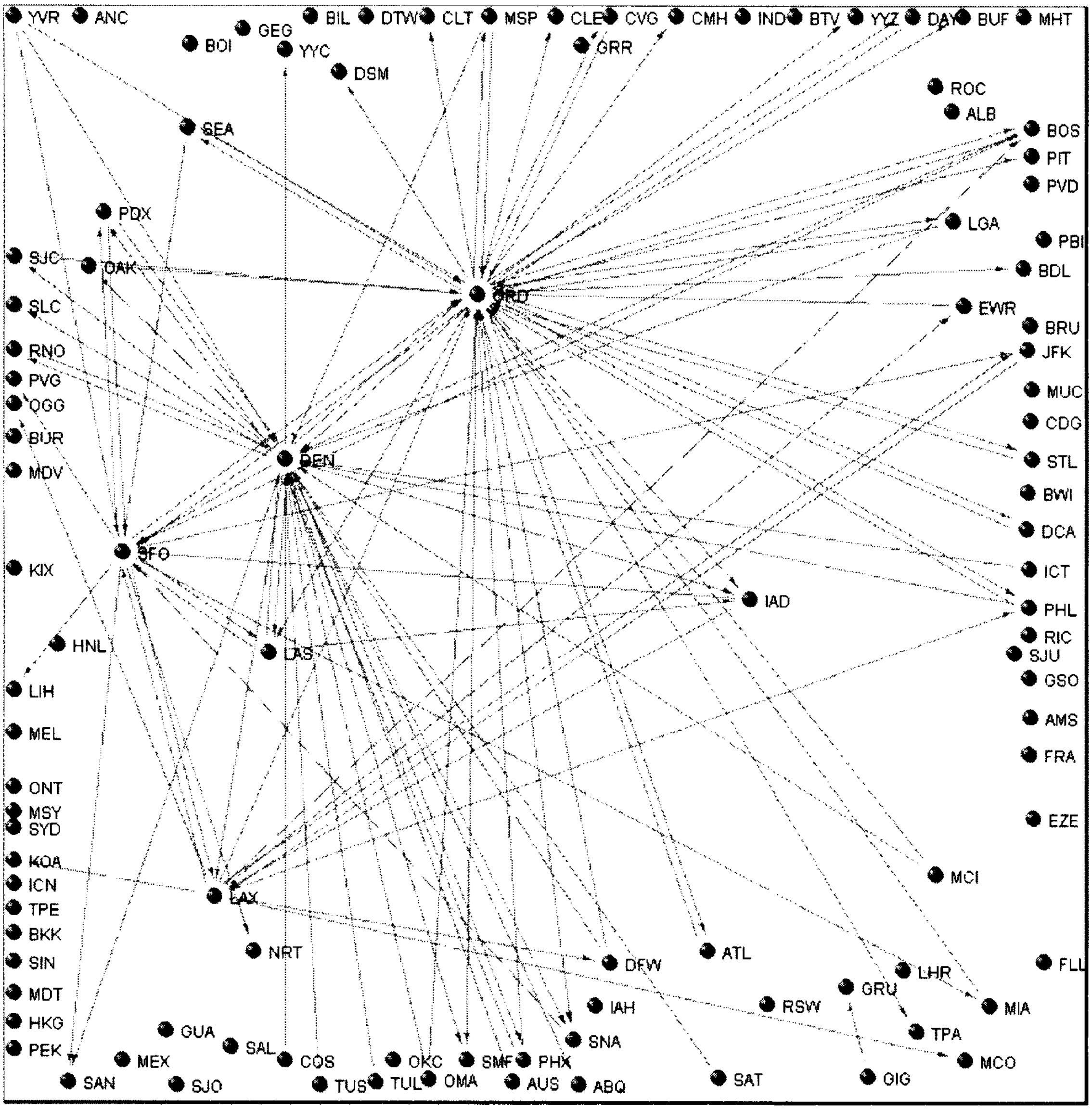


Figure 92: UAL City-Pair Network as of 21z

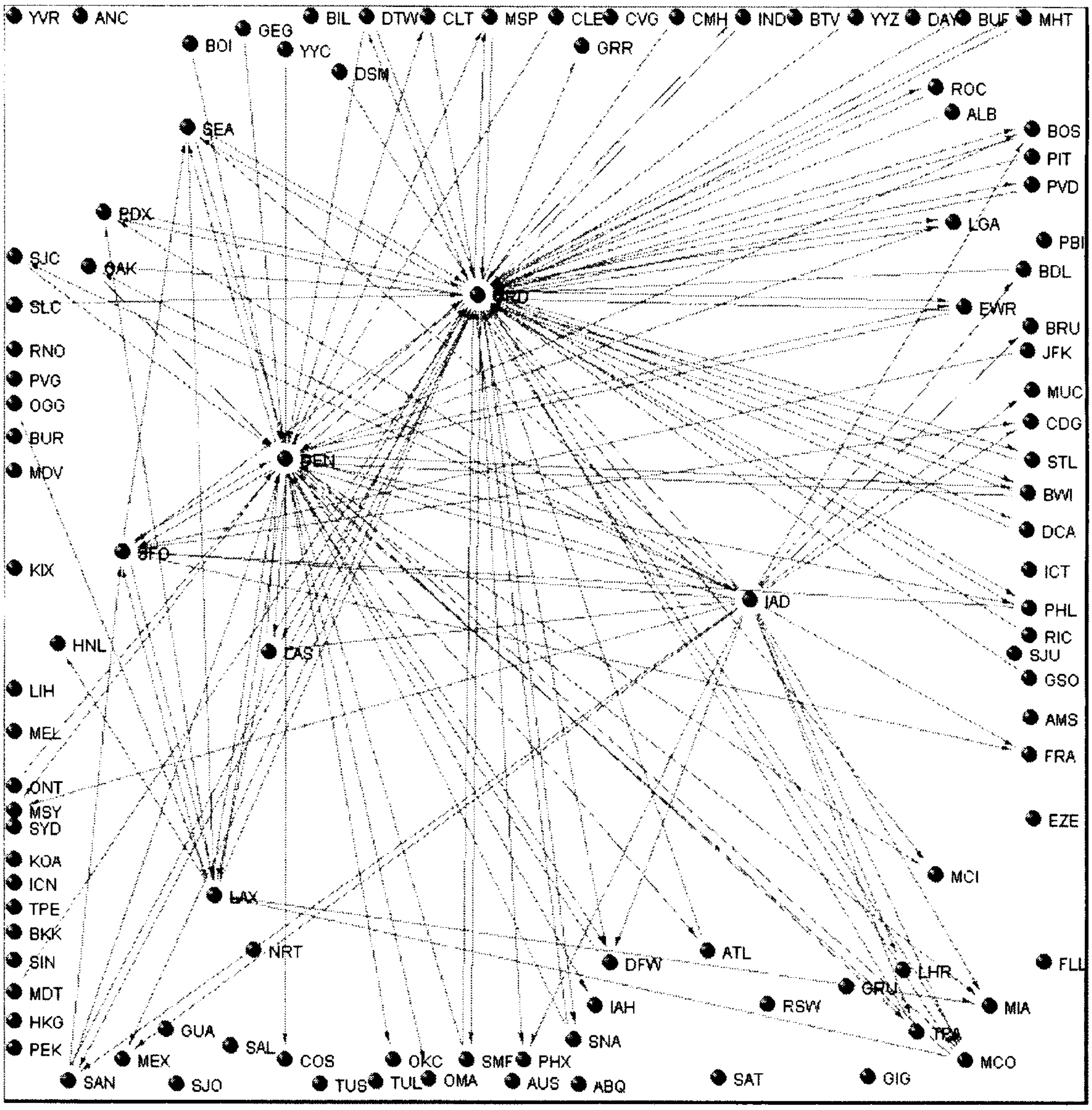


Figure 93: UAL City-Pair Network as of 22z

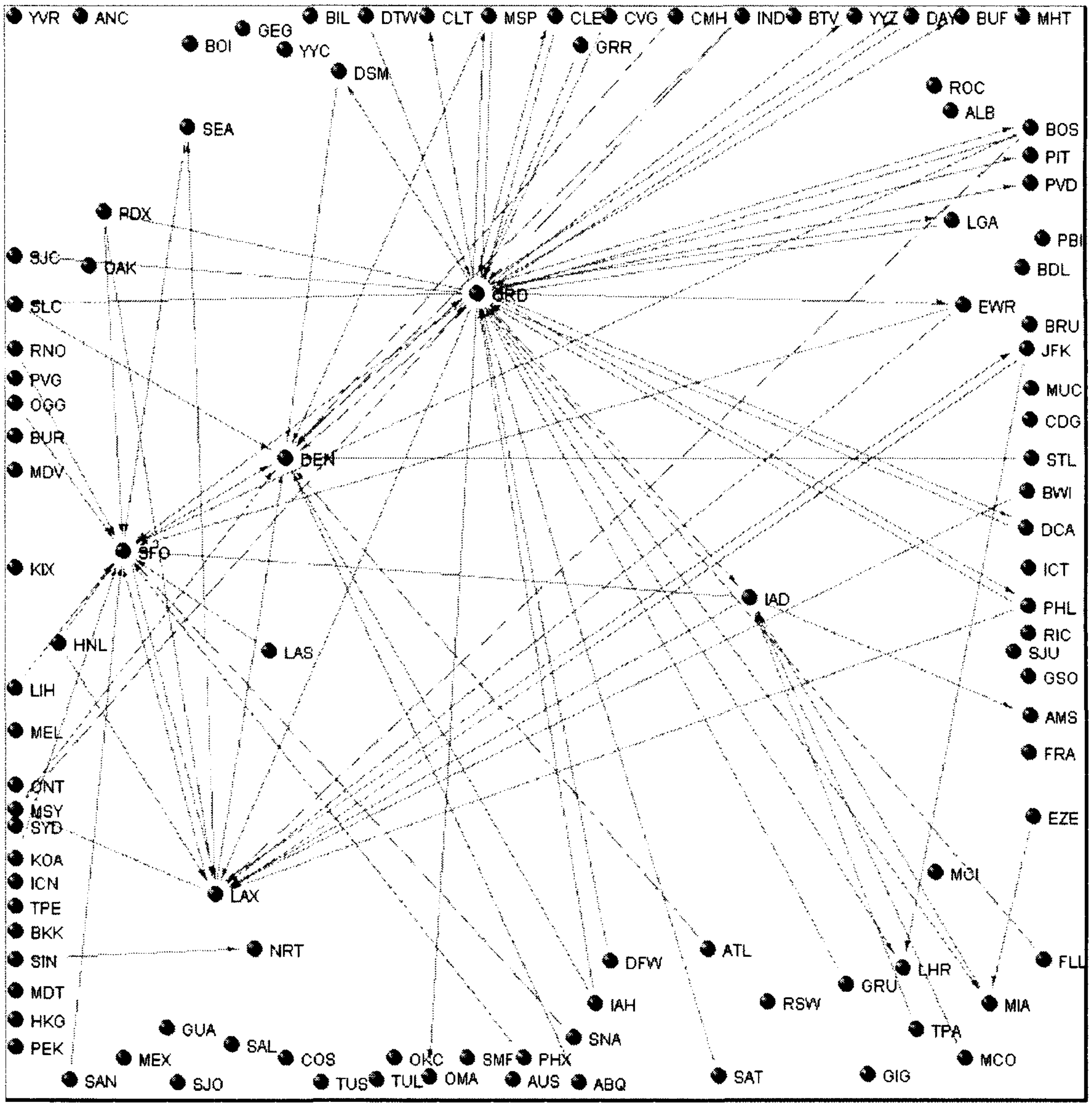
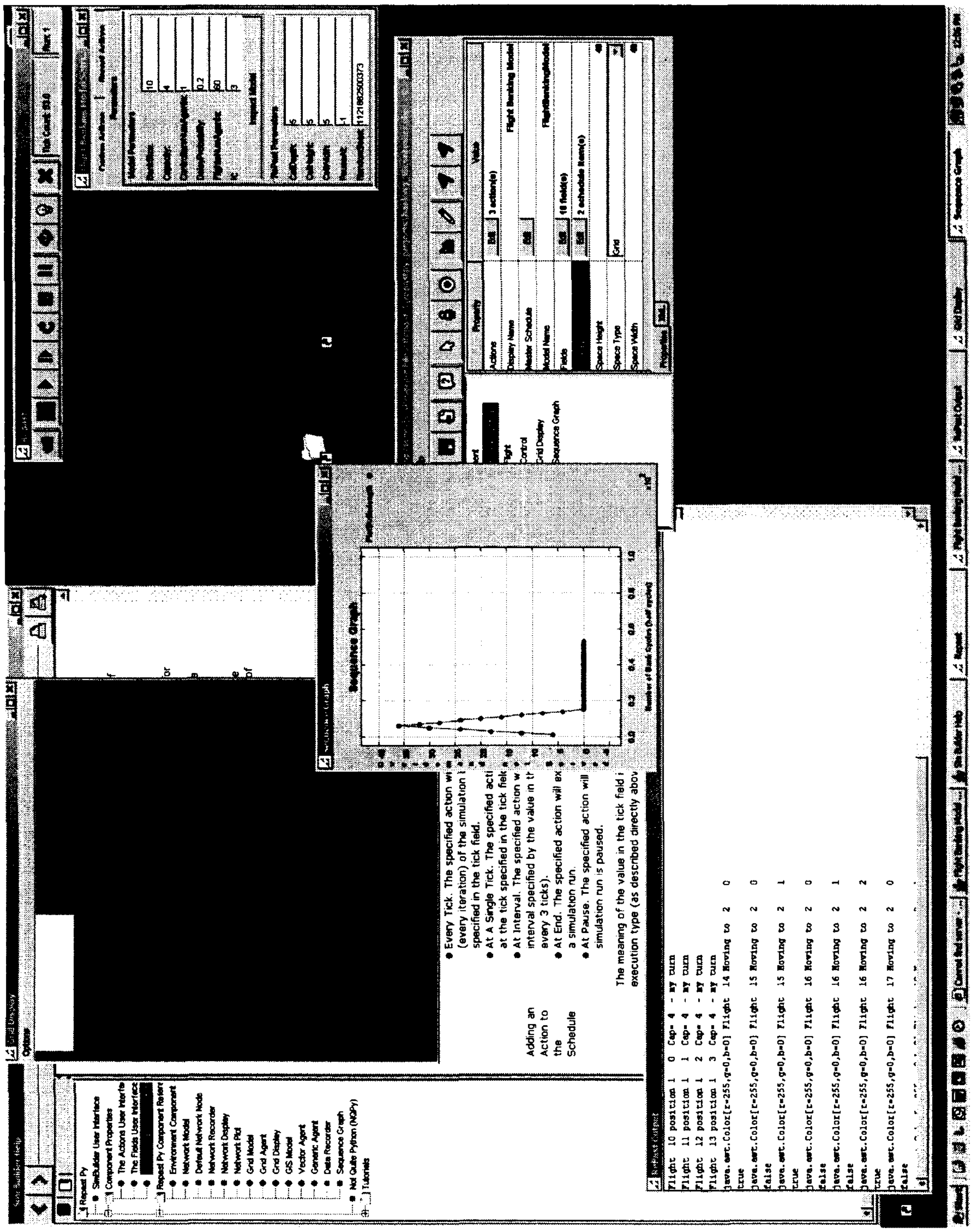


Figure 94: UAL City-Pair Network as of 23z

APPENDIX B:

USING REPAST PY



.Figure 95: Typical RePast Development Screens

One of the key elements of this investigation was to find capable modeling platforms that required only minimal investment in their operation, as to maximize the ability for subject-matter experts to contribute to the system modeling effort. After an extensive search, and trial of a number of platforms, it seemed Repast met all the requirements. Other platforms, such as NetLogo, met the requirement for simplicity of use, but had limited modeling capability.

From their website (RePast, 2011), "The Repast Suite is a family of advanced, free, and open source agent-based modeling and simulation platforms that have collectively been under continuous development for over 10 years" The software affords quick and easy development of agent models, data collection and analysis, and visualization. The collection of software libraries provide necessary functions for a basic simulation, such as initiating other software elements known as agents, timing, graphic user interface for user input, etc. There are different versions available, ranging from Repast for High Performance Computing (Repast HPC) to RePast Py (for Python programming language) the most simple, used for this study. The suite, supported by a large user community, continues to expand, is well documented, and the authors offer very useful training courses.

Compared to some other platforms specialized for ease of use, RePast does require an investment to use. However, the return is a highly capable and fully configurable platform. To use the series of Repast libraries, the modeler has to be familiar with compiled programming language such as C++, Java or C#, and the use of an integrated development environment (IDE) such as Eclipse. For someone without object-oriented programming experience, the learning curve for using Repast can be substantial. Repast Python, one of the alternate versions available, affords much of the same functionality but simplifies the access to the libraries. It uses a graphical user interface that calls some of the same software libraries, but requires only selection of model elements (such as data charting) without having to code these functions from scratch, or even build main programs that call these sub-routines.

Repast Py, unlike some of the other simplified user-oriented agent modeling platforms, allows the agents to have specialized, programmable behaviors. This scripting is written in Not Quite Python (NQP), a subset of the python language hosted within Repast Py. This makes the investment to both establish a basic agent-based platform and specialized agent behaviors relatively simple compared to the capability of the simulation. Figure 95 shows a typical development set-up for Repast Py. In this snapshot of a desktop during a development session, the output screen, control windows, sequence graph and file structure are shown. These basic simulation features are native to the Repast software, but are invoked through various user preferences in the main modeling window. These inherent elements, along with simulation timing and data recording, minimize a modeler's time spent building a basic simulation, and allow concentration on the details of an agent's actions and the variables they interact with.

When you open a new model in Repast, you mush choose one of three different types of basic models, GIS, Network or Grid, as shown in Figure 52, that best represents the system of study. You can then add features like a display which will show your agents as they perform the simulation, a data logger, a graphic output of any variable, and of course, agents, the performing "action" elements of the simulation.

The model itself will be assigned actions, fields, and a schedule for its actions. In Figure 96, an example of a model's definition, we can see the selected model elements, including flight and controller agents, a grid display, and a sequence graph. We can also see the access to the action, schedule and field editors, and the model type (in this case, a grid). Shown below the model window is a typical action editor for the model level. These model-level actions typically include initiating agents, assigning variables, values, etc. In this case, the model actions are used to synthesize the flight schedule and assign dependencies according to user-defined inputs.

Each agent, like the "flight" agent shown in Figure 97, has defined actions, a schedule and associated data and variables they access and manipulate (Figure 98 & Figure 99). Since agent specifics are written in NQP, there is tremendous flexibility in agent behavior and inter-agent interaction. Unlike other software that only offer set actions, here they can be fully scripted by the modeler if they so choose. The other model features, like graphing and data logging, are similarly defined.

Using the Repast Suite, a modeler has the flexibility to use inherent simulation features to quickly build a simulation with little software coding experience. But it also allows for customization or scratch creation of any element to suit their specific needs.

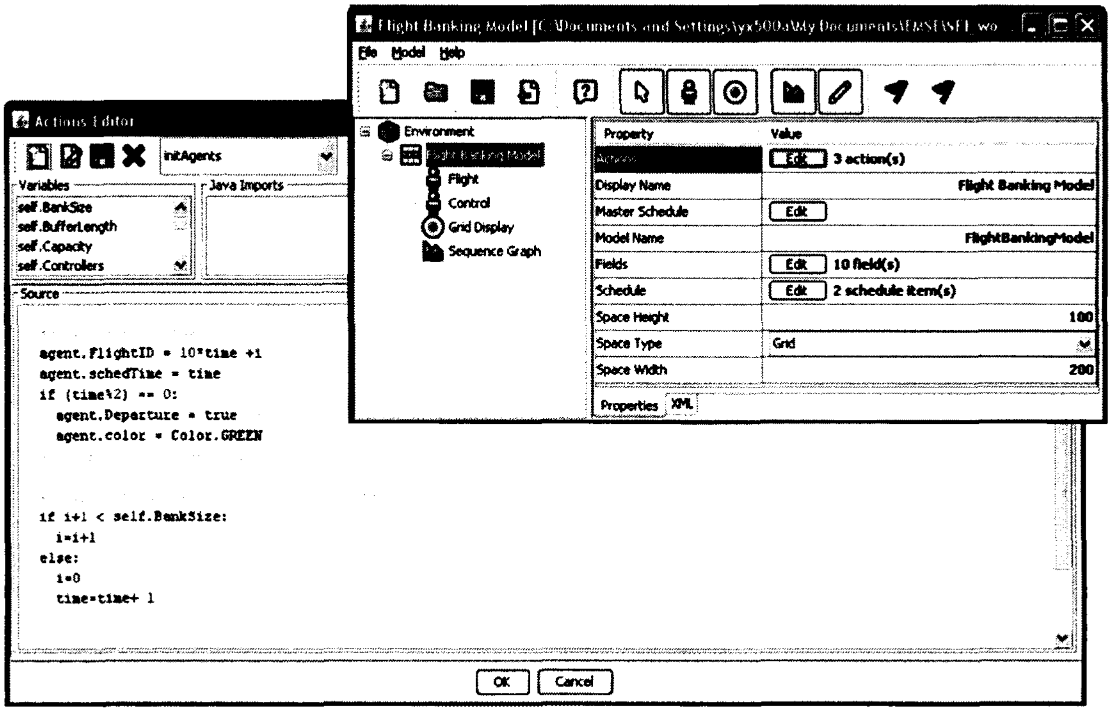


Figure 96: The Flight Banking Model & Model Actions Editor

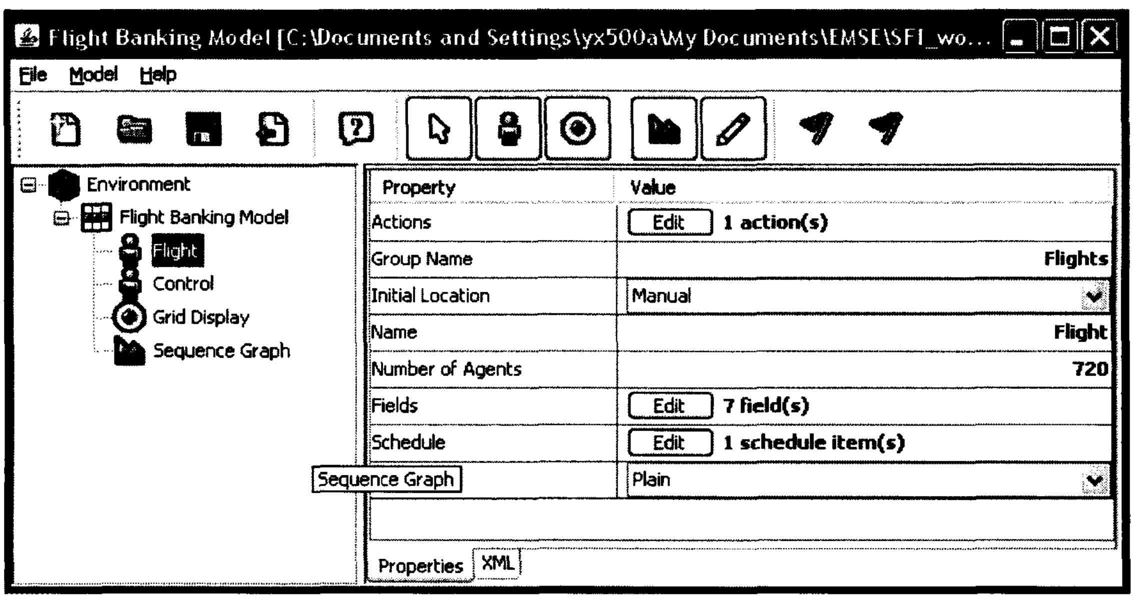


Figure 97: Flight Agent Definition in Repast

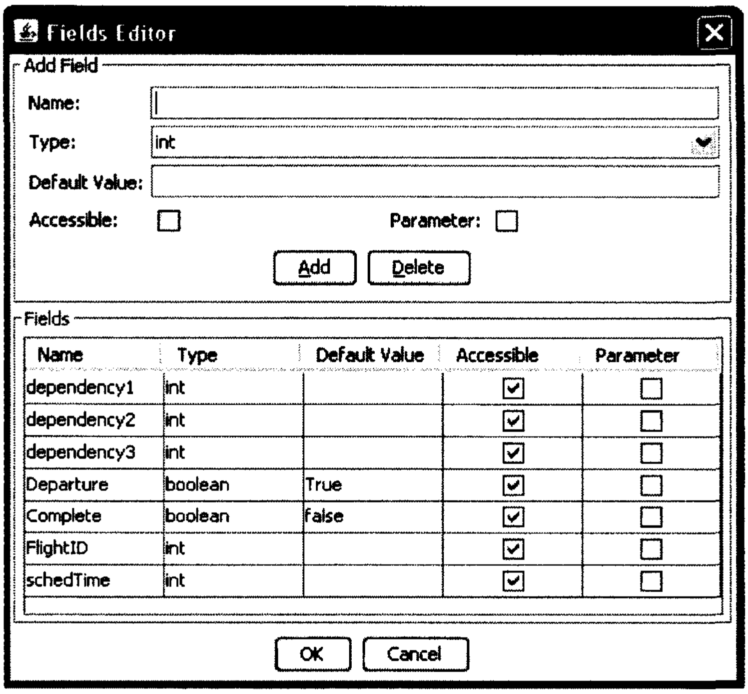


Figure 98: REPAST Fields Editor

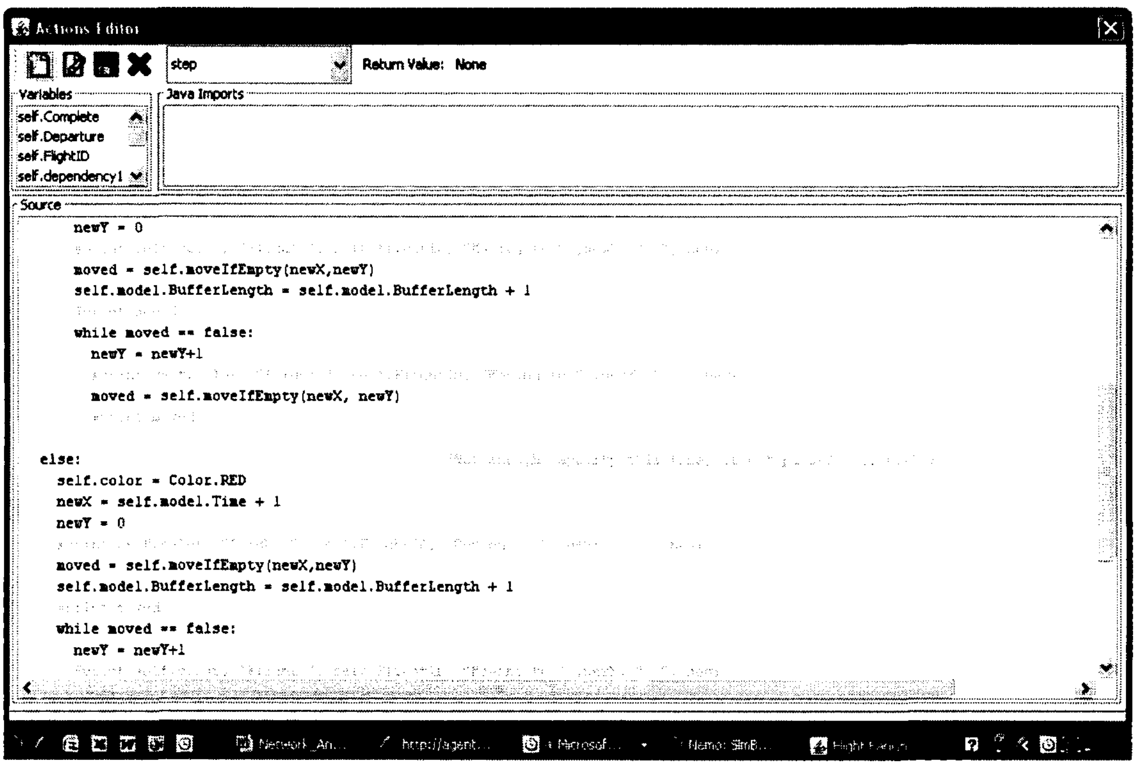


Figure 99: Repast Agent actions Editor

APPENDIX C

TRANSIMS

While there were lots of simulation platforms for generic network and agent models, it seemed there should be platforms dedicated to transportation networks, fleet systems, etc. There are models of air transport systems such as TAAM (Total Airspace and Airport Model), but as discussed in the literature review above, these all seemed unsuited for the work at hand.

However, TRansportation ANalysis and SIMulation System (TRANSIMS), developed as open source originally as a grant from the Department of Transportation seemed different. Rather than a single tool it was "an integrated set of tools developed to conduct regional transportation system analyses." It is a cellular automata model, a specialized agent variant, comprised of 4 major modules, and uses road and transit networks as well as transit schedules as *inputs*. Though it was clearly specialized to analyze road traffic behavior, its use of networks as *inputs* to an *agent* environment was very intriguing. Its main purpose was address issues akin to those of schedule delay: congestion and potential alleviation with the addition of flow management controls. Indeed, the approach seemed right-minded, though the focus of this software is clearly on generating a realistic demand profile for traffic rather than concentrating on control solutions robust to a wide range of demand profiles. Even with this caveat, it seemed TransSims was a fine place to start. Ultimately however, the system's focus on demand and specialization to automotive traffic made its use ineffective. But in exercising the installation and use, many useful features of such an analytical toolset were identified and later became requirements.

Transims Installation

During the installation of TranSims, there were a number of obstacles to overcome. Firstly, the file size is daunting: the executable portions (w/o databases) are 235 MB as a Zip file. At the time of installation, it only ran on a UNIX machine, immediately limiting accessibility to many potential users (though there are now multiple versions, mitgating some of this constraint). Another frustration was the apparent file structure required: The instructions imply that the user can create their own TranSims home directory and simulation project directory, and the file structure will always refer to these parent directories. It seemed only a TranSims Directory using the *exact* file and directory names as "suggested" in the instructions.

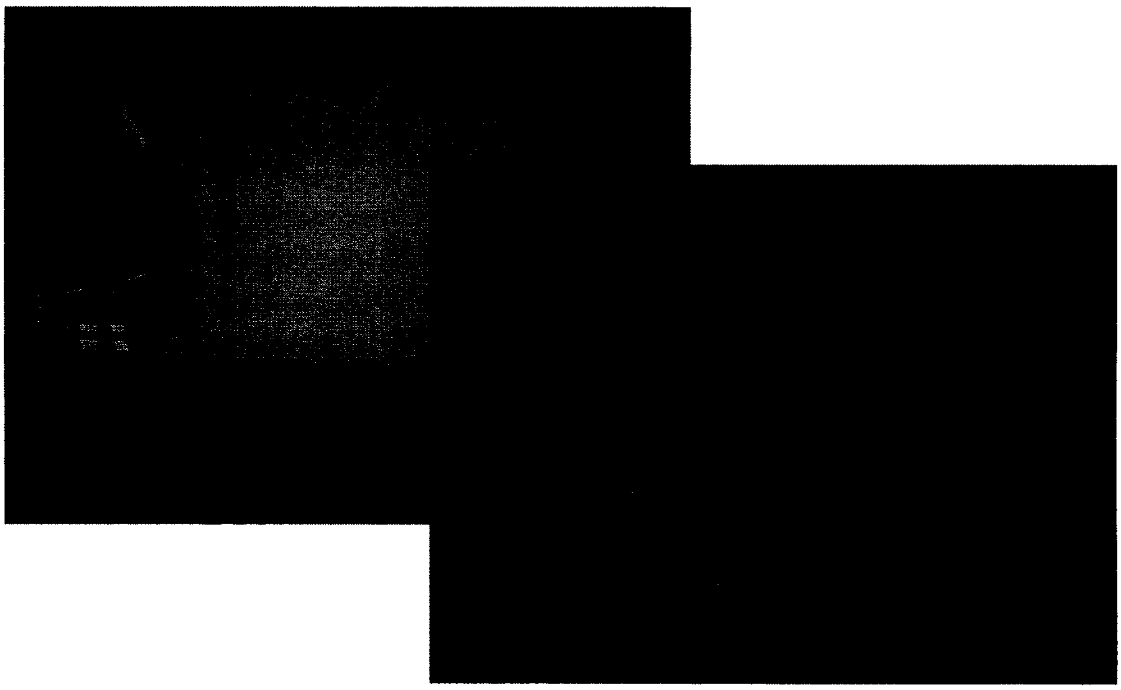


Figure 100: Screen Shots – TranSims, wrapper running

It is not clear that TranSims is intended for casual use: documentation is limited, and had not been kept current to changes in the GUI. For example, it would be helpful to have an index to the TranSims manual and specifically the file names it described.

As a scientific tool, validation is also a concern: the installation guide, provided, is a nice walk through, but it doesn't provide detailed information about the program's operation or about the data structure of the myriad of input and output data files beyond notional diagrams (also useful, but not sufficient). A mapping of the various data file names to the description of "this is calculated this way, and recorded like this" would make the software much more user friendly to folks who don't use it every day, and possible to validate the results.

TranSims in now a portion of the Travel Model Improvement Program (TMIP) at the U.S. Department of Transportation (DOT). Their web site states "...all have recognized the need for better information about the potential impacts and trade-offs of transportation alternatives." Their stated goals are very much aligned with the goals of this research: "To develop and improve analytical methods that respond to the needs of planning and environmental decision making processes." While TranSims can certainly fill this bill to a large degree, it seems like so many modelers in aviation, the tool's complexity deters its use as a means to gain insight and *explore* and *discover.*

After some minor frustration with the instructions not exactly matching the menus, I was able to make the visualization run. Unfortunately, I was unable to fully understand what I was seeing from the key alone. I assume there may be additional information in the manual. As a commercial product, I feel the GUI could use some improvement to make it used friendly (intuitive) for occasional users, assuming that was a goal.

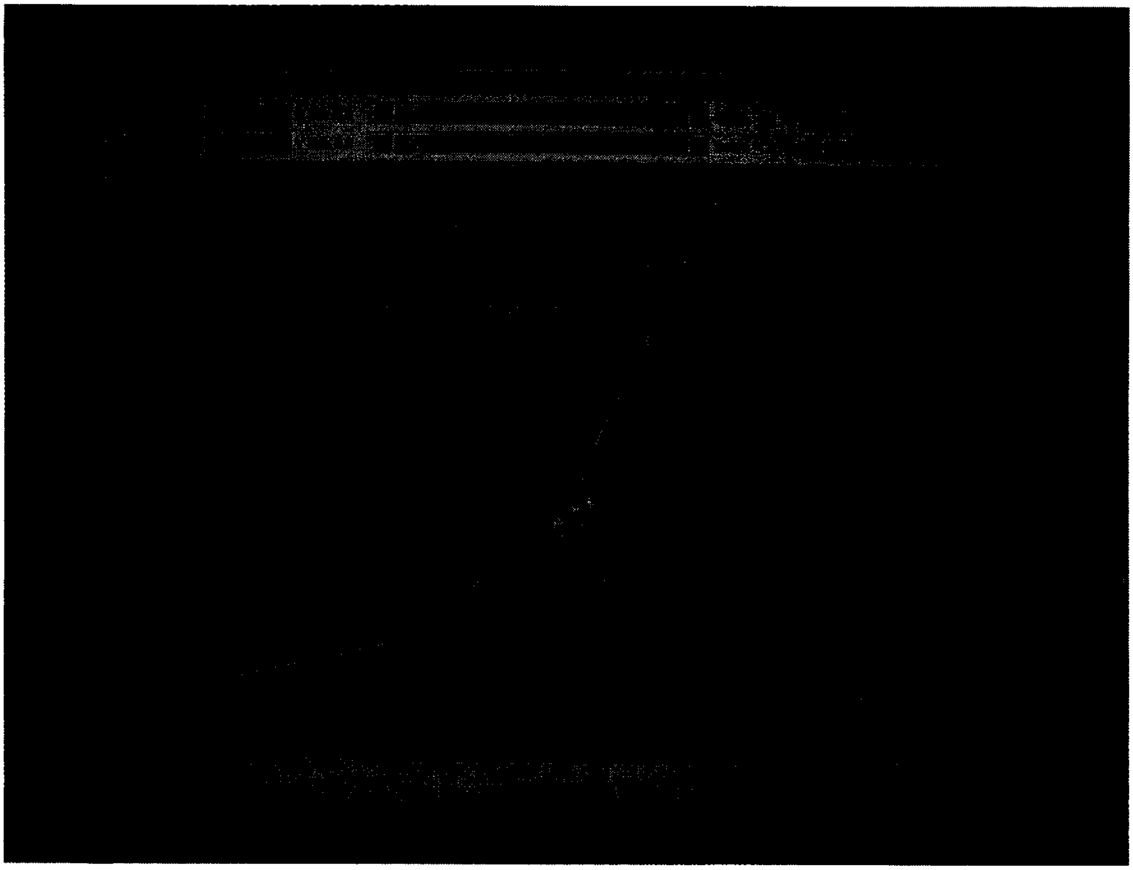


Figure 101: Screen Shot – TranSims Visualizer

APPENDIX D

STRUCTURED INTERVIEWS FOR NETWORK PARAMETER SELECTION

Many people were consulted when selecting schedule integrity as the main focus of the agent and network analyses in this study. To capture a comprehensive view of these subject-matter-experts' (SME) opinions while also allowing flexibility for a wide variety of system stakeholders, a semi-structured interview was used.

The interview questions and selected responses are provided below. In general, it seemed that delay vs. facility capacity was a common concern with most of the participants, and became the focus of this research.

SME #1

Field of Practice	ATS benefits assessment
Years of Experience in this practice	13
Portion of ATS you're most involved in	Commercial Aviation
Principle ATS issues of concern?	Flight delay, airport and airspace capacity
Metrics which may be applicable?	Average delay, facility capacity, equipment cost
Do you know of studies/methods which measure these metrics?	NFM (National Flow Model, proprietary software), Total Airspace Modeler (TAAM, a commercial ATS model, NASA VAMS)
Do you trust those measures are reliable?	To the degree that the models address the question, yes. Our models require careful calibration based on historical capacity performance. They are generally queuing models which rely on both good historical demand and capacity estimates.
Are there mitigations to any concerns you may have for these measures	We rely on historical data from similar operations at other locations to fill in any missing calibration data.
Utility for such metrics?	Very useful. Policy decisions, airline business strategy and spending allocations rely on delay and capacity information

SME #2

Field of Practice	ATS operations development
Years of Experience in this practice	6
Portion of ATS you're most involved in	System-wide (i.e. GA, commercial, military)
Principle ATS issues of concern?	Airspace access and equity, cost, efficiency of travel
Metrics which may be applicable?	Per-flight delay and who's delayed, Average delay, facility capacity, required equipment cost, time per trip (per mile), minimum requirements for system participation
Do you know of studies/methods which measure these metrics?	Some, but most are oriented towards OEP airports and airline operations
Do you trust those measures are reliable?	Shouldn't be the only system in consideration. There's a lot of ATS out there, and it could be made more useful for operators outside part 121
Are there mitigations to any concerns you may have for these measures	Need way to measure the system more holistically
Utility for such metrics?	Very useful. Policy decisions, equipment mandates

SME #3

Field of Practice	Airport Operations
Years of Experience in this practice	22
Portion of ATS you're most involved in	US FAR Part 139 airport, OEP airport
Principle ATS issues of concern?	Capacity (total movements), noise, emissions
Metrics which may be applicable?	Per-flight delay, Average delay, max delay, facility capacity, demand, misconnections, transient vs. destination travel
Do you know of studies/methods which measure these metrics?	Yes, NASA and MITRE both have models. There are also many commercial products
Do you trust those measures are reliable?	Yes, but I'm not sure about new procedures
Are there mitigations to any concerns you may have for these measures	??
Utility for such metrics?	Very useful. Community agreements, Policy decisions, equipment mandates

SME #4

Field of Practice	GA operator
Years of Experience in this practice	??
Portion of ATS you're most involved in	Private aviation
Principle ATS issues of concern?	Access to all airports in all weather, cost
Metrics which may be applicable?	Average delay, max delay, facility capacity at GA airports with limited facilities
Do you know of studies/methods which measure these metrics?	There was SATS. They measured capacity and GA aircraft delay
Do you trust those measures are reliable?	Yes, but don't know much about the details of their study
Are there mitigations to any concerns you may have for these measures	n/a
Utility for such metrics?	Would hope such compelling results would facilitate fielding new operations at GA airports…soon?!

VITA

Sheila R. Conway
Department of Engineering Management and Systems Engineering
Old Dominion University
Norfolk, Virginia

Sheila R. Conway earned her Bachelor of Science in Mechanical Engineering and Master of Science degrees concurrently from the Massachusetts Institute of Technology in 1989. She is a member of Tau Beta Pi engineering honor fraternity and the Pi Tau Sigma mechanical engineering honor society.

Her professional experience includes over 25 years of engineering design and analysis. In her present position at The Boeing Company, Sheila is responsible for research, development and implementation of new aircraft separation standards to improve airline flight operations efficiency while reducing their environmental impact for communities. In her past position at NASA Langley Research Center, she explored new air transportation systems and operations that can more efficiently use National Airspace System resources to enable future growth and transformation worldwide. She also has experience in transport-category aircraft flight deck design and experimental flight testing.

Sheila has supported a number of international standards organizations developing technical requirements for new aviation operations and equipment. At NASA, she supported the development of Automatic Dependent Surveillance – Broadcast (ADS-B) technology that has become the foundation of new worldwide aviation operations. She currently supports the International Civil Aviation Organization (ICAO) Separation and Safety Panel, complementing the member-state regulatory and control authority representatives as the technical advisor from the aerospace industry.

Sheila is a commercial pilot and instrument flight instructor, and holds a Fédération Aéronautique Internationale (FAI) Silver Badge in Soaring.