Dynamic Strategic and Tactical Air Traffic Flow Control

Mostafa Terrab and Saaju Paulose
Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute

Troy, NY 12180–3590

Abstract **We consider the problem of dynamically controlling the flow of aircraft heading towards an airport for which we expect a reduction in capacity due to unfavorable weather conditions. We use a stochastic programming formulation corresponding to a minimization of delays costs based on a probabilistic forecast of the capacity of the destination airport. Two types of control actions are considered: (1) ground-holds to be imposed on aircraft at their airport of origin beyond their scheduled departure time, in order to avoid costlier airborne delays; and (2) airborne delays to meter the arrival of aircraft at the destination airport. Together, these actions amount to a delay policy with a strategic (ground-holds) as well as a tactical component (airborne delays). The purpose of the model is to find policies that strike an optimal balance between the strategic actions and the costlier tactical actions. Numerical examples are based on demand and capacity data for Boston Logan Airport and focus on the following issues: (1) comparison of delay policies obtained using the stochastic programming formulation with other delay strategies; (2) impact of the timing of capacity-forecast updates on the quality of solutions; (3) impact of dynamic policies on the distribution of delays and costs among different classes of users.**

1 Introduction

Anyone who flies regularly on U.S. commercial airlines is aware of the congestion problem in the air traffic network. Indeed, even though the bottlenecks of this system are only a few major airports that sometimes operate close to capacity, because of the concentration of traffic at these major airports (70% of all emplanements take place at 28 major commercial airports) practically all airlines and all passengers are affected by this problem. The airport capacity problem can be dealt with in the long-term through the construction of new airports and runways, the use of larger aircraft, better air traffic control technology, and economic and regulatory measures to encourage better airline scheduling practices. In the short-term, we can only try to manage existing demand in order to reduce the impact of unavoidable delays. This can be accomplished through control actions that can be broadly classified into two categories: (1) strategic actions to be taken *before* the aircraft has taken-off, consisting of ground holds to be imposed beyond the scheduled departure time of the flight when it is otherwise ready to depart (and sometimes cancellations), and (2) tactical actions to be taken *after* the aircraft is airborne, including rerouting, speed reductions, and low-altitude delays at the vicinity of the destination airport.

An article in the February 1991 issue of *IEEE Spectrum* cites a 1990 report by the U.S. Department of Transportation putting the yearly cost of delays to the U.S. airline industry at \$5 billion. The same article attributes 53% of delays to weather conditions. Indeed, the problem is not so much an intrinsic lack of capacity but rather that the capacity of an airport to accommodate landings and take-offs depends greatly on highly variable weather conditions that are hard to predict even a few hours in advance. At Boston Logan airport, for example, the runway capacity can decrease from a peak capacity of 120 operations (landings and take-offs) per hour in ideal weather conditions down to 60 operations per hour in unfavorable weather conditions, with 1987 data, for example, showing this occurring about 15% of the time.

Because airport capacities can be difficult to predict and because airborne delays are costlier than ground delays, an optimal delay policy has to strike a balance between "pessimistic" policies that impose an excessive amount of ground holds and may result in unused capacity at the destination airport, and "optimistic" policies that allow on-time take-offs and may result in costly airborne delays. Furthermore, a delay policy should be updated as more

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accurate weather information becomes available.

For the purpose of air traffic flow management, the Federal Aviation Administration (FAA) operates the Air Traffic Control System Command Center (ATCSCC) in Washington, D.C. Weather and airline schedule information throughout the U.S. is collected at this facility and is used to determine and issue ground holds for flights headed towards airports for which a reduction of capacity is expected. This is done airport by airport by estimating the evolution of the capacity of a given destination airport a few hours in advance, and then assigning flights to that capacity in a first-come, first-served manner, based on scheduled arrival times.

The air traffic flow management problem has begun to attract the attention of researchers only recently. To our knowledge, Odoni [2] is the first to suggest a mathematical modeling approach to the flow management problem. Andreatta and Romanin-Jacur [1] propose a dynamic programming solution to a single-time-period problem. Richetta [4] proposes a stochastic program formulation where the decision variables correspond to actions on groups of flights. The stochastic programming formulation presented here is an extension of an integer programming formulation for the multiple-time-period case proposed in Terrab [5] (and briefly reviewed in the following section) and uses decision variables relative to individual flights.

2 Model Formulation

We consider operations at a single destination airport, airport Z, for which we expect a reduction in capacity during some time interval $[t_1, t_2]$ (typically, of a few hours duration). We denote $\mathcal{F} = \{1, 2, \cdots, F\}$ the set of all flights scheduled to land at airport Z during $[t_1, t_2]$. Our approach is to discretize the time axis by subdividing $[t_1, t_2]$ into a set $\mathcal{T} = \{1, 2, \cdots, T\}$ of consecutive time periods (each time period of duration, say, 10 or 15 minutes), and define K_i to be the landing capacity of airport Z for time period i. In this approach, we consider only the landing capacity of the destination airport, because take-offs are usually not affected by weather conditions.

To better motivate the probabilistic formulation, we first describe a simple deterministic formulation corresponding to the case where all the capacities K_i's are *deterministic* quantities. (The deterministic case has also a practical value as there are instances where airport capacities can be forecast exactly.)

2.1 Deterministic Formulation

If the capacity of airport Z is known deterministically, it becomes possible to completely avoid costly airborne delays and match capacity with arriving flights utilizing ground holds exclusively. Therefore, we need not consider airborne delays in the mathematical formulation of the deterministic problem. We use the following notation:

- $\mathcal{I}_f$ is the set of indices of all time periods during which flight f can land at airport Z.
- $\mathbf{x} = \{x_{fi}\}_{f \in \mathcal{F},\, i \in \mathcal{I}_f}$ is the vector of decision variables such that $x_{fi} = 1$ if flight f is assigned to land during time period i; $x_{fi} = 0$ otherwise.
- c_{fi} is the cost of delaying flight f on the ground to time its landing at airport Z during time period i.

The following 0-1 program solves the deterministic single-airport problem:

$$\text{minimize} \quad \sum_{f \in \mathcal{F}} \sum_{i \in \mathcal{I}_f} c_{fi} x_{fi} \tag{1}$$

$$\text{subject to} \quad \sum_{f \in \mathcal{F}} x_{fi} \leq K_i, \quad \forall i \in \mathcal{T}; \tag{2}$$

$$\sum_{i \in \mathcal{I}_f} x_{fi} = 1, \quad \forall f \in \mathcal{F}; \tag{3}$$

$$x_{fi} \in \{0, 1\}, \quad \forall (i, f). \tag{4}$$

Constraints (2) assure that the number of flights landing during time period i does not exceed capacity K_i, and (3) assure that each flight is assigned to some time period. Because the constraint matrix of this 0-1 program is totally unimodular, the linear programming (LP) relaxation of (1)–(4) yields integer solutions. In fact, it can be shown (c.f. [5]) that (1)–(4) can be formulated as a minimum-cost-flow in a capacitated-network, allowing algorithmic solutions that are even more efficient than general LP algorithms.

2.2 Stochastic-Dynamic Formulation

The stochastic scenario assumes that a number $C > 1$ of capacity scenarios can materialize and that, sometime before the earliest departure time of all aircraft headed towards airport Z, we are given a probabilistic forecast for the evolution of the capacity of airport Z by specifying, for each capacity scenario c, a probability of occurrence p_c. Here, even though we present a general formulation, for more clarity we will use the actual numerical example based on 1991 schedule data for Boston Logan Airport examined in Section 3. Consider a situation where we expect a weather front to hit the airport area around 5:30 pm and reduce its landing capacity by 50% (see Fig. 1).

At 12 pm, the time at which we have to make a decision for the first flight scheduled to land at Logan after 5:30 pm, we can only assign a probability of occurring, p_2, to the reduced-capacity scenario CAP-2. With probability $p_1 = 1 - p_2$ the weather front will not affect the

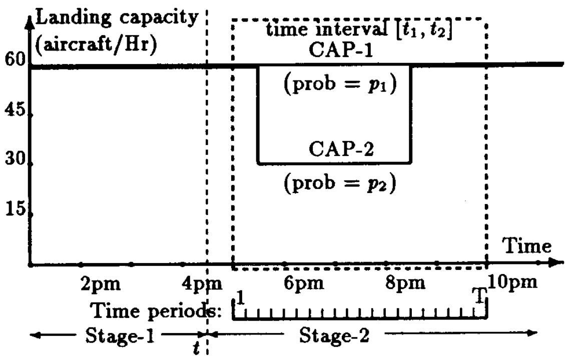

Figure 1: *Capacity Scenarios*

airport and the capacity will remain at its highest level of 60 landings per hour (CAP-1). At 5:30 pm we can observe whether the weather front has actually hit the airport or not. We can then take recourse action for flights arriving at the airport in the form of airborne delays, and assign ground holds for flights that have not yet taken-off, depending on the actual capacity scenario in place. To keep the formulation general, we will assume that deterministic capacity information is available at some time t before 5:30 pm; this would be the case, for example, if we use a capacity forecast system. In what follows, the time interval before time t will be referred to as "Stage 1" and the flights scheduled to take-off before time t as "Stage 1 flights;" the time interval after time t will be referred to as "Stage 2" and the flights scheduled to take-off after time t as "Stage 2 flights" (see Fig. 1).

For each flight f we define 0-1 decision variables as follows: $x^c_{fij} = 1$ if flight f is scheduled in Stage 1 to land during time period i, and rescheduled in Stage 2 to land during time period j for capacity scenario c; $x^c_{fij} = 0$ otherwise. For a Stage 1 flight f, the Stage 1 assignment to time period i is effected through a ground hold computed to time the arrival of flight f during time period i *without* any airborne delay, while the reassignment to time period j involves an airborne delay of duration equal to the difference between time period i and time period j, and should depend on the capacity scenario in effect during Stage 2. For a Stage 2 flight f, on the other hand, the decision variables x^c_{fij} are defined only for $i = j$, reflecting the fact that for such a flight there is only one Stage 2 decision corresponding to an assigned landing time period for each capacity case c.

The reassignment (during Stage 2) of a Stage 1 flight to a different landing time period than the one assigned at departure time can be effected through any combination of airborne control such as rerouting, speed reduction, and low-altitude delays immediately before landing. Indeed our formulation allows for all such actions. However, experimental results show that optimal delay policies involve no rerouting and a negligible amount of speed reduction, even though rerouting actions are assigned smaller costs than low-altitude delays, and speed reductions are assigned smaller costs than ground delays (to reflect savings in fuel relative to regular cruising speed). For rerouting, the reason is that, in this formulation, it is only used for hedging against costly low-altitude delays, and ground holds are a cheaper means of accomplishing the same thing. It remains that rerouting could be an important instrument of flow management if other elements of the air traffic network, such as airways, way-points, or sectors, are congested (this paper assumes that the destination airport is the only congested element). The reason for almost no speed reductions, on the other hand, has to do with the fact that such actions apply only during the cruising part of the flight which is very short for medium-haul flights and non-existent for short-haul flights. It is therefore useful to think of airborne delays as referring only to low-altitude holds in what follows.

To each decision variable x^c_{fij} is assigned a cost c_{fij} that, for a Stage 1 flight, includes both a ground cost component (corresponding to the Stage 1 assignment to time period i) and an airborne cost component (corresponding to the Stage 2 reassignment to time period j), and, for a Stage 2 flight, includes only a ground cost component. The same argument used to justify considering only ground holds in the deterministic formulation applies here: we need not consider airborne delays for Stage 2 flights because airborne delays are costlier than ground delays and because capacities are known deterministically in Stage 2.

The resulting 0-1 stochastic program is:

$$\text{minimize} \sum_{c \in \mathcal{C}} p_c \, [\sum_{f \in \mathcal{F}} \sum_{i \in \mathcal{I}_f} \sum_{j \in \mathcal{J}_{fi}} c_{fij} x^c_{fij}] \qquad (5)$$

Subject to

$$\sum_{f \in \mathcal{F}} \sum_{\{i:(i,j) \in \mathcal{I}_f \times \mathcal{J}_{fi}\}} x^c_{fij} \le K^c_j, \quad \forall j \in \mathcal{T};\ \forall c \in \mathcal{C}; \qquad (6)$$

$$\sum_{i \in \mathcal{I}_f} \sum_{j \in \mathcal{J}_{fi}} x^c_{fij} = 1, \quad \forall f \in \mathcal{F},\ \forall c \in \mathcal{C}; \qquad (7)$$

$$\sum_{c \in \mathcal{C} \setminus \{1\}} \sum_{j \in \mathcal{J}_{fi}} x^c_{fij} - (C-1) \sum_{j \in \mathcal{J}_{fi}} x^1_{fij} = 0, \quad \forall f \in \mathcal{F}^1, \forall i \in \mathcal{I}_f; \qquad (8)$$

$$x^c_{fij} \in \{0,1\}, \qquad \forall\ (c,f,i,j); \qquad (9)$$

where:

- $\mathcal{C} = \{1, \cdots, C\}$ is the set of capacity scenarios in the probabilistic forecast;
- $\mathcal{F}^1$ is the set of Stage 1 flights;

- $\mathcal{J}_{fi}$ is the set of feasible landing time periods for flight f if it is scheduled to time period i in Stage 1, based mainly on fuel and allowable flight-plan considerations; and
- K_i^c is the landing capacity of airport Z during time period i if capacity scenario c materializes.

Constraints (6) and (7) are capacity and assignment constraints relative to each capacity scenario. Constraints (8) are defined only for Stage 1 flights and reflect the fact that a decision to allow a Stage 1 flight f to take-off has to be made *before* knowing which capacity case will materialize. The constraints insure that if we have $x_{fij}^c = 1$ for some $(i\ j\ c)$, we have, for any other capacity case c', $x_{fik}^{c'} = 1$ for some time period k, thus forcing the Stage 1 take-off decision (index i) to be the same for each capacity scenario.

Note that (8) are *complicating constraints* in the sense that, without them, the problem reduces to C *independent* deterministic problems, each one corresponding to a capacity scenario in the probabilistic forecast (i.e., the constraint matrix for (5)–(7) is totally unimodular). However, even though it can be shown (c.f. [3]) that the addition of constraints (8) breaks the total unimodularity property of the constraint matrix, in practice the LP relaxation of (5)–(9) yields integer solutions in the vast majority of cases. We had to construct an example with a peculiar objective function to find a non-integer extreme point of the polytope. This suggests that the integrality property of solutions is strongly linked to the structure of the cost vector. Indeed, numerical results (see Section 3) suggest that it has to do with the fact that, because many flights have the same cost functions in our numerical examples, there are several optimal solution to (5)–(7) and that for some of them constraints (8) are self enforcing.

3 Experimental Results

The following numerical examples use 1991 schedule and capacity data for Boston Logan Airport. We consider the situation depicted in Fig. 1, with two capacity scenarios. Ground delays for all flights are assigned a cost of \$1,000/hour, with airborne delays twice as costly (these are realistic cost figures reflecting operating costs for a midsize commercial jet aircraft).

3.1 Trade-Offs Between Ground Holds and Airborne Delays

Fig. 2 shows the results of solving (5)–(9) for different values of p_1/p_2 and compares the level of total airborne delays to that of total ground delays for optimal policies. As can be expected, with good weather conditions (a high

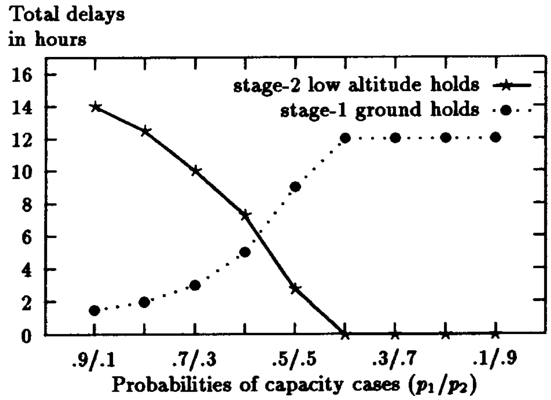

Figure 2: *Trade-off between ground holds and airborne delays*

p_1/p_2 ratio) few ground holds are necessary, the optimal delay policy allowing for a large amount of airborne delays as these are incurred only rarely. On the other hand, as the weather forecast worsens the optimal policy relies almost entirely on ground delays to hedge against costlier (and more likely) airborne delays.

3.2 Comparison With Other Delay Strategies

This numerical experiment compares the performance of different delay policies. Fig. 3 shows the results of using three different delay strategies: (1) FCFS-1 and FCFS-2 correspond to *deterministic* approaches to the problem and consist of considering a deterministic capacity forecast (CAP-1 for FCFS-1, CAP-2 for FCFS-2) and assigning flights to available capacity in a first-come, first-served basis, according to scheduled arrival times, a policy comparable to present practices (of course, policies are revised when a different capacity scenario materializes; the lower envelope of the curves FCFS-1 and FCFS-2 can be interpreted as the "best" deterministic approach possible); (2) STOCHASTIC corresponds to the optimal delay strategy obtained from solving (5)–(9); and (3) PERFECT corresponds to policies computed assuming that we have perfect knowledge about capacities, i.e., that at 12 pm we always know which capacity scenario will materialize.

The results show that the probabilistic approach (STOCHASTIC) yields policies that, in terms of total expected delay costs, are superior to any first-come, first-served deterministic approach, and are close to the PERFECT policy.

The above numerical experiment assumes that we have to wait until 5:30 pm to determine which capacity case will materialize by simple observation. If we use a forecast system, such information will be available earlier. The

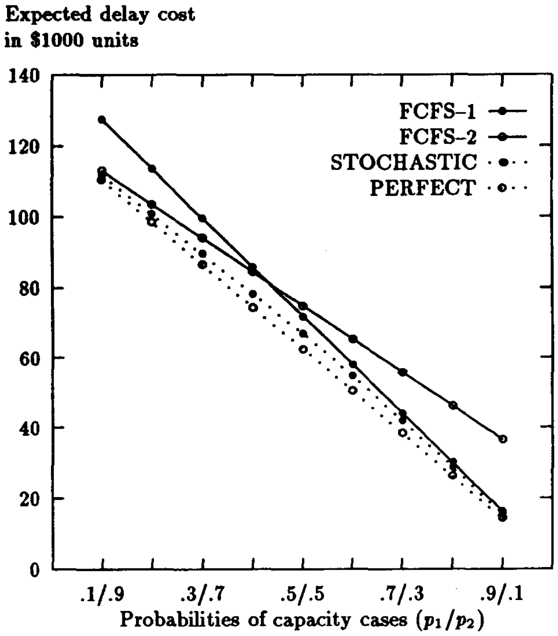

Figure 3: *Comparison with other delay strategies*

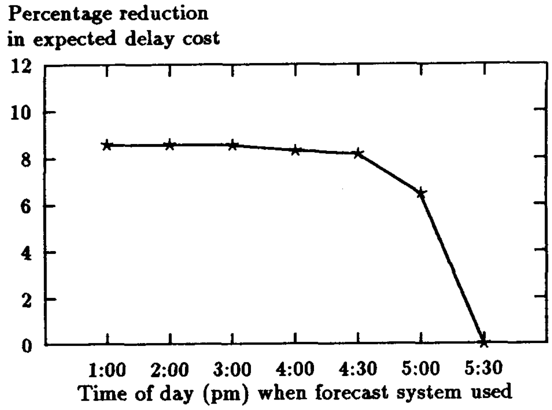

Figure 4: *Impact of timing of capacity forecast updates*

next experiment is intended to evaluate the benefits of advance information.

3.3 Value of Early Capacity Information

Fig. 4 compares the savings in total expected delay costs for developing delay policies that use early capacity information, relative to waiting until 5:30 pm. This corresponds to using different values for time t in the formulation, i.e., solving (5)–(9) with sets $\mathcal{F}^1$ of various sizes. It shows savings in total costs of about 8% for knowing capacity information at 4:30 pm, with almost no gain for earlier information. The interpretation of these results leads us to discuss an interesting structural insight into the problem: optimal ***dynamic*** policies tend to impose very little ground delays on Stage 1 flights. A very simple two-flight example to illustrate this phenomenon can be found in [6], but it should be intuitively clear why this is true: an optimal dynamic delay policy will allow as much on-time takeoffs for Stage 1 flights as possible, in order to permit as much "fine tuning" of the delay policy as possible through ground holds on Stage 2 flights, thus taking full advantage of deterministic capacity information available in Stage 2. The opposite strategy—imposing excessive ground holds on Stage 1 flights—would lead to a greater amount of unused capacity at the destination airport in the event of high capacity scenarios.

This observation also explains why the experiment of Fig. 4 does not show much benefit for capacity information before 4:30 pm: there are already enough Stage 2 flights taking-off after 4:30 pm that can be used for this "fine tuning," so that having capacity information before that time is of little value (i.e., the new optimal solution is simply obtained by switching the roles of some Stage 1 and Stage 2 flights). This last observation also confirms our suspicion about the existence of multiple optimal solutions, explaining the integrality of solutions of the LP relaxation of (5)–(9) (see Section 2.2).

The above observation points to a practical drawback of optimal dynamic policies based on minimizing total expected delay costs. Because Stage 2 flights incur most of the ground holds and because Stage 2 flights tend to be short-haul flights, dynamic policies will consistently penalize short-haul flights in favor of long-haul flights. This bias is reinforced when we consider that delay costs for flights will depend on the size of the aircraft operating the flight, as we now investigate.

3.4 Distribution of Delays Among Categories of Users

So far we have taken the delay costs to be uniform across all flights. The following experiment introduces a ***combinatorial*** element in the problem by considering individual delay costs that reflect aircraft size. To generate individual costs, three groups of aircraft are considered: wide-body jets, medium-size jets, and small commuter aircraft with ground delay costs of $2,000/hour, $1,200/hour, and $800/hour, respectively. The aircraft mix used is 20% wide-body jets, 40% medium-size jets, and 40% commuter aircraft, reflecting the actual aircraft mix at Logan Airport. We compare several delay strategies in terms of the amount of average total (ground + airborne) delays they impose on each aircraft type, with the results shown in Table 1.

The row "Stoch-comb" of Table 1 corresponds to the op-

Table 1: *Distribution of delays among aircraft types*

Flow management strategy	Avg. delays in minutes			Expected delay cost
	small size	medium size	large size	
Stoch-comb	21.61	6.40	0.00	$37,987
Stoch-comb-limit	19.52	8.25	0.62	$39,714
Stoch-comb-alpha	16.03	9.63	4.86	$42,294
Stoch-avg	15.00	10.22	6.36	$43,989
FCFS	13.48	10.43	9.31	$48,909

timal delay strategy obtained from solving (5)–(9) using combinatorial costs and assuming $p_1 = .7$ (and $p_2 = .3$). Not surprisingly, the results show that the optimal (combinatorial) delay policy assigns as many delays as possible to small aircraft, before assigning any delays to medium-size ones, and no delays to large aircraft. Therefore, since most short-haul flights are operated by small aircraft, introducing the combinatorial aspect reinforces the bias against short-haul flights inherent in dynamic policies.

We compare four different strategies to try to introduce more equitability in delay distribution. "Stoch-comb-limit" is obtained from the same formulation used for "stoch-comb" except that we set a limit on the amount of delay that can be imposed on any given flight (we used 75 minutes). The delay policy obtained is slightly more equitable than the "Stoch-comb" policy, at the expense of an increase in total expected delay costs. The policy "Stoch-comb-alpha" is obtained by solving (5)–(9) and by temporarily disturbing the delay cost curves for individual flights to show an increase in the cost of delaying the same flight continuously, thus hoping for a solution that distributes delays among flights. Mathematically, we used cost functions such that, for all i, $c_{f(i+1)} = c_{fi}(1+\alpha)$, for some fixed coefficient $\alpha > 0$. The delay policy "Stoch-avg" is obtained from solving (5)–(9) using the same average delay cost for all flights as was done in earlier experiments. The results for the last two strategies show a better distribution of delays among users, with an increase in total expected delay costs. For these last two strategies, even though the delay policies are obtained by temporarily using "artificial" cost functions, the costs shown in the last column of Table 1 are still computed using combinatorial costs for comparison purposes. In fact, for these two strategy, flights cannot be distinguished on the basis of their costs; the remaining differences in average delay per flight type are entirely due to the previously mentioned bias of dynamic policies in favor of Stage 1 flights, and the fact that there is a greater proportion of large aircraft among Stage 1 flights. Finally, "FCFS" corresponds to a policy obtained with a deterministic approach using the "best" deterministic capacity scenario (i.e., the capacity scenario with the lowest expected delay cost—CAP-1 in this case) and assigning flights to this capacity in a first-come, first-served manner based on scheduled arrival times. The result show a good distribution of delays among flight categories, but with a large increase in total expected delay costs.

4 Concluding Remarks

The above results point to the need for mathematical models and decision support tools for air traffic flow management that explicitly take into consideration the uncertainty in weather conditions. Besides their potential in providing support for day-to-day flow management, these tools could also provide guidance in using capacity forecast systems.

The results also show that there are equity issues in using stochastic and combinatorial information, because of the inherent bias of dynamic policies against short-haul flights and of combinatorial policies against small aircraft. Clearly, such equity issues will have to be dealt with in any real life implementation of automated flow management. Nevertheless, we have illustrated the ability of the proposed formulation to somewhat redistribute delays among classes of users.

Finally, it should be noted that a major assumption of the single airport formulation is that the departure times corresponding to the ground holds are always feasible. This may of course not be a valid assumption in some cases, e.g., when ground holds create departure congestion at the origin airports. The authors are presently working on multi-airport formulations that extend the single-airport formulation described here.

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