SYSTEM-OF-SYSTEMS SIMULATION FOR ANALYZING THE EVOLUTION OF AIR TRANSPORTATION

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Abstract

The effective evaluation of future air transportation architectures requires an approach suitable for system-of-systems to produce both tactical and strategic-level decisions in consideration of technological, policy, socio-economic, and multimodal aspects. Towards this goal, the objective of the research reported in this paper was to employ a systems-of-systems-oriented approach to craft a simulation of one of the key networks in air transportation: the capacity network. Principles of network science and multiagent simulation applied in concert form the core of the simulation. While the representations of the individual systems are basic, the higher level approach allows for new ways to optimize at the aggregated network level, determining the best topology (i.e., configuration of nodes and links). The initial results develop a set of high-level behavioral rules and network structure which show promise for satisfying key goals such as delay reduction and reasonable robustness in the system response.

1 Introduction

This paper presents initial results from a simulation that combines application of network science and agent-based modeling with the purpose of generating and evaluating future air transportation system (ATS) architectures. The motivation for this study is the desire to better understand possible trajectories of evolution for a national air transportation system under transformation. Since studies of transformation must link together not only the technical aspects of the ATS, but also the political, socio-economic, and multimodal aspects, the foundation for the simulation is a system-of-systems (SoS) approach. Our particular system-of-systems approach includes both resources and stakeholders as explicit and active entities in the model and is based upon the foundation for transportation modeling presented to the community by Lewe and DeLaurentis [1] at the 2004 ICAS Congress. The results reported herein are only some of the first fruits from the ongoing pursuit of several critical research questions that lie at the heart of successful transformation. Two of these research questions are summarized next.

The presence of multiple, independent, self-interested entities make achieving transformation difficult—ultimately there is no central design authority for air transportation. *Under this recognition, how does one examine the ATS and find means to influence it under conditions of incomplete control?* The primary thrust in this research question is to find patterns of structure and behavior that produces an ATS that is scalable and generally robust. Here we adopt the definition that a scalable system is one whose performance does not degrade with changes in demand, which is a specific case of robustness. In this context, the making a point prediction without testing against external factors and system feedbacks that occur over time (a frequent occurrence) is not valid. Instead, the objective must be to explore how the ATS emerges over time under an ensemble of plausible scenarios. A singular, "optimal" solution is not pursued, but it is expected that important patterns in good (and bad) solutions will emerge. In the present paper, emphasis is placed on the analysis of networks that bind transportation service providers and infrastructure providers as well as the interactions they exhibit in molding the resource network (vehicles, airports, etc.). Together, the interactions and the evolving networks underpin all transportation activity.

The concept of network then becomes the central mathematical construct for the studies. A very insightful encapsulation of the multiple networks in the ATS as well as the various layers within the resource networks has been presented by Holmes [2]. These are summarized in Table 1, and it is important to note that each topology operates on a different time scale. This aspect becomes crucial when trying to understand how these networks interact. For example, the *capacity network* has its nodes as points of entry, or portals, into the transportation system, the links are service routes between nodes, and the time scale is slower than the mobility, crew, and transport networks. *How these network topologies actually evolve, and how robust they are to disruption, are the key open research questions and are thus topics of current research.*

Table 1: Networks in the ATS

Network	**Node (N) & Link (L)**	**Time scale**
Transport	N: Aircraft, ATC L: Communications	minutes
Crew	N: Airports L: Missions	hours
Mobility	N: Arr./Dep. Locations L: Passenger trips	day
Capacity	N: Airports L: Service Routes	months

In our initial research, we have focused primarily on the evolution of the capacity network and, through simulation, the linkage between the mobility and capacity networks. Further, since such networks can only arise via economic imperative, the use of multiagent simulation (MAS) to mimic the real world, where stakeholders of various types interact with each other and the environment based upon self-interest, becomes a logical element in the simulation. The interest in and perceived value of "multi-modeling approach" for transportation is growing as attested by Conway [3] and Wieland [4]. This hybrid simulation approach is described below, after a review of its constituent analysis methodologies.

Generating possible trajectories for the future of air transportation is an exceedingly complex undertaking, let alone determining the best from among these many possibilities. Thus, the ultimate *methodological objective* for this ongoing research is to provide a mathematic model of the system-of-systems that through simulation at multiple levels can produce the desired transportation architectures. The ultimate *problem-oriented objective* is to use the method to develop realizable concepts that reach transformation goals. These goals consist of rules of behavior and network patterns that lead to scalability in the metrics that matter most in the ATS: reduced delay, increased throughput, and enhanced robustness.

The present simulation tool and results reported in this paper could augment currently used national level analysis tools such as the Airspace Concept Evaluation System (ACES) [5], a fast time analysis tool focused on the transport network developed by NASA Ames, and the NAS Strategy Simulator, a system dynamics based tool that seeks to examine the capacity network developed by Ventana Systems for the FAA. What is missing from most simulations is the system-of-systems methodology foundation that spans all the relevant inputs and dynamics, and the ability to examine structure and evolution of the interrelated network topologies that constitute the ATS.

The remainder of this paper is organized as follows. First, a brief glimpse of the scope and lexicon for the system-of-systems approach is introduced. Next, the simulation that has been developed for the capacity network and its core algorithms are presented. Finally, several results that demonstrate the capabilities are described along with concluding remarks.

2 System-of-Systems Modeling Synopsis

System-of-Systems problems consist of multiple, heterogeneous, distributed systems embedded in networks at multiple levels that evolve over time. A comprehensive modeling and analysis framework for air transportation as a system-of-systems problem has been proposed by the authors [6]. Only its basic lexicon is briefly summarized here so that its application for future air transportation architectures as described in this paper can be appreciated.

2.1 A Modeling Lexicon

A system-of-systems problem must be examined in its full scope (categories) as well amongst its layered collection of networks (levels). A generic lexicon has been crafted and its use for understanding the air transportation system-of-system is shown in Fig. 1. The categories highlight the presence of a heterogeneous mix of engineered and sentient systems together constituting the dimension of the problem. For each category, there is a hierarchy of components. To avoid confusion with ambiguous derivations (e.g., system → System-of-Systems → architecture), the lexicon employs the unambiguous use of Greek symbols to establish the hierarchy. This is a formalization of the use demonstrated in the last sub-section. Alpha (α), Beta (β), Gamma (γ), and Delta (δ) indicate the relative position within each category. The collection of α entities and their connectivity determines the construct of a β-level network and likewise, a γ-level network is an organized set of β networks. Hence, the δ-level can be described as a network with varying levels of α,β,γ networks and at each higher level the number of combinatorial possibilities increases. Thus, the actions of one stakeholder may be tailored in order to shape actions of others if there is an understanding of the dynamics at the higher levels (β, γ, δ, etc.).

		← System of Systems Dimensions →			
	Level	**Resources**	**Operations**	**Economics**	**Policy**
Base Level	α (ϑ 10^6)	Vehicles & Infrastructure (e.g. aircraft, ATC facility)	Operating a Resource (e.g., pilots, crew, maintenance)	Economics of building/operating/buyin/ selling/using a single resou	Policies relating to single resource use (e.g. type certification, flight procedures, etc.)
↑ Network of Networks ↓	β (ϑ 10^4)	TRANSPORT Collection of resources for a common function (e.g. airport, etc)	CREW Operating resource networks for common function (e.g. airline)	MOBILITY Economics of operating/buying/selling /leasing resource networks	Policies relating to multiple vehicle use (e.g. airport traffic mangt, noise policies, etc.)
	γ (ϑ 10^2)	Resources in a Transport Sector (e.g. air transportation)	Operating collection of resource networks (e.g. ; commercial air Ops)	CAPACITY Economics of a Business sector (e.g. Airline Industry)	Policies relating to sectors using multiple vehicles. (safety, accessibility, etc.)
	δ (ϑ 10^1)	Multiple, interwoven sectors (resources for a national transportation system)	Operations of Multiple Business Sectors (i.e. Operators of total national transportation system)	Economics of total national transportation system (All Transportation Companies)	Policies relating national transportation policy
	ε (ϑ 10^0)	Global transportation system	Global Operations in the world transportation system	Global Economics of the world transportation system	Policies relating to the global transportation system

Fig. 1. Lexicon for Understanding Air Transportation as a System-of-Systems

This use of the lexicon provides value at two levels: first, the breadth of the problem and subsequent imperative to move beyond (across) domain stovepipes is evident, and second, the categorizations help effectively guide the *later modeling activities*. The variety of decision-makers involved in transportation can be identified, engaged, and included in the discussion. Through subsequent modeling, the probabilities for solutions at the γ- or δ-levels can be formed by aggregating the α- and β-level entities. It is also important to note the number of entities at each level may vary tremendously, likely by orders of magnitude. For example, in Fig. 1, estimates are given for the number of entities at each level, ranging from 10^6 to 10^2 in just two level shifts.

3 Transportation Simulation Model

The heart of the technical approach for generating transportation architectures is the combination of network modeling (via network science) with agent-based modeling (ABM) within one simulation, essentially a "synthesis code" for air transportation systems. The agents represent stakeholder behavior rules and these rules drive the evolution of the network. Concepts from network science enable discernment of good, or bad, outcomes over a collection of outcomes. From this, patterns in the results can be sought. The next two sub-sections of this major section describe the important fundamentals of network science and ABM as well as how they were applied in this study.

3.1 Network Science

3.1.1 Description

The participation of systems in multiple networks that determine the connectivity must be analyzed properly, as argued throughout this paper. The family of all these networks is amenable to modeling through a variety of important constructs developed recently in the emerging field of network science. In our research, network science is being proposed as a means of representing the connectivity across the multiple levels in SoS problems.

Recent developments in network science provide a mathematical basis for discovering patterns in the structure of network topologies and dynamics on networks, exemplified well by the work of Barabasi in the exploration of diverse networks (such as the WWW and internet) which were found to be scale-free networks.[7] In this process, the identified networks are defined by the connectivity (links) between entities (nodes) which form a network "topology". Very little formal work has taken place to fully explore the conceptual modeling of air transportation using network science, and further, using network science results to identify traits of preferred future architectures. The papers by Conway [8] and Holmes [2] at the 2004 ICAS Congress in Yokohama recognize and advocate that network science warrants examination for fundamental studies of air transportation. The authors have also produced some new findings in this area [9].

Given a network topology, statistical properties can be measured to indicate certain behaviors of that network. Multiple types of links can exist between nodes, including: directed, un-directed, weighted and un-weighted. In undirected networks, links form a unilateral connection between nodes; in directed networks, the links are directional between nodes. Moreover, in un-weighted networks, all links have the same weight; in weighted networks, each link may have a different weight. A limited set of network science metrics are introduced below to quantify the differences between the nodes in each network and the differences between the network topologies.

Degree is the number of links connected to a given node. In un-directed networks, each node has a single degree quantity, while in directed networks each node has values for in-degree, out-degree, and all-degree measures.

Shortest path is the shortest distance (in number of links, *d*) between a given node pair (d_{ij}) in a network. Thus, *average shortest path (l)* is the mean of the shortest paths for all node pairs in a network. For un-weighted networks, average shortest paths are measured in number of links; in weighted networks, average shortest paths will consist of the least costly paths between each pair of nodes (not necessarily the path with the least number of links).

Clustering coefficient for a given node is the number of triangles centered on that node, divided by the number of triples centered on each node. It is a measure of the cohesiveness, or cliquishness, of a collection of nodes. The *average clustering coefficient* is the mean of all the clustering coefficients of all the nodes in a network. In this context, the number of triangles for a node is the number of distinct three-link, three-node closed paths which contain that node. Further, the number of triples for a given node is the number of distinct two link paths centered along that node.

For example, for the network in Fig. 2, the degree of A and D is three. The respective clustering coefficients are $C_A = C_D = 2/3$ & $C_B = C_C = 1$ and the network average is $C_{avg} = 5/6$. The avg. shortest path is $l = 7/10$.

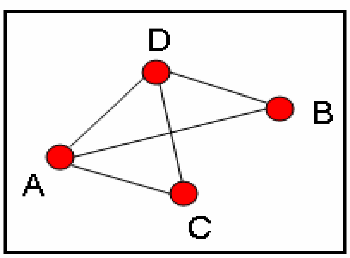

Fig. 2. Simple Network Example

3.1.2 Mapping to transportation system metrics

In order to be of practical use, these network-theoretic characterizations must be translated, or mapped, into the metrics that are germane to the ATS networks identified in Table 1—e.g. capacity/throughput, delay, and robustness. An initial mapping has been completed for this purpose; however, the details of this are beyond the scope of the paper. Therefore, in the following paragraph, we simply summarize the process and give a glimpse of the metrics developed so that later simulation results can be comprehended.

The data source for statistical studies of the capacity network is the U.S. Bureau of Transportation Statistics (BTS) [10]. The first step is relating the degree of an airport to its number of operations as well as its average number of annual delayed operations. From these two relations, the airport capacity is estimated in terms of its maximum number of allowable links, i.e. max degree. The quality of fit for these statistical relations has been found to be quite good. For example, the degree vs. annual delay operations for the average of two months in 1990 is well represented by a second-order polynomial with a quality of fit parameter of 0.92, as shown in Fig. 3.

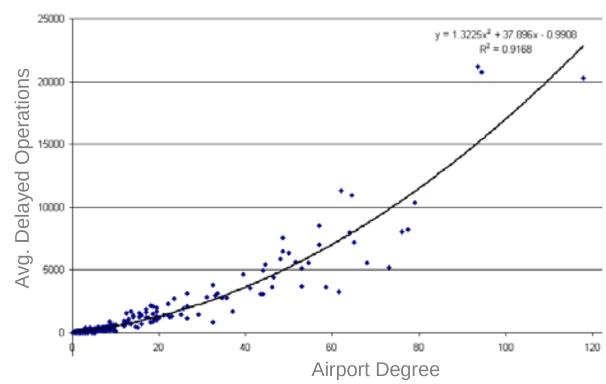

Fig. 3. Relationship between degree and average delay operations

Finally, a new measure of merit that encapsulates capacity and delay and can be easily measured from the topology is obtained called "nodal saturation", defined in Eq. (1).

$$nodal\ saturation = \frac{current\ degree}{max\ degree} \qquad (1)$$

The complete statistical analysis and synthesis for the mapping will be reported in a paper to be presented later this year [11].

3.2 Agent-based Simulation

3.2.1 Description

While network science may prove useful in representing the connectivity at multi-levels in an SoS, the heterogeneous nature of various systems involved—especially the sentient ones that are represented in the operations, economic, and policy categories—must also be addressed.

There is a need for modeling the interaction of human and technological systems that are driven by enterprise organizations and their preferences. However, a crucial point must be made here with regard to preferences: *It is important to move beyond simply understanding the influence of human preference on a design to the point of including human preference and behavior patterns explicitly inside the SoS problem boundary along with the products/systems that must be designed.*

To actually embed behaviors in SoS operation, it is necessary to employ modeling that reflects the competition and cooperation that drives stakeholder behavior and determines their actions to manipulate the resources within the SoS. It is proposed that agent-based modeling (ABM) may be well-suited for this task and therefore worth investigation for this role. Agent-based models employ a collection of autonomous decision-making entities called agents. Each agent is imbued with simple rules of behavior that direct their interaction with each other and their environment. The mathematical representation of agent rules is often quite simple, but the resultant system-wide behavior is often more complicated, often unexpected, and thus instructive. Conceptually speaking, this approach differs from the two traditional means of scientific inquiry: Induction, the discovery of patterns from data, and Deduction, proving theorems from axioms. Agent-based models seek to allow the individual agents to interact in an environment based on their own rules, and the modeler observes the result. The ultimate goal in employing ABM is not to prove, but to understand the processes and patterns that may appear. When complex behavior (such as learning and adapting) and/or complicated interactions between entities (social, political dynamics) are expected, the approach may indeed be the only way to uncover the behavior that emerges at the system level. Multiagent simulation (MAS), in particular, refers to applications in which multiple agent types are present.

The “Jet-Wise”[12] agent model developed at Mitre is an excellent example that seeks to capture the behaviors of airlines and their impact. The prior-mentioned ACES model also uses an agent-based approach, though its focus lies in the aggregation of individual flights in the NAS (aircraft operations from gate departure to arrival). While the present simulation model employs MAS as well, it is unique for its scope, its linkage with network topology analysis, and its use within a rigorous system-of-systems framework.

3.3.2 Current Stakeholder Agent Models

The evolution of the capacity network is directed by stakeholder agents that make choices based on simple rules which represent their own self interest. Broadly speaking, these choices include the advancement of alternate modes of intercity travel (e.g. ground modes) and by reconfiguring the capacity network (e.g. spreading the demand in the air capacity layer more evenly via a point-to-point travel instead of hub-and-spoke). In the particular scope of the present study, two stakeholders (agent classes) are implemented: service providers and infrastructure providers. The simplified logic for both agent types is provided in Fig. 4 and Fig. 5.

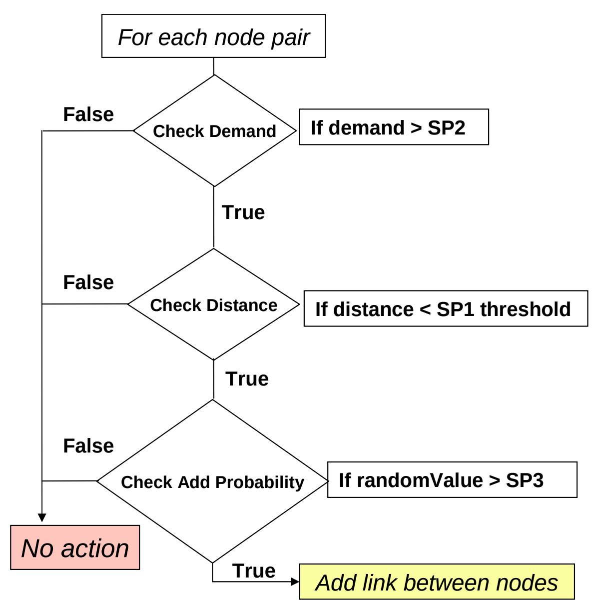

Fig. 4. Service Provider Agent Logic

The goal of the service provider (SP) agent is to meet as much of demand as possible within its market niche. Presently, the model includes both a long-distance and a regional type SP. The goal of the infrastructure provider (IP) agent is to minimize delay by maintaining adequate capacity in the network. The variables involved in these logic statements (**SP1-3**, **IP1-3**) are described below along with their initialization settings.

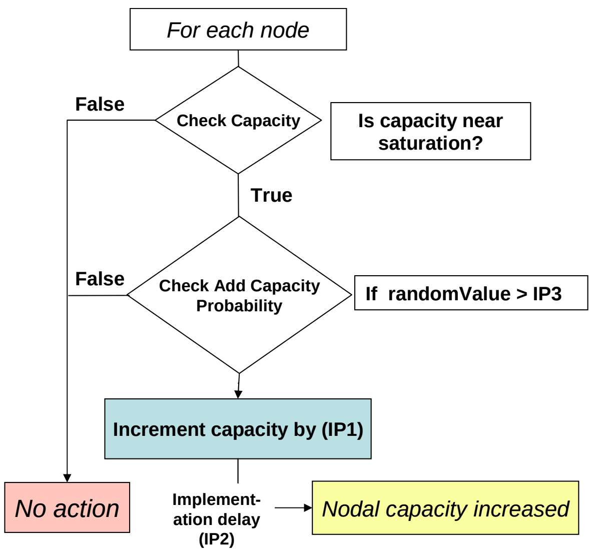

Fig. 5. Infrastructure Provider Agent Logic

3.3 Integrated Simulation

The overall framework for the integrated simulation is as follows: stakeholder agents (e.g. service providers, infrastructure providers) act to evolve an initialized capacity network under various scenarios (see Fig. 6). Each agent employs its logic to guide its decisions and then actions. In subsequent time steps, the agent sees consequences from the environment and updates its behaviors. As this process unfolds, the magnitude and shape of the mobility network (demand) also changes, and the actions of agents must respond to this by manipulating the capacity network topology. Thus, a family of new network topologies is created over time, and their structure and behavior is tracked using the network-theoretic analysis. The key question is: Do the evolved networks exhibit good performance both in terms of capacity and robustness? To address this question, a network evaluator is employed to compare the evolved networks to topologies that do exhibit preferred behaviors. Using this method, the evaluator can function as the search direction generator for a design/optimization problem.

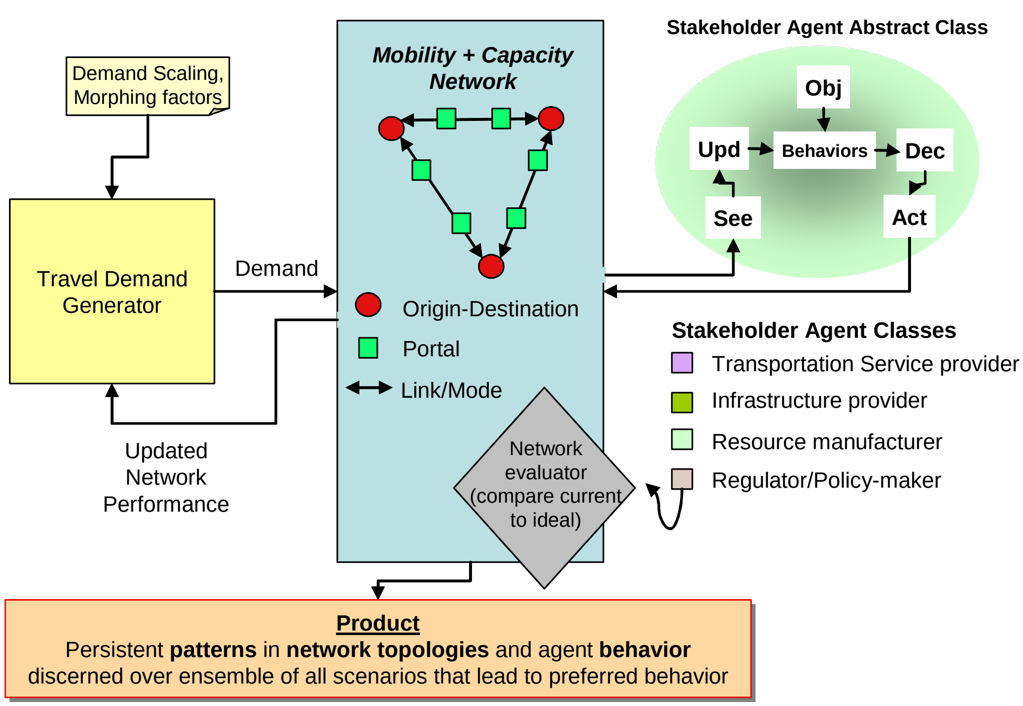

Fig. 6. Integrated Simulation Framework

The simulation is initialized with settings for the agents, an initial network topology, and scenario-specific parameters. The definition of and baseline settings for the SP and IP agents are shown in Table 2 and Table 3. The number of parameters is small but is appropriate for examination at the γ-level. If a study was being conducted at the β-level or below, clearly more sophisticated models of SP and IP logic would be in order. This is indicative of the usefulness of the multi-scale modeling perspective.

Table 2: Service Provider Agent Settings

Parameter	Baseline Settings
Add Probability	Long **SP3L** = 0.2 Reg. **SP3R** = 0.8
Delete Probability	Long Dist. **SP3L-D** = 0.2 Regional **SP3R-D** = 0.5
Add Threshold	Long Dist. **SP2L** = 40 Regional **SP2R** = 20
Delete Threshold	Long Dist **SP2L-D** = 30 Regional **SP2R-D** = 15
Minimum Length Threshold	Long **SP1L** = 200 miles Regional **SP1R** = 0 miles
Maximum Length Threshold	Long Dist. **SP1L** → None Regional **SP1R** = 340 miles
Type	Air carrier

Table 3: Infrastructure Provider Agent Settings

Parameter	Baseline Settings
Add Probability	**IP3** = 0.95
Delete Probability	0.0
Threshold	100 units
Average Time to Implement	**IP2** = 45 time steps (~ 1 year)
Percent Change	**IP1** = 0.1

The network and simulation environment is initialized using Bureau of Transportation Statistics (BTS) data from the 1990 U.S. air transportation system overlaid on a 16x25 cell map. The 16x25 system was used due to the geographical proportion of the continental United States. The system is built with information regarding cell type based on U.S. census data, origin destination matrices and node initial capacities based on BTS data, and finally with cell demands based on the work of Lewe [1]. A snapshot of the JAVA-based graphical interface and display of the simulation is shown in Fig. 7.

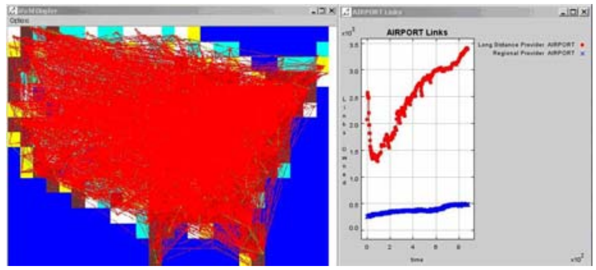

Fig. 7. Simulation Interface Snapshot

3.4 Scenarios

The search for patterns in simulation results takes place across an ensemble of scenarios. In the present case, scenarios of interest are representations of demand in the mobility network. The shape of the demand and its changes is as important as the magnitude of change expected in the future (e.g. "3X"). Two scenarios were considered in the pilot study:

BASE—taking initially the demand structure of 2004 U.S. system, demand grows evenly within this structure at a rate sampled from a uniform distribution from 01% to 5%.

POPSHIFT—starting from the 2004 system, the *structure* of demand changes dramatically starting in the second year, with significant urban-urban demand shifting towards more small-medium regions. This mimics demographic shift to a more dispersed style of life, requiring distributed transportation.

4 Sample of Simulation Results

The first concept study asks whether there is a relationship between amount of new capacity added to the network and the time it takes to achieve the upgrades in terms of time-evolved global network properties. The results, summarized here, indicate that a flexible, agile and timely capacity management capability is critical. This concept is discovered by examining two key parameters: the capacity added by IP agent (multiplier of current node capacity), (**IP1**), and the time to implement by IP (in ~weeks), (**IP2**). The specific objectives are the delay and robustness surrogate metrics: average node saturation (shown here) and average clustering coefficient, respectively. "Lower is good" for the saturation measure while "Higher is good" for the clustering. The results for the average saturation response for both the BASE and POPSHIFT scenarios are illustrated in Fig. 8 and Fig. 9. A pattern appears across both scenarios in which a common line of demarcation separates regions of acceptable and unacceptable network saturation.

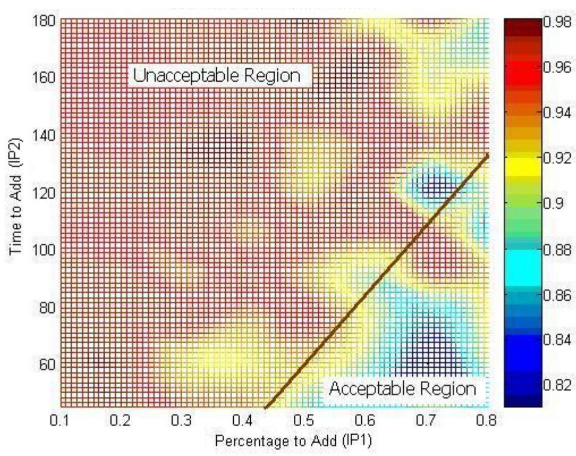

Fig. 8. Network Saturation under Infrastructure Provider Behaviors – BASE Scenario

The combination of healthy additions of capacity (high **IP1**) in a rapid manner (low **IP2**) is required behavior from the IP to moderate network saturation and thus minimize delay. Further, there appears to be a particular set of ratios of (**IP1/IP2**) which delineate acceptable and unacceptable regions. The primary implication is that agility is needed in shaping the capacity network. *The IP must add/move capacity quickly, inside the action time of SP business decision loops (i.e., "how quick" is just as important as "how much").*

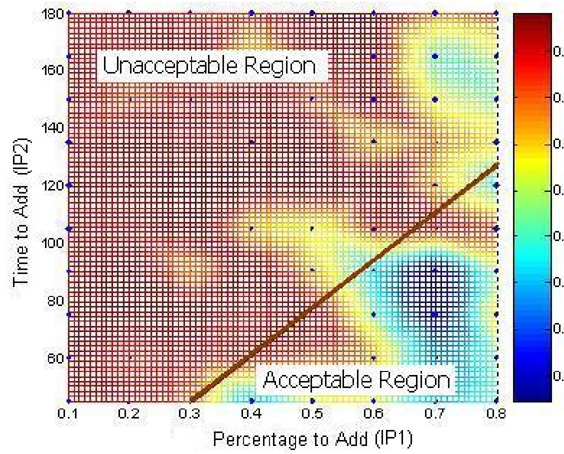

Fig. 9. Network Saturation under Infrastructure Provider Behaviors – POPSHIFT Scenario

A second simulation study investigates the consequences of differentiated activity levels among the two types of service providers. Specifically, the probability of adding a link if thresholds are met for both long-distance (**SP3L**) and regional service provider (**SP3R**) are varied. In this case, the measure of goodness that is displayed (Fig. 10) is the average clustering coefficient. This result was run under the BASE scenario. The results in this case are not as clear in terms of the implication of ratios of behavior, although low activity levels in the long-distance provider appear to increase the system-wide average (and thus the system-wide robustness).

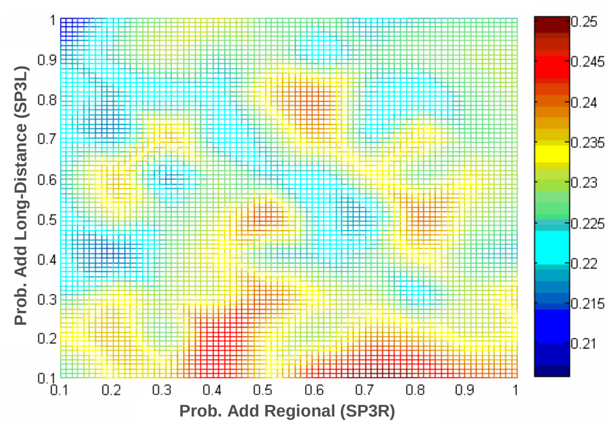

Fig. 10. Average Clustering Coefficient under Service Provider Behaviors – BASE Scenario

5 Conclusion

Key research questions concerning the proper evaluation of future air transportation architectures as systems-of-systems are presented, emphasizing a network topology analysis perspective. A new system-of-systems approach is employed to develop a simulation of air transportation networks. Two analysis results are produced to exemplify use of the SoS simulation. The first uncovers a particular pattern in the behavior associated with managing capacity of the NAS capacity network. Specifically, the effectiveness of avoiding saturation and thus delay in the NAS is dependent on a proper ratio of the amount of capacity increment added and the speed at which this action can be implemented. The concept, then, is one of a flexible and intelligent capacity management. The second concept explores the impact of behaviors of service providers on the overall capacity network. The results in this case are still preliminary, though the hope is that further work can uncover a correlation between actions of regional and longer-distance service providers. While the findings are the results of a "conceptual design process", they can motivate and inform those organizations seeking to achieve sustainable transformation in a complex, evolving system-of-systems.

6 Acknowledgements

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