

Airline Schedule Recovery in Collaborative Flow Management with Airport and Airspace Capacity Constraints

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Abstract

This paper presents a modeling methodology to assess a range of operational concepts for collaborative flow management. The particular focus is on the problem of airline schedule recovery in conditions where both airports and airspace sectors are capacity limited due to conditions such as weather events or system outages. This model is embedded in a dynamic simulation environment representing the US National Airspace System (NAS). The airline schedule recovery model is based on an optimization formulation that allows a representation of adaptive airline behavior in current and future operations. The schedule recovery options considered include ground delay, re-routing and flight cancellation. The paper presents simulation results using an idealized square grid system, along with initial results of model integration into the Boeing National Flow Modeling tool.

Introduction

Flow management is an increasingly significant part of the air traffic management service both in the United States and in Europe. Increasing traffic growth is likely to continue to outpace capacity enhancements, and weather disruptions will continue to cause reductions in capacity at airports and in the airspace. Thus, flow management's role in balancing capacity and demand is likely to continue to grow.

The focus of flow management in the US is primarily airport arrival capacity limitations, whereas European flow management is focused on limited air traffic control sector capacities. Both systems have developed automation tools to compute ground delay responses when demand is predicted to exceed capacity, but the underlying algorithms are quite different due to the inherent difference between the single airport constraint problem and the problem involving a network of constrained sectors. Additionally, the US system is now experiencing a growing need to protect airspace sectors from overload, particularly due to convective weather

systems. Thus, flow management in the US is taking on an increasing role in coordinating combined re-routing and delay strategies to avoid sector overloads. Concurrently, European service providers are exploring methods to use re-routing in addition to ground delay to improve user efficiency and system utilization.

Participation in decision making in flow management in the US has in recent years included a significant involvement by airspace users, through the Collaborative Decision Making (CDM) paradigm. CDM includes significant data exchange and shared automation tools for both the airline operations control (AOC), the ATC system command center (SCC) and traffic management in ATC en route centers (ARTCC). Collaborative decision making is also being explored in the European system, with a number of unique challenges including the fact that the computational complexity of the airspace constraint problem is significantly higher than the single airport problem in the US system. The "ration by schedule" (RBS) concept applied in US CDM may have an analogy in the sector network problem, but is clearly considerably more complex. Additionally, questions about equity in allocating scarce resources become significantly more difficult when each flight crosses multiple constrained resources.

On both sides of the Atlantic it seems clear that a significant extension to the flow management service will be needed in coming years. This extension will need to include a more complete set of constraints, i.e. combined airport and airspace resources, a complete set of delay, re-routing and cancellation options and real-time collaboration between service provider and airspace users.

This paper presents an initial implementation of an analysis capability to explore a range of collaborative flow management operational concepts for such an extended flow management service. The focus in this paper is on a modeling methodology for airline

schedule recovery, which is part of the Boeing National Flow Modeling (NFM) tool. The NFM is a major component of the Boeing ATM preliminary design toolset [1-2], aimed at supporting trade studies on ATM operational concepts and architectures in early phases of major modernization steps.

Related Work

The history of US flow management and CDM is summarized in [3], describing the fundamental tenant of SCC allocating resources and individual users deciding how to most effectively use their allocation. The limitations of current US en route flow management initiatives such as miles-in-trail restrictions are discussed in [4], and optimization is proposed as the most viable methodology to tackle the combined airport and airspace problem. The significant efficiency benefits achieved after CDM implementation are discussed in [5]. The issue of uncertainties in forecasting is treated in [6], with a conclusion that periodic schedule peaks over predicted capacity will compensate for possibly conservative forecasts. The issue of equity in ground delay strategies is discussed in [7], and [8] makes a strong case for the near-term need to tackle the multi-resource flow problem in the US. On-going development of the CRCT re-routing tool is documented in [9], with the focus on a graphical user interface and automatic assessment of sector demand vs. capacity under manually selected re-routing scenarios.

The current flow management algorithm used in Europe is compared with two constraint programming based approaches in [10]. Another approach is proposed in [11], where a pricing policy is sought that would lead users to select a plan that minimizes system congestion. On-going efforts to develop collaboration with users in Europe are described in [12-14].

Considerable work has been done on the development of optimization-based solutions to problems in air traffic flow management. Initially, there was a focus on the development of optimal solutions to the ground-holding policy problem. Solutions to the static and dynamic versions of this problem for a single airport are presented in [15-16] with the multiple airport problem addressed in [17]. Subsequently, there has been work on general models for airline schedule recovery or irregular airline operations. A survey of the state-of-the-practice is presented in [18]. Optimization models for airline schedule recovery, focusing on the aircraft resource, include [19-22] and have been based primarily on network and multicommodity network formulations. A GRASP formulation is presented in [23]. A

formulation of the problem with en route capacities is described in [24] while the irregular operations problem for crew management is described in [25]. Heuristics for delay propagation mitigation, potentially suitable for incorporation in a rule-based model of AOC operations are described in [26]. Few papers have addressed the airline schedule recovery or AOC modeling problem from the standpoint of representation in a large-scale flow model. A discrete event model of an AOC was described in [27] which represented the AOC as a multi-agent, multi-class queuing system.

Airline Schedule Recovery Model

The purpose of the airline schedule recovery model is to represent a variety of current and future adaptive airline behaviors in which airlines react to forecasts of reduced airport and airspace capacities by replanning the flight schedule. This model is embedded in a large-scale simulation of flow in the national airspace (the Boeing NFM) and is being used to explore a variety of flow management questions. The timescale for this analysis is the day of operations. At various points during an NFM simulation of a single day the planner is called upon to create a forecast of future system capacity, an allocation of forecast capacity to each airline, and invoke for each airline, the airline schedule recovery model. The scope of the planner is all uncommitted flights, that is, all flights that have not yet departed.

A primary input to the model, besides the original airline schedule, is an allocation of airport and airspace capacity to the airline. The primary output of the model is a new flight schedule in which, for each flight leg, there is a decision to fly the flight as originally scheduled, cancel the flight, or replan it. Replanned flights will be assigned a new (later) departure time and/or a new flight plan (re-route). The schedule is constructed by the model to maximize its assessed value and, at the same time, be feasible with respect to capacity constraints. Additional constraints having to do with the feasibility of flying the replanned schedule are also imposed.

Major Assumptions

1. Airline schedule recovery is applicable to all uncommitted flights. Thus, it is assumed that a separate, more tactical, planning process exists for dealing with the previously committed flights. It is assumed here that an uncommitted flight is a flight that has not yet departed, but more complex definitions of committed and uncommitted operations are possible and may be used to account for time delays between planning

and execution. However, it is likely that the methodology presented here can be extended to include committed operations in the replan.

2. A centralized authority (SCC) creates, at each planning point, a forecast of system capacities and an allocation of these capacities to each airline. In connection with assumption 1 the process includes some accounting of capacity used by the committed flights. It is assumed that the central authority creates a forecast of such capacity use and reduces it from the total forecast system capacity prior to the allocation to individual airlines. These interactions between SCC and AOC are shown schematically in Figure 1. Also shown is the possibility of an iterative process between SCC and the AOC's in the allocation of forecast capacities.

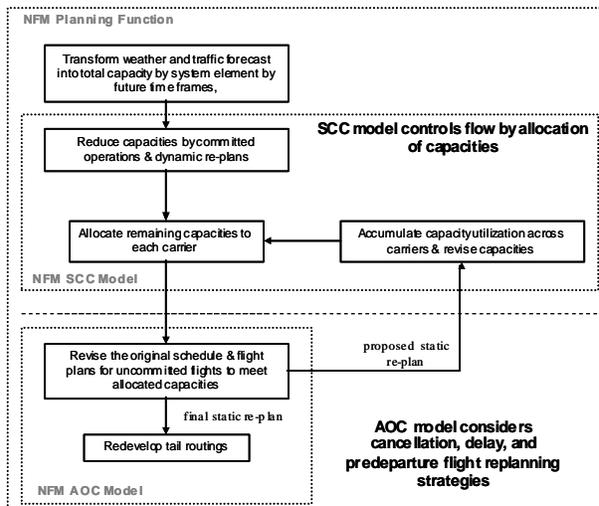


Figure 1. SCC/AOC Interactions

3. A single, but flexible, representation is used for all airlines. Flexibility comes from control parameters that determine the kinds of replanning strategies considered by the airline (e.g. cancellations, delays, flight re-routes) and the objective function that drives the replanning process.
4. The airline resources that are included are the aircraft and the gates. Replanned schedules are made to be compatible with the numbers of these required to execute the original schedule. There is no accounting for the flight crew resource.
5. System capacity elements under consideration are airport arrival and departure rates and en route sector occupancy limits. An airline is not allowed to tradeoff airport arrival versus departure rates since they are separately allocated. An airplane is considered to be using only one of these system elements at any given

time, and the time required to travel through a sector is assumed to be independent of the number of airplanes occupying that sector.

6. An optimization approach is used to maximize the value of the resultant schedule subject to capacity and other operational constraints. An important reason for using optimization (as opposed to a rule-based or other approach) is to provide for consistency of results relative to system objectives so that one concept is not shown to be better than another because of a model artifact. The objective function assigns value to each flight equal to the product of the planned aircraft capacity (# of seats), the flight leg distance, and an effectiveness function depending on the arrival delay (see Figure 2). We refer this value as effective seat miles and this allows for cancellations (given a value of zero) and delays to be commensurate. The S-shape of the curve in Figure 2 reflects the fact that multiple small delays may be less costly than a single large delay. Other, more complex and/or airline specific, objective functions can also be considered which could account more directly for both cost and revenue related components of the replanned schedule. Note that this objective function is based on flight leg independence, that is, each leg is given a value independent of the way in which other legs are replanned.

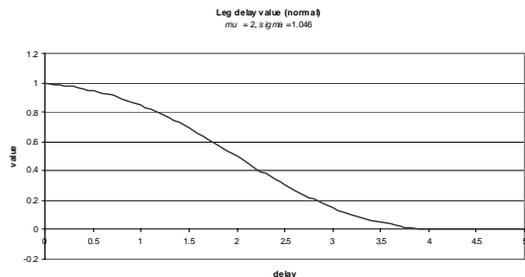


Figure 2. Flight Leg Value versus Arrival Delay

7. Each flight leg is assumed to be cancelled or flown by the same aircraft assigned to that leg in the original schedule. Thus, the original airplane itineraries (sequences of flight legs) are preserved with the possible exception of some cancelled flights. Flights are cancelled in cycles, i.e. a sequence of legs beginning and ending at the same airport. An exception is made for allowing flights to be cancelled to the end of an itinerary in order to preserve feasibility. Except for the implicit repositioning flight that may be required in this exceptional case, repositioning flights are not generally allowed.

Phased Development Plan

Figure 3 shows a phased development plan allowing for some relaxation of assumptions 6 and 7. Horizontally, the objective function development has two phases. Phase 1 allows only the leg-based objective function while phase 2 would consider an objective function based upon the passenger connecting paths resulting from the replanned schedule. Such an objective is particularly important in representing the value of maintaining connect bank integrity in the replanned schedules. Vertically, there are three aircraft (tail) swap or substitution options (A, B, and C). Swap option B allows a flight to be flown by any aircraft of the same type while option C allows substitution of any type. Option C is considered undesirable because it requires direct consideration of additional detailed operational issues, such as crew scheduling, which are currently considered to be out of scope in the model. The current implementation and results are based upon model 1A and assumptions 1-7 described above.

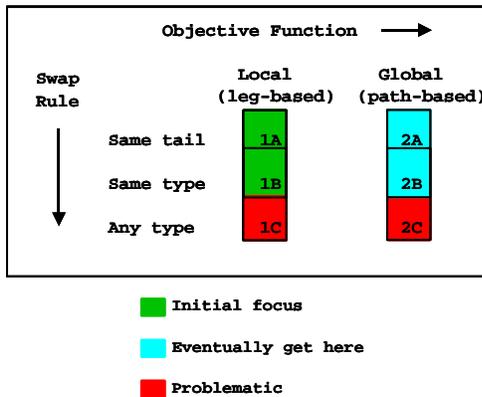


Figure 3. AOC Model Development Plan

Formulation

The formulation makes use of the idea of discretizing time into uniform small time slices. The idea is that key system elements (i.e. airport departure rates, airport arrival rates, sector occupancies, and airline/airport gates) have limited capacity which may be expressed as a function of time. The planner will develop a plan which is feasible with respect to the capacities allocated to an airline for each system element and time slice combination. These combinations of system elements and time slices can be called resources. There will be a capacity constraint for each resource. Figure 4 shows a flight plan which is complete, aggregate, and relative. The plan is *complete* because it goes from gate to gate, *aggregate* because it ignores the fine structure of the routes and waypoints within the en route sectors, and *relative* because it can be translated in time based

upon an assigned departure time (pushback from the gate). Also shown in the figure is the associated system element usage for each relative time slice in the plan (where “G” is for gate, “0” means no constrained element is used, “T” is for takeoff, “1” is for sector 1, etc.). This figure embodies a key assumption that the time slice is small enough so that it is reasonable to assume that at most one system element is used in each time slice. Note that when a departure time is assigned to the flight plan then an arrival time can be inferred along with a vector of resource usage for the time slices of interest.

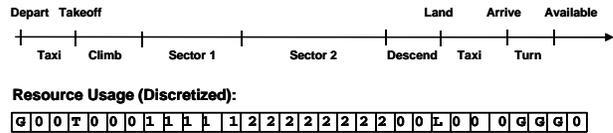


Figure 4. Discretized Flight Plan

The optimization formulation involves creating multiple strategies for each original flight leg for various combinations of alternative flight re-routes and planned departure delay. Each strategy can be given an objective function score by calculating the effective seat mile value from the inferred arrival delay, airplane capacity (# of seats), and flight leg distance. The problem is then to select at most one strategy for each flight leg to maximize the total effective seat miles (i.e. the value of the replanned schedule). If no strategy is selected for a flight leg then that leg is cancelled. The selection of strategies is subject to the resource and flyability constraints. The resource constraints follow directly from the discussion above for Figure 4. Flyability constraints are relatively simple for model 1A. That is, the next flight in an airplane itinerary must be scheduled at a time on or after the arrival of the previous leg plus a minimum turn time. Additionally, flight legs can only be cancelled in cycles, that is, sequences of legs starting and ending at the same airport.

The optimization problem described above can be formulated as an integer linear program (ILP) and solved using commercially available software. However, that is not the approach used here. Instead, a proprietary approach has been developed which is both extensible and can solve the problem in a fraction of the time needed to solve the general ILP using commercial software. This is particularly important because the replanning problem must be solved many times in the context of a single simulation experiment.

SCC Model

Though not the primary focus of this paper, we end this section with a few comments on the SCC model.

perfect forecast and multiple replanning points in the presence of forecasting error. Also, the section concludes with a preliminary result comparing the effectiveness of the airline schedule recovery model with a ground delay program using ration by schedule (RBS) as implemented in the Boeing NFM.

Perfect Forecast

The first set of results is for a single replanning point and for a perfect forecast, that is, the case where the forecast weather and actual weather are the same. This case was constructed using the idealized square world geometry. There are 21 total airports with 10 in the west, 10 in the east, plus a centralized hub. There is a single airline operating a hub-spoke system with a schedule serviced by 20 airplanes. A 10-airplane “complex” operates 6-legged itineraries in a pattern of E-H-W-H-E-H-W (“E” for East, “H” for Hub, and “W” for West) while another 10-airplane complex operates 6-legged itineraries in the reverse pattern of W-H-E-H-W-H-E. The second complex is initiated a short time after the first. Note there are three connecting banks in each complex. Figure 6 shows this case with the focus on a single itinerary of the pattern 11-21-1-21-11-21-1. A storm of long duration is positioned West of the hub and moves slowly to the North. The timing of this storm is such that it does not interfere with the first flight from 21 to 1 but does interfere with the return trip from 1 to 21. Although the storm was given three intensity levels, it is assumed here that airport and airspace capacities are reduced to zero in each of these levels while, everywhere else, capacities are assumed to be unlimited. Note that, in such a case, the optimization problem in model 1A can be solved for each airplane itinerary completely independently.

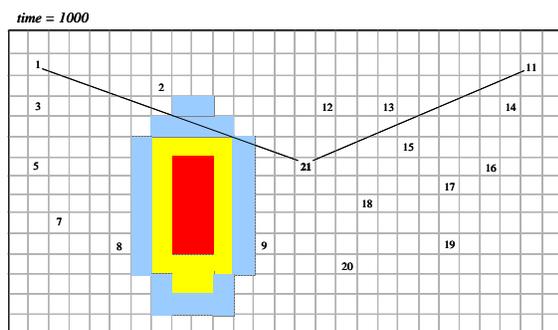


Figure 6. A Single Itinerary Case

Table 1 shows the single itinerary results for different assumptions on the strategies available to the airline. The left-hand portion (first “panel”) of the table describes the original schedule and gives the flight distance along with the scheduled departure and arrival times. This schedule, perfectly executed, obtains a score of 4683 effective seat miles assuming an airplane capacity of 1 seat. The second panel shows the result assuming that only the departure delay (D Del) strategy is available to the airline. The inferred arrival delay (A Del) determines the reduced flight value. Since the airplane ends up trapped in the west there are massive delays in the last four flights of the itinerary which give those flights zero value and reduce the normalized itinerary score to 0.33. The third panel adds the cancellation strategy as a possibility. Even though the first flight from 21 to 1 misses the storm, that flight is cancelled as part of an out-and-back to avoid being trapped in the west and improve the total system score to 0.63. Finally, the fourth panel shows the high value of flight replanning in this scenario (score of 0.99) since the second flight can be kept intact with the return flight re-routed to avoid the storm. Table 2 shows the same sorts of comparisons but for the entire schedule. Again, the high leverage for pre-departure flight re-routing is indicated in the results for this scenario.

Imperfect Forecast

The next set of results focus on the value of additional replanning points in the presence of forecast uncertainty. The airport geometry and schedules are the same as described in the previous analysis. Here, however, two new weather scenarios are included. Both involve a strong (intensity = 1) 250 by 150 mile elliptical (oriented due north) convective storm, which starts at 1000, reaches peak dimensions at 1300, starts to diminish at 1700 and disappears at 2000. Both start SW of the hub traveling at 40 mph. The difference between the scenarios is that in the first the storm track is north whereas in the second the storm track is NE (50°). This difference is of considerable consequence in that in the second scenario the hub is shut down for two hours (1600 – 1800).

Original Plan Executed					DDelay Only				+ Cancellations				+ Flight Replan			
Org	Des	Dst	Dep	Arv	Replan	DDel	ADel	Eff	Replan	DDel	ADel	Eff	Replan	DDel	ADel	Eff
11	21	725	06:20	08:00	No	0	0	1.00	No	0	0	1.00	No	0	0	1.00
21	1	836	09:00	10:50	No	0	0	1.00	-	-	-	0.00	No	0	0	1.00
1	21	836	11:10	13:00	No	500	500	0.00	-	-	-	0.00	Yes	10	20	0.97
21	11	725	14:00	15:40	No	470	470	0.00	No	0	0	1.00	No	0	0	1.00
11	21	725	16:20	18:00	No	460	460	0.00	No	0	0	1.00	No	0	0	1.00
21	1	836	19:00	20:50	No	430	430	0.00	No	40	40	0.92	Yes	10	30	0.95
Score = 4683 (1.00)					Score = 0.33				Score = 0.63				Score = 0.99			

Table 1. Single Itinerary Results

DDelay	Cancel	Replan	Score
✓	-	-	0.41
-	✓	-	0.54
✓	✓	-	0.63
-	✓	✓	0.70
✓	-	✓	0.79
✓	✓	✓	0.87

61% on original plan
 12% cancelled
 8% delayed
 9% flight replanned
 10% delayed & flight replanned

Table 2. System Effectiveness

Table 3 describes the forecasting error parameters used in this analysis.

Parameters	Base	Slope
Timing	0.0	0.20
Initial location	0.0	20.0
Radius	0.0	2.50
Track angle	10.0	2.0
Velocity	10.0	2.0
Intensity	0.0	0.0

Table 3. Forecasting Error Parameters

The dominant errors are angle and velocity. These are severe enough that for scenario 2, 50% of the random forecasts at 1000 predict that the storm will not touch the hub.

Figures 7 and 8 provide results in terms of schedule effectiveness where 1.0 is the effectiveness of the schedule if there were no storms. Two baseline or

bounding conditions are provided. The first, the perfect forecast, is the result if there were no forecasting errors. The second, the null forecast, is the result if the original schedule was attempted. Four forecasting and replanning points were employed – at 0600, 1000, 1400 and 1800. Only the 0600 replanning point was used for one forecast, the 0600 and 1000 for two forecasts, etc..

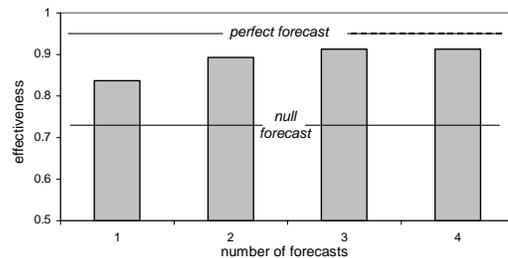


Figure 7. Scenario 1 - Storm Misses the Hub

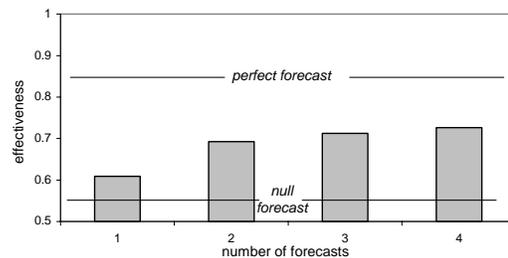


Figure 8. Scenario 2 - Storm Hits the Hub

The performance of the replanner in scenario 1 is extraordinary, particularly given the magnitude of the forecasting errors and given that it has only a point forecast with which to work. The storm and the

associated forecasts, though, only involve the en route and a limited number of spoke airports and thus does not threaten network integrity.

The performance of the replanner for scenario 2 suffers from the very condition of loss of network integrity. As noted above, 50% percent of the forecasts at 1000 for scenario 2 predict that the storm will not overlap the hub, even though in reality it will. The result is that 50% of the replans at 1000 involve schedule tweaking instead of major re-banking. Thus, when the hub actually goes out of operation, massive en route delays ensue. Adding forecasting and replanning points at 1400 and 1800 only modestly improves performance even though forecasting accuracy is considerably improved. The reason for this is that by 1400 the number of committed operations is such that the replanner has a limited number of options.

NFM – AOC/SCC Comparison with RBS

A final set of results are shown in Figure 9 for the model as integrated into the Boeing NFM and compared with the results of a ground delay program computed by the ration by schedule (RBS) approach. The case under consideration is a “bad day” scenario taken from ETMS traffic data for 7/10/01 and consists of 53K IFR flights using 17K aircraft flying between 12K city pairs. A 4 hour local weather event is simulated that reduces ORD capacity from 202 to 40 operations/hour while assuming no en route disruption. It is assumed that both the AOC and RBS approaches have the benefit of a perfect forecast and that capacity reduction can be predicted 3 hours ahead. In the RBS case there is no AOC interaction and the results of the algorithm are simply translated into the effective seat miles metric for all flight legs involving ORD. In the AOC case the airline schedule recovery module accounts directly for the effective seat mile metric in its optimization process. Again, the results are shown for all flight legs involving ORD.

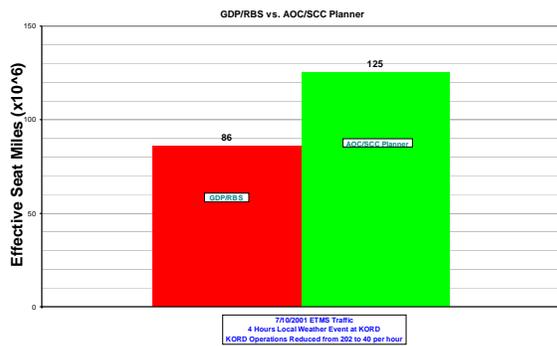


Figure 9. AOC/SCC versus RBS Comparison

Figure 9 shows the benefit of adaptive airline behavior as the AOC model achieves nearly 50% greater schedule effectiveness on the flights in question.

Summary and Next Steps

This report marks the conclusion of a first major phase of development of an airline schedule recovery model and its implementation and integration into the Boeing NFM and a simpler idealized geometry simulation called QADFLO. Preliminary results are available and have been presented here from both QADFLO and the NFM but with greater emphasis, to this point, on QADFLO. It has been concluded that the replanning methodology is computationally feasible even in the large scale NFM simulation environment. It has also been observed that the replanned schedules for model 1A are very effective, as long as the forecast of future capacities is accurate. In part this seems to be associated with the high value of the pre-departure flight re-routing strategy, which is contingent on a reliable model of sector capacity.

The next phase of development will focus on improving the model in certain respects, but perhaps more importantly, on use of the model within the NFM to support ATM operational concept trade studies and flow management investigations. With respect to the airline schedule recovery modeling, a minimal list of recommendations for future exploration and development are noted here:

1. Develop and implement a formulation for model 1B to allow the substitution of any airplane of the same type for a flight leg.
2. Develop and implement formulations for models 2A and 2B to allow for direct consideration of passenger path connectivity in the creation of replanned schedules.
3. Determine methods to account for forecast uncertainty in schedule replanning (besides, for example, using capacities inferred from a single point forecast).
4. Utilize the super-AOC concept, that is the replanning of all airline schedules simultaneously, in an analysis of the benefits of fully centralized versus decentralized planning. Develop concepts for global equity to be used by the centralized authority.
5. Develop a methodology for computing limits on airspace capacity.
6. Expand the scope of the airline schedule recovery model to include committed operations.
7. Develop a validation methodology with respect to the representation of current practice.

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Key Words

Air traffic management, flow management, airline schedule recovery, collaborative decision making, optimization, modeling, simulation.

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