Eighth USA/Europe Air Traffic Management Research and Development Seminar (ATM2009)

Evaluating a New Formulation for Large-Scale Traffic Flow Management

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Abstract— **In this paper, we introduce a new aggregate air traffic flow management model. Our integer programming model uses as a starting point the model recently introduced by Bertsimas, Lulli and Odoni. It employs a new set of more general airspace constructs that allow both more complex airspace elements to be represented as well as more aggregate-level modeling. We provide experimental results that indicate both the computational effectiveness of this model and its potential for decision support. We also discuss and provide general insights into the role of aggregate models in supporting traffic flow management for future air traffic management systems such as NextGen and SESAR.**

Keywords-air traffic management; traffic flow management; strategic flow management; optimization

I. INTRODUCTION

Little consensus exists today on the nature of the roles and responsibilities of air traffic flow management (ATFM) under future air traffic management (ATM) systems. It is also not surprising that there is no widely accepted architecture. At the same time, one can certainly identify important problem solving needs as well as general solution approaches. In the past few years, there has been a modest amount of research into large-scale ATFM models. While, to date, these have not been used in practice, research has advanced to the point that problems encompassing entire continents are becoming tractable.

Many feel that such models should play a role in ATFM in future ATM systems. One theme that has emerged for the use of these models is to provide a view, early in the day, of an optimal response at the aggregate level to future demand and capacity levels predicted for later in the day. Such a view would be most valuable when weather disturbances were predicted that could severely impact airport and airspace capacity.

In this paper, we propose modifications to a model recently developed by Bertsimas, Lulli and Odoni (BLO) in [4]. While the BLO model is computationally effective, it is limited in its ability to effectively address a range of aggregate-level flow management problems. The goal of our work is to address this limitation and to investigate the usefulness and computational properties of the resultant model. Further, we investigate the potential role in future ATM systems of aggregate-level flow models. Our starting point is the three-tiered ATFM framework now described.

A. Framework

We propose a three-tier layered approach to future ATFM planning and control (see Figure 1), which reflect three levels of planning fidelity and planning horizons in ATFM. Tier 1 captures at a lower level of detail the complex interactions between demand and constraints on the capacity of important shared resources, while leaving room for making tactical and even real-time "opportunistic" decisions at the more detailed levels of Tier 2 and Tier 3 to best exploit available resources.

Tier 1 – Strategic. Tier 1 ATFM would be driven by continent-wide models. Such models would be run several times per day, incorporating available updates of weather forecasts and recent weather history. An ATFM plan for several hours in the future, or even an entire day, would be updated after each run and made available to all stakeholders. The plan would specify aggregate aircraft flows and the number, type, and scope of various ATFM interventions. Coordination between airport and airspace programs is assumed. Major airspace reconfigurations would be specified.

Tier 2 – Tactical. The output of the Tier 1 model would include a traffic flow plan that indicates the time-dependent aircraft flows expected for the remainder of the day. Tier 2 functionality would plan and control specific ATFM initiatives and specify the details of regional airspace reconfiguration. The underlying decision models would involve subsets of flights defined by temporal and geographic restrictions. Versions of Tier 2 models exist today, e.g., the models used to plan and control ground delay programs and airspace flow programs.

Tier 3 – Opportunistic. The models of Tiers 1 and 2 would develop plans involving multiple flights over significant time frames. In a dynamic setting, however, at every time instant, the set of possibilities that might have been true when forward-looking models were run would turn into a single outcome that is true. This calls for hedging to ensure that resources are available that can exploit unanticipated capacity windfalls or other opportunities, when they manifest themselves, while still maintaining the feasibility of contingency plans for unexpected downturns in weather conditions. Tier 3 would provide tools poised to enact these fast-response mechanisms when the appropriate circumstances present themselves. Tier 3 tools would be transaction-oriented and would operate in real time. Reference [1] analyzes the potential benefits of such models and their use, using slot credit substitution as a prototype.

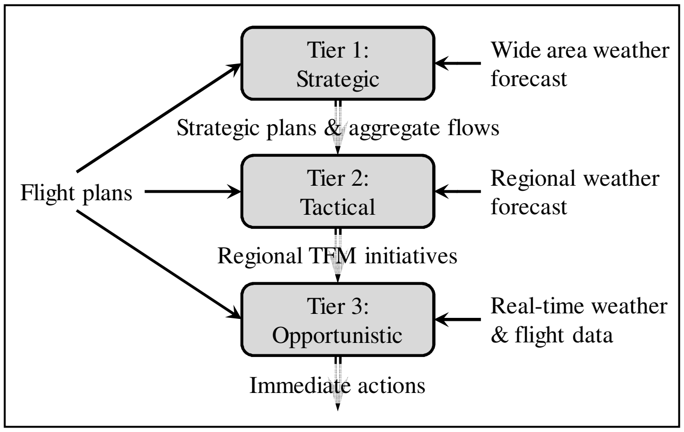

Figure 1 – Hierarchy of future ATFM tools

On good weather days, it is possible that only the Tier 1 model would be executed and there would be no need for the Tier 2 or 3 models. On the other hand, if specific ATFM initiatives are needed to address problem areas, more detailed (Tier 2) models would be used for such tasks as the assignment of flight-specific 4-D trajectories to the Tier 1 flows or the apportionment of those flows among flight operators. Generally, Tier 2 models would address localized problem areas such as managing arrivals at a specific airport or flows through a congested portion of airspace.

Potential roles a Tier 1 model could play under next-generation air traffic control (ATC) systems include the following:

- ***Strategic planning:*** Currently, daily strategic planning teleconferences are held involving the Federal Aviation Administration (FAA) air traffic control system command center, other FAA facilities and flight operators. Their purpose is to provide the flight operators with a view of the anticipated trouble spots and planned FAA control actions. Such a strategic plan is exactly what a Tier 1 model would provide.
- ***Predicting congestion:*** While Tier 1 models would employ optimization, they should be able to do a better job than current tools (e.g., Monitor Alert) at predicting congestion by taking into account various system-level interactions.
- ***Coordinating traffic management initiatives (TMIs):*** The Tier 1 model would identify the need for specific TMIs (e.g., ground delay programs) and coordinate their execution.
- ***Dynamic airspace configuration (DAC):*** Under future ATM systems, use of the airspace should become much more flexible, requiring DAC. At a high level, Tier 1 models would play a role in identifying DAC needs.

B. *Strategic Model Background*

Models for modern ATFM planning and control were initially developed for tactical applications, beginning with ground-holding strategies proposed by Odoni in [11]. Continued development led to formalized models for ground holding for both single [15] and multiple [16] airports. Each of these problems spawned additional follow-up work considering both stochastic and dynamic features that might be included, as well as feeding development of strategic models.

Strategic models have been slower to develop for a variety of reasons. Some of the first models to include ground and airborne delay, as well as airspace capacity, were [6] and [8], but both were unwieldy due to size limitations. One of the first readily solvable large-scale models was [2]. An extension of [2] was developed in [9] to address the peculiarities of this problem in a European context.

The work in [2] was followed by the same authors in [3], which included not only ground holding and airborne delay, but also allowed for the possibility of each flight having more than one route. Several other models have addressed both delay and routing decisions simultaneously, including [14] in a control context and [10] in a network flow context.

The most recent evolution of such strategic models is seen in the BLO model [4] mentioned previously. In this integer programming formulation, the framework of [2] was combined with the routing options in [3] to produce a powerful and flexible model.

Thus far, we have introduced a philosophy for modeling ATM at various levels of fidelity and provided a background for similar work done in this field. In the remainder of this paper, we describe two features that are essential to aggregate ATFM models. Then, the implementation of these two features, in the framework of [4] is described. Finally, a case study illustrating the utility of the proposed features is presented.

II. FEATURES OF STRATEGIC MODELS

In addition to those general characteristics mentioned previously, we have identified two specific features that are critical to large-scale ATM models. Both of these characteristics enhance modeling flexibility in ways that allow for analyzing future scenarios and including operator decision making. In this section, we describe these two characteristics, several methods by which they might be implemented in any strategic model, and our proposed implementation strategy.

A. *Reduced Airspace Complexity*

Most strategic models of air traffic rely on the current sector paradigm used in ATC. While this scheme is effective in managing tactical operations, it leads to several problems when applied to large-scale strategic models. These problems are outlined below:

1. Because there are so many sectors to include, such problems may become too large to solve efficiently.
2. Because the majority of sectors are used far below their capacities, their inclusion only increases model size, not necessarily the utility of solutions.
3. Defining an accurate capacity for each sector is a difficult problem. Defining capacities for many sectors simultaneously only compounds this difficulty and magnifies any erroneous assumptions.

4. In future ATC systems, sectors may be defined dynamically or replaced entirely by a different construct.

As a result of these challenges, we propose to treat the airspace in a different and more flexible fashion than previous models. We will define capacity constraints only on portions of the airspace that represent disruptions. These "volumes" will represent the only capacity constraints in the airspace at any given time. They are not necessarily contiguous nor correspond to any set of sectors. Thus, the airspace between volumes is assumed to have sufficient capacity.

In practice, local demand-capacity imbalances outside the volumes may arise during operations (e.g., flow at a waypoint). Such imbalances are beyond the scope of strategic models, as they can likely be handled with tactical ATC actions. At the same time, a natural addition to the model presented in this paper would be the capability to dynamically generate additional airspace constraints (volumes) based on an initial solution to the model using the initial volumes. Such an approach is a form of *constraint generation*, which is commonly used in mathematical programming to solve large-scale problems.

An advantage of using volumes to model constrained areas is that model complexity is reduced. This arises because flights are not tracked on their paths through unconstrained airspace. Rather, only the exit from one constrained resource and the subsequent entry to another are tracked. This leaves planning routes between constrained elements out of a strategic model, and places it at the operator's discretion.

An example case with three volumes and several network links that a flight may use are shown in Figure 2. In this example, two routes using volumes are shown, as well as an alternate route that avoids the volumes. In such a case, capacity constraints for the system are defined for V_1, V_2, V_3, and airports O and D. Note that in general a volume will have multiple entry and exit points and there are multiple alternatives for defining volume capacity. These features make our volumes much more general than the sector models used in BLO (see §III for model details).

The volume concept is in some ways analogous to the use of flow constrained areas (FCAs) and airspace flow programs (AFPs), which have been implemented in the United States. FCAs are dynamically identified and AFPs dynamically implemented to respond to predicted capacity-demand imbalances.

There are many methods by which airspace volumes might be defined, although each presents unique challenges in defining the volume boundaries and capacity. In many ways, however, the challenges in defining capacity are the same as those faced for traditional sectors.

Possibly the simplest method to define airspace volumes is using the current centers. Defining such volumes would certainly reduce model complexity, but may also introduce other problems. For example, the volumes would be contiguous, and all airspace would be capacitated – thus losing some of the advantage gained by volumes. Also, because centers are so large, it may not be reasonable to identify a single number as the center capacity. Despite this uncertainty, limiting flights in some way in each center would achieve reasonable traffic levels.

It may also be useful to define volumes around multiple airport systems. Take, for example, the New York metropolitan area. There are five commercial airports within 50 miles of the central business district (LGA, EWR, JFK, HPN, ISP), as well as several major general aviation airports. Naturally, the operations at each of these airports influence one another in tactical (terminal area and beyond) matters. But, for strategic purposes, it is reasonable to consider the aggregate flow to each airport as being equivalent. Thus, a volume could be drawn to encircle these airports, and their flows combined.

There are additional questions about defining the capacity of such metroplex volumes, as well as the entry and exit points used by the flows. However, each of these issues can be addressed as part of future research.

Perhaps the most promising method by which to define volumes currently, however, is using weather data. According to the FAA's OPSNET system, 68 percent of flights delayed in 2008 cited severe weather as the cause of the delay. The definition of such weather-based volumes could be left to automated systems based on weather radar/forecasts or may include expert judgment in defining location and evolution. An example of a current system that fills a similar role is the Collaborative Convective Forecast Product (CCFP), developed by the FAA and the National Oceanic and Atmospheric Administration.

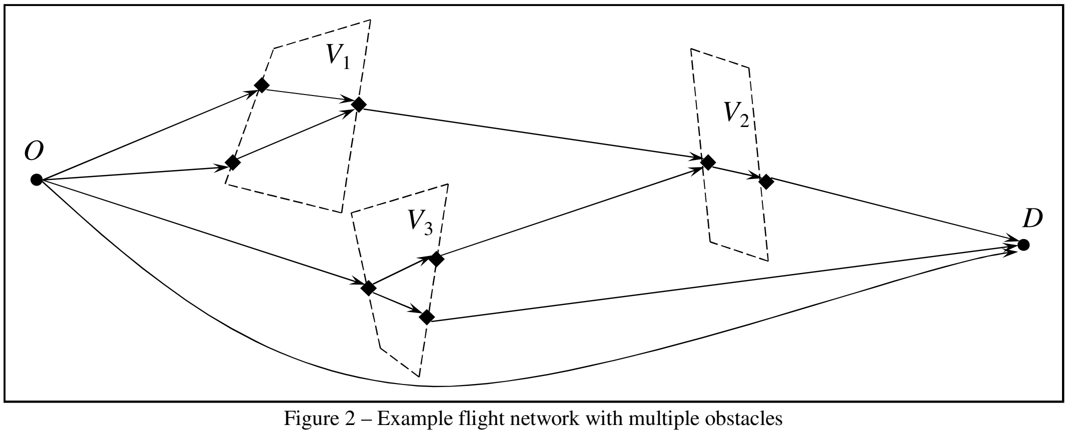

Figure 2 – Example flight network with multiple obstacles

As with any volume, it is difficult to assign a capacity to a weather-based volume. Whether considering volumes or sectors, the nominal capacity must be reduced according to the severity of the weather present. There has been research ([7], [12], [13]) on relating throughput and weather coverage that may be immediately applicable to estimating capacities for such volumes.

B. Delay Propagation

Another area of concern in a strategic flow model is delay propagation caused by one physical aircraft operating multiple flights consecutively. Under most conditions, delays to flights earlier in the day are a strong predictor of delays later in the day [5]. Thus, a model that does not consider the connections between a single physical aircraft operating multiple flights over the course of a single day will underestimate delays. One method for enforcing this physical constraint is suggested in [4]: defining connected pairs of flights.

This approach, however, introduces several difficulties. First, increasing the proportion of flights included in such pairs increases run time, as shown in [4]. Further, defining such flight pairs may be a difficult problem, particularly when many compatible flights are arriving and departing. In reality, the definition of these pairs is contained in proprietary data controlled only by the airlines.

At a small airport (or for a small airline's operations), identifying these connections from historical data is straightforward: one flight comes in, and then another goes out approximately one hour later. At even moderately large airports (and particularly at airline hubs), identifying these pairs becomes extremely difficult.

As a result, we propose a more flexible method of managing flight connections. Each airline operates various groups, or fleets, of aircraft that are essentially equivalent. In managing irregular operations, flight dispatchers swap which aircraft operate each flight, based on which are available at certain time. We model this process as a network flow problem.

Because aircraft within a given fleet are considered equivalent and can be used interchangeably, a non-label-conserving methodology such as network flow can be applied. In each discrete time period, there are various aircraft that arrive, aircraft that depart, and aircraft already waiting on the ground. To see an example of these flows in a network diagram, refer to Figure 3.

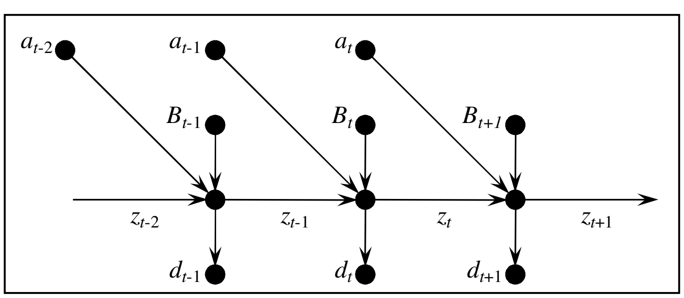

Figure 3 – Sample airport flow model

In this example, each column of nodes represents a discrete time period. The incoming flows along the top of the figure (a_t) represent arrivals, and the outgoing flows along the bottom (d_t) represent departures. Each of these quantities can be represented as a sum of decision variables. The incoming flows in the center (B_t) represent aircraft that become available at time t to operate departures (e.g., after completing maintenance). Flows between time periods (z_t) represent aircraft that are waiting on the ground and are immediately available to operate a departure. The diagonal lines represent a physical constraint whereby aircraft must wait one time period on the ground before they are prepared to operate a departure.

Given such supplies, demands, and flows, it is apparent that conservation equations can be defined. In this manner, any incoming aircraft within the fleet may be used to operate any outgoing flight.

The flexibility enabled by this flow model comes at the cost of increased model complexity as a result of the introduction of the intermediate flows between time periods. Thus, the best aircraft connection implementation will include a combination of flight pairs and flow models at judiciously chosen airports.

III. Model Structure

In this section, we describe the structure of the optimization model used in this work. This builds heavily upon the BLO formulation mentioned previously. Much of the notation and several of the constraint sets are identical to those proposed by BLO, but are repeated here for clarity.

The essence of this optimization model is to plan departure and arrival times, as well as routes for each flight, while obeying capacity constraints on various airspace elements. The objective is to minimize a general description of flight delays.

Much of the novelty of the original BLO model lies in the routing options provided for each flight. In that model, each flight has a set of sectors that it may traverse. For each sector, a forward adjacency list is defined, thus creating a separate (and potentially unique) network over which each flight may travel. The many networks are linked by common capacity constraints.

Using the airspace volumes proposed in §II.A, we have defined the network as containing airports and airspace volumes. For each volume, a set of nodes is defined for each flight listing the possible entry and exit points. An example of this construct is shown in Figure 4. In this case, nodes 1 and 2 are entry points to volume V_1, while 3, 4, and 5 are exit points. By properly defining constraints, the volume dwell time may be varied based on the entry-exit point pair.

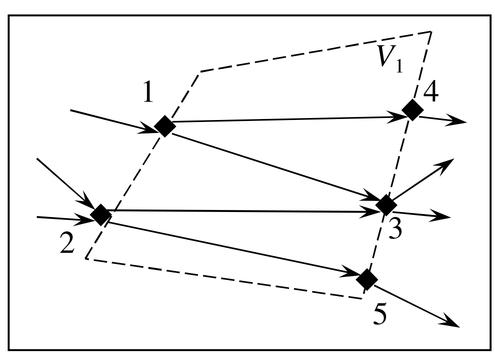

Figure 4 – Sample network connectivity inside single volume

In this section, the various parts of the model are introduced: decision variables, constraint sets, and objective function. Model notation is summarized in the appendix.

A. Decision Variables

Two sets of decision variables are used in this model. To specify different stages of flight operations, the w class is used, and to identify the flow of aircraft between time periods, the z class is used.

The binary $\left\{w_{k,t}^{f}\right\}$ variables are defined as follows:

$$w_{k,t}^{f} = \begin{cases} 1 & \text{if flight } f \text{ arrives at element } k \textbf{ by} \text{ time } t \\ 0 & \text{Otherwise} \end{cases}$$

This **by** property indicates that once a variable's value has been set to one, all values for subsequent time periods for the same combination of k and f will also be equal to one. This mechanism was introduced in [2] and was again used in [4]. Here, "element k" represents a point in space, e.g., the entry point to a volume.

The second class of decision variables $\left\{z_{k,t}^{h}\right\}$ represents the flow of aircraft of a given fleet h between time periods t and t+1 at a single airport k. The utility of this flow formulation will be explained in greater detail in §III.B.3.

B. Constraints

Four classes of constraint sets define the feasible set of solutions for this problem. The four classes include capacity, network connectivity, aircraft connectivity, and structural. The constraint sets (in capacity and aircraft connectivity) that differ from those proposed in [4] will be noted in each section.

1) Capacity

To accurately model operations, physical capacity constraints must be enforced. The first elements of the model to which these apply are the airports. It is necessary to limit the number of departures and arrivals in each time period.

Departure capacity is enforced as shown in (1). The term inside the summation will only be equal to one during the time period a flight actually arrives at the airport. During all other time periods, the value of the decision variables at t and t-1 will be equal. Summing over all flights yields the total number of flights that arrive in this time period.

$$\sum_{\substack{f \in F \mid \\ O^f = k}} \left(w_{k,t}^{f} - w_{k,t-1}^{f} \right) \le D_{k,t} \qquad \forall k \in K, t \in T \qquad (1)$$

Arrival capacity is enforced likewise in (2), subject to a capacity limit $A_{k,t}$. In the work presented here, the tradeoff between arrivals and departures is not considered.

$$\sum_{\substack{f \in F \mid \\ D^f = k}} \left(w_{k,t}^{f} - w_{k,t-1}^{f} \right) \le A_{k,t} \qquad \forall k \in K, t \in T \qquad (2)$$

Enforcing capacity on the new airspace volumes is more complex because there is a non-zero dwell time associated with crossing the volume. As a result, the volume occupancy for the previous time period must be considered, as shown in the first term in (3). The second term represents the number of flights that enter the volume over the set of possible entry points, while the third represents the number of flights that exit from the volume over the set of possible exit points. The boundary condition that the volume is empty at time 0 is stated in (4).

$$I_{v,t} = I_{v,t-1} + \sum_{f \in F} \sum_{e \in \varepsilon_v^f} \left(w_{e,t}^{f} - w_{e,t-1}^{f} \right) - \sum_{f \in F} \sum_{x \in \chi_v^f} \left(w_{x,t}^{f} - w_{x,t-1}^{f} \right)$$

$$I_{v,t} \le V_{v,t} \qquad \forall v \in V, t \in T \qquad (3)$$

$$I_{v,0} = 0 \qquad \forall v \in V \qquad (4)$$

This formulation of volume capacity constraints makes the explicit assumption that capacity is constrained by the maximum number of flights that may simultaneously occupy a portion of airspace. Other formulations could be applied, for example, one which considered the number of flights crossing some boundary in a time period.

2) Network Connectivity

Several constraints are necessary to enforce the connectivity and transit time between elements shown in Figure 4. These are equivalent to those proposed in [4], but are repeated for clarity. An element in this context is either an airport or a volume entry/exit node.

Constraint (5) ensures that a flight may only have arrived at an element from a single predecessor element.

$$w_{j,t}^{f} \le \sum_{e \in N_j^f} w_{e,t-p_{j,e}^f}^{f} \qquad \forall f \in F, j \in \left\{ S^f \setminus O^f \right\}, \; t \in T_j^f \qquad (5)$$

Constraint (6) ensures that, from any given element, a flight may travel to one of its successor elements.

$$w_{j,\bar{T}_j^f}^{f} \le \sum_{e \in P_j^f} w_{e,\bar{T}_e^f}^{f} \qquad \forall f \in F, j \in \left\{ S^f \setminus D^f \right\} \qquad (6)$$

Constraint (7) expands (6) by limiting a flight to visit only one of its successor elements.

$$\sum_{e \in P_j^f} w_{e,\bar{T}_e^f}^{f} \le 1 \qquad \forall f \in F, j \in \left\{ S^f \setminus D^f \right\} \qquad (7)$$

3) Aircraft Connectivity

Two constraint sets are included to ensure schedule conformity of physical aircraft as was proposed earlier.

The first case applies when flight pairs to be operated by the same aircraft are specified a priori, as may be the case for very small airports/operations. The physical constraint that the outgoing flight cannot depart until after the incoming flight has arrived and waiting some time on the ground is enforced in (8).

$$w_{O^{f_2},t}^{f_2} \le w_{D^{f_1},t-g^f}^{f} \qquad \forall \left(f_1, f_2 \right) \in C, t \in T_{O^{f_2}}^{f_2} \qquad (8)$$

The alternative method of enforcing aircraft connectivity is to apply flow conservation at individual airports. This means that the number of compatible aircraft leaving an airport during a time period must be less than the sum of the number entering and those already on the ground. Aircraft on the ground may be those that have already operated a flight and are awaiting an outgoing leg or those that have been waiting since before the planning period began. This latter type is referred to in this model as a "scheduled originating flight" and is denoted $B_{k,t}^{h}$.

The flow diagram in Figure 3 shows this relation. It is notable in the figure that arrivals in each time period are not available to operate a departure until sometime later than their actual arrival time. This lag represents the "turn time" necessary for an aircraft between operating two flights. While this example shows a turn time of only one period, considering a turn time of a different length would be simple.

Unfortunately, enforcing conservation of flow in this manner adds an additional set of decision variables to the base model. However, the deleterious effect on model size can be limited by carefully choosing which combinations of fleet and airport should be modeled in this fashion.

To enforce this constraint, the number of arrivals and departures in each time period is represented as a function of the decision variables, as in constraints (1) and (2). The added complication is that the quantity is summed over each fleet, as shown in (9) and (10).

$$d_{k,t}^{h} = \sum_{\substack{f \in F \mid \\ O^f = k, \\ J^f = h}} \left(w_{k,t}^{f} - w_{k,t-1}^{f} \right) \qquad \forall h \in H, k \in K_h, t \in T \tag{9}$$

$$a_{k,t}^{h} = \sum_{\substack{f \in F \mid \\ D^f = k, \\ H^f = h}} \left(w_{k,t}^{f} - w_{k,t-1}^{f} \right) \qquad \forall h \in H, k \in K_h, t \in T \tag{10}$$

The conservation relation mentioned previously is then enforced in (11). Boundary conditions are shown in (12).

$$z_{k,t-1}^{h} + a_{k,t-q^h}^{h} + B_{k,t}^{h} = z_{k,t}^{h} + d_{k,t}^{h} \qquad \forall h \in H, k \in K_h, t \in T \tag{11}$$

$$z_{k,t-1}^{h} = 0 \qquad \forall h \in H, k \in K_h \tag{12}$$

4) Structural

To prevent flights from being canceled without cost, each flight must have the decision variable representing arrival at its destination fixed to one, as shown in (13). This constraint can be relaxed, and a cost added in the objective function to 1 - $w_{D^f, \bar{T}_{D^f}^f}^{f}$ to model cancellations.

$$w_{D^f, \bar{T}_{D^f}^f}^{f} = 1 \qquad \forall f \in F \tag{13}$$

To enforce the **by** property of the decision variables, constraint (14) is required.

$$w_{j,t-1}^{f} \le w_{j,t}^{f} \qquad \forall f \in F, j \in S^f, t \in T_j^f \tag{14}$$

In addition, the $\left\{ w_{j,t}^{f} \right\}$ decision variables must be binary, as shown in (15).

$$w_{j,t}^{f} \in \{0,1\} \qquad \forall f \in F, j \in S^f, t \in T_j^f \tag{15}$$

Finally, the flow variables $\left\{ z_{k,t}^{h} \right\}$ must be non-negative.

$$z_{k,t}^{h} \ge 0 \qquad \forall h \in H, k \in K_h, t \in T \tag{16}$$

C. Objective Function

The objective of this optimization is to minimize a cost function that incorporates both ground and airborne delays. The total cost of a delay is expressed as the difference between the cost, had that entire delay been taken in the air, and the cost of the portion of the delay taken on the ground.

Given the specification proposed for the decision variables, computing delay costs in this manner is easier than the traditional method of summing arrival and delay cost. Arithmetically, however, the two methods are equivalent.

The expression showing the cost if all delay is taken in the air is shown in (16), and that for the savings realized by taking delays on the ground is shown in (17).

$$c_{T,t}^{f} = C_a \left(t - R_d^f \right)^{1+\varepsilon} \tag{17}$$

$$c_{G,t}^{f} = \left(C_a - C_g \right) \left(t - R_a^f \right)^{1+\varepsilon} \tag{18}$$

The exponent is included in each cost coefficient to guarantee marginally increasing delay costs. This property helps to enforce equity, as it will favor assigning a small amount of delay to two flights rather a large amount to one.

The objective function is stated in (19). As in other parts of the model, the departure or arrival time of each flight is inferred by summing over all time to find the one time period for which the **by** variables indicate a difference.

$$\min_{f \in F} \left[\begin{array}{l} \sum_{t \in T_{D^f}^f} c_{T,t}^{f} \left(w_{D^f,t}^{f} - w_{D^f,t}^{f} \right) \\ - \sum_{t \in T_{O^f}^f} c_{G,t}^{f} \left(w_{O^f,t}^{f} - w_{O^f,t}^{f} \right) \end{array} \right] \tag{19}$$

IV. Experiment

To test the performance of these new model features, a case study using realistic data was developed. In this section, the development of this case study is described, and example results, as well as sensitivity analysis, are presented.

A. Description of Scenario

Because considerable input data is needed for this model, certain tradeoffs were necessary between realism and tractability. A summary of the realism included for various input data to this case study is shown in Table 1.

The data used for the case study came from July 20-21, 2005, for the continental United States. This day featured heavy storms in the upper Midwest, as well as weather activity over south Texas and off the East Coast. These storms interrupted not only the airspace, but also impacted airport operations. In the following sections, the assumptions used in building this data set are outlined.

TABLE 1 – DESCRIPTION OF CASE STUDY DATA

Data	Level of Realism	Source
Schedule	U.S. domestic flights for carriers with >1% of traffic	BTS
Route	Great circle track from origin to destination	-
Airspace volumes	Forecasted CCFP volumes	CCFP
Fleets	Each carrier's set of aircraft treated as individual fleet	-

1) Schedule and Fleet

The schedule data for this model was drawn from the Bureau of Transportation Statistics On-Time Performance database. Individual flight records were examined for flights that were scheduled to depart from somewhere in the United States with a destination also in the United States. Flights travelling within only Hawaii, Alaska, or the Caribbean were excluded, leaving 19,710 flights. The schedule data for these flights were processed into ten minute time bins.

Each individual carrier was modeled as a single fleet. While this is a coarse assumption given that most carriers have several aircraft types that cannot be substituted for one another, it was necessary given the level of granularity provided by the data source. This led to 20 unique fleets.

Flight cancellations were permitted in the model at a cost equivalent to 24 units of ground delay.

2) Volume and Airport Capacity

The weather radar and CCFP regions for this July 20, 2005 at 1300Z are shown in Figure 5. Based on this data, several steps were taken to model the airspace volumes and their capacities. First, the volumes were defined using the regions in 0900Z CCFP report for 1300Z. Of the three regions that appeared in this report, only the large one in the north central United States has any marked effect on traffic. As a result, the other two volumes were treated as impassible, and their capacities set to zero.

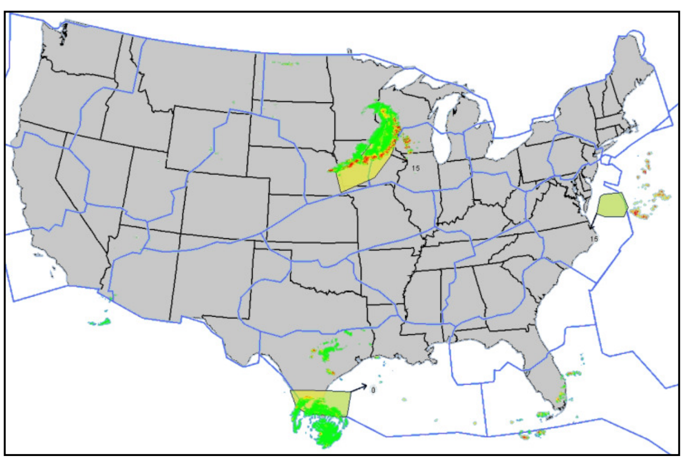

Figure 5 – Map of United States with CCFP from 0900Z (for 1300Z) and observed weather from 1300Z on July 20, 2005

To model the capacity of the large volume under the severe weather shown, a baseline volume capacity first had to be established. Using flight track data from August 24, 2005, traffic counts inside this volume for each minute of the day were calculated. Then, the baseline capacity was taken to be the 95th percentile of these counts. The baseline under these assumptions was that 72 flights could occupy the volume simultaneously (a maximum of 90 appeared in this data set, for which 72 was the 95th percentile).

Finally, to account for the effect of severe weather on the volume capacity, the first strategy proposed in [13] was applied. According to the simple model in that paper, most sectors' capacities behave according to the model shown in Figure 6. We assume that this logic extends to the arbitrary volumes used in this analysis. The vertical line shows the coverage (15 percent) and corresponding available capacity (25 percent) in the case study.

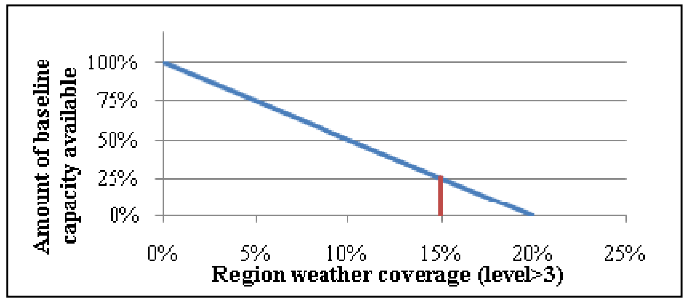

Figure 6 – Simple model for relating weather and capacity

In addition to the weather affecting en route traffic, several airports were adversely affected by weather or other impediments. On July 20, 2005, Ground Delay Programs (GDPs) were initiated at SFO, ORD, MDW, EWR, and ATL. The Planned Aircraft Arrival Rate (PAAR) for each 15 minute time period was used in this case study to model the capacity of each airport. Although the implementation of each GDP did not correspond with the 0900Z forecast time of the CCFP mentioned previously, the rates are typical of those used at these airports during other GDPs.

Airports not involved in a GDP, or not reporting severe weather, were assumed to be operating with nominal visual capacities.

3) Route

The 19,710 flights traversed 264 different airports. The routes for each flight were constructed artificially using Great Circle (GC) tracks, according to the following logic:

If the GC track did not cross a volume, then the flight was assigned a single direct route between origin and destination.

If a flight's GC route crossed a volume, then the two intersections of the GC route and the volume were used as the entry and exit points. The alternate route for such flights was constructed arbitrarily. The assumption was made that *some* uncapacitated path around the volume exists that is 25 percent longer than the GC distance. This path construction logic mimics that shown in Figure 2 with only a single volume.

Flights were assumed to travel at a uniform speed between origin and destination.

B. Results

Several sets of results are shown in this section. Detailed results for the case study outlined previously, as well as an examination of model sensitivity, are shown. These models were solved using Xpress 2008 on a dual processor Xeon system with 16GB of memory.

1) Baseline Case Study

Several airports, as well as the disruption in the upper Midwest provide the areas of greatest interest in this case study. The flow over time through the main volume is shown in Figure 7. The line appearing near the top of the figure represents the capacity impact of the storm. As expected, the model fully utilizes capacity during the impacted period.

As a result of the capacity constraints and high utilization of the volume airspace, some flights were rerouted, as shown in Figure 8. The flights destined for MSP, DEN, and ORD were rerouted on account of capacity constraints in the volume. The flights to BOS, as well as south Florida were rerouted because of the disruption off of the East Coast.

Figure 9 shows the average arrival delay of flight arriving at ORD airport. While the magnitude of the delays is low, the trend follows the typical delay propagation pattern seen at most disrupted airports with large afternoon and evening delays.

The model assigned ground delays to many flights to control flows into the volume and various airports. The size of these ground delays are shown in Figure 10. The delay impact to IAH was caused by the severe weather disturbance in the area, as well as the reduced airport capacity. The large volume in the upper Midwest resulted in many delays to flights to the major airports in that region. These results suggest that ground delay programs should have been implemented (and, in practice were) at these airports.

In general, these results are quite positive. They suggest that the model is directing actions which are not only logical, but reasonably consistent with observed trends. However in most cases, the magnitude of the effects observed here are too small. This is likely an artifact of the capacity estimates used, as well as the routing assumptions. Future work will address both of these shortcomings.

2) Capacity Sensitivity Analysis

The second set of results presented demonstrates the sensitivity of the model to changes in various input parameters. For this analysis, several changes to nominal capacity values were made to compare the results.

The baseline case again corresponds to that examined in the previous section, and the other two cases represent an increase or decrease of all capacities by 10%. Where rounding was necessary, the smallest integer less than the real value was used. Delay propagation constraints were included. A comparison of results is shown in Table 2.

The trends observed in this table are consistent with expectations and reality. With increasing capacity, the objective function (and thus, delay quantities) decreased. In addition, the number of cancellations and rerouted flights decreased with increasing capacity. Further work is required to validate the strength of these trends, but it important that the model performance is consistent in this manner.

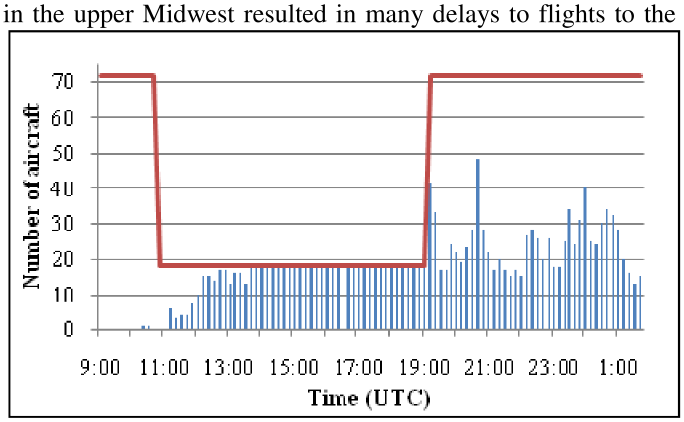

Figure 7 – Volume capacity and throughput

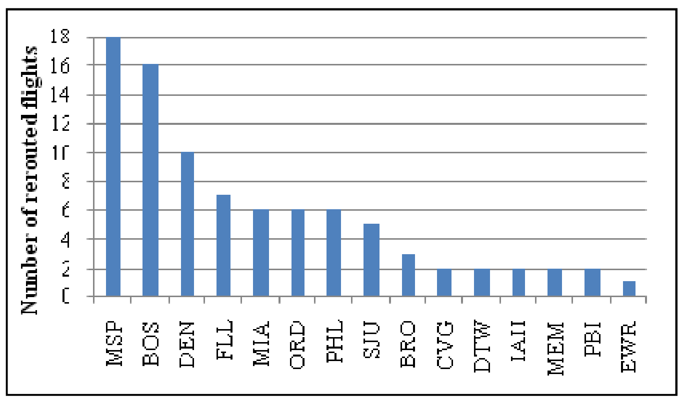

Figure 8 – Number of rerouted flights (by destination airport)

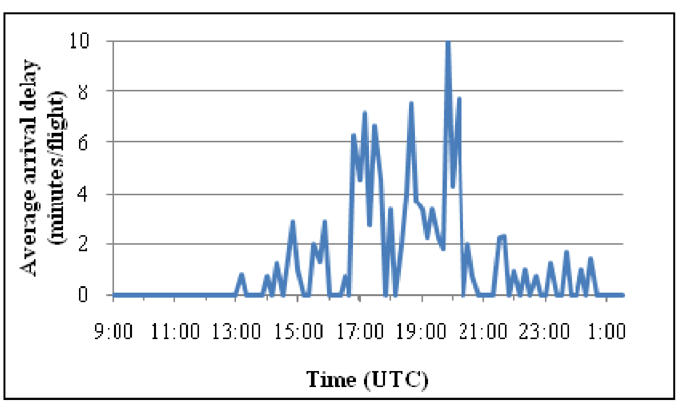

Figure 9 – Average ground delay for flights arriving at ORD

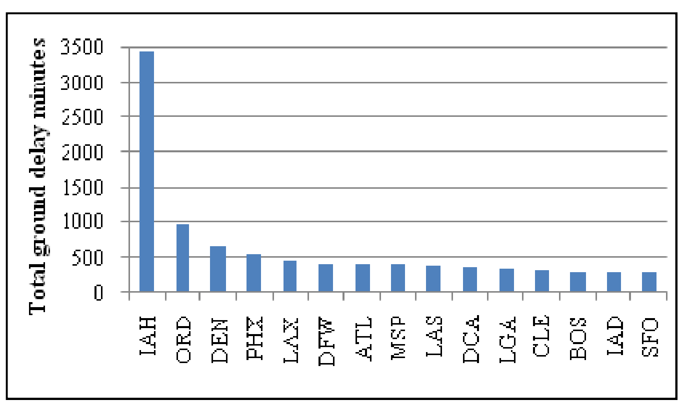

Figure 10 – Total ground holding imposed on flights (by destination airport)

TABLE 2 – SENSITIVITY ANALYSIS WITH RESPECT TO CAPACITY

Statistic	Decreased Capacity	Baseline	Increased Capacity
Objective function value	5882	3494	3175
Total ground delay (minutes)	41050	20220	17620
Total airborne delay (minutes)	2790	2310	2040
Number of cancellations	38	32	32
Longest arrival delay (minutes)	150	100	100
Number of rerouted flights	119	96	83
Number of nodes for branch & bound	1	1	1
Solution time (seconds)	892	752	895

V. CONCLUSIONS

In this paper, we have introduced several important concepts to enhance strategic traffic flow management. First, a general framework for ATFM models was outlined. Then, two important features for strategic ATFM decision models were proposed. The new features include using airspace volumes in place of sectors and a comprehensive model of delay propagation. In several ways, these features may reduce model complexity and increase flexibility when compared to existing modeling constructs.

In the case study, we showed that the model strategically delayed and rerouted flights in response to the various capacity reductions in place around the airspace. Also, it was shown that the model is especially sensitive to changes in capacity, as should be expected from considering real operations. The experiments demonstrated that nationwide problems can be efficiently solved.

There are many extensions from this work under consideration. The primary area of interest is in strengthening the processing of input data, and including the consideration of accurate flight routes. Another major area of interest is in generating volumes (or other new airspace structures) from various data sources. In the modeling arena, work will be undertaken to strengthen the formulation to increase the model's utility as a tool for evaluating scenarios. Each of these enhancements should improve the performance of the model, as well as the realism of the solutions.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support of the National Aeronautics and Space Administration Airspace Systems Program under ARMD NRA: NNH06ZNH001

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Appendix

Table 3 – Model Notation

Notation	Description	Notation	Description	Notation	Description
T	Set of time periods	O^f	Origin airport of flight f	C_a	Unit cost for air delay
F	Set of flights	D^f	Destination airport of flight f	C_g	Unit cost for ground delay
K	Set of airports	R_d^f	Scheduled departure time of flight f	$K^h \subset K$	Fleeted airports for fleet h
V	Set of volumes	R_a^f	Scheduled arrival time of flight f	$B_{k,t}^h$	Scheduled originating flights of fleet h at airport k at time t
H	Set of fleets	N_j^f	Next elements a flight f may traverse immediately following j	C	List of connected flight pairs
$D_{k,t}$	Departure capacity of airport k at time t	P_j^f	Previous elements a flight f may have traversed immediately prior to j	J^f	Fleet of flight f
$A_{k,t}$	Arrival capacity of airport k at time t	ε_v^f	Possible entry points to volume v for flight f	q^h	Ground time required after flight in fleet h, before aircraft is able to operate an outgoing flight
$V_{v,t}$	Number of flights permitted to simultaneously occupy volume v at time t	χ_v^f	Possible exit points from volume v for flight f	g^f	Ground time required after flight f, before aircraft is able to operate another flight
S^f	Set of airspace elements that flight f may traverse	$I_{v,t}$	Number of flights in volume v at time t	$p_{i,j}^f$	Transit time between element i and element j for flight f
T_e^f	Feasible time period for flight f to visit element e				
$\underline{T}_e^f$	Beginning of feasible time period				
$\overline{T}_e^f$	End of feasible time period				