NASA/CR–2011-217066

Investigation of the Impact of User Gaming in the Next Generation National Airspace System

George C. Hunter and Huina Gao
Sensis Corporation, Seagull Technology Center, Campbell, California

March 2011

NASA STI Program . . . in Profile

Since its founding, NASA has been dedicated to the advancement of aeronautics and space science. The NASA scientific and technical information (STI) program plays a key part in helping NASA maintain this important role.

The NASA STI program operates under the auspices of the Agency Chief Information Officer. It collects, organizes, provides for archiving, and disseminates NASA's STI. The NASA STI program provides access to the NASA Aeronautics and Space Database and its public interface, the NASA Technical Report Server, thus providing one of the largest collections of aeronautical and space science STI in the world. Results are published in both non-NASA channels and by NASA in the NASA STI Report Series, which includes the following report types:

- TECHNICAL PUBLICATION. Reports of completed research or a major significant phase of research that present the results of NASA programs and include extensive data or theoretical analysis. Includes compilations of significant scientific and technical data and information deemed to be of continuing reference value. NASA counterpart of peer-reviewed formal professional papers, but having less stringent limitations on manuscript length and extent of graphic presentations.

- TECHNICAL MEMORANDUM. Scientific and technical findings that are preliminary or of specialized interest, e.g., quick release reports, working papers, and bibliographies that contain minimal annotation. Does not contain extensive analysis.

- CONTRACTOR REPORT. Scientific and technical findings by NASA-sponsored contractors and grantees.

- CONFERENCE PUBLICATION. Collected papers from scientific and technical conferences, symposia, seminars, or other meetings sponsored or co-sponsored by NASA.

- SPECIAL PUBLICATION. Scientific, technical, or historical information from NASA programs, projects, and missions, often concerned with subjects having substantial public interest.

- TECHNICAL TRANSLATION. English-language translations of foreign scientific and technical material pertinent to NASA's mission.

Specialized services also include creating custom thesauri, building customized databases, and organizing and publishing research results.

For more information about the NASA STI program, see the following:

- Access the NASA STI program home page at *http://www.sti.nasa.gov*

- E-mail your question via the Internet to help@sti.nasa.gov

- Fax your question to the NASA STI Help Desk at 443-757-5803

- Phone the NASA STI Help Desk at 443-757-5802

- Write to:
  NASA STI Help Desk
  NASA Center for AeroSpace Information
  7115 Standard Drive
  Hanover, MD 21076-1320

NASA/CR–2011-217066

Investigation of the Impact of User Gaming in the Next Generation National Airspace System

George C. Hunter and Huina Gao
Sensis Corporation, Seagull Technology Center, Campbell, California

National Aeronautics and
Space Administration

Langley Research Center
Hampton, Virginia 23681-2199

Prepared for Langley Research Center
under Cooperative Agreement NNA07CN32A

March 2011

Acknowledgments

The authors would like to thank Dr. Lance Sherry of George Mason University for his assistance and management of this project, Mr. Diego Escala for the software design and development of the gaming strategies, Dr. Natalia Alexandrov of NASA for her oversight and technical guidance, and WSI for their aviation weather and traffic data used in this study.

Available from:

NASA Center for AeroSpace Information
7115 Standard Drive
Hanover, MD 21076-1320
443-757-5802

Table of Contents

1 Introduction

Over the past three decades, growth in the demand for air transportation has exceeded the growth in the national airspace system (NAS) capacity. In recent years the NAS traffic volume has been near capacity. Systems operating near capacity inevitably have delays and it is no surprise that NAS delays have increased in recent years. The desire to minimize delay costs has placed focus and attention on the NAS air traffic management (ATM) system. Substantial research and development activities have been underway to make the ATM system as efficient as possible.

In dealing with the increased demand, the ATM system has had to delay or reroute larger numbers of flights. The ATM problem, however, has a large number of different solutions that may be used to achieve similar levels of system throughput and delay. But these solutions are not all equal as judged by NAS operators. User business models are not easily accounted for in the ATM solution, so an ATM solution that produces good overall throughput and delay may be undesirable according to users if, for instance, high-value flights are delayed where lower valued flights could have been delayed. Or again, users may have preferred routings which the ATM system is not aware of.

One initiative that has helped to provide user representation in the ATM solution is the collaborative decision making (CDM) process [1]. The CDM process addresses this issue by bringing users (referred to here as airline operation centers [AOCs]) and ATM providers together for information exchange and cooperative planning. Such cooperative planning has been instituted, for instance, for the purpose of planning airport slot control strategies and rerouting strategies. While the CDM initiatives have met with much success, they have also introduced the potential for AOCs to manipulate the system in unforeseen, unintended, and perhaps undesirable ways, from a system-wide, synoptic perspective.

This type of manipulation is sometimes referred to as “gaming” the system. For instance, under this definition one gaming example is an operator requesting to use a particular capacity element (gate, runway, airspace sector, etc.) of the system with the hidden intention of not using that particular element. The reason for this action could be that the AOC knows that the element has high value to a competitor.

On the other hand, an AOC merely deciding on whether or not to use a system capacity element, and factoring in the likely actions of other operators in the system, would not necessarily be referred to as gaming. This study is not concerned with determining an appropriate definition for gaming. Instead, we investigate several models of user decision making behavior which could be considered to be gaming behavior.

The potential for gaming behavior in the future NAS will likely grow as decision making is increasingly distributed to users. For instance, increased levels of user involvement in the traffic flow management process may evolve via a number of mechanisms, including increased collaboration and information sharing, improved mechanisms for indicating preferences, and market-based traffic flow management.

The goal of this study is first to develop a high-fidelity simulation tool to allow researchers to investigate various aspects of traffic flow management (TFM) user decision making, and second to use the tool to perform a study of NAS gaming. Key questions are: To what extent can user decision-making degrade system performance? Can the system be configured to dis-incentivize, limit, or avoid undesirable user decision making that degrades system performance or leads to system instabilities such as a "race-to-the-bottom" scenario?

This study partially addresses these questions by designing, programming and testing different decision making strategies into the AOCs. These schemes are not tailored for specific scenarios, but rather are designed to represent different algorithmic approaches, in general, that AOCs apply throughout their NAS-wide operations. We then investigate emergent system dynamics and interactions between AOCs and TFM.

1.1 Executive summary findings

This section summarizes the findings of this study. The findings are as follows.

Significant performance variations in gaming scenarios. Our results suggest that NextGen gaming does not reduce to a few principles. Several different gaming strategies can be envisioned, and each strategy has its own variants. For instance, the competitive-15 versus competitive-30 strategies shows significant differences, with the 15 minute time horizon showing much better performance. Furthermore, different users can select from different strategies, and very likely will use multiple strategies simultaneously in different scenarios. These many possible combinations make for an enormous problem space. In our investigation so far of this problem, we find that the performance of the different user groups can vary dramatically along these dimensions. Slight modifications in a strategy (such as the competitive strategy look ahead time, see below), or a relatively minor increase in the number of users implementing a strategy can significantly alter results. Also, when different users implement the same strategy, one user may experience delay reduction while the other experiences a delay increase. Their different flight schedules, for instance, can cause such different results. We experimented with limited numbers of gaming users and strategies, but even in that limited problem space found significant performance variations. While some trends are evident, our results suggest the NextGen gaming problem is not easily generalized into a relatively few, simple principles.

NAS performance degradation. Gaming strategies often degrade the performance of other AOCs and non AOC flights, and most gaming combinations of the two AOCs degraded the overall NAS performance. Not surprisingly, one AOC performance can change radically depending on the strategy of the other AOC.

Increase in system congestion. Gaming strategies are not concerned with managing demand within capacity constraints, and in general cause increases in airspace or airport congestion. In our experiments, all but the cooperative behavior aggravate system congestion. The observed congestion increases are not a major operational impact. Nonetheless, it is an impact of the gaming strategies and reveals that such gaming scenarios involve a third "player." In addition to the two AOCs (or more generally N AOCs), there is also the service provider that may be impacted by the shifting of the demand profile and thus increase in congestion. That is, NAS-wide user gaming can be viewed as a third-party game: the participating airlines, non-participating airlines, and the service provider. Of course such user-induced congestion is possible only to the extent that users can influence the strategic TFM initiatives.

Unintended consequences. In addition to increasing delay of other AOC flights and non AOC flights, and aggravating system congestion, gaming strategies can ultimately have the unintended consequence of aggravating own fleet total delay. This consequence could serve as a gaming disincentive if TFM service provider strategies could be designed to ensure that such unintended delay occurs.

Categories of gaming effects. We began this study with three categories that describe the user intent: cooperative, competitive and strategic. Our results suggest different types of outcomes that do not map to these intent categories. The effects are more complicated given that there are various combinations of strategies implemented by the users. We found that the results can be, at least in principle, categorized into four qualitative categories which are helpful in describing and grouping the impact of the gaming actions. First, a strategy (operating within a given environment) may improve its own performance and also improve the overall NAS. We refer to such a strategy as egalitarian. Second, a strategy may improve its own performance, while degradation to other flights, if any, is less significant. Therefore the overall NAS performance improves. We refer to such a strategy as utilitarian. Third, a strategy may improve its own performance, while degradation to other flights is more significant. Therefore, the overall NAS performance degrades. We refer to such a strategy as aggressor. Finally, a strategy may degrade its own performance, while degradation to other flights is more significant. Obviously the overall NAS performance degrades. We refer to such a strategy as spoiler.

Best strategies. The best gaming performance, for an AOC's own flights and for the overall NAS delay, we found, was produced by the competitive-15 strategy. The strategic-surplus and cooperative were the next best, providing slight aggregate improvement. The strategic-WCRD provided enhanced or degraded results, depending on the other AOC-specific operating characteristics.

Dynamic strategies. The effectiveness of AOC strategies depends on the strategies in use by the other users. This suggests that dynamic strategies could be designed to react to the strategies currently in use by the other AOCs. This could induce dynamic strategies to be implemented by other AOCs.

Race the bottom. The possibility of gaming strategies reacting to other gaming strategies brings with it a range of possible system evolutionary pathways, including both equilibrium and divergent outcomes. For instance, one possibility is the race-to-the-bottom scenario, where gamers counter each other with spoiler strategies. The NAS devolves to further levels of decreasing performance as users successively activate such gaming strategies.

Hybrid strategies. Sophisticated users would likely implement more complex hybrid strategies which simultaneously pursuing different strategies for different markets, or even different flights, depending on the tactical scenario.

1.2 Executive summary research recommendations

This section summarizes questions raised by the findings outlined in the previous section, as well as the recommendations for further research. The recommendations are as follows.

<u>Investigate causality</u>. More research is required to determine the underlying causality of how gaming actions affect the performance of other AOC flights and overall NAS performance. How exactly is performance degraded or improved, and how can these causes be dis-incentivized and incentivized, respectively?

<u>Evaluate flight delay cost outcomes</u>. In addition to the delay metric, future NextGen gaming research should evaluate the effect of gaming strategies on the flight delay cost results of the AOCs and non AOC flights. Is it possible, for instance, to degrade delay performance but improve (reduce) the overall flight delay cost?

<u>Refined investigations</u>. We have developed various gaming strategies, but further levels of detail are needed to ensure these strategies are realistic. Also, additional strategies should be considered.

<u>Investigate the problem space</u>. As we concluded above, the problem space is complex and large. Further investigation is required to explore the space and learn more about the impact of NextGen gaming strategies.

<u>Investigate incentivizing users</u>. Further research is required to investigate service provider strategies and rules of the road to (i) create a gaming equilibrium so as to avoid undesirable dynamics, chaos, and race-to-the-bottom scenarios, and (ii) force users away from undesirable gaming strategies such as spoiler and aggressor strategies.

<u>Model dynamic strategies</u>. Research is required to model and evaluate dynamic users who do not adhere to a static strategy, but use a time-varying strategy which switches between strategies depending on the actions of the other AOCs.

<u>Model hybrid strategies</u>. Research is required to model and evaluate hybrid users who do not adhere to a global strategy, but use a dynamic hybrid strategy which simultaneously implements different strategies in different markets or flights, depending on which is most profitable for each given scenario.

2 Design of Hypothetical NextGen Gaming Strategies

This section describes our design of three different categories of gaming strategies for experimentation: cooperative, competitive and strategic. Cooperative strategies consider proposed delays or reroutes from the TFM service provider. Competitive strategies derive alternative delays or reroutes and strategic strategies consider competing traffic.

As this section shows, our strategies are based on high-fidelity models. The flight delay cost includes several detailed components and they are applied to each flight individually.

Furthermore, the decision making strategies are based on detailed flight information both for own flights and for the flights of other AOCs. This flight information includes the flight congestion cost, broken down by airspace and airport components. And the decision-making strategies derive actions at the flight level.

This high level of fidelity supports accurate gaming models. Individual AOCs, however, are concerned with a wide range of detailed operational, cost and marketing factors that are beyond the scope of this study. For instance, their operational decisions can be influenced by the presence of very important person (VIP) passengers, which we do not model in this study.

2.1 Simulation platform

We use the Probabilistic NAS Platform (PNP) simulation tool [2-3] to investigate the gaming problem in this effort. PNP supports the modeling and simulation of AOC decision making and gaming in a meta-simulation environment. The architecture and design of the future NAS is not yet precisely defined, but increasing levels of CDM are likely. This means that there is an increased potential for gaming. Researchers are beginning to address this issue. Ideally, the future NAS can be designed to preclude or at least minimize user gaming.

We enhance PNP with supporting capabilities so that researchers can investigate this question. In particular, for any given future NAS, an important question is: What types of games are possible and what is their impact? Figure 2.1 illustrates the PNP architecture and how the AOC clients communicate with PNP.

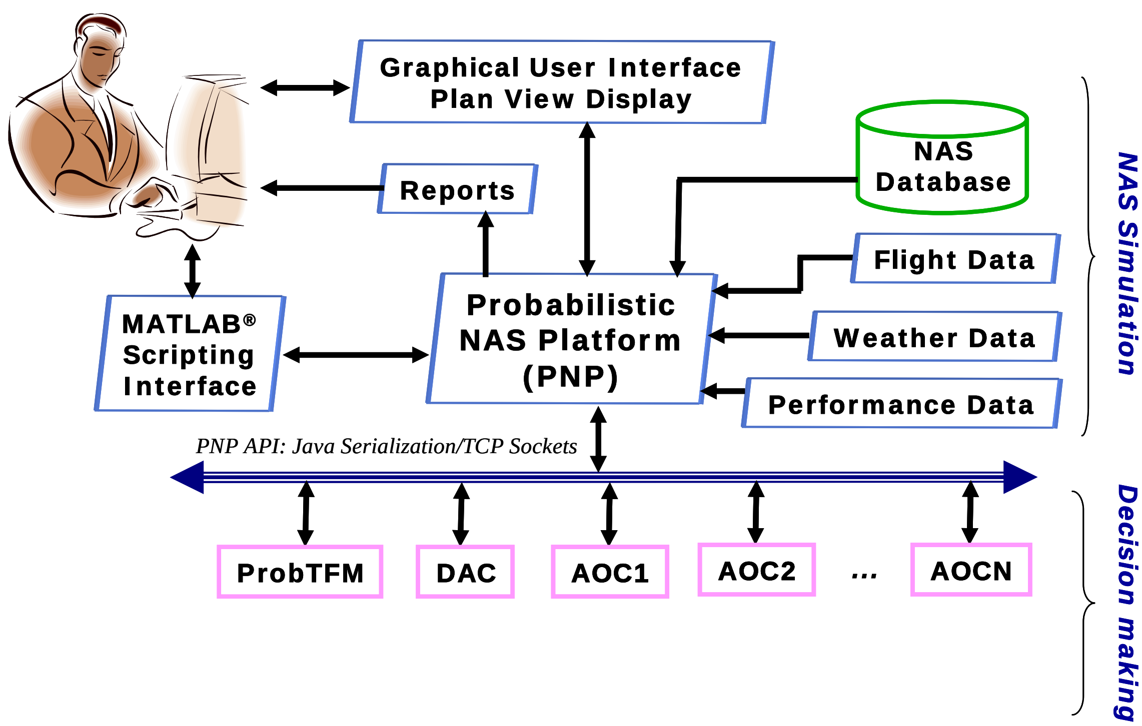

Figure 2.1 PNP architecture with AOC clients included.

Our solution approach begins with AOC clients that represent actual airline teams. They have access to all the traffic data, but can make TFM initiatives only for their own aircraft. The intention is not necessarily to represent all aircraft, so we do not necessarily require all flights to map to an AOC client. On the other hand, we can create a generic AOC client that handles all flights, using generic decision making logic, not handled by the other AOC clients.

AOC clients may not alter flights that are scheduled to depart in the current time bin. Those flights may be altered only by the TFM client (ProbTFM in this case). Flights scheduled to depart in future time bins may be altered by the AOC clients. Therefore there are no direct interactions between the AOC and TFM clients.

There of course may be indirect interactions between the AOC and TFM and DAC clients, as their respective actions alter the future system state on which the other clients will operate.

2.2 Model functional requirements

This section describes our functional requirements. These requirements support the modeling of future, hypothetical NextGen gaming actions. The functional requirements for our AOC models are as follows:

1. The TFM client (ProbTFM) shall have access to data describing all AOC actions.

2. The AOC clients shall implement the same algorithm to compute flight congestion cost, threshold and rankings that the TFM client normally does. This allows the AOC clients to forecast which of its flights are likely to be delayed or rerouted and take proactive actions accordingly.

3. The AOC look-ahead time window (AOC_LAT_START and AOC_LAT_STOP) shall be user specifiable (default values are 4 and 1 time bins, respectively). Each AOC has its own AOC_LAT_START and AOC_LAT_STOP values. The specified start and stop bins specify which flights may be delayed or rerouted. Specifically, the look-ahead time window is obtained by adding AOC_LAT_START and AOC_LAT_STOP to the current time bin, to obtain two future time bins. Aircraft which are scheduled to depart within that time window (inclusive) are available for delay or reroute. For example, the AOC_LAT_STOP default value of 2 indicates that flights scheduled to depart in the second time bin immediately following the current time bin are available for delay or reroute. AOC_LAT_START must be greater than or equal to AOC_LAT_STOP.

4. The AOCs shall be provided with the nominal TFM suggested delays and reroutes for any flight which the AOC may decide to delay or reroute. That is, the TFM procedure should run in a look-ahead mode in AOC, where it generates its delays and reroutes for future time bins (not the current time bin as it usually does).

5. The AOCs will be supplied with, or be able to save, the history of the TFM suggested delays and reroutes for its flights. That is, in a given time bin, the AOC needs to know not only the current nominal TFM suggestions for a flight, but also the nominal TFM suggestion for the flight from previous time bins.

6. The AOC decision making logic shall be user specifiable.

7. The AOC client actions and subsequent TFM action for each flight shall be logged and available for both post-processing purposes, and run-time purposes such as AOC learning.

8. AOC clients shall have a specified scope. An AOC's scope determines which aircraft it may control. The scope may be defined as a particular (real) airline, in which case the AOC may control only flights belonging to that airline, or the scope may be generic in which case the AOC may control all flights not otherwise under the control of a different AOC.

9. The number of AOCs and their scope shall be user specifiable.

10. The number of AOCs shall be variable from 0 to 20.

2.3 Model design

This section describes the AOC decision making logic. Note that the AOC module runs its own TFM procedure in a look-ahead mode that is independent of the TFM client. AOC clients only take proactive actions for future flights that will depart between AOC_LAT_START and AOC_LAT_STOP. Although this procedure is independent, the AOC uses the TFM algorithm (the algorithm implemented in ProbTFM in this case), giving the AOC insight into the likely TFM initiatives.

2.3.1 AOC planning horizon parameters

We use two planning horizon parameters. They are user specifiable and AOC specific. The AOC look-ahead time window, defined by the two parameters AOC_LAT_START and AOC_LAT_STOP, indicates the time window in which the AOC may implement delay or reroute for a flight. These values are specified in terms of the number of time bins from the current time bin.

For example, suppose the current time bin is t. Then an AOC_LAT_START value of 4 indicates the AOC look-ahead time window begins in the t+4 time bin. Similarly, an AOC_LAT_STOP value of 1 indicates the AOC look-ahead time window stops in the t+1 time bin. Only flights of that airline with scheduled departure times that fall into that time window (inclusive) are considered by the AOC client for delays or reroutes. That is to say, in this example, the AOC is able to examine and make flight plan changes for flights that are scheduled to depart within the [t+1, t+4] time window.

The default values are 4 and 1 for AOC_LAT_START and AOC_LAT_STOP, respectively. The maximum value is 6 for AOC_LAT_START. The minimum value is 1 for AOC_LAT_STOP. And AOC_LAT_START must be greater than or equal to AOC_LAT_STOP.

2.3.2 Distinguishing causes of high congestion cost

A flight may have a high TFM cost because the NAS capacity elements it transits (sectors and the two airports) have forecasted reduced capacity (e.g., due to weather) or have forecasted high demand, or some combination of the two. Metrics can be computed to indicate the relative importance of capacity reduction versus demand increase, for a particular flight. We use our weighted capacity reduction to demand ratio metric. First, we define the capacity reduction to demand ratio for any given sector or airport, in a given 15 minute time bin:

$$CRD_i = \frac{CR_i}{D_i} \quad (2.1)$$

where

CRD_i = Capacity reduction to demand ratio for *i*-th element (airport or sector),
CR_i = Capacity reduction for *i*-th element (clear weather capacity – capacity Probability Mass Function (PMF) mode),
D_i = Demand for *i*-th element (demand PMF mode).

The *CR* value is computed as the clear weather capacity minus the mode of the forecasted capacity PMF. The *CRD* metric is non-negative. A value of zero indicates that capacity reduction is not the cause of congestion cost. On the other hand, a value near unity indicates that both capacity reduction and demand are roughly equal causes of congestion cost. And a large positive value indicates that capacity reduction is the main cause of the congestion cost. We then compute the weighted capacity reduction to demand ratio metric, for a flight, as:

$$\mathrm{WCRD} = \sum_{i=1}^{N} \mathrm{CRD_i} \times \mathrm{ECC_i} \quad (2.2)$$

where

W*CRD* = The weighted capacity reduction to demand ratio for a flight,
ECC_i = Congestion cost for *i*-th element (airport or sector, computed by the TFM algorithm).

The *WCRD* is an aggregate *CRD* metric for a flight, weighted toward those elements that contain the most congestion cost for the flight. Some AOC decision schemes incorporate the *WCRD* metric to help in deciding whether preemptive action should be taken. For instance, a large *WCRD* value suggests that inaction may be effective, since the congestion cost for the flight is caused by other flights which may deviate. On the other hand, a value near zero suggests that inaction will not be effective, since the congestion cost for the flight is caused by capacity reduction (e.g., due to weather), which likely will not improve.

2.3.3 Overview of delay cost

There are different types of cost that may be incurred as a result of flight delay at different levels. In practice, in order to maintain punctuality and predictability, the AOC adds minutes of buffer to their schedules. However, the term "cost of delay" in this EDD does not include these AOC strategic buffer delays. It refers only to the delay that is incurred on a day-to-day basis, where they are measured against planned activities. We use term “primary delay cost” to represent the direct cost of delayed flight due to at-gate, taxi, en-route or holding delays. These may be caused by a number of factors, such as TFM decisions, AOC technical problems or weather change. And, the term “network delay cost” denotes the cost associated with the subsequent delays that are attributed to an initial primary delay. These delays may propagate throughout the entire network.

An important factor in the AOC decision making process is the delay cost of each flight. Delay cost may be computed simply based on time and fuel. But for excessive delays (longer times), additional costs are incurred such as overtime costs and passengers missing connections. AOCs account for this type of non linear cost of delay and we consider four factors that contribute to it: aircraft type, delay magnitude and time of day, and schedule interactions. These factors are discussed in the following sections.

The aircraft type determines the baseline operating cost that is primarily related to the fuel usage. We define four aircraft size categories: small (0-65 seats), medium (65-150 seats), large (150-250) seats and super (>250 seats). We also define three delay duration categories: 0-15 minute delay, 16-64 minutes and more than 65-minute delay. For each delay duration, “low,” “base” and “high” cost scenarios have been calculated, to furnish a range of costs for the purposes of comparison.

Table 2.1 Primary ground delay cost without network effect ($/min).

	0-15 min delay			16-64 min delay			>=65 min delay		
	cost scenario			cost scenario			cost scenario		
Aircraft seats	low	base	high	low	base	high	low	base	high
<65	0.588	0.882	12.642	8.232	18.8895	42.1155	15.876	36.897	71.589
65-150	1.176	1.764	20.874	12.936	29.253	64.7535	24.696	56.742	108.633
150-250	1.323	2.058	30.282	27.048	54.096	106.5015	52.773	106.134	185.955
>250	1.764	3.087	46.305	32.1195	66.738	150.234	62.475	130.389	233.73

Tables 2.1 and 2.2 are derived delay cost statistics in dollars based on a linear interpolation of the original tables in study [4]. They provide ground and en-route statistics used in our current implementation but do not include any delays that are caused to future flights because of lack of aircraft or crew at another location (the network delay).

For example, in a low cost scenario, a 10 minute ground delay of a small aircraft only costs $0.588×10, or $5.88 in terms of the primary delay cost. For the same cost scenario, a 20 minute ground delay of a large aircraft costs the AOC about $8.232×20, or $164.64.

Table 2.2 Primary en-route delay cost ($/min).

	0-15 min delay			16-64 min delay			>=65 min delay		
	cost scenario			cost scenario			cost scenario		
Aircraft seats	low	base	high	low	base	high	low	base	high
<65	0.588	0.882	12.642	8.232	18.8895	42.1155	15.876	36.897	71.589
65-150	1.176	1.764	20.874	12.936	29.253	64.7535	24.696	56.742	108.633
150-250	1.323	2.058	30.282	27.048	54.096	106.5015	52.773	106.134	185.955
>250	1.764	3.087	46.305	32.1195	66.738	150.234	62.475	130.389	233.73

Delay magnitude and time of the delay. As with the baseline cost, the delay cost associated with network effects is expected to increase nonlinearly. Network effects are small for short delays of, say, less than five minutes because the main effect of this delay is on the direct operating cost due to the longer flight time and the airlines build some slack into their schedules to accommodate delay.

Longer delays, on the other hand, can disrupt gate scheduling and ramp activities, disrupt crew scheduling and result in overtime labor rates. Importantly, longer delays can also cause later flights to be delayed due to lack of airframe or crew availability. These delays can propagate throughout the network until the end of the day. Figure 2.2 gives an example of the network effect. The data reveal both the time of day dependence and a length of delay dependence. Both of these factors influence the network delay (or ripple effect), where early flights impact subsequent flights and therefore increase overall cost of those delays. Data and analysis come as the courtesy of Dr. Steve Waslander and Mercer Management Consulting, 2003.

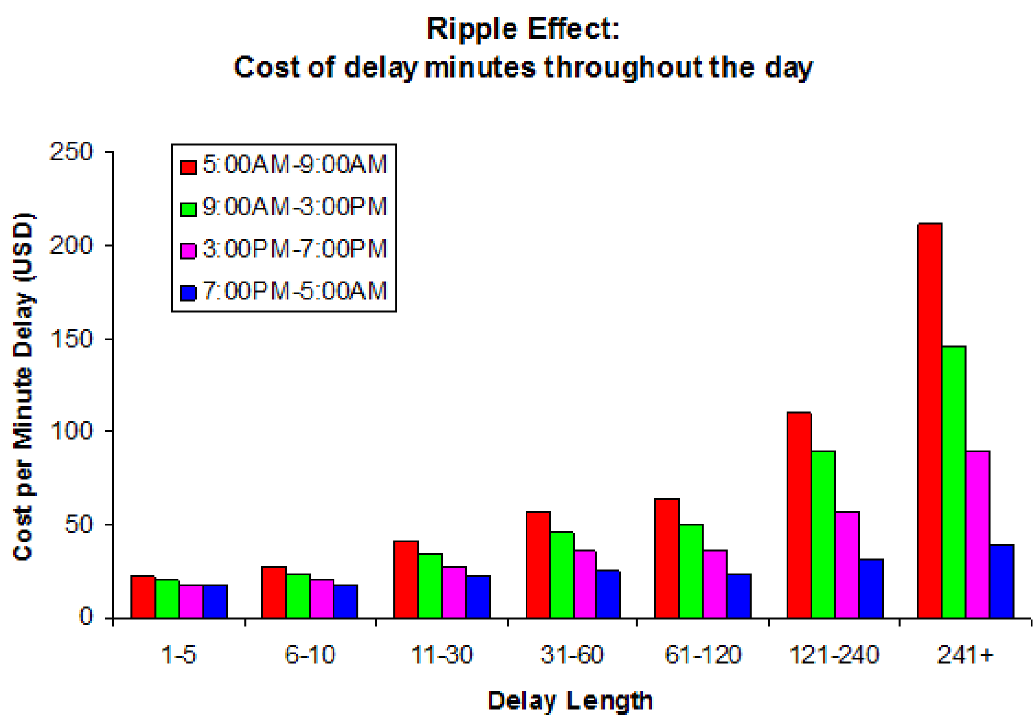

Figure 2.2 Delay cost for a European low cost carrier for all flights from Oct 2000-Oct 2002.

The unit cost of the baseline delay serves as a benchmark for estimating the network delay cost. Our approach relies on a data-driven study [5], in which delay propagation was analyzed using actual American Airlines schedule data. We adopt their concept of a "delay multiplier" (DM) to quantify the magnitude of the network effect caused by the initial primary delay. The detailed DM numbers are provided in Fig. A.1 in the Appendix. For a baseline delay of 10 minutes at 6:15 AM, the DM value is 1.62. So, approximately 1.62×10, or 16.2 minutes of total delay may be expected when the network effect is taken into account. As a result, a further 16.2–10, or 6.2 minutes reactionary delay is generated in addition to the primary delay of 10 minutes.

In order to quantify the price of these reactionary delays, we use the numbers in Table 2.3 as the average network cost of per minute delay. These values are computed by averaging the primary delay costs over a variety of aircraft types and converting to dollar values. They address the AOC's expenses related to fuel, maintenance, agent penalty, ground handling, airport, aeronautical charges en-route ATC, and so forth. As a continuation of the previous example, when in a low cost scenario, the additional 6.2 minutes yield a cost of 6.2×1.76, or $10.94. As Table 2.3 indicates, network delays greater than 15 minutes would cause substantially escalated network cost.

Table 2.3 Average cost for network effect ($/min).

	0-15 min delay			16-64 min delay			>=65 min delay	
	cost scenario			cost scenario			cost scenario	
low	base	high	low	base	high	low	base	high
1.76	2.72	32.56	22.38	48.73	104.99	43.00	94.74	177.43

<u>Schedule interaction</u>. To model the total network delay costs, we also consider another factor, the effect of "hubbing." Flights are often tightly scheduled to squeeze more flying time out of each plane. The greatest impact of delay happens when it causes customers to miss connections or cause aircraft to miss their next operation. Thus, in a hub-and-spoke network, connecting flights to the hub should have higher delay costs due to this effect. We use the following empirical method to identify these inbound flights.

In the preprocessing phase, the PNP server computes the unimpeded scheduled arrival time for each flight from the demand data. For a given AOC client and hub airport pair, we calculate the total number of scheduled arrivals and scheduled departures for each 30-minute time bin. Figure 2.3 provides an example of United Airlines and its main hub, Chicago O'Hare International Airport.

We assume that a sharp increase in arrivals followed by a large number of departures indicates a connecting or banking event. These connections are likely to be tightly scheduled (within one hour) so that delays on inbound flights affect the carriers' performance adversely and extensively. We identify the time windows with arrival banking immediately followed by departures (the yellow circles in Fig. 2.3 indicate these arrival banks).

Not every flight that is scheduled to arrive in these periods, however, is an important inbound flight that needs to be on time. So we define an inbound flight be a flight that has more than 125 seats (in other words, larger than a B737 aircraft) and that is scheduled to arrive at the AOC's hub in a yellow-circled time period. The AOC clients have the option to assign higher delay costs to these inbound flights, using a user-specifiable multiplier coefficient *B* based on the banking status of a departure.

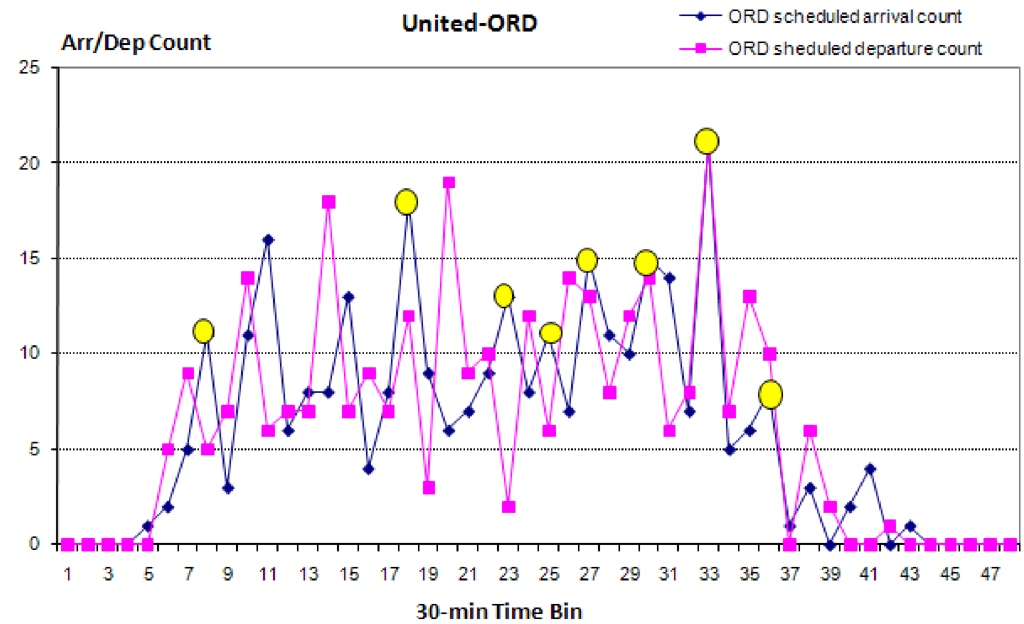

Figure 2.3 Schedule arrival and departure counts for United Airline-Chicago ORD airport for 2007-8-30 with yellow circles indicating arrival banks.

<u>Costs of passenger delay</u>. The passenger cost of delay reflects the costs that can be associated with the passenger compensation. More importantly, it is closely related to the opportunity cost of potential revenue loss due to future loss of market share as a result of lack of punctuality. Thus, it is an important consideration when calculating total delay costs. We use an average of \$0.44 per passenger, per delay minute [4] and we assume that the total cost of passenger delay is proportional to the length of the delay, the aircraft capacity and the flight load factor.

In our current cost model, frequency to that location is not considered. The mathematical formula to calculate the cost of passenger delay is:

$$\mathrm{PassDelayCost} = 0.44 \times \mathrm{CAP} \times \mathrm{LOAD} \times \mathrm{BaselineDelay} \quad (2.3)$$

where

CAP = Number of aircraft seats,
$LOAD$ = Average aircraft loading,
$BaselineDelay$ = Amount of primary delay of the aircraft (min).

The LOAD factor is a user-specifiable, AOC-specific parameter with a default value of 70%, 80% and 90% in the low, base and high scenarios. So for an aircraft size of 100 seats with an aircraft load factor of 80%, a 10-minute primary delay incurs a total of 100×80%×10×0.44, or \$352 in passenger delay cost. Note that this passenger delay cost is not an actual AOC cost.

Rather, this cost is merely used in the AOC decision making logic to avoid excessive passenger delays and potential market share loss.

Model of AOCs total delay cost. In this section, we summarize the total cost of flight delay. We refer to this metric as the flight delay cost (FDC). It incorporates the cost of baseline delay, the network effects and potential market share loss previously defined. FDC, which in our context results from ground delay and/or pre-departure reroute, is a flight specific indicator, calculated by the AOC and whose value is generally private. Here is the definition of FDC.

$$\begin{aligned} \mathrm{FDC} &= \mathrm{PrimaryDelayCost} + \\ &(1 + \mathrm{InBd} * \mathrm{B}) \times \mathrm{BaseNetworkCost} + \mathrm{PassDelayCost} \end{aligned} \tag{2.4}$$

where

$InBd$ = The weighted capacity reduction to demand ratio for a flight,
B = Positive coefficients that are AOC specific and user specifiable with a default value of 1.

If a flight is an inbound flight to a hub in a banking scenario, it will have additional cost on top of the base average delay cost at the network level. As a result, the AOC will be more reluctant to delay or reroute this type of flight.

2.3.4 Comparison factors

From the AOC's perspective, comparisons with the major competitors may be an essential factor in their decision process. For example, for marketing purposes, they might be concerned with how delays are distributed between users. We know that mean delay plays an important role in AOC's daily operation. However, of equal or greater importance is the timing and distribution of these delays. Consider, for example, a hub-and-spoke network. Here it would be better if all aircraft were to arrive and depart with the same (smaller) delay, rather than having just a few arrivals with a very long delay. So we consider two comparison factors, the mean comparison factor (MCF) and variance comparison factor (VCF), respectively. MCF indicates whether the delay is assigned proportionally between departing flights in a given time bin, and VCF reflects whether the uncertainty of delay is distributed evenly. For current time bin *t*, MCF is defined as:

$$\mathrm{MCF[i]} = \frac{\mathrm{SD}_{[i][t]} / \mathrm{NT}_{[i][t]}}{\mathrm{SD}_{[j][t]} / \mathrm{NT}_{[i][t]}} \tag{2.5}$$

where

$SD_{[i][t]}$ = Total delay suggested for AOC *i*'s flights in time bin *t*,
$NT_{[i][t]}$ = Number of AOC *i*'s flights scheduled to depart in time bin *t*,
$SD_{[j][t]}$ = Total delay suggested for competitor *j*'s flights in time bin *t*,
$NT_{[j][t]}$ = Number of competitor *j*'s flights scheduled to depart in time bin *t*.

The VCF metric is defined as:

$$\text{VCF}[i] = \frac{\text{VAR}[i][t]}{\text{VAR}[j][t]} \qquad (2.6)$$

where

$VAR[i][t]$ = The variance of suggested delay for AOC i's flight in time bin t,
$VAR[i][t]$ = The variance of suggested delay for competitor j's flight in time bin t.

Note that MCF and VCF are merely subjective factors. From the AOC perspective, MCF (or VCF) values of one or less indicates a favorable delay distribution. But MCF (or VCF) values of greater than one indicates an undesirable situation, in which the AOC client perceives too much delay or too much unpredictability.

2.3.5 Classes of AOC decision making logic

This section discusses three classes of AOC decision making logic which successively build on each other. These classes are motivated by previous investigations of AOC decision making in cooperative and competitive environments [6-7]. They are ordered in terms of sophistication, intent and user-gaming. The structure of each algorithm is given below.

<u>Cooperative</u>. Cooperative decision making uses only solutions suggested by the TFM algorithm. The only decision is a yes/no decision for each flight, on whether or not to implement the suggested delay or reroute. Figure 2.4 summarizes this logic.

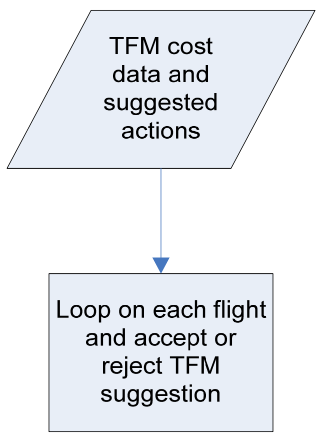

Figure 2.4 Overview of the cooperative AOC decision-making logic.

There are two sub types of cooperative decision making, where the time bin in which to accept the TFM suggestion is either (i) fixed or (ii) computed.

In the fixed scheme, the TFM suggestion is accepted in a predefined time bin and is specified in terms of the number of time bins from the current time bin using the variable NBins_Depart. Suppose the current time is t, an NBins_Depart value of 2 means the TFM suggestion is used when, and only when the flight's scheduled time of departure is in time bin t+2. For any change to the flight plan, NBins_Depart must fall within the AOC look-ahead time window.

$$AOC\_LAT\_START \geq NBins\_Depart \geq AOC\_LAT\_STOP \qquad (2.7)$$

Figure 2.5 shows the process for this cooperative-fixed scheme. Note that flights that are early in the day, whose scheduled departure time bins are prior to the NBins_Depart time bin, are not considered by the AOC for delay or reroute. The default value of NBins_Depart equals AOC_LAT_STOP+1.

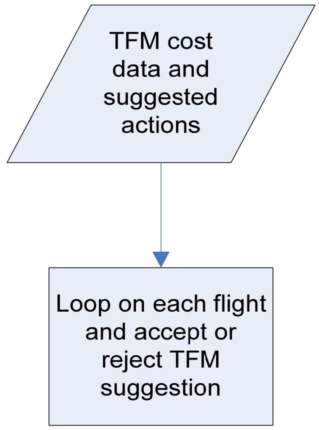

Figure 2.5 Cooperative fixed-scheme AOC decision-making logic.

In the computed scheme, the AOC determines when and if to accept the TFM suggestion. The nominal algorithm to be implemented is explained next and the flowchart is shown in Fig. 2.6. First define the congestion cost of flights computed by the TFM algorithm as flight congestion cost, FCC. FCC is the sum of element congestion cost (ECC) that the flight transits throughout the flight.

1. In the earliest time bin in which a flight may be delayed or rerouted, no action is taken (i.e., the TFM suggestion is not accepted).

2. In subsequent time bins, the TFM suggestion is ignored if the initial FCC (i.e., not including the TFM-suggested delay or reroute) is less than it was in the previous time bin, and otherwise accepted.

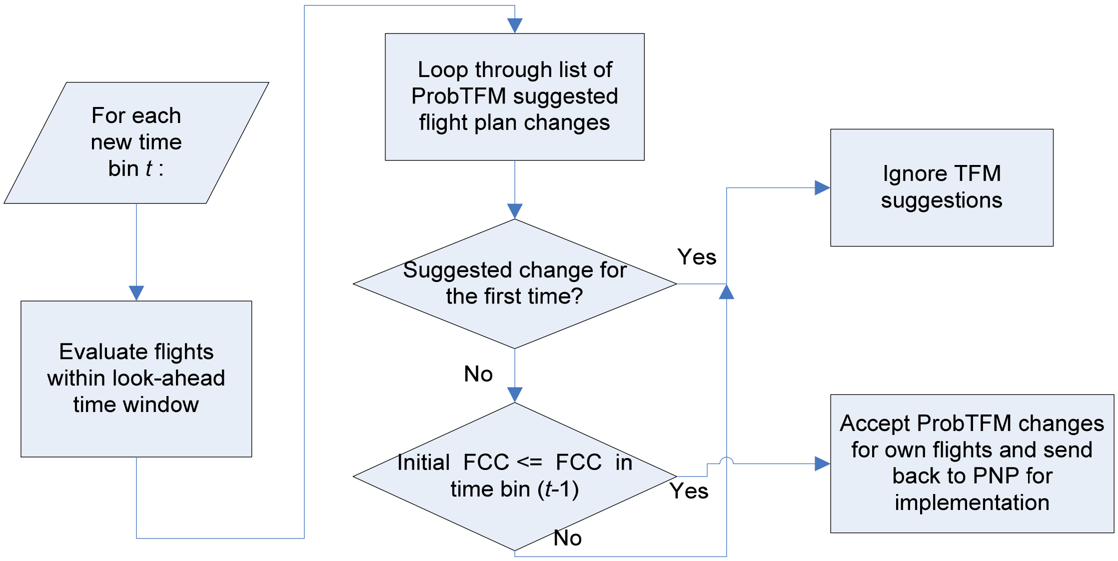

Figure 2.6 Cooperative Computed-scheme AOC decision-making logic.

<u>Competitive</u>. This class of AOC decision-making procedure builds on the cooperative logic. In the competitive logic, the AOC either derives its own delays or reroutes (rather than using the TFM-supplied options) or it opts to either cooperate or ignore TFM suggestions based on some criterion. There are two sub types of competitive decision making, where the decision to accept the TFM suggestion is either (i) time-based or (ii) comparison-based.

In time-based competitive decision making, the AOC investigates the possibility of delaying the flight less than is suggested by the TFM algorithm. The candidate delay values are in increments of 15 minutes (i.e., the equivalent of a time bin), ranging from 15 minutes (1 time bin) up to the greatest multiple of 15 that is less than the TFM suggested delay. At each new time bin *t*, given TFM suggested actions, the competitive algorithm selects the desired amount of delay.

Multiplier, a user specifiable parameter, is used to compute the alternative delay. The delay value (picked by the AOC) equals the minimum between 15×*Multiplier* and the TFM suggested delay. The parameter Multiplier has a default value of 1. These alternative delays are designed in an attempt to reduce congestion costs, but only to a necessary magnitude. For instance, the TFM-suggested delay may be longer than needed. If the TFM suggestion is a reroute rather than a delay, then this type of decision-making simply accepts the reroute. Figure 2.7 summarizes this logic.

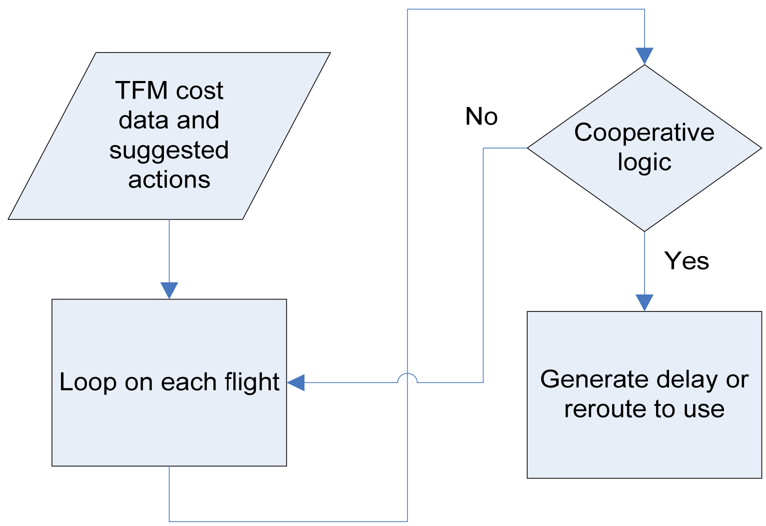

Figure 2.7 Time-based competitive AOC decision-making logic.

Next is the comparison-based competitive logic. Based on the scheduled flight time, the AOC first classifies the TFM suggested flights into short-haul or long-haul categories. Flights having a flight time of less than 90 minutes are defined as short-haul and otherwise long-haul. For every flight category and given the current delay allocation, the AOC calculates the comparison metric MCF (VCF) defined in Eqs. 2.5 and 2.6. If the AOC believes the delay distribution has been unfavorable, then the AOC chooses no action and relies on other AOC clients to resolve the congestion problems. Otherwise the AOC selects the cooperative logic. Figure 2.8 describes this logic.

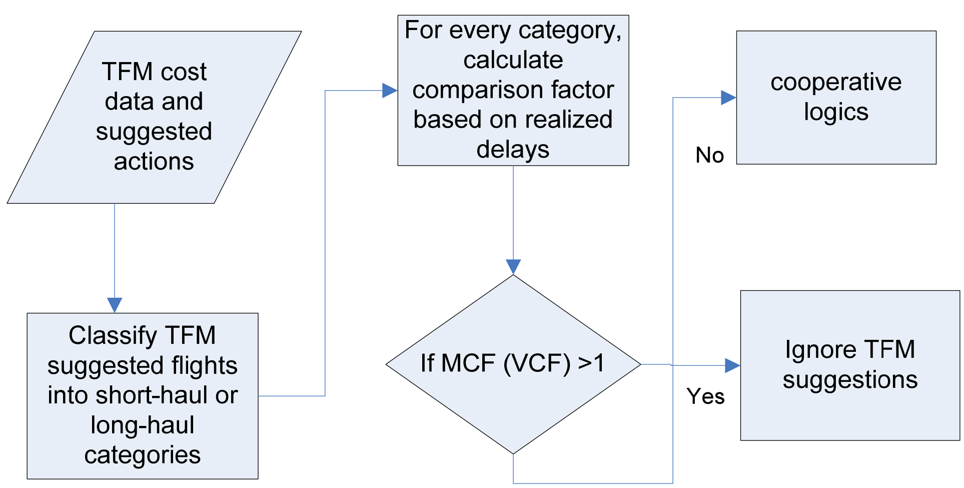

Figure 2.8 Comparison-based competitive AOC decision-making logic.

<u>Strategic</u>. In this class of decision making, the AOC clients can decide whether or not to cooperate and whether or not to derive their own delays or reroutes. Furthermore, they can choose alternative flights for delay other than the ones suggested by the TFM algorithm, or even

choose alternative solutions other than TFM suggestions. Under this framework, the alternatives are generated not only to reduce congestion cost, but also to consider other traffic that is not under the control of the AOC, and also in a way to integrate the AOC's economic model. Specifically, we consider three types of behavior in this strategic class.

In the first type of strategic logic, the parameter WCRD (see Eq. 2.2) is used to decide on action versus inaction. When WCRD is greater than unity, then the AOC takes no action on the flight. Instead, the AOC realizes that other flights may delay or reroute, thus solving the congestion problem. On the other hand, when WCRD is less than or equal to unity, then the AOC uses the strategies in the competitive framework for this flight. The logic is summarized in Fig 2.9.

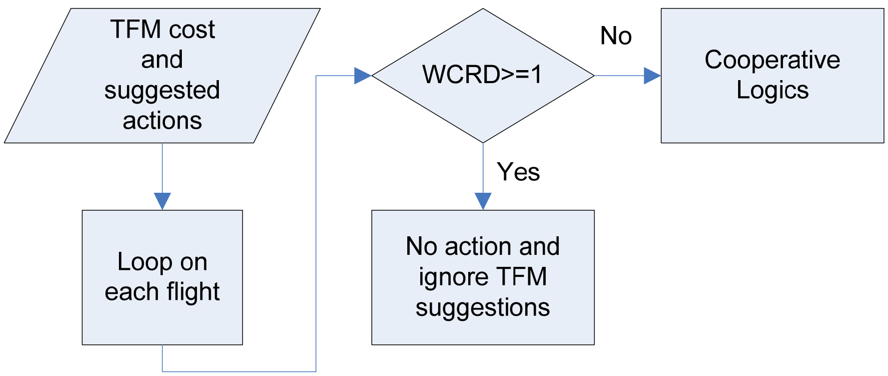

Figure 2.9 First-type strategic AOC decision-making using WCRD.

The second type of strategic behavior can be characterized as follows: the AOC computes the weighted difference between the flight ground delay cost FDC and the flight congestion cost (FCC) in order to decide which flight to delay. We borrow the economic term "surplus" to denote this difference.

$$\text{Surplus} = \text{FDC(FRC)} - \text{FCC} \times \text{M} \quad (2.8)$$

Parameter M is an AOC-specific user specifiable multiplier, ranging from 0 to 1. It reflects the relative AOC decision making preference between reducing the congestion it produces and minimizing its own delay cost. The default value of M is 1.

The value of surplus is applied as a rescoring rule to rank all the candidate flights (including the initial ones suggested by the TFM algorithm). Flights with higher FDC have higher surplus values and should be less likely to be chosen for delay or reroute by the AOC client. Given the FDC, AOC clients are more willing to delay flights having higher FCC values. Thus, AOC clients will sort the flights in accordance with the computed surplus value. Then the AOC will pick a certain number of flights for delay or reroute, starting with the one that has the minimum surplus value. Figure 2.10 illustrates this logic.

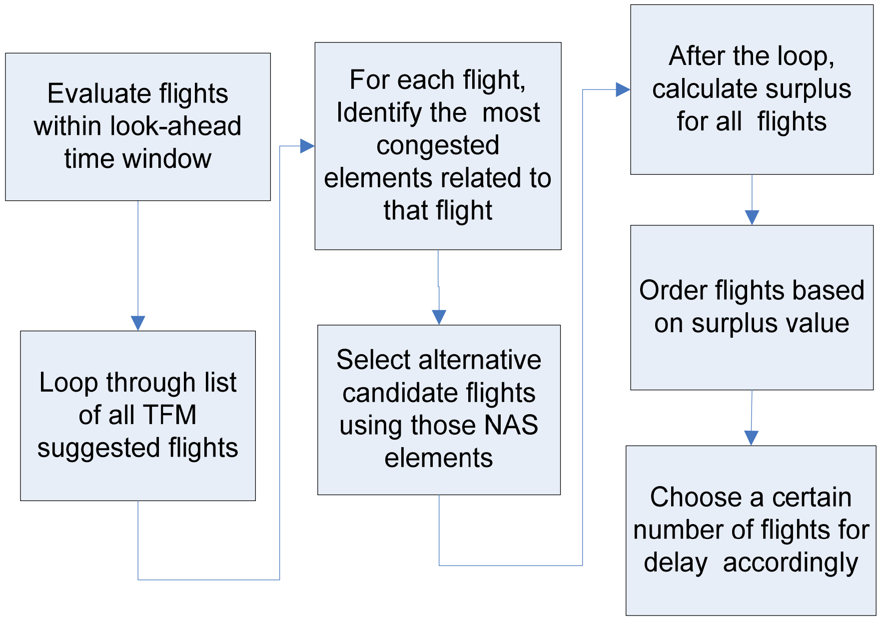

Figure 2.10 Second-type strategic AOC decision-making logic using Surplus.

In the third type of strategic behavior we continue to use AOC_LAT_STOP and AOC_LAT_START to specify the time window in which the AOC evaluates the TFM suggestions. But we use the additional parameter N_Element_Look to specify the number of NAS elements (airport and sectors) to search when the AOC client tries to find the most congested elements of the TFM suggested flight.

This strategy also uses TOT_Alt_Flights to define the total number of alternative flights to be selected. For example, a TOT_Alt_Flights value of 10 and an N_Element_Look value of 3 means that the AOC will examine the top 3 congested elements related to the flight being evaluated. The AOC first searches for flights that transit all three of them. The AOC next searches for flights that transit two of them, and then finally flights that transit one of them until the total number of flights found sums up to 10. It is possible that the AOC client will find less than 10 at the end of the search. Both N_Element_Look and TOT_Alt_Flights are AOC-specific and user specifiable. The default value of N_Element_Look is 3 and TOT_Alt_Flight is 10.

The incentive of the third type of AOC strategic behavior is to find alternative solutions with respect to user preferences. In this type of decision logic, the AOC computes the flight delay cost (FDC) for both the ground delay and reroute options for a flight that is suggested for ground delay (or reroute) by the service provider. If the ground delay cost exceeds the DVR multiplied by the reroute delay cost, then the AOC chooses to reroute the flight. Otherwise, the AOC accepts the ground delay. The solution AOC chooses might be the opposite of the TFM suggested action.

2.3.6 TFM decision making logic

Depending on the AOC actions, congestion may or may not be resolved. For flights departing in the current time bin, the decision-making process for the TFM client is to use ProbTFM to resolve any residual congestion.

AOC clients can take proactive actions to reduce congestion in lieu of responding to congestion when it happens. However, it is also likely that AOC clients desire to minimize their own response and to let their competitors resolve the congestion problem. Furthermore, an AOC client may even intentionally jeopardize competitors' flight plans. The TFM client should be aware of these possibilities, and use appropriate responses to penalize undesirable decisions that will lead to a degraded system.

To penalize these undesirable AOC actions, we modify the flight congestion cost. We use a penalty function to increase the flight congestion cost for flights belonging to AOCs that have taken undesirable actions in the recent time bins. The penalty function constitutes to a new, adjusted congestion cost (ACC) for flight *f* (scheduled to depart in time bin *t*) in the following way:

$$\mathrm{ACC}_f^t = \mathrm{FCC}_f^t + \sum_{k=1}^{|N[t-1]|} (\mathrm{FCC}_k^{t-1} - \mathrm{Congestion\ Threshold}) \times \lambda \qquad (2.9)$$

$$N[t-1] = \{ i \mid \frac{\mathrm{FCC}_i^{t-1} - \mathrm{CongestioThreshold}}{\mathrm{Congestion\,Threshold}} \geq 10\,\%, i \in \mathrm{AOC}^i \} \qquad (2.10)$$

The congestion threshold is a predefined cut-off value determined by the TFM service provider. The first term in the right-hand side of Eq. 2.9 is the flight congestion cost computed by ProbTFM by aggregating congestion cost of sectors and airports flight *f* will transit. The second term is the penalty part that is the sum of excess congestion from the previous time bin.

The user-specifiable parameter λ represents the percentage increase in the congestion cost due to a penalty. The default value of λ is set to be 1.

N [*t*–1] is a set containing all the flights that belong to AOC *i* and that departed in the previous time bin *t*–1 and exceeded the congestion threshold by more than 10%. |N [*t*–1] | is the cardinality of the set.

The procedure taken by the TFM decision logic is as follows:

1. For the previous time bin (*t*–1), for each AOC client, select departed flights with a FCC value that was 10% above the congestion threshold.

2. Among the selected flights, aggregate the excess congestion for the time bin *t*–1 and compute the adjusted congestion cost (ACC) according to Eq. 2.9.

3. Identify the flights to be delayed or reroute with respect to ACC values and the congestion threshold specified.

Compliant AOCs, which ensure that their high congestion cost flights remain below the congestion threshold, incur no such penalties as described above. Therefore, this decision-making penalty implemented in ProbTFM does not introduce any strange TFM decisions in these compliant cases.

3 Investigation of Impact of Gaming Strategies

In this section we describe results of NAS gaming simulation experiments using the user gaming behaviors described in Section 2.

3.1 Experiment outline

This section discusses the experiment scenario, demand structure and design.

3.1.1 Scenario

For this experiment, we use Nov.16 (Thursday), 2006. The NAS traffic volume was relatively high, with 58,259 instrument flights. As Fig. 3.1 shows, the NAS weather was severe with a round of late season storms affecting the Midwest and Northeast corridor.

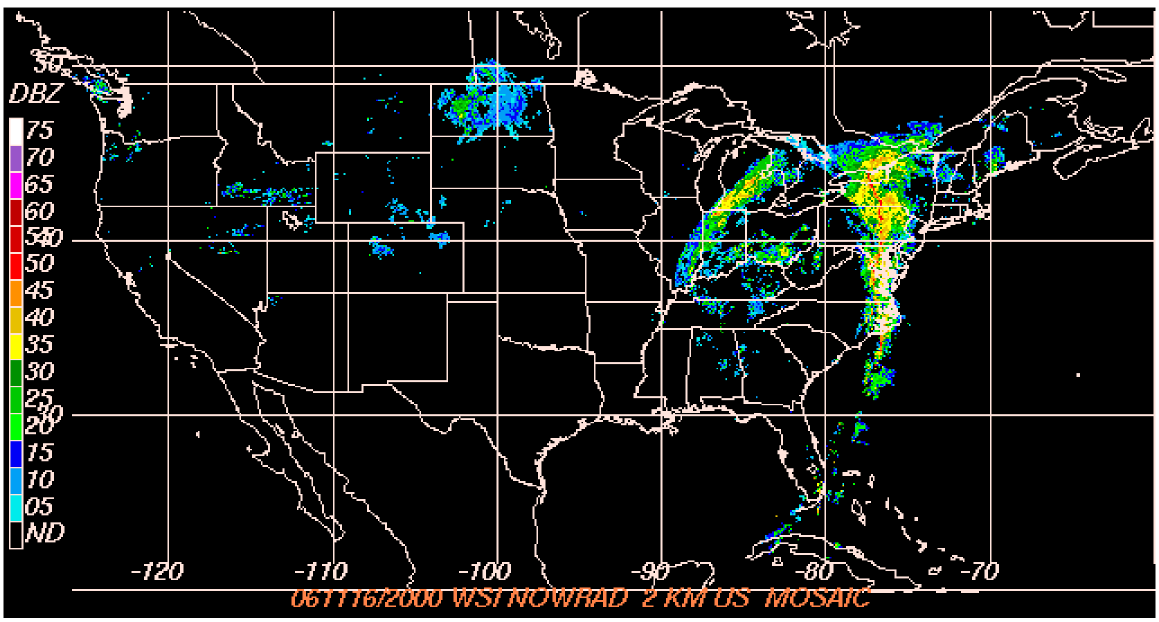

Figure 3.1 Nexrad national mosaic reflectivity image from November 16, 2006.

3.1.2 Demand structure

The demand set contains information on flight plan, including flight number, aircraft type, departure and arrival airport, and scheduled departure time. We consider in total 10 commercial carriers (listed in Table 3.1, column 1). They represent 30-40% of the total NAS operations in this demand data. AAL (American Airline) and EGF (American eagle) are represented as one carrier. This is because their operations are jointly scheduled regularly regardless of their separate flight plans. Similarly we also merge COA with BTA, and ACA with JZA.

Column 2 in Table 3.1 specifies the hub airports being considered for every commercial carrier. In column 3, we provide a list of the time windows we determined to represent banking events of the corresponding inbound flights. They are denoted by 15-minute time bins.

Table 3.1 Scheduled arrival time for inbound flight (ICAO code).

Carrier	**Hub Apt**	**15-minute Time Bins (Inbound Flight Scheduled Arrival)**
SKW	DEN	27,28, 35,36,41,42,47,48,55,56,63,64,69,70
	ORD	15,16,17,18,25,26,45,46,53,54,55,56,63,64,65,66
	LAX	25,26,69,70,73,74,79,80
FLG	MEM	19,20,37,38,57,58
	DTW	13,14,33,34,39,40,47,48,61,62
NWA	MSP	19,20,25,26,27,28,35,36,43,44,49,50,57,58,71,72
	DTW	19,20,27,28,33,34,39,40,45,46,53,54,61,62,67,68
	MEM	17,18,19,20,39,40,57,58,59,60
UAL	DEN	21,22,31,32,45,46,47,48,61,62,65,66,71,72
	ORD	15,16,35,36,45,46,49,50, 53,54,61,62,65,66,71,72
	IAD	45,46,63,64,65,66
	SFO	33,34,43,44,53,54
DAL	ATL	13,14,19,20,31,32,39,40,41,42,43,44,47,48,53,54,59,60,61,62
	SLC	29,30,53,54,67,68,71,72
	CVG	15,16,39,40,57,58,61,62
USA	CLT	17,18,25,26,31,32,37,38,43,44,49,50,57,58,65,66,67,68
	PHL	17,18,33,34,41,42,49,50,59,60

SWA	MDW	17,18,21,22,23,24,27,28,33,34,43,44,53,54,63,64,69,70
	LAS	29,30,33,34,42,44,59,60,65,66,73,74
	PHX	25,26,33,34,55,56,61,62,67,68,77,78
	HOU	25,26,37,38,49,50,53,54,65,66
AAL **EGF**	DFW	19,20,21,22,23,24,27,28,37,38,39,40,45,46,51,52,55,56,59,60,63,64,71,72
	ORD	15,16,19,20,27,28,33,34,37,38,47,48,59,60,65,66
COA **BTA**	IAH	19,20,27,28,43,44,57,58,65,66
	EWR	13,14,15,16,37,38,39,40,55,56,57,58,63,64
	CLE	15,16,17,18,25,26,31,32,41,42,47,48,55,56,61,62
ACA **JZA**	YYZ	15,16,27,28,33,34,43,44,49,50,57,58,67,68
	YUL	11,12,33,34,35,36,47,48,57,58
	YVR	23,24,35,36,37,38,55,56,67,68
	YYC	33,34,35,36,57,58

In our experiments we implement two AOC groups. These groups consist of different commercial carriers. The first AOC group, which we label as “AAL,” is comprised of American Airline, American eagle, Continental and Northwest Airline. The second AOC group, which we label as “UAL,” includes United Airline, US Airways, Southwest, SkyWest and Air Canada. These two AOC teams account for roughly 33% of the total NAS-wide operation in this demand data. These groupings were selected to reflect on-going strategic alliances. United, Air Canada and US Airway are often teamed up while Continental, Delta and Northwest are also often teamed in flight scheduling and code shares.

3.1.3 Experiment design

For computational efficiency we implement a distributed server-client architecture that includes three PCs, as shown in Fig. 3.2. Most of our experiments involve 10 commercial airlines which we divide into the two airline groups described in Section 3.1.2.

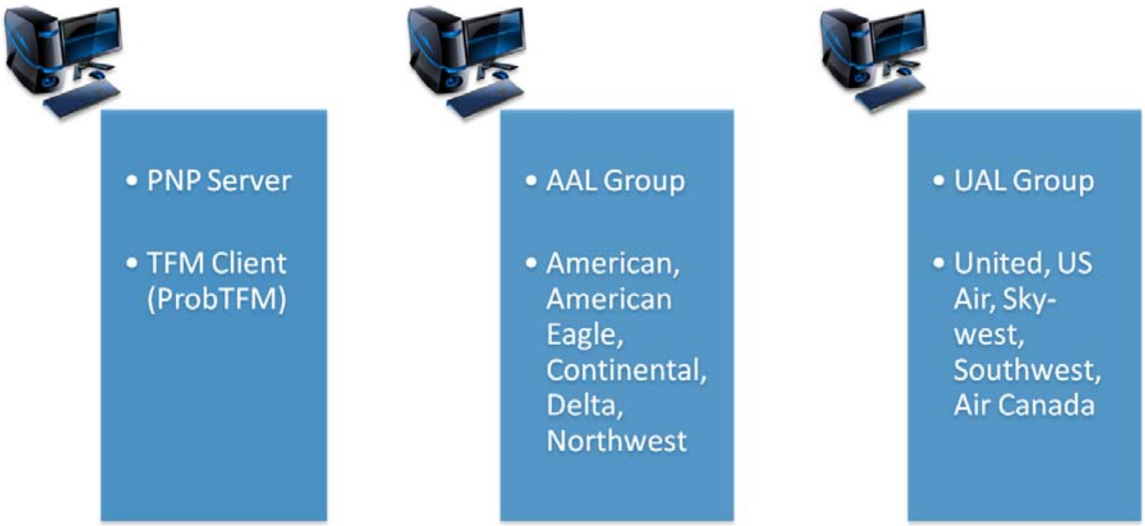

Figure 3.2 Simulation server-client architecture configuration.

The goal of this experiment is to gain insights on consequence of distributed TFM decision making in terms of overall NAS performance. Therefore we first make a baseline simulation run in which no gaming strategies are used. We next implement single-AOC gaming strategies, followed by simulation runs in which both AOC groups use the same strategies, and finally simulation runs in which the two AOC groups use different strategies.

3.2 Gaming strategies

This section summarizes the gaming strategies simulated in our experiment. See Section 2.3 for the algorithmic details of these strategies. As Fig. 3.3 illustrates, we experiment with four different gaming strategies.

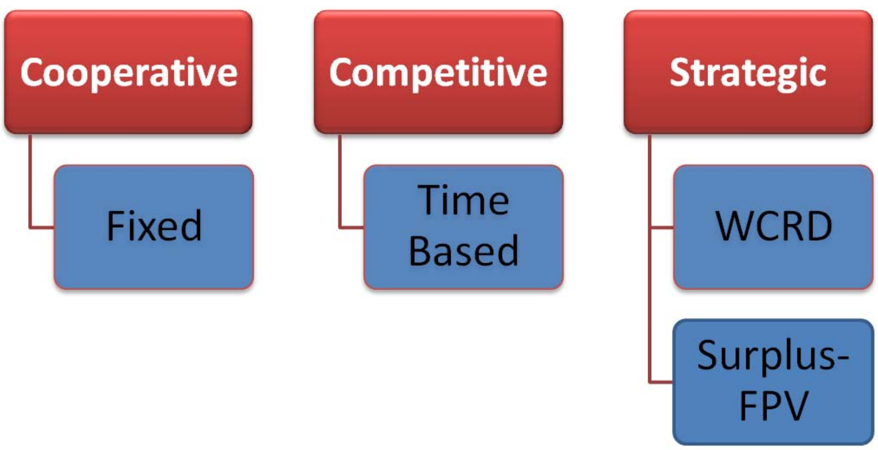

Figure 3.3 The four different gaming strategies fall into three categories.

The fixed cooperative strategy uses only TFM solutions that are planned, but not yet imposed, by the TFM service provider. Therefore, the only decision this strategy makes is whether or not to implement the suggested delay or reroute. Users accept the initiative in order to lock it in, and avoid possible additional delays that may be added in the TFM planning phase. Users reject the initiative in order to avoid taking an unnecessary delay that will be reduced in the planning phase. Figure 3.4 illustrates this strategy.

Figure 3.4 The cooperative-fixed strategy.

In time-based competitive strategy, the AOC derives its own initiative rather than using the TFM-supplied options. In this case the AOC's initiative is tailored to its business model. By implementing its own TFM initiative, the user hopes to avoid the service provider solution which may have longer delay, or otherwise create greater delay cost because it fails to account for the user's business model. Figure 3.5 illustrates this strategy.

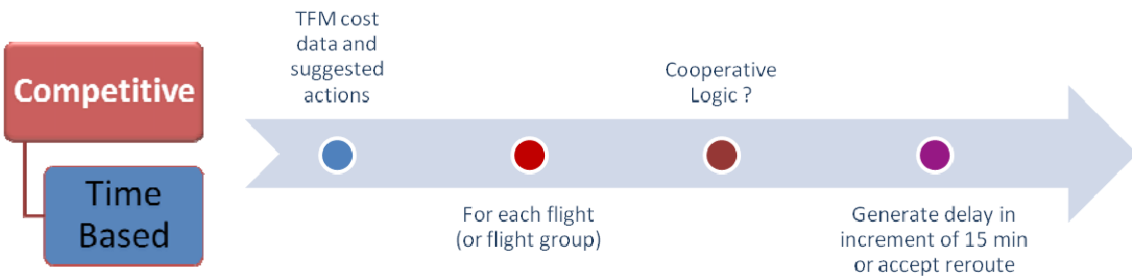

Figure 3.5 The competitive time-based strategy.

Strategic strategies take flights of other users into account. In the WCRD strategy, the AOC considers the likely *cause* of the forecasted congestion, which is creating the need for a pending delay or reroute. For instance, a pending delay or reroute may be caused by heavy demand. On the other hand, the TFM initiative may be due to capacity reductions, caused by various types of inclement weather.

While the service provider and the users cannot change the weather, they can manage the demand profile with delays and reroutes. This WCRD strategy exploits this by implementing the cooperative-fixed strategy when capacity reduction is the source of the forecasted congestion, but ignoring pending delay or reroutes when heavy demand is the problem. In other words, this strategy holds out on implementing a TFM initiative when it is possible that other AOCs may resolve the congestion problem. Figure 3.6 illustrates this strategy.

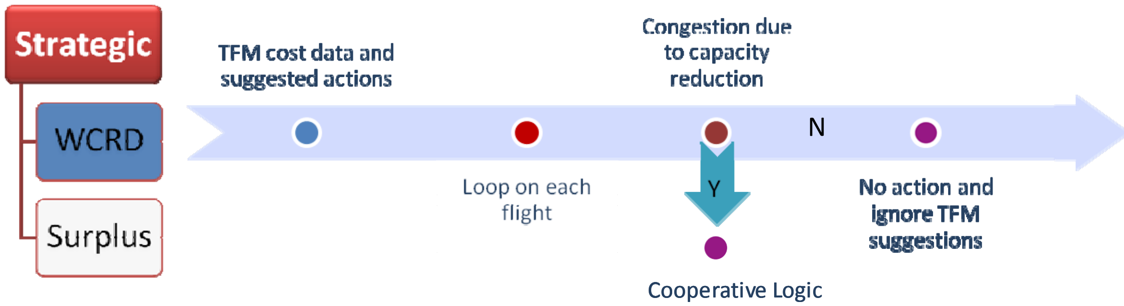

Figure 3.6 The strategic WCRD strategy.

In the strategic-surplus strategy, the users search for lower cost flights which it can delay to avoid delays on its higher cost flights. By evaluating the demand of other users along with its own demand, the user computes the forecasted congestion. The user next determines the flight congestion cost of its own flights. That is, it determines which of its own flights can best reduce congestion by delay or reroute. The user then computes a weighted difference between the flight delay cost and the flight congestion cost in order to find the best flights to delay or reroute. Figure 3.7 illustrates this strategy.

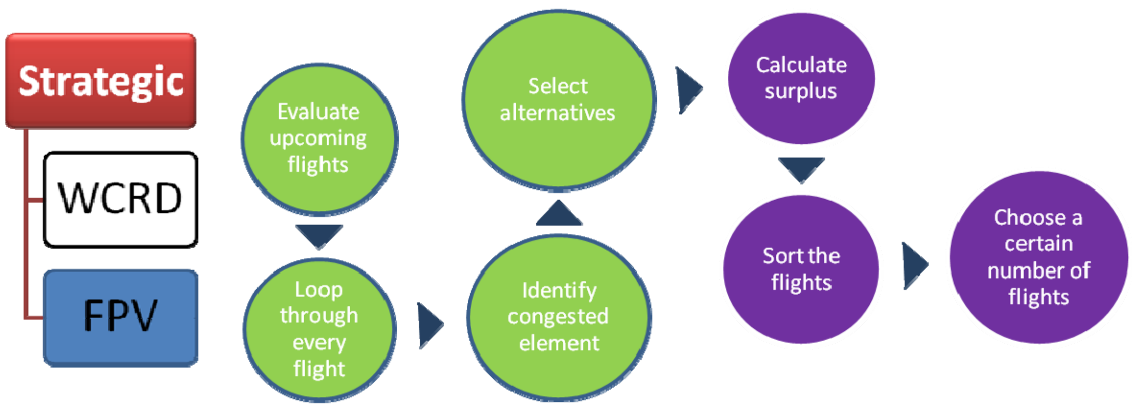

Figure 3.7 The strategic surplus strategy.

3.3 Results

This section discusses the results of our user gaming experiments. For our simulated day, we divide the flight delays into three categories: the AAL group, the UAL group, and the other flights which do not follow any gaming strategy. And we compare these delays, under various experimental conditions, to the baseline case where no strategies are used.

3.3.1 Single AOC results

We begin with the less complex case of a single AOC (the AAL group) using gaming strategies while the UAL group joins the non AOC flights in merely adhering to the TFM service provider's initiatives. Figure 3.8 shows such results in the case of medium TFM activity. At this medium level of TFM activity the NAS wide delay is about 15-20 minutes per flight which is reasonable for this heavy weather and heavy traffic scenario.

In addition to the baseline case, Fig. 3.8 shows results for five experiments where the two AOCs use the same strategy. Our five experiments use the four different strategies described in Section 3.2. The competitive strategy is run twice using a 15 minute and 30 minute look-ahead time (LAT) horizon, for a total of five cases.

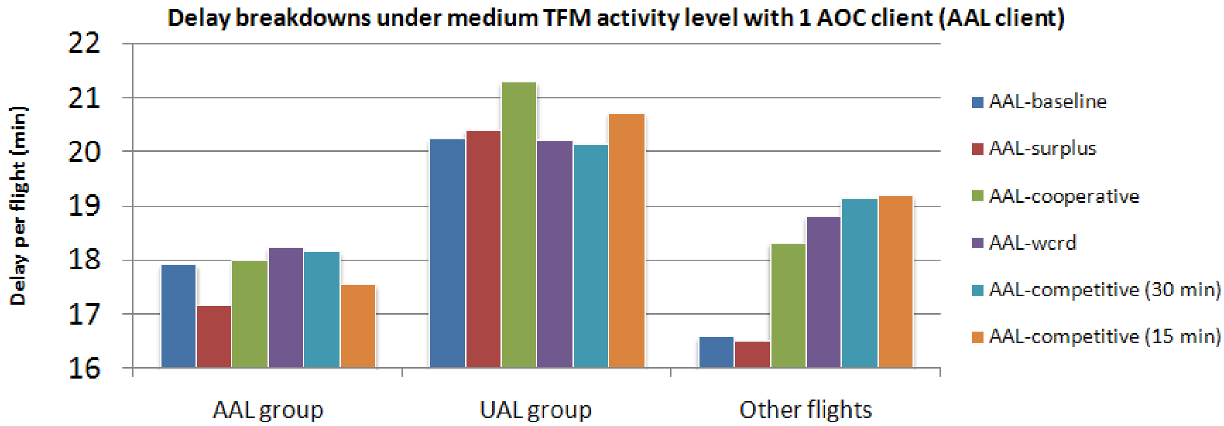

Figure 3.8 Gaming experiment results for a single AOC using the same strategy.

In the baseline run where no gaming strategies are used by any users, the UAL group has significantly greater delay than the non AOC flights (20 minutes per flight compared to 16.5 minutes per flight, respectively). This indicates that the UAL group has a greater fraction of flights involved in congested airspace and airports. This congestion is due to some combination of reduced capacity due to weather impacts and high demand. In any case, the UAL group has a demand structure that differs considerably from that of the non AOC flights.

Likewise, when the AAL group engages in gaming behavior, the impact on the UAL group differs from that on the non AOC flights. As Fig. 3.8 shows, The UAL group flights experience .5 to 1.0 minutes of delay per flight increase when the AAL group uses the competitive-15 and the cooperative strategies, respectively. Otherwise the UAL group flights experience little overall delay change when the AAL group uses any of the other three strategies.

The non AOC flights, on the other hand, experience 1.5 to 2.5 minutes of delay per flight increase for all AAL group strategies except the strategic-surplus strategy.

The AAL group flights experienced .5 and .9 minutes of delay per flight decrease when they use the competitive-15 and the strategic-surplus strategies, respectively. Otherwise they experience little overall change, though particular flights were improved. Gaming actions do not necessarily improve the overall delay primarily for two reasons.

First, just as a gaming action can cause flights outside the AOC to be delays, so too such actions can have the unintended consequences of delaying own flights. In such case these unintended consequences can be difficult to predict since the NAS delay and rerouting decisions are complex and can have far reaching implications. Delaying or cancelling even a single flight can have implications that persist for several hours later [3].

Second, gaming strategies that focus on the flight delay cost may reduce the overall fleet delay cost but not the overall fleet delay.

3.3.2 Dual AOC results

We next examine the more complex case of two AOC groups using gaming strategies. We begin with both groups using the same strategy. We repeat the Fig. 3.8 experiments, except that the UAL groups use the same strategies that the AAL group uses. Figure 3.9 shows these results, again in the case of medium TFM activity.

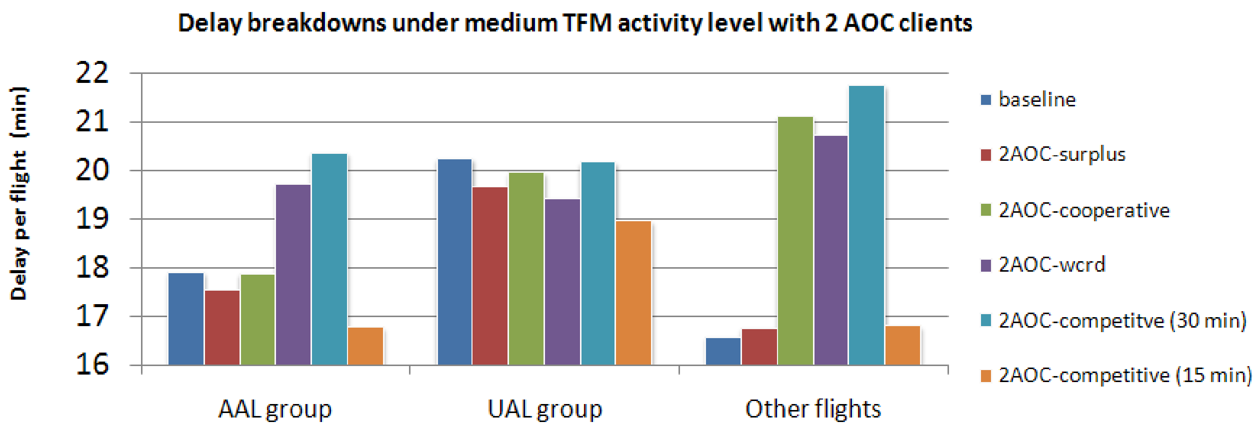

Figure 3.9 Gaming experiment results for two AOCs using the same strategy.

Compared to the Fig. 3.8 experiments, when the UAL group implements gaming strategies its delay consistently improves. Only in the competitive-30 does its overall delay remain unchanged. In all four of the other strategies its delay reduces, anywhere from a fraction of a minute per flight to almost two minutes per flight.

On the other hand, the AAL group delays mostly degrade, illustrating the impact of the gaming actions of flights outside the AOC. Interestingly, the competitive-15 delay does improve for the AAL group (as well as for the non AOC and the UAL group).

But the non AOC flights degrade significantly for the cooperative, competitive-30, and strategic-WCRD. In these cases the non AOC flights delay increases by 2.8, 2.7 and 2.0 minutes per flight, respectively.

These degradations in the AAL group and in the non AOC flights, when the UAL group implements several of the gaming strategies, suggests a *race to the bottom* scenario, where the NAS evolves to levels of decreasing performance as users activate gaming strategies. For instance, consider the scenario where the AAL group implements the strategic-WCRD strategy and the UAL group then responds in kind. The AAL group's initial action increased delay in the non AOC flights by 85k minutes. The UAL group's response then increased the AAL group flights by 15k minutes and increased the non AOC flights by an additional 75k minutes, for a total of 90k additional minutes of delay. In other words, the AAL group's initial action added 85k minutes of delay, and the UAL group's response then added an additional 90k minutes of delay, for a total of 175k minutes of total delay added due to the two gaming actions.

Given the two-AOC results in Fig. 3.9, the results of the cooperative, competitive-15 and strategic-surplus are straightforward. In all of these cases, where both the AAL and UAL groups use identical strategies, we find improvement in own flight and degradation in the non AOC flights. That is, the delay decreases for users following these strategies, and the delay increases for users not following any strategy.

The delay reductions were most significant in the competitive-15 strategy, with just over one minute per flight delay reduction. More significant was the delay increase for the non gaming flights, particularly in the cooperative case. While in the competitive-15 and strategic-surplus cases the non gaming flights experienced only minor delay increases (less than 0.3 minutes per flight), in the cooperative case the non gaming flights experienced a delay increase of more than 4.5 minutes per flight.

These results also demonstrate the differences and potential interactions between the AAL and UAL groups. For the UAL group, any of the five strategies improved the overall delay, with the competitive-15 providing the best delay reduction.

But in the competitive-30 and the strategic-WCRD cases, the AAL group experienced delay increases. This indicates interaction between the AAL and UAL groups, and that the UAL group was able to achieve delay reduction at the cost of delay in the AAL group. In both cases it is a net, NAS-wide, loss. That is, the AAL total delay increase exceeds the UAL delay decrease by about 20,000 and 40,000 minutes for the strategic-WCRD and competitive-30 cases, respectively.

This degradation in NAS performance is substantially greater when the non AOC flights are included. These flights experience an additional 175k minutes of delay increase. These results indicate the serious performance degradation that can result from all three types of gaming strategies (that is, the cooperative, competitive-30 and strategic-WCRD strategies). For these three gaming strategies, the total NAS-wide delay increase is about 175k, 230k and 175k minutes, respectively, or about 3-4 minutes per flight.

The competitive-15 and strategic-surplus strategies, on the other hand, are more benign in two-AOC cases. As noted above, in both cases the user benefits and non AOC flights experience delay increase, but the increases are minor. Indeed, in both cases the net NAS delay is reduced. The total delay reduction is about 6k and 15k minutes for the competitive-15 and strategic-surplus strategies, respectively. These translate into NAS-wide delay reductions of about .1 and .25 minutes per flight, respectively.

These results suggest the following distinction between gaming strategies. First, in principle a strategy may improve not only own performance but other flights as well. We refer to this as an *egalitarian* type of strategy. None of our strategies exhibit this type of performance, and such a strategy would not qualify as a gaming strategy under our definition.

Second while a strategy improves own performance, it may also improve other flights or its degradation of other flights is sufficiently minor that the net, NAS-wide, performance improves. We refer to this as a *utilitarian* type of strategy.

Third, a strategy's degradation of other flights may be significant such that the net, NAS-wide, performance degrades. We refer to this as an *aggressor* type of strategy. This particular experiment demonstrates that the competitive-15 and strategic-surplus strategies can play utilitarian roles whereas the cooperative, competitive-30 and strategic-WCRD strategies can play aggressors roles.

3.3.3 Impact of gaming strategies on system congestion

In addition to the impact that gaming strategies have on the delay of own flights, flights of other AOCs, and non AOC flights, such strategies also impact airspace and airport demand time histories. In our experiments overloading of airspace and airports occurs when the loading, as measured in 15-minute time intervals, exceeds the weather-impacted capacity. Such overloading occurs in the NAS, and controllers can temporarily modify sector capacity by up to three operations to accommodate demand fluctuations. Also, regional and tactical flow initiatives, such as path stretching S-turns, help to smooth these fluctuations.

Therefore our congestion metric is a measure of the service provider workload necessary to accommodate such overloading. Gate delays and strategic reroutes are used to manage such overloading, but these strategic initiatives do not replace the regional and tactical flow initiatives, and should not be used to eliminate all possible congestion. Such a zero-tolerance policy is too conservative. It would escalate delay to unreasonable levels and is not representative of NAS operations.

Our congestion metric indicates the effectiveness of the gate delays and strategic reroutes and any mitigating factors, such as the gaming strategies present in these experiments. As Fig. 3.10 shows, our gaming experiments generally increase the airspace congestion.

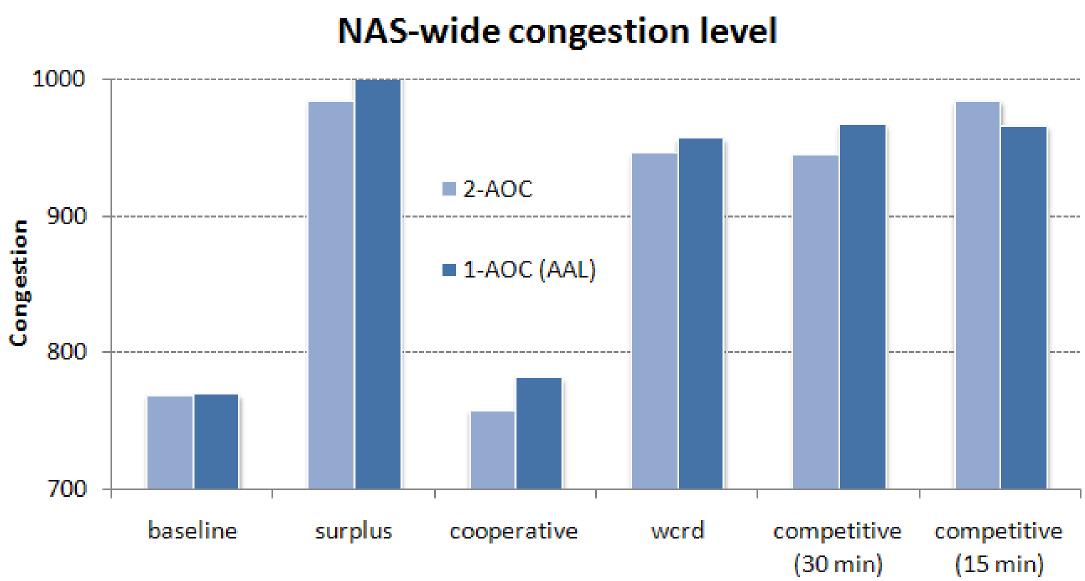

Figure 3.10 NAS airspace congestion (#operations) for the single and dual AOC experiments.

The Fig. 3.10 results show that while the cooperative strategy does not increase airspace congestion, the other four strategies do increase congestion by 200 operations over the course of the day. Airspace congestion occurs over hundreds of different sectors and several hours, and so tens of 15-minute time intervals. This means that the additional 200 operations fall into thousands of sector-time intervals.

Therefore this congestion increase is not a major operational impact. Nonetheless, it is an impact of the gaming strategies and reveals that such gaming scenarios involve a third "player." In addition to the two AOCs (or more generally *N* AOCs), there is also the service provider that may be impacted by the shifting of the demand profile and thus increase in congestion. That is, NAS-wide user gaming can be viewed as a *third-party game*: the participating airlines, non-participating airlines and the service provider. Of course such user-induced congestion is possible only to the extent that users can influence the strategic TFM initiatives.

3.3.4 Time histories of gaming strategy impacts

As is typical, in our November 16, 2006 scenario the weather is heaviest in the afternoon and early evening. Likewise the congestion and delay are heaviest in these time periods. In this section we examine the delay time histories of AAL flights, UAL flights and the non AOC flights for four different gaming strategies which the AAL group and UAL group both use. Figures 3.11, 3.12 and 3.13 show the time histories for the strategic-surplus strategy.

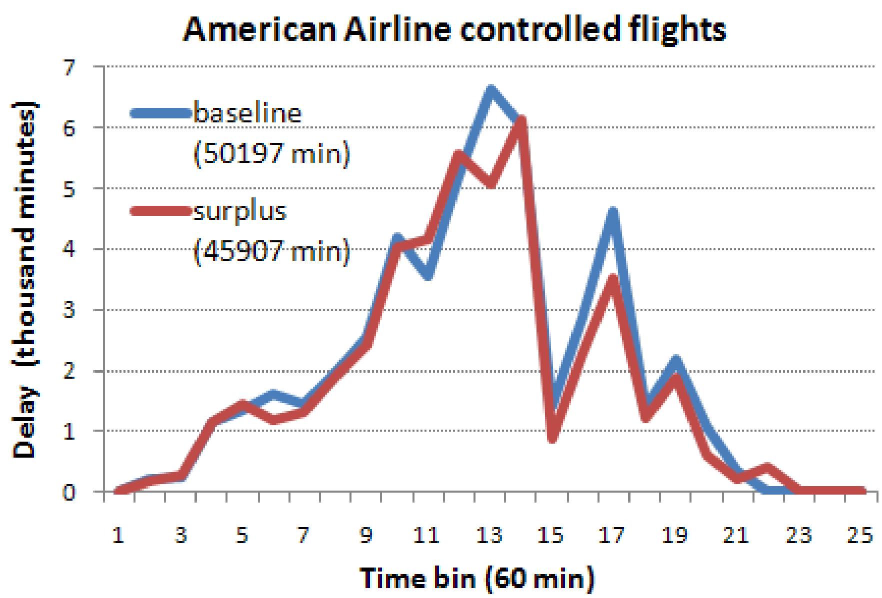

Figure 3.11 Delay time histories for AAL flights (not the entire AAL group) for both baseline and strategic-surplus cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.11 shows that the AAL flights experience an 8.6% delay reduction compared to the baseline case. The delay reduction appears throughout the day, roughly proportional to the baseline delay.

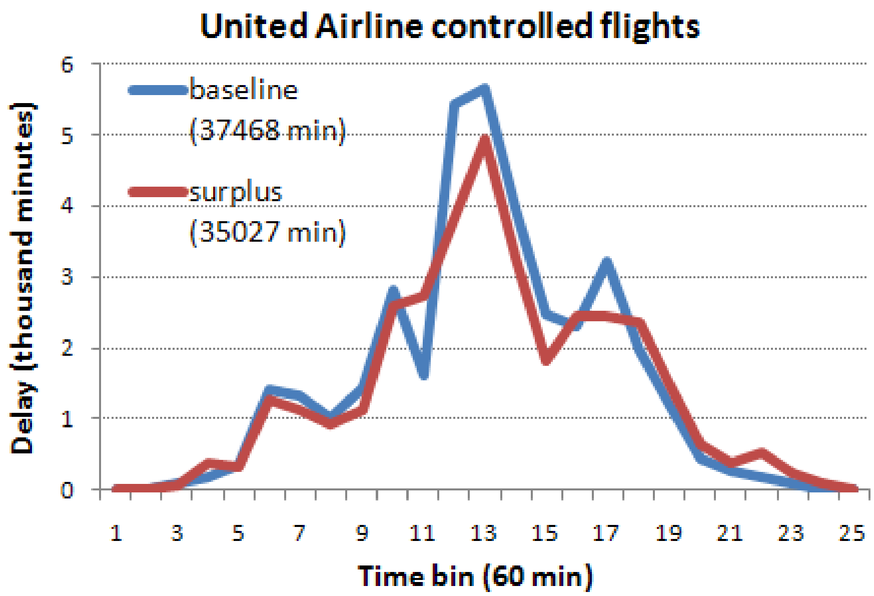

Figure 3.12 Delay time histories for UAL flights (not the entire UAL group) for both baseline and strategic-surplus cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.12 shows that the UAL flights experience a 6.5% delay reduction compared to the baseline case. As with the AAL flights, the delay reduction appears throughout the day, roughly proportional to the baseline delay, such that the majority of the delay reduction is achieved during the peak hours. The surplus strategy intelligently helps the airlines to find reasonable low-cost substitutes for important flights that are originally suggested for delays. This strategy shows its values during the peak hours.

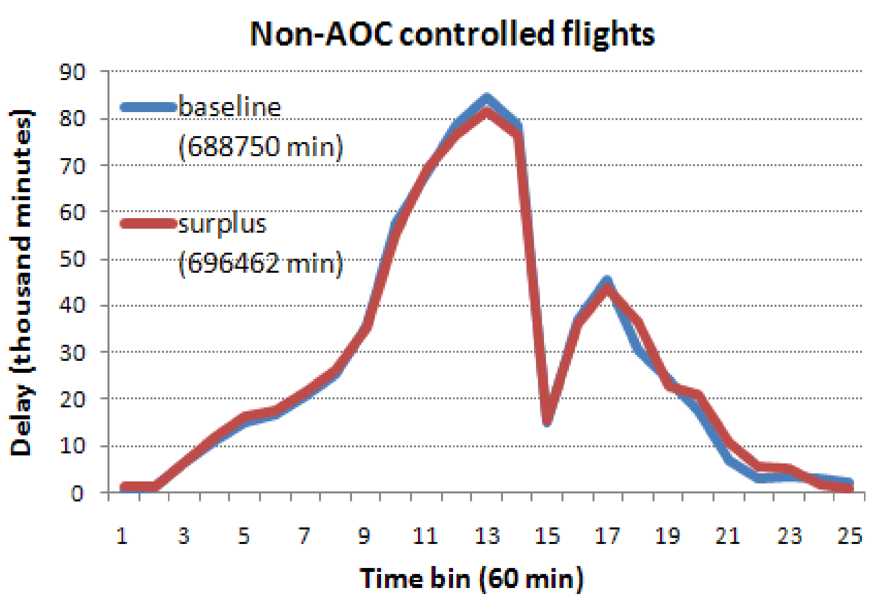

Figure 3.13 Delay time histories for the non AOC flights for both baseline and strategic-surplus cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.13 shows that the non AOC flights experience a 1.1% delay increase compared to the baseline case. During the peak hours these flights experience a slight delay reduction, but it is offset by delay increases late in the day.

Figures 3.14, 3.15 and 3.16 show the time histories for the strategic-WCRD strategy.

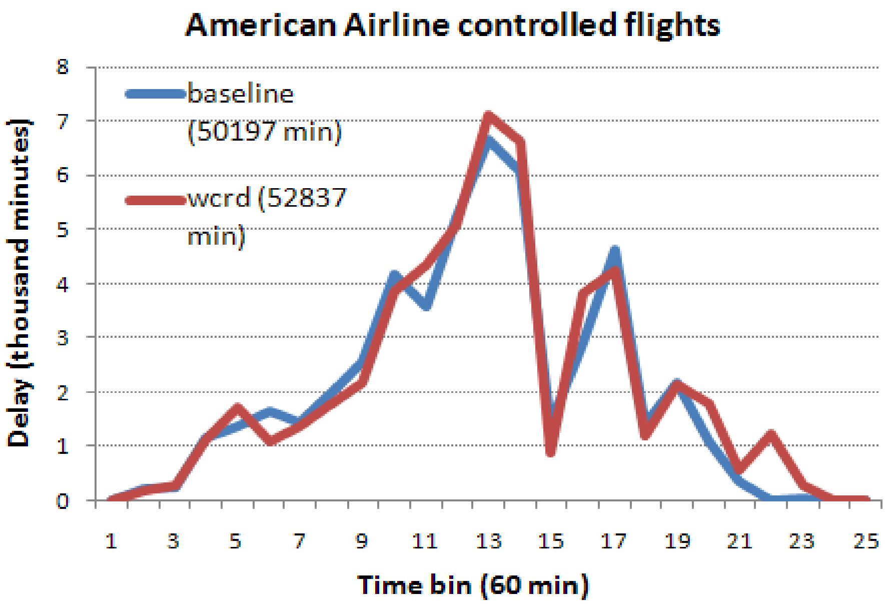

Figure 3.14 Delay time histories for AAL flights (not the entire AAL group) for both baseline and strategic-WCRD cases. In the latter, both the AAL and UAL groups implement the strategy.

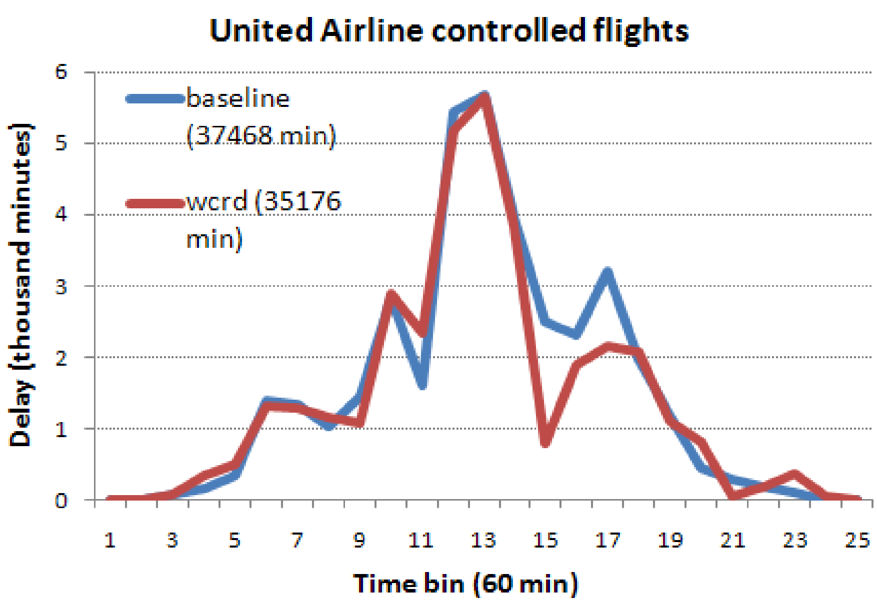

Figure 3.15 Delay time histories for UAL flights (not the entire UAL group) for both baseline and strategic-WCRD cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.14 shows that the AAL flights experience a 5.0% delay increase compared to the baseline case. The delay increase appears mainly at the peak delay period and at the end of the day.

Figure 3.15 shows that the UAL flights experience a 6.1% delay reduction compared to the baseline case. The delay reduction does not occur during the peak delay period but in the following hours.

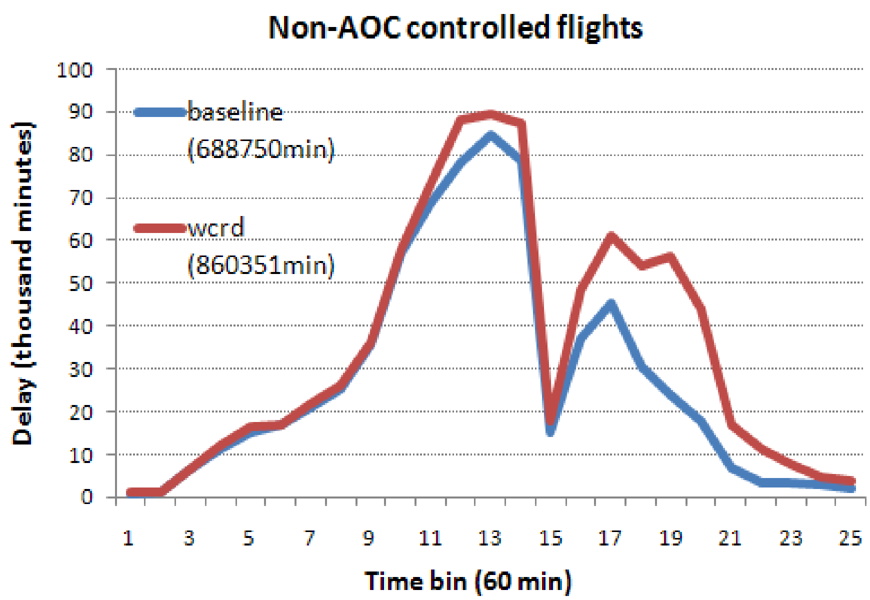

Figure 3.16 Delay time histories for the non AOC flights for both baseline and strategic-WCRD cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.16 shows that the non AOC flights experience a significant 20% delay increase compared to the baseline case. Some of this delay increase occurred during the peak delay period, but as with the UAL flights, the bulk of the delay difference (in this case delay increase) occurred later in the day. The fact that the UAL delay reduction slightly precedes the significant delay increase of the non AOC flights (evident in Figs. 3.15 and 3.16) suggests a causal relationship, as the UAL flight delay reductions are likely causing significant delays in the non AOC flights. Results such as these would serve as strong motivation for non gaming users to implement gaming strategies.

Figures 3.17, 3.18 and 3.19 show the time histories for the cooperative strategy.

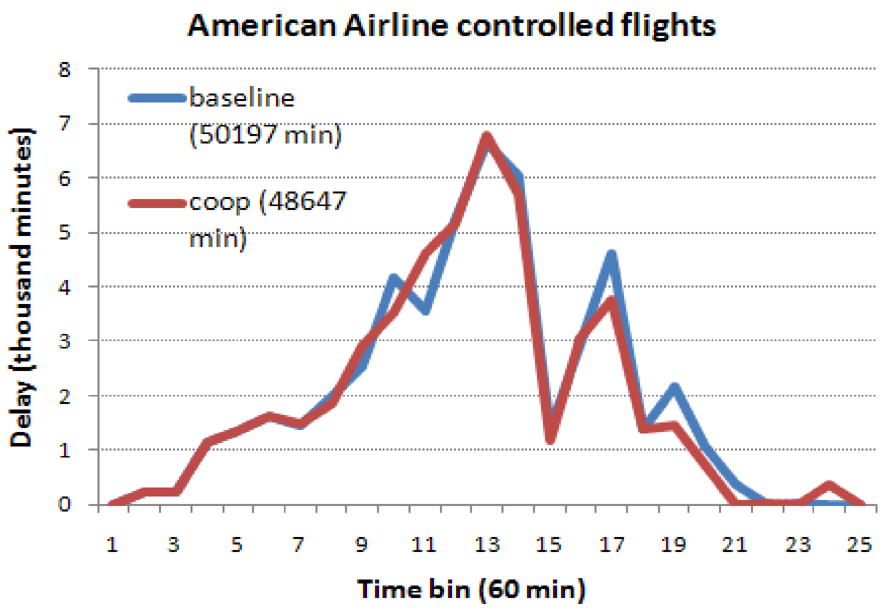

Figure 3.17 Delay time histories for AAL flights (not the entire AAL group) for both baseline and cooperative cases. In the latter, both the AAL and UAL groups implement the strategy.

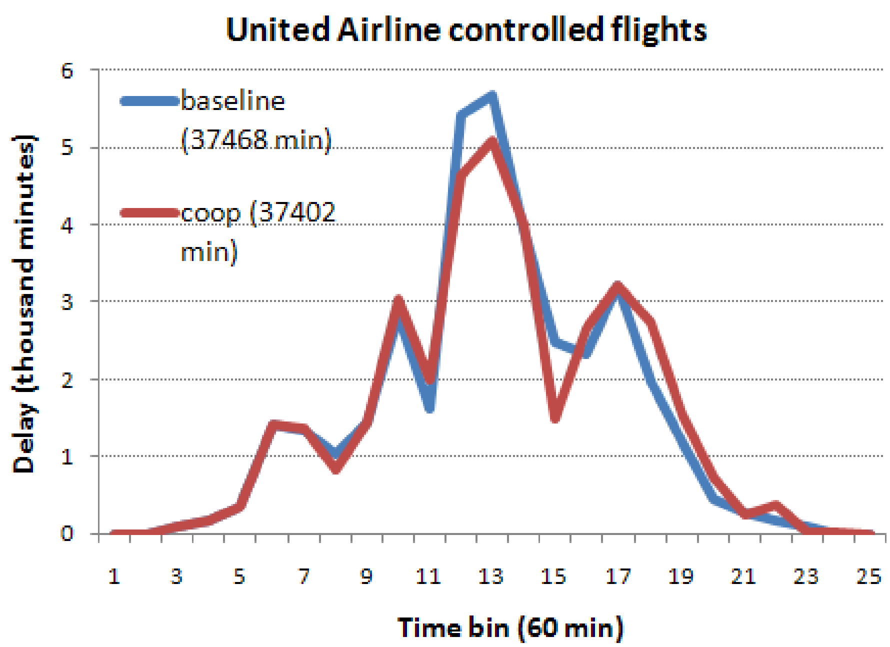

Figure 3.18 Delay time histories for UAL flights (not the entire UAL group) for both baseline and cooperative cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.17 shows that the AAL flights experience a 3.1% delay reduction compared to the baseline case. The delay reduction appears mainly toward the end of the day.

Figure 3.18 shows that the UAL flights experience a marginal delay reduction. These flights do experience a significant delay reduction during the peak delay period, but it is offset by delay increases later in the day, possibly caused by the AAL group gaming actions.

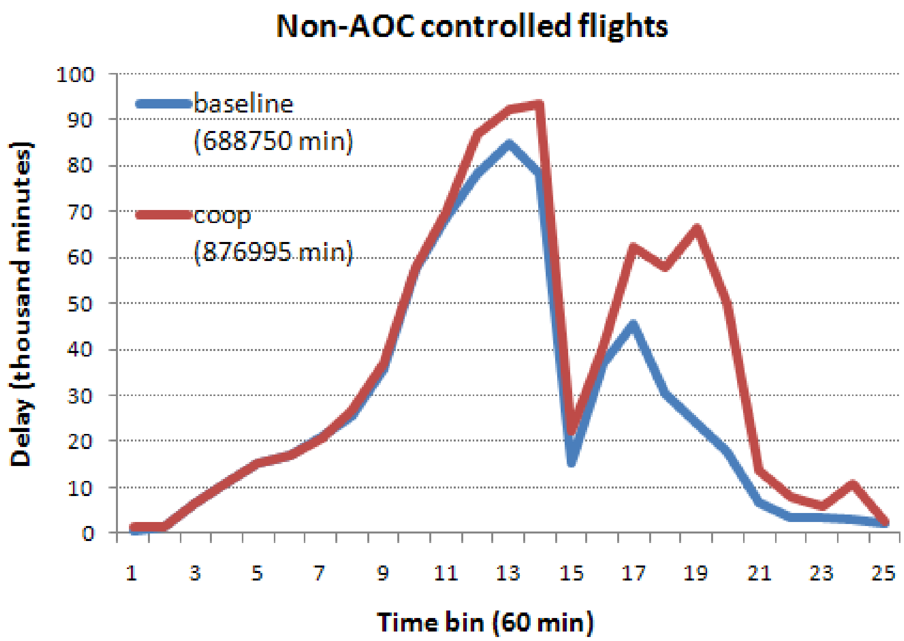

Figure 3.19 Delay time histories for the non AOC flights for both baseline and cooperative cases. In the latter, both the AAL and UAL groups implement the strategy.

As with the strategic-WCRD case, Fig. 3.19 shows that the non AOC flights experience a significant 27% delay increase compared to the baseline case. And again, while some of this delay increase occurred during the peak delay period, along with the UAL flights, the bulk of the delay increase occurred later in the day. Perhaps the AAL group actions caused this and the UAL flight delays. In any case, the non AOC flights significant delay was caused by relatively small delay savings elsewhere.

Figures 3.20, 3.21 and 3.22 show the time histories for the competitive-15 strategy.

Figure 3.20 shows that the AAL flights experience a 7.8% delay reduction compared to the baseline case. The delay reduction appears both during the peak delay period and toward the end of the day.

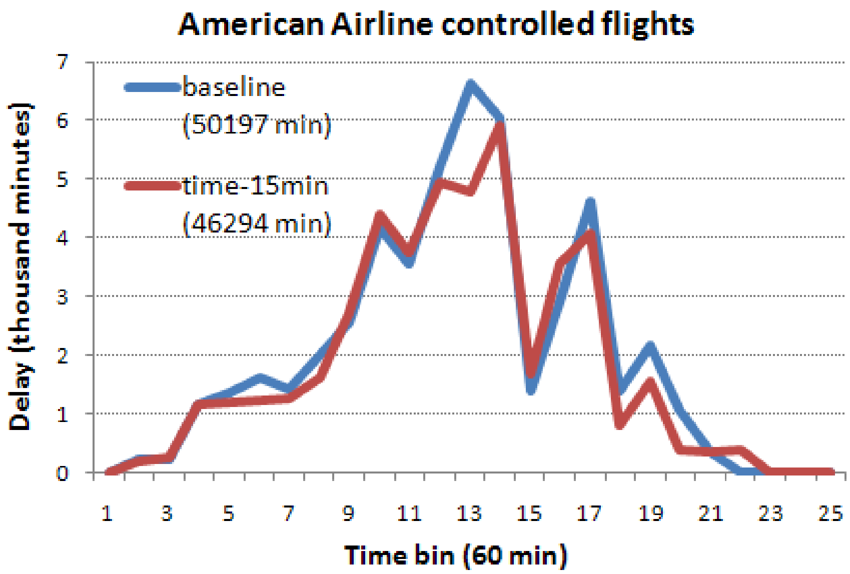

Figure 3.20 Delay time histories for AAL flights (not the entire AAL group) for both baseline and competitive-15 cases. In the latter, both the AAL and UAL groups implement the strategy.

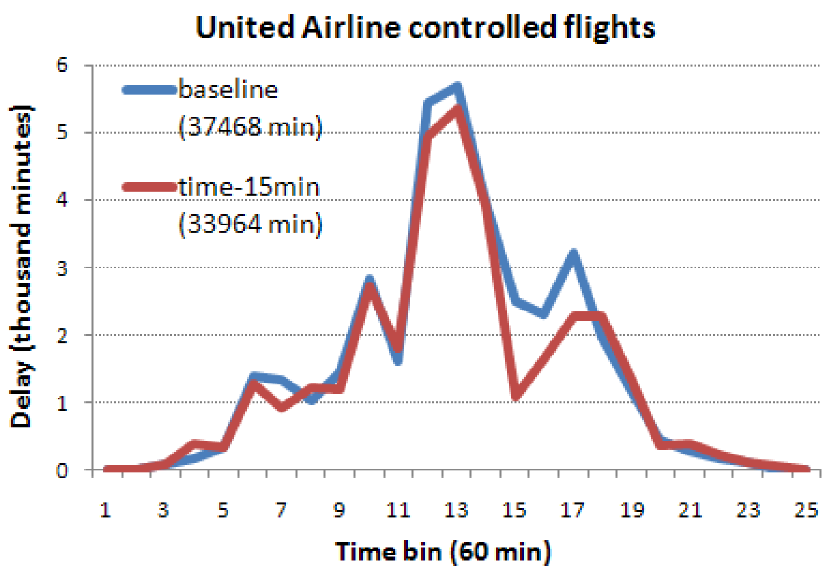

Figure 3.21 Delay time histories for UAL flights (not the entire UAL group) for both baseline and competitive-15 cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.21 shows that the UAL flights experience a 9.3% delay reduction compared to the baseline case. These flights do experience a significant delay reduction during the peak delay period and even more so in the immediately following period.

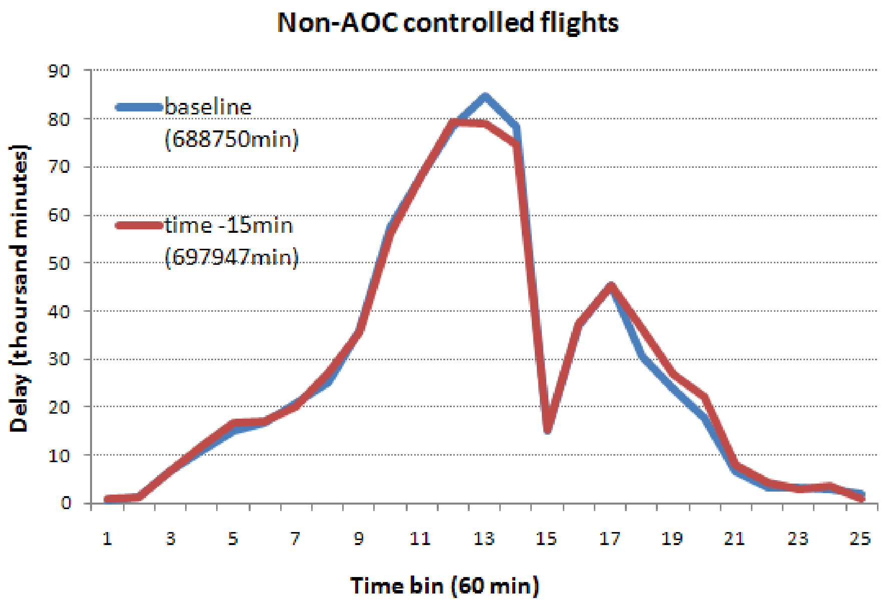

Figure 3.22 Delay time histories for the non AOC flights for both baseline and competitive-15 cases. In the latter, both the AAL and UAL groups implement the strategy.

Figure 3.22 shows that the non AOC flights experience only a slight delay increase (1.3%). Interestingly these flights experience, along with the AAL and UAL flights, a delay decrease during the peak delay period. This is offset, however, by a delay increase later in the day. Unlike the other strategies, the competitive-15 is more benign from the perspective of the non AOC flights.

Clearly strategies such as the competitive-15 are desirable, although Fig. 3.8 shows that even this is not a consistent finding as the non AOC flights incur delay increase when only the AAL group implements the competitive-15 strategy. Obviously there is not a linear trend in performance as increasing numbers of flights adopt gaming strategies.

Strategy	Participating Airlines	Non participating airlines	Service provider
Cooperative	Preferred	Harmful	No change
Strategic-surplus	Preferred	Acceptable	Slight workload
Strategic-wcrd	Some preferred	Harmful	Slight workload
Competitive (15 min)	Preferred	Acceptable	Slight workload
Competitive (30 min)	Some preferred	Harmful	Slight workload

Figure 3.23 Summary of findings for the dual AOC experiment.

Figure 3.23 summarizes our findings for the implications when both the AAL and UAL groups implement a strategy.

3.3.3 Heterogeneous gaming strategies

We next examine heterogeneous gaming strategies in which the AAL and UAL groups implement different strategies. Figure 3.24 shows the results of two such experiments, along with the baseline case and a single-AOC case for comparison.

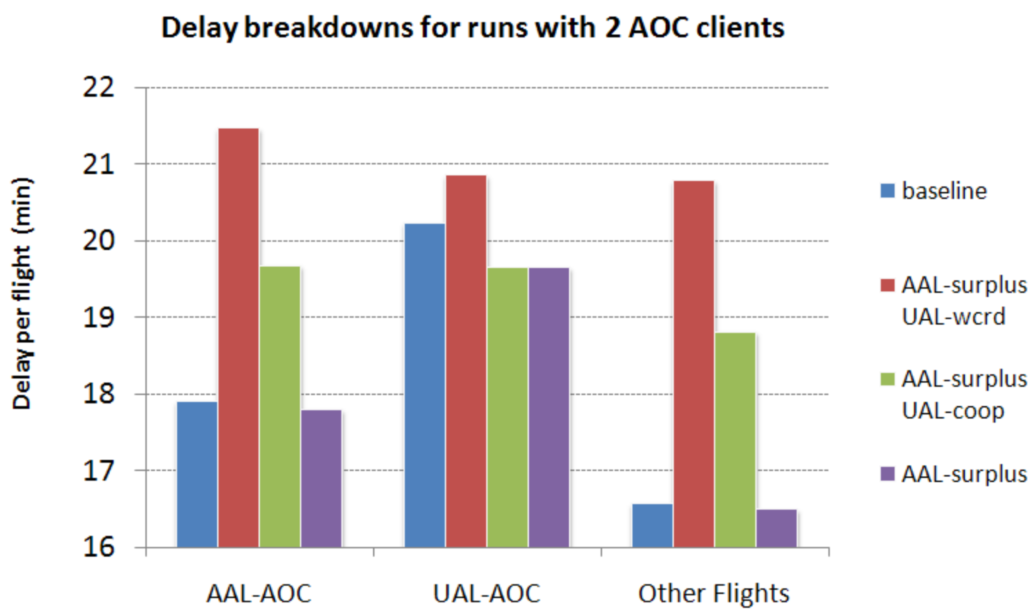

Figure 3.24 Gaming experiment results for two AOCs using different strategies.

The Fig. 3.24 results show that both heterogeneous gaming experiments the AAL group flights incurred increased delay whereas the UAL group flights experienced a delay reduction in the case were the AAL group used the strategic-surplus strategy and the UAL group used the cooperative strategy. As with the AAL group, the non AOC flights also incurred increased delay in both experiments.

Neither of the experiments in Fig. 3.24 improved the delay for both the AAL and UAL groups. We note, however, that in the case were the AAL group used the strategic-surplus strategy and the UAL group used the strategic-WCRD, while the UAL group incurred delay, the AAL group and the non AOC flights, incurred significantly greater delay. This raises the specter of a gaming strategy which seeks to harm performance of other flights, even at the cost of harming one's own flights, but to a lesser degree. We refer to this as a *spoiler* type of strategy and it easy to see how it could contribute to a *race to the bottom* dynamic, discussed in Section 3.3.2.

We note that in this particular case, the UAL group spoiler strategy depends on the strategy in use by the other users. This suggests that dynamic strategies could be designed to react to the strategies currently in use by the other AOCs. And of course sophisticated users would likely implement more complex hybrid strategies which switch between a set of strategies depending on the tactical scenario.

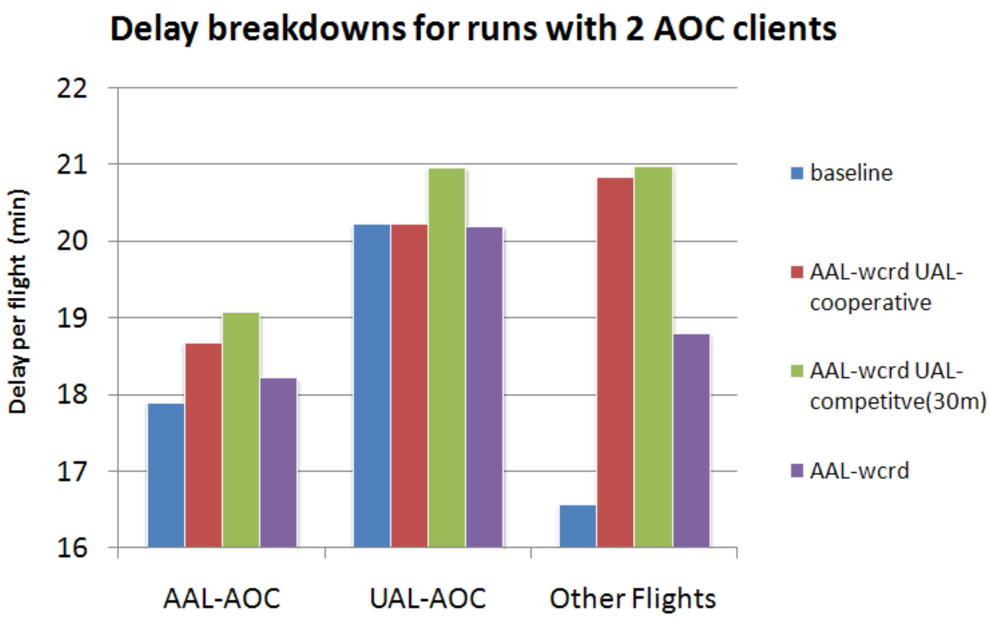

Figure 3.25 Gaming experiment results for two AOCs using different strategies.

Figure 3.25 shows the results from two more heterogeneous gaming strategies. As with the Fig. 3.24 results, these results do not show consistent delay reduction for the AOC groups. We again note, however, that these results suggest a possible *race to the bottom* scenario. In this case, if the AAL group first implements the strategic-WCRD strategy then it could be advantageous for the UAL group to counter with the cooperative strategy. As Figs. 3.8 and 3.25 show, such a counter move significantly increases delay for all other flights (AAL group and non AOC flights) while the UAL group delay remains unchanged.

4 Conclusions and Recommendations

This section presents the conclusions and recommendations of this effort. This section repeats the conclusions and recommendations given in the Executive Summary Sections 1.1 and 1.2.

4.1 Conclusions

We have developed models of NAS user gaming strategies to evaluate possible gaming actions and consequences in a future environment of increased collaboration, real time information sharing, and user influence on traffic flow management decision making. We have experimented with these models in our PNP NAS-wide simulation. Our conclusions are:

Significant performance variations in gaming scenarios. Our results suggest that NextGen gaming does not reduce to a few principles. Several different gaming strategies can be envisioned, and each strategy has its own variants. For instance, the competitive-15 versus competitive-30 strategies shows significant differences, with the 15 minute time horizon showing much better performance. Furthermore, different users can select from different strategies, and very likely will use multiple strategies simultaneously in different scenarios. These many possible combinations make for an enormous problem space. In our investigation so far of this problem, we find that the performance of the different user groups can vary dramatically along these dimensions. Slight modifications in a strategy (such as the competitive strategy look ahead time, see below), or a relatively minor increase in the number of users implementing a strategy can significantly alter results. Also, when different users implement the same strategy, one user may experience delay reduction while the other experiences a delay increase. Their different flight schedules, for instance, can cause such different results. We experimented with limited numbers of gaming users and strategies, but even in that more limited problem space found significant performance variations. While some trends are evident, our results suggest the NextGen gaming problem is not easily generalized into a relatively few, simple principles.

NAS performance degradation. Gaming strategies often degrade the performance of other AOCs and non AOC flights, and most gaming combinations of the two AOCs degraded the overall NAS performance. Not surprisingly own performance can change radically depending on the strategy of the other AOC.

Increase in system congestion. Gaming strategies are not concerned with managing demand within capacity constraints, and in general cause increases in airspace or airport congestion. In our experiments, all but the cooperative behavior aggravate system congestion. The observed congestion increases are not a major operational impact. Nonetheless, it is an impact of the gaming strategies and reveals that such gaming scenarios involve a third "player." In addition to the two AOCs (or more generally N AOCs), there is also the service provider that may be impacted by the shifting of the demand profile and thus increase in congestion. That is, NAS-wide user gaming can be viewed as a third-party game: the participating airlines, non-participating airlines and the service provider. Of course such user-induced congestion is possible only to the extent that users can influence the strategic TFM initiatives.

Unintended consequences. In addition to increasing delay of other AOC flights and non AOC flights, and aggravating system congestion, gaming strategies can ultimately have the unintended consequence of aggravating own fleet total delay. This consequence could serve as a gaming disincentive if TFM service provider strategies could be designed to ensure that such unintended delay occurs.

Categories of gaming effects. We began this study with three categories that describe the user intent: cooperative, competitive and strategic. Our results suggest different types of outcomes that do not map to these intent categories. The effects are more complicated given there are various combinations of strategies implemented by the users. But we found that the results can be, at least in principle, categorized into four qualitative categories which are helpful in describing and grouping the impact of the gaming actions. First, a strategy (operating within a given environment) may improve own performance and also improve the overall NAS. We refer to such a strategy as egalitarian. Second, a strategy may improve own performance and degradation to other flights, if any, is less significant. Therefore the overall NAS performance improves. We refer to such a strategy as utilitarian. Third, a strategy may improve own performance and degradation to other flights is more significant. Therefore, the overall NAS performance degrades. We refer to such a strategy as aggressor. Finally, a strategy may degrade own performance but degradation to other flights is more significant. Obviously the overall NAS performance degrades. We refer to such a strategy as spoiler.

Best strategies. The best gaming performance, for own flights and for the overall NAS delay, we found was produced by the competitive-15 strategy. The strategic-surplus and cooperative were the next best, providing slight aggregate improvement. The strategic-WCRD provided enhanced or degraded results, depending on the other AOC-specific operating characteristics.

Dynamic strategies. The effectiveness of AOC strategies depends on the strategies in use by the other users. This suggests that dynamic strategies could be designed to react to the strategies currently in use by the other AOCs. This could induce dynamic strategies to be implemented by other AOCs.

Race the bottom. The possibility of gaming strategies reacting to other gaming strategies brings with it a range of possible system evolutionary pathways, including both equilibrium and divergent outcomes. For instance, one possibility is the race-to-the-bottom scenario, where gamers counter each other with spoiler strategies. The NAS devolves to further levels of decreasing performance as users successively activate such gaming strategies.

Hybrid strategies. Sophisticated users would likely implement more complex hybrid strategies which simultaneously pursue different strategies for different markets, or even different flights, depending on the tactical scenario.

4.2 Research recommendations

In addition to the findings summarized in the previous section, this section summarizes questions raised by these findings, and the recommendations for further research. The recommendations are as follows

Investigate causality. More research is required to determine the underlying causality of how gaming actions affect the performance of other AOC flights and overall NAS performance. How exactly is performance degraded or improved, and how can these causes be dis-incentivized and incentivized, respectively?

Evaluate flight delay cost outcomes. In addition to the delay metric, future NextGen gaming research should evaluate the effect of gaming strategies on the flight delay cost results of the AOCs and non AOC flights. Is it possible, for instance, to degrade delay performance but improve (reduce) the overall flight delay cost?

Refined investigations. We have developed various gaming strategies, but a further level of detail is needed to ensure these strategies are realistic. Also, additional strategies should be considered.

Investigate the problem space. As we concluded above, the problem space is complex and large. Further investigation is required to explore the space and learn more about the impact of NextGen gaming strategies.

Investigate incentivizing users. Further research is required to investigate service provider strategies and rules of the road to (i) create a gaming equilibrium so as to avoid undesirable dynamics, chaos, and race to the bottom scenarios, and (ii) force users away from undesirable gaming strategies such as spoiler and aggressor strategies.

Model dynamic strategies. Research is required to model and evaluate dynamic users who do not adhere to a static strategy, but use a time-varying strategy which switches between strategies depending on the actions of the other AOCs.

Model hybrid strategies. Research is required to model and evaluate hybrid users who do not adhere to a global strategy, but use a dynamic-hybrid strategy which simultaneously implements different strategies in different markets or flights, depending on which is most profitable for each given scenario.

Appendix A

This section presents the delay multiplier values referenced in Section 2.

	Initial delay (mins)															
Time	7.5	22.5	37.5	52.5	67.5	82.5	97.5	112.5	127.5	142.5	157.5	172.5	187.5	202.5	217.5	232.5
0615	1.21	1.62	2.03	2.44	2.86	3.27	3.68	4.10	4.51	4.92	5.33	5.75	6.16	6.57	6.98	7.40
0645	1.21	1.64	2.06	2.48	2.91	3.33	3.76	4.18	4.61	5.03	5.45	5.88	6.30	6.73	7.15	7.57
0715	1.21	1.63	2.06	2.48	2.90	3.33	3.75	4.17	4.59	5.02	5.44	5.86	6.28	6.71	7.13	7.55
0745	1.20	1.61	2.02	2.43	2.84	3.25	3.66	4.07	4.48	4.89	5.30	5.71	6.12	6.53	6.94	7.35
0815	1.19	1.58	1.96	2.35	2.73	3.12	3.50	3.89	4.28	4.66	5.05	5.43	5.82	6.20	6.59	6.97
0845	1.18	1.53	1.88	2.24	2.59	2.94	3.30	3.65	4.00	4.36	4.71	5.06	5.41	5.77	6.12	6.47
0915	1.17	1.51	1.85	2.19	2.53	2.87	3.22	3.56	3.90	4.24	4.58	4.92	5.26	5.60	5.94	6.28
0945	1.16	1.47	1.79	2.10	2.42	2.73	3.05	3.36	3.68	3.99	4.31	4.62	4.94	5.25	5.57	5.88
1015	1.14	1.43	1.72	2.01	2.30	2.59	2.88	3.17	3.46	3.75	4.04	4.32	4.61	4.90	5.19	5.48
1045	1.14	1.42	1.69	1.97	2.25	2.53	2.80	3.08	3.36	3.64	3.92	4.19	4.47	4.75	5.03	5.30
1115	1.13	1.40	1.66	1.93	2.20	2.46	2.73	2.99	3.26	3.52	3.79	4.06	4.32	4.59	4.85	5.12
1145	1.13	1.38	1.63	1.88	2.13	2.39	2.64	2.89	3.14	3.40	3.65	3.90	4.15	4.40	4.66	4.91
1215	1.11	1.34	1.56	1.79	2.01	2.24	2.47	2.69	2.92	3.14	3.37	3.59	3.82	4.04	4.27	4.49
1245	1.11	1.33	1.55	1.77	1.99	2.21	2.43	2.65	2.87	3.09	3.31	3.53	3.75	3.97	4.19	4.41
1315	1.11	1.33	1.54	1.76	1.98	2.20	2.41	2.63	2.85	3.07	3.28	3.50	3.72	3.94	4.16	4.37
1345	1.09	1.28	1.47	1.66	1.85	2.03	2.22	2.41	2.60	2.79	2.98	3.16	3.35	3.54	3.73	3.92
1415	1.09	1.26	1.44	1.62	1.79	1.97	2.15	2.32	2.50	2.68	2.85	3.03	3.20	3.38	3.56	3.73
1445	1.09	1.26	1.43	1.60	1.77	1.95	2.12	2.29	2.46	2.64	2.81	2.98	3.15	3.32	3.50	3.67
1515	1.09	1.26	1.43	1.60	1.77	1.94	2.11	2.28	2.45	2.62	2.79	2.97	3.14	3.31	3.48	3.65
1545	1.08	1.24	1.40	1.55	1.71	1.87	2.03	2.19	2.35	2.50	2.66	2.82	2.98	3.14	3.30	3.45
1615	1.08	1.23	1.38	1.53	1.68	1.83	1.98	2.13	2.28	2.43	2.58	2.73	2.88	3.03	3.18	3.33
1645	1.07	1.21	1.35	1.48	1.62	1.76	1.90	2.04	2.18	2.32	2.45	2.59	2.73	2.87	3.01	3.15
1715	1.06	1.19	1.32	1.45	1.57	1.70	1.83	1.96	2.08	2.21	2.34	2.47	2.59	2.72	2.85	2.98
1745	1.06	1.17	1.29	1.41	1.52	1.64	1.75	1.87	1.98	2.10	2.22	2.33	2.45	2.56	2.68	2.79
1815	1.05	1.15	1.24	1.34	1.44	1.53	1.63	1.73	1.82	1.92	2.02	2.12	2.21	2.31	2.41	2.50
1845	1.04	1.12	1.21	1.29	1.37	1.46	1.54	1.62	1.71	1.79	1.87	1.96	2.04	2.12	2.20	2.29
1915	1.04	1.11	1.18	1.25	1.33	1.40	1.47	1.55	1.62	1.69	1.76	1.84	1.91	1.98	2.05	2.13
1945	1.03	1.09	1.14	1.20	1.26	1.32	1.37	1.43	1.49	1.55	1.60	1.66	1.72	1.78	1.83	1.89
2015	1.02	1.07	1.11	1.15	1.20	1.24	1.29	1.33	1.37	1.42	1.46	1.50	1.55	1.59	1.64	1.68
2045	1.02	1.06	1.10	1.14	1.18	1.22	1.26	1.29	1.33	1.37	1.41	1.45	1.49	1.53	1.57	1.61
2115	1.01	1.04	1.06	1.09	1.11	1.14	1.16	1.18	1.21	1.23	1.26	1.28	1.31	1.33	1.36	1.38
2145	1.00	1.01	1.02	1.03	1.04	1.05	1.06	1.07	1.08	1.09	1.10	1.11	1.12	1.12	1.13	1.14
2215	1.00	1.01	1.02	1.02	1.03	1.03	1.04	1.05	1.05	1.06	1.07	1.07	1.08	1.09	1.09	1.10
2245	1.00	1.01	1.02	1.03	1.04	1.05	1.05	1.06	1.07	1.08	1.09	1.10	1.11	1.11	1.12	1.13
2315	1.00	1.01	1.02	1.02	1.03	1.04	1.04	1.05	1.06	1.06	1.07	1.08	1.08	1.09	1.10	1.10

Source: adapted from Beatty, Hsu, Berry & Rome

Figure A.1 DM multiplier data.

References

[1] Wambsganss M, “Collaborative Decision Making Through Dynamic Information Transfer,” Air Traffic Control Quarterly, 4:107-123, 1997.

[2] Hunter G, Boisvert B and Ramamoorthy K, “Advanced Traffic Flow Management Experiments for National Airspace Performance Improvement,” Winter Simulation Conference, Washington, DC, December, 2007.

[3] Hunter G., “Toward an Economic Model to Incentivize Voluntary Optimization of NAS Traffic Flow,” AIAA ATIO Conference, Anchorage, AK, September, 2008.

[4] Performance Review Unit, Eurocontrol, "Evaluating the True Cost to Airlines of One Minute of Airborne or Ground Delay", University of Westminster Final Report, May, 2004.

[5] Beatty R, Hsu R, “Preliminary Evaluation of Flight Delay Propagation through an airline schedule”, 2nd USA/EUROPE Air Traffic Management R&D Seminar, Orlando, 1998.

[6] Waslander S, Raffard R, Tomlin C, “Market-based air traffic flow control with competing airlines,” submitted to AIAA Journal of Guidance, Dynamics and Control, February 2007.

[7] Raffard R, Waslander S, Bayen A, Tomlin C, “A cooperative distributed approach to multi-agent eulerian network control: Application to air traffic management,” in 2005 AIAA Conference on Guidance, Navigation and Control, San Francisco, CA, 2005

REPORT DOCUMENTATION PAGE						Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
01- 03 - 2011	Contractor Report	

4. TITLE AND SUBTITLE	5a. CONTRACT NUMBER
Investigation of the Impact of User Gaming in the Next Generation National Airspace System	
	5b. GRANT NUMBER NNA07CN32A
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Hunter, George; Gao, Huina	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER 305295.02.07.07.02

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	8. PERFORMING ORGANIZATION REPORT NUMBER
NASA Langley Research Center Hampton, VA 23681-2199 George Mason University Fairfax, VA 22030	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
National Aeronautics and Space Administration Washington, DC 20546-0001	NASA
	11. SPONSOR/MONITOR'S REPORT NUMBER(S) NASA/CR-2011-217066

12. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified - Unlimited
Subject Category 03
Availability: NASA CASI (443) 757-5802

13. SUPPLEMENTARY NOTES

This report was prepared for Langley Research Center under NASA Ames Research Center Cooperative Agreement NNA07CN32A with George Mason University. Langley Technical Monitor: Natalia Alexandrov

14. ABSTRACT

Over the past three decades, growth in the demand for air transportation has exceeded the growth in the national airspace system (NAS) capacity. Systems operating near capacity inevitably have delays and NAS delays have increased in recent years. The desire to minimize delay costs has placed attention on the NAS air traffic management (ATM) system.One initiative that has helped to provide user representation in the ATM solution is the collaborative decision making (CDM) process. CDM addresses this issue by bringing users (referred to here as airline operation centers [AOCs]) and ATM providers together for information exchange and cooperative planning. Such cooperative planning has been instituted, for instance, for the purpose of planning airport slot control strategies and rerouting strategies. While the CDM initiatives have met with much success, they have also introduced the potential for AOCs to manipulate the system in unforeseen, unintended, and perhaps undesirable ways, from a system-wide, synoptic perspective. This type of manipulation is sometimes referred to as "gaming" the system. This study uses a high-fidelity simulation tool to investigate several models of user decision making behavior which could be considered to be gaming behavior and the emergent system dynamics and interactions between AOCs and traffic management.

15. SUBJECT TERMS
Air Transportation; Complex Decision Making; Gaming; National Airspace System

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			STI Help Desk (email: help@sti.nasa.gov)
					19b. TELEPHONE NUMBER *(Include area code)*
U	U	U	UU	50	(443) 757-5802

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18