AN AGENT-BASED MODEL FOR ANALYZING CONTROL POLICIES AND THE DYNAMIC SERVICE-TIME PERFORMANCE OF A CAPACITY-CONSTRAINED AIR TRAFFIC MANAGEMENT FACILITY

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Abstract

Simple agent-based models may be useful for investigating air traffic control strategies as a precursory screening for more costly, higher fidelity simulation. Of concern is the ability of the models to capture the essence of the system and provide insight into system behavior in a timely manner and without breaking the bank.

The method is put to the test with the development of a model to address situations where capacity is overburdened and potential for propagation of the resultant delay though later flights is possible via flight dependencies. The resultant model includes primitive representations of principal air traffic system attributes, namely system capacity, demand, airline schedules and strategy, and aircraft capability. It affords a venue to explore their interdependence in a time-dependent, dynamic system simulation.

The scope of the research question and the carefully-chosen modeling fidelity did allow for the development of an agent-based model in short order. The model predicted non-linear behavior given certain initial conditions and system control strategies. Additionally, a combination of the model and dimensionless techniques borrowed from fluid systems was demonstrated that can predict the system's dynamic behavior across a wide range of parametric settings.

1 Introduction

National Airspace System improvement plans focus on improvements to today's Air Traffic Control systems, but it is becoming clear this approach may not satisfy future air-traffic demand.[1] System transformation will require changes in methods and policies for traffic management that consider the interplay of capacity, demand, and aircraft capability as well as the influence of operational and environmental constraints. However, comprehensive transformation policies have been hard to develop and equally difficult to model.

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 operations 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 that issues of system safety and stability for new operations in light of demand uncertainties can be rigorously addressed.

The literature suggests that agent-based models may be applicable: Many authors suggest that this approach can provide insight into the operational viability of complex systems such as air transportation. Agent models can also provide a means to explore the effect of transformation mechanisms on system operations, e.g. policy changes, social norms, and technology development.

1.1 General Modeling Aptitudes

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 National Airspace System (NAS). As Wieland et al [2] point out, modeling air traffic management "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." Their claim is that a useful NAS simulation 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 NAS model is a "grand challenge," yet they believe, necessary and obtainable.

Actually, NASA has recognized the need for a more systemic method for some time. They commissioned Krozel [3] to review all the Free Flight research related to distributed air traffic management, a widely accepted development concept. He identified not only the existing research, but also the research needs that were not being met more generally. In summary, he found that at the time, there were no tools capable of assessing both new and traditional NAS operations simultaneously, and therefore assessing their interactions.

Sheate [4] complains that standard NAS policy decisions have led 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 air traffic management arena have continued to use methods more suited to regularly-behaved systems to develop strategy[1]. Apparently, this is a pervasive problem throughout the policy community. In fact, Bankes [5] 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. Addressing this same concern, Iyer [6] offered that the "basic contribution of complexity theory [to planning] is its focus on systemic interactions at various scales…" that can address uncertainty.

1.2 Agent Based Modeling

Agent-based modeling (ABM) 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. ABM uses agents to execute model functions. They are the active components of an agent based simulation.

Agents are 'autonomous' in that they have interfaces to the general simulation, but carry within them their own ability to perform tasks without a centralized controller. Agents are interactive entities that may also exploit salient but generally localized behavior of system or environmental elements. Because of their autonomy, agents generally are not optimizing or even 'satisficing' system goals. However, even with simple rules to determine each agent's actions, higher-order system behaviors can emerge. Jennings [7] and Jennings and Wooldridge [8] offer further detail, 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.

Jennings would most likely agree that ABM is not well suited to all systems. However, he outlines his argument in favor of ABM of complex systems, saying complex system development requirements and ABM are highly compatible. He argues that ABM is particularly well suited to 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 dependencies and interactions in complex systems

However, he also admits that these same properties can lead to issues of unpredictability and apparent chaotic behavior. Unpredictability is a problem in the simulation world because it makes internal validation very difficult when exact results cannot be repeated. The lack of deterministic behavior is also a problem for validation. 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 paramount. From recent literature, Bankes [9] summarizes three reasons why ABM is potentially important: i) the unsuitability of competing modeling formalisms to address the problems of social science, (ii) the ability to use agents as a natural ontology for many social problems, and (iii) 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, systems of differential equations and statistical modeling, are viewed as imposing restrictive or unrealistic assumptions that limit many applications. 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 approaches, and certainly not by agent implementations of standard methods. A model still has to be appropriately defined to describe significant features for the system served. Additionally, addressing issues such as homogeneity requires not only more effort in model specificity, but also more information related to distributions of variables or behaviors. These data may not be available. A homogeneous population model might be of sufficient fidelity for describing some systems, while an assumed (but erroneous) normal distribution, for example, might yield misleading results. A more complex or detailed model (e.g. at the agent rather than the aggregate level) is not necessarily more accurate.

Bonabeau [10] claims that 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, like Jennings, he acknowledges difficulties in building agent models of large systems because of the myriad low-level details and the "extremely computation intensive and therefore time consuming" model that results.

Arthur suggests agents are a natural way to deal with ill-defined or complicated "reasoning" within a system, often induced by inclusion of humans. 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.

1.3 Agent Modeling of ATM

Moss expresses the view that "Policy analysis has to start with observation and the specification of a problem to be solved." From here, appropriate analysis tools can be defined. Moss, Iyer, and others suggest that deterministic and even stochastic approaches to complex policy development are incompatible, though they all conclude that ABM may be applicable.

The air transport research community has attempted to model particular attributes of the NAS, but there hasn't yet been a method capable of answering questions regarding the systemic response to substantive changes in operations. To date, agent-based, elemental simulations have proven too expensive and unwieldy to complete. Parametric simulations have failed to provide the flexibility to be used as design tools.

The dearth of appropriate analytical tools is not due to a lack of demand, or trying: It has proven difficult indeed. Calls for systemic simulation for operational design of the NAS to researchers in the trenches from responsible government officials continue to accrue [11].

The majority of researchers in the area have joined Wieland et al. in suggesting that ABM is one of only a few appropriate modeling solutions currently available. Holmes and Scott [12] say, "Proposed ideas for changing the NAS should not be contemplated lightly, due to the sheer size and complexity of the system. Instead it will require a fundamental reconsideration of how such complex systems are analyzed and designed if the system to evolve remains productive and viable. Traditional methods for analyzing changes to complex systems fail when applied to highly dynamic and interconnected system such as the Internet or the NAS." They go on to outline their case for using agents operating on network structures as a viable analytical alternative, and as framework for future NAS design as well.

However, modeling is not simply an emulation or simulation of all the entities or behaviors in a complex system. As discussed, such extensive simulations would generally be extremely difficult and expensive to build. Nonetheless, it is hypothesized that purpose-specific models of sufficient fidelity would be feasible. The difficulty arises in selecting the appropriate system attributes that can capture the behaviors of interest, and using suitable abstractions of them in a model.

To further scope the model used to assess the ABM method for this study, it is focused on a specific research topic: For this test case, the model is intended to explore the dynamic system response to service policies at capacity-limited airports reflected by flights nominally operating by a reserved schedule or 'slot'.

2 The Model

The model emulates 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 flights* operating in or out of a hub airport facility (fig 1).

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

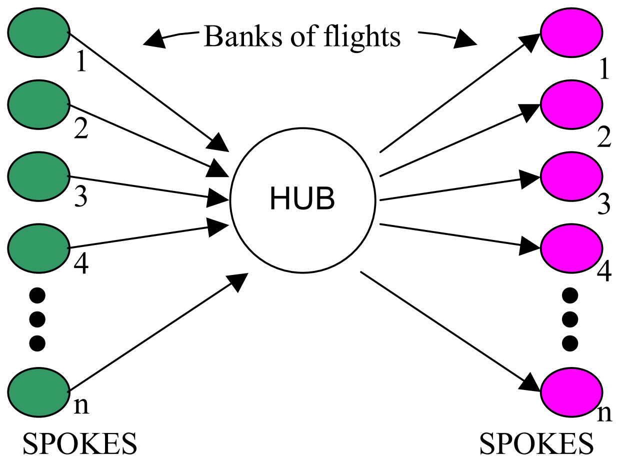

Figure 1: The model

At each time slice in this discretized model, flight agents will "request" service at the facility, representing a bank of flights for that time *t*. The flight will operate as long as the capacity of the facility has not been exceeded. If for some reason demand at that rush (time) exceeds capacity, the flight is rescheduled.

To capture potential dynamic behavior caused by an airline's linking of one flight to another in a previous bank (by crew, equipment, connecting passengers, etc.), flights in banks 2 through D were randomly assigned an average of *k* dependencies with flights in a previous bank. For example in figure 2, 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.

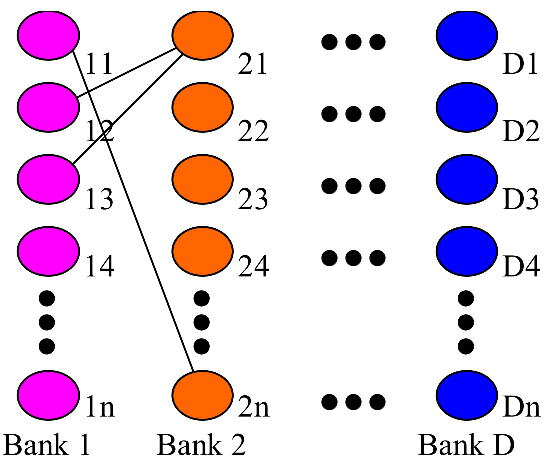

Figure 2: Flight Dependencies

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*.

Finally, 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.

With these abstractions of the system in hand, coding the simulation was relatively straightforward. REPAST PY [13] 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).

A set number of flight agents per bank were initiated and named according to their nominal scheduled (time slot for operation). Using *k*, dependencies were also assigned 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 as "operated") until the capacity of the airport was met. Any remaining flights in the bank were rescheduled for the next bank.

Three different strategies to order flights within the banks were used in this study; original schedule followed by rescheduled or delayed flights, earliest scheduled flights first, or random draw.

3 Using the Model: An Initial Experiment

3.1 Experiment Design

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.

3.2 Results

The model demonstrated both stable and unstable behaviors: In some configurations, delays grew to a certain level and then remained relatively constant. In other instances, delays grew seemingly unbounded. Interestingly, even without inter-flight dependencies there were also instances where delays seemed stable, but then would suddenly grow quickly. For example, compare the first 15 cycles in figure 3 with the subsequent response: the change implying a threshold condition was exceeded.

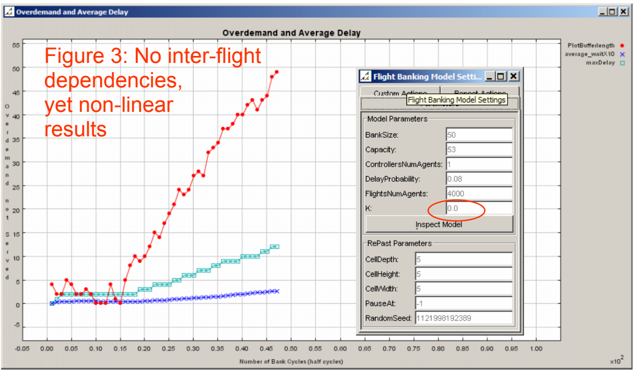

Figure 3: No inter-flight dependencies, yet non-linear results

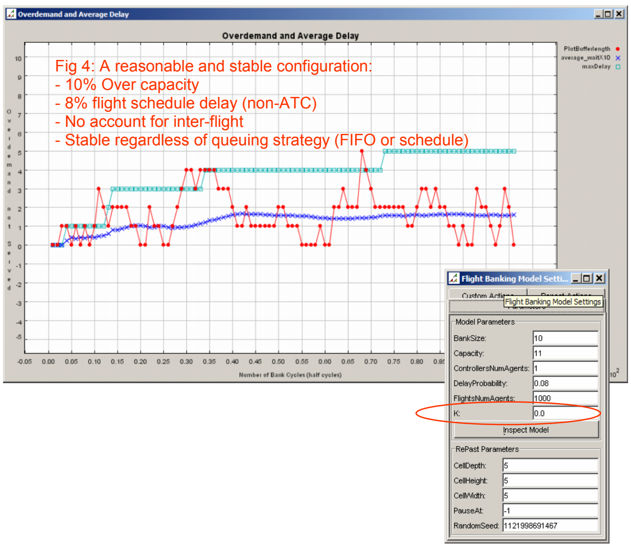

Fig 4: A reasonable and stable configuration:
- 10% Over capacity
- 8% flight schedule delay (non-ATC)
- No account for inter-flight
- Stable regardless of queuing strategy (FIFO or schedule)

From a facility perspective, where flight dependency is less of a factor, the model predicts reasonable stability as long as there is approximately 10% greater capacity than demand. Also influential was the ability of flights to meet their scheduled slot (non ATC related delay). With these parameters bounded and flight dependencies unaccounted, the model predicts stability (fig. 4) regardless of the ATC strategy used to clear aircraft in a service queue.

However, flight dependencies are critical to airline business models and practical operational considerations. With an assumption of total dependence between flights, certain ATC actions and capacities are predicted to lead to run away delay (fig. 5), while an alternative strategy proved more stable (fig. 6).

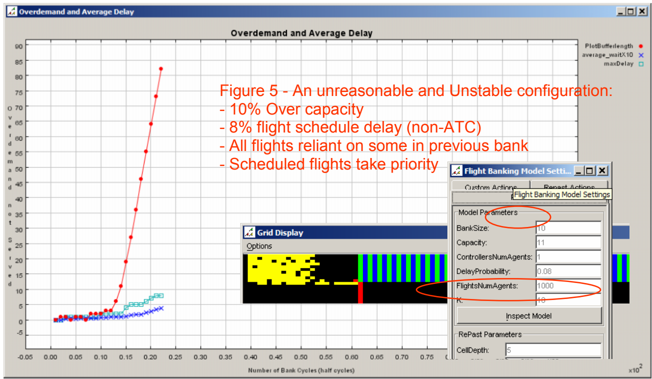

Figure 5 - An unreasonable and Unstable configuration:
- 10% Over capacity
- 8% flight schedule delay (non-ATC)
- All flights reliant on some in previous bank
- Scheduled flights take priority

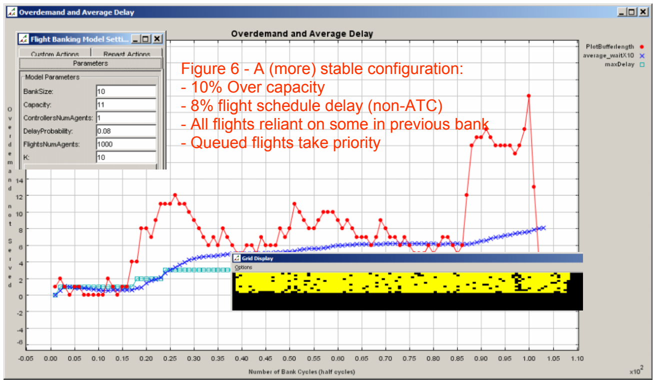

Figure 6 - A (more) stable configuration:
- 10% Over capacity
- 8% flight schedule delay (non-ATC)
- All flights reliant on some in previous bank
- Queued flights take priority

3.3 Discussion

After exploring the experiment space, varying flight delays, queuing strategy and the dependencies while keeping demand and capacity constant, it appeared that there was a relationship across these variables. The point at which the system became sensitive to flights missing their slots appeared to be dependent on the ATC strategy for ordering and serving

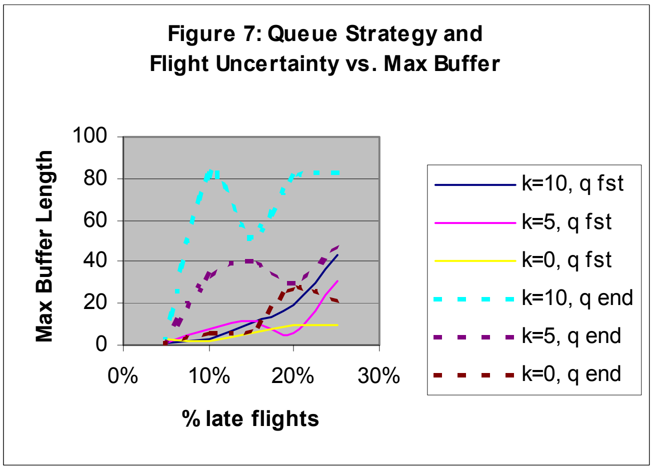

Figure 7: Queue Strategy and Flight Uncertainty vs. Max Buffer

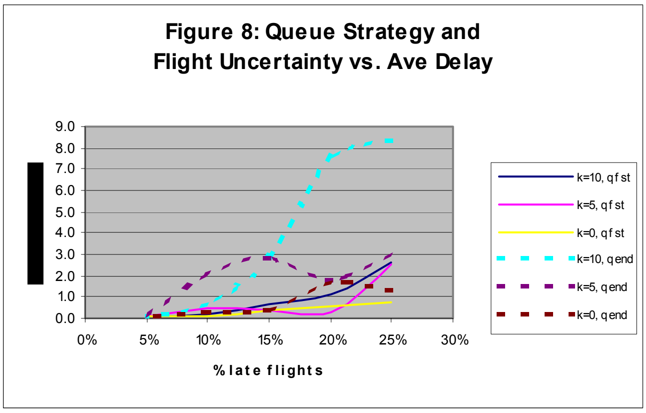

Figure 8: Queue Strategy and Flight Uncertainty vs. Ave Delay

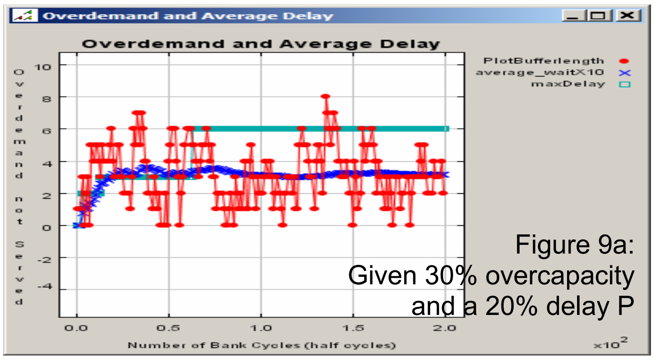

Figure 9a: Given 30% overcapacity and a 20% delay P

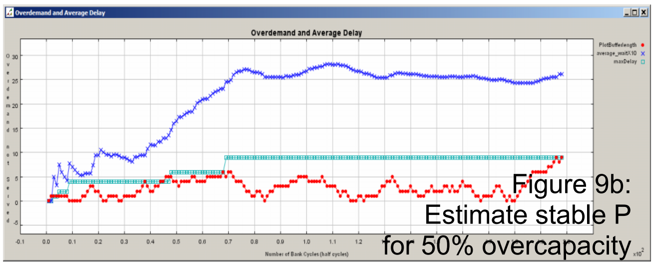

Figure 9b: Estimate stable P for 50% overcapacity

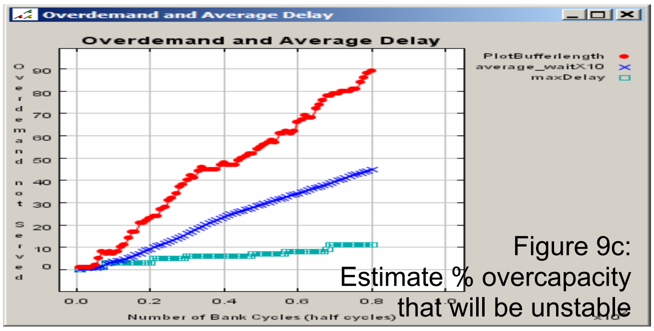

Figure 9c: Estimate % overcapacity that will be unstable

waiting flights. This was true for both the maximum experienced buffers (Fig. 7) and the average delay (fig. 8).

The data revealed what appeared to be a relationship between overcapacity (capacity-bank size) and the probability of a flight missing its expected slot. In many cases, the average delay also demonstrated behavior similar to a second order oscillator. Dimensionless techniques borrowed from fluid systems 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, γ, was estimated as:

$$\gamma \sim \frac{Cmax - N}{Cmax} \quad \frac{1}{P}$$

Using this concept of γ, the data from what appeared to be a near-critically damped case (Fig 9a) was used to successfully predict a stable tolerance for delay given 50% overcapacity (fig. 9b) or an unstable overcapacity threshold for a given *P* (fig. 9c).

4 Conclusions

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.

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 capturing the interactions at various scales within this complex, dynamic system.

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