Strategic Aircraft Flow Re-allocation vs Dynamic Air Traffic Flow Management

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Abstract

In several European countries, including Germany, Italy and Spain, the flag carriers typically connect national airports to major foreign airports using a couple of national hubs. If one airport often experiences congestion due to airport capacity restrictions, then, beyond adopting the necessary air traffic flow management measures, it is advisable to redirect some demand from the more congested airport to the less congested one.

The purpose of this paper is two-fold.

First, we present an original aggregate model for estimating delays. The model we propose, in the domain of Air Traffic Flow Management models, extends previous approaches by simultaneously taking into account three important issues: (i) the model explicitly incorporates uncertainty in the airport capacities using scenarios; (ii) it also considers the trade-off between airport arrivals and departures, crucial issue in any hub airport; and (iii) it takes into account the interactions between the two hubs.

The second aim is to provide a quantitative appreciation of the overall capacity gain to be achieved through reallocation of demand. This can be indirectly evaluated by a measure of the overall delays: a major reduction in delays will obviously indicate an increase in the overall capacity of the system.

Computation of numerical instances clearly shows in quantitative terms the benefits of demand re-allocation.

Keywords: ATFM model, hub and spoke operations, stochastic programming, strategic flow management, decision analysis.

1 Introduction

The worldwide growth in air traffic during the last several decades has been dramatic. As a result, air traffic management has become increasingly crucial. Air Traffic Management (ATM) consists of all processes that support the goal of safe, efficient, and expeditious aircraft movement. In addition to the tactical separation services provided by Air Traffic Control, a more "macroscopic" management of traffic flows is used to address system-wide efficiency. Generally speaking, Air Traffic Flow Management (ATFM) considers strategic procedures which aim to detect and resolve demand-capacity imbalances by adjusting aggregate traffic flows to match scarce capacity resources. ATFM initiatives can be classified according to their time horizon (see [18]). Long-term initiatives, such as the construction of new runways typically aim to increase capacity. Medium-term approaches, such as the use of slot auctions or congestion pricing, are mostly administrative or economic in nature, and try to alleviate congestion by modifying spatial or temporal traffic patterns. Short-term approaches consider the operational adjustment of air traffic flows to match available capacity, and typically span a planning horizon that is less than 24 hours. These operational ATFM initiatives attempt to mitigate the congestion that may arise from unforeseen disruptions as efficiently as possible. Such periods of congestion arise frequently when bad weather causes sudden capacity reductions. The most popular approach, by far, in resolving these short-term periods of congestion, has been the allocation of ground delays. In the U.S., for instance, the FAA implements approximately 500 Ground Delay Programs (GDPs) per year. Ground delays refer to the idea that flights are delayed prior to their departure; the reason being that it is generally both safer and less costly to delay flights on the ground, rather than flights that are airborne. The Ground Holding Problem considers the development of strategies for allocating ground delays to aircraft, and has received considerable attention (see [2, 6, 16] to mention just a few of the most recent ones).

Yet in spite of their prominence and the considerable focus on the development of appropriate decision support tools, several issues with regard to the allocation of ground delays remain wide open. A first issue is the stochastic nature of the capacity reductions (e.g. due to bad weather conditions), and the allocation of ground delays in this setting. During September and October 2002, for instance, 111 GDPs were executed in the U.S. Only 17% of these GDPs ran to their completion (that is, according to the initial plans implemented by air traffic managers). This statistic clearly shows that most GDPs are revised during operations, since air traffic managers are generally not able to foresee capacity fluctuations. As such, decision models that explicitly take into consideration uncertainty may improve ATFM operations. For these reasons the proposed model explicitly incorporates uncertainty in the airport capacity. This important issue will be addressed through the use of scenarios. The model discussed in this paper is based on a generalization of the traditional ground holding model, known as the capacity allocation model. Unlike most models that are concerned only with arrival capacity, the proposed model will also take into account a second important issue, i.e., the possible trade-off between arrival and departure capacities, that are absolutely critical in most hub airports. Finally, a third issue is the network impact that results when ground delays are imposed at different, interdependent airports. In the U.S., for instance, there have been situations during which 10 GDPs were executed simultaneously (see [17]). Clearly the use of GDPs, which only address capacity reductions at a single airport, do not take into account the system-wide effects of these interdependent decisions. In the European airport network, it is quite common that a flag airline of a Nation uses a couple of hub airports. This is the case of Spain, Germany and Italy, just to mention a few. The hubs are the airports most responsible for propagating delays to the remaining airports of the network. The model proposed in this paper, allows for an exchange of flows between the hub airports of the same Nation. This exchange of flows is something that is already practiced by some airlines. The key concept is that for passengers that use the hub airports only for transfer purposes, it is absolutely irrelevant in which airport they have to transfer, as long as there is a good flight connection. Therefore, to some extent, at least a partial exchange of traffic can be moved from one hub airport to the other one. Although we do not fully take into account all the network consequences, we believe that considering the (couple of) hubs incorporates most of such consequences. To better address these three issues, namely: uncertainty, arrival-departure capacity trade-off and network effects, we decided to build a macroscopic model rather than a microscopic one. In other words the proposed model will suggest how many flights should be delayed during each time period under consideration, rather than providing detailed suggestions on how much delay should be imposed on each single flight.

It is also important to note that this macroscopic approach is perfectly consistent with the Collaborative Decision-Making (CDM) paradigm in ATFM (see [8]). The models presented in this paper concur with this approach due to their focus on aggregate capacities, as opposed to the consideration of individual flights. Given these aggregate capacity profiles, CDM procedures could be used to distribute the slots among individual flights. Notice that in the extreme case where all operations were run by a single airline, our model will find how many flights should be delayed (and this is a decision that belongs to the ATFM Authority) while the airline will decide which individual flights should be delayed (this is a decision that belongs to the airline). In the more realistic case where more than one airline is using the airport, then there will also be the need of an intermediate decision, i.e., how many flights of each company should be delayed. This again could be resolved through CDM measures. Typically, at a European hub airport, half of the traffic is carried out by one company (the flag company).

In the paper we will also test our model on a few numerical instances in order to provide a quantitative evaluation of the capacity gain that can be achieved through reallocation of demand. An indirect measure of it will be a major reduction of the overall delays. Computational results clearly confirm these expectations.

The paper is organized as follows: In Section 2, we formally describe the capacity allocation problem. In Section 3, we present a formulation for the tactical capacity allocation problem. Computational experiments and analyses of these models are given in Section 4. Finally, Section 5 contains conclusions and indications for future research.

2 Problem Description

In this paper, we propose a multi-airport capacity allocation problem to manage congestion phenomena in ATFM. Generally speaking, our objective is to compute an optimal mix of arrivals and departures for a given network of airports, that is, a mix of arrivals and departures that minimizes the total delay over all the airports during the periods of congestion.

To be more precise, we consider a given set of airports $\mathcal{K}$ and, for each airport, a given demand for both arrivals and departures during a time horizon $[0, T]$ for which we expect congestion. The time horizon is discretized into time periods. The resulting demands can be represented by set of parameters $D_\tau^{h,k}$, where h denotes the origin airport, k the destination airport, and τ the requested take-off time. If we use $FT^{h,k}$ to represent the flight time between airports h and k, $D_\tau^{h,k}$ implies a demand for departures at airport h during time period τ and a demand for arrivals at airport k during time period $\tau + FT^{h,k}$. Later on in this paper, $D_\tau^{h,k}$ will be used to denote the cumulative demand of departures up to time period τ. We represent the airport capacity by a so-called airport capacity envelope, which incorporates the trade-off between arrivals and departures. Specifically, for each airport $k \in \mathcal{K}$ and time period $t \in \{1, \ldots, T\}$ the airport capacity envelope $\mathcal{E}(k, t)$ denotes the feasible combinations of arrivals and departures at airport k during time period t. We note that a pair of airports is connected if there exists a non-zero air traffic flow between the two airports. To summarize, the resulting problem can now be stated as follows. Given the parameters described above, compute for any time period t and for any airport of the network k the delay-optimal flow of in-bound and out-bound flights while satisfying the capacity constraints on the mix of arrivals and departures at each airport of the network during each time period. The resulting model can incorporate both deterministic and stochastic problem data.

In the *Deterministic Case*, all problem parameters (e.g. the airport capacities and the en-route flight times) are assumed to be deterministic and known. There are several reasons to study a deterministic problem. First, there are situations where it is reasonable to assume that capacities can be forecast with little error. This is typically true for airports located in areas where changes in weather conditions are relatively predictable and where weather patterns, once established, remain stable for longer periods of time. Another motivation for the use of deterministic models is that they form the basis for the development of stochastic models. The deterministic capacity allocation model was first introduced by Gilbo (see [12]), who proposed an optimisation model to resolve short-term periods of congestion. Subsequently, this model was extended (see [13]) by considering both airport (i.e. runway) and fix capacities jointly as a single system resource. In related papers (see [9, 10]), Dell'Olmo and Lulli proposed capacity allocation models that incorporated both the single- and the multi-airport version of the problem. They proposed an efficient dynamic programming formulation for the single-airport capacity allocation problem. The single-airport capacity allocation problem has also been studied within the context of Collaborative Decision Making by Hall (see [15]). This approach was based on a constraint-coordinated decomposition of the airport capacity allocation problem. In this model, airlines are decision-makers, that adjust their arrival-departure mix at the airport during a ground delay program based on their internal trade-offs. The model was analyzed using a simulation study that investigated the impact of the mentioned methodology on the air transportation system during GDPs.

In the *Stochastic Case*, addressed in this paper, we consider situations where airport capacity is uncertain. As a result, the airport capacity envelopes $\mathcal{E}(k,t)$ are represented as random variables. In most stochastic programming applications, however, a complete and accurate description of a complex stochastic process may be difficult to obtain. As such, it is common to consider a finite set of scenarios, where each scenario describes a possible trajectory of the random variables over time. This assumption implies that we are assuming random variables with finite support (see Birge and Louveaux [5]).

It is important to note that in the stochastic framework, the assignment of both ground and airborne holding delays are used as control decisions to define the appropriate mix of departures and arrivals. In fact, using exclusively ground delays may lead to too conservative decision policies based on the worst case scenario. The assignment of airborne holding delay allows a more efficient use of the airport capacity and helps in hedging against uncertainty.

3 The Stochastic Programming Formulation

As discussed in the previous section, we assume that the information on the airport capacity is given by a discrete time stochastic process $\{\omega_t\}_{t=1}^{|\mathcal{T}|}$ defined on some probability space $(\Omega, \mathcal{F}, \mathcal{P})$. Under the hypothesis of a random vector with finite support, then $\Omega = (\omega^1, \ldots, \omega^r)$ with probabilities $p^1, \ldots, p^r$. Each scenario represents a realization of the random variable corresponding to an elementary atom $\omega \in \Omega$. The relationship between scenarios is represented via a scenario tree $\Im$, which captures the evolution of all information trajectories over time. At any node of the tree, there are several branches to indicate possible outcomes of the future which is modelled by random variables (associated with each node of the tree). Such a construction allows us to specify the events and probabilities in a natural way by conditioning on the events leading up to the current stage. Each scenario is represented by a path from the root node (at stage 1) to a leaf node (at stage T) of the scenario tree. Note that with the exception of leaf nodes, all other nodes of the scenario tree may belong to more than one scenario.

In our model, we assume that the flight time between each pair of airports is the same for all the aircraft. In our aggregate model, this hypothesis is reasonable since it does not introduce a too large approximation especially if we limit our attention to commercial aviation airports, as in our case.

The deterministic version of this problem has been formulated in [10]. Here, we formulate the problem as a multi-stage stochastic integer program, using the following notation:

$\mathcal{S} \equiv$ is the set of scenarios each denoted by s,

$D_t^{h,k} \equiv$cumulative requested number of departures from airport h to airport k up to time t,

$FT_s^{h,k} \equiv$ flight time between airports h and k in scenario s,

$\mathcal{K} \equiv$ set of airports,

$\mathcal{T} \equiv$ set of decision time intervals,

$\mathcal{E}_s(k,t) \equiv$ capacity envelope of airport k at time t in scenario s,

$p_s \equiv$ probability of scenario s,

$c_g \equiv$ cost due to one period of ground holding,

$c_a \equiv$ cost due to one period of airborne holding.

Given this notation, the decision variables can be defined as follows:

$d_s^{h,k}(t)$: the number of departures from airport h to airport k by time t in scenario s,

$a_s^{k,h}(t)$: the number of arrivals at airport k from airport h by time t in scenario s.

The decision variables represent cumulative numbers of departures and arrivals at the given airport for each time period. Therefore, they are non-decreasing functions of the time periods. The resulting objective function is the expected weighted average delay (to be minimized).

$$Min \sum_{s \in \mathcal{S}} p_s \sum_{k,h \in \mathcal{K}, t \in \mathcal{T}} [c_a(a_s^{k,h}(t) - D_{t-FT_s^{h,k}}^{h,k}) - (c_g - c_a)(d_s^{k,h}(t) - D_t^{h,k})]$$

The decision variables are subject to the following conditions:

$$\begin{aligned}&(\sum_{k\in\mathcal{K}} d_s^{h,k}(t) - d_s^{h,k}(t-1),\\ &\quad \sum_{j\in\mathcal{K}} a_s^{j,h}(t) - a_s^{j,h}(t-1)) \in \mathcal{E}_s(h,t)\end{aligned} \qquad \forall h\in\mathcal{K},\ \forall t\in\mathcal{T},\ \forall s\in\mathcal{S}. \tag{1}$$

$$d_s^{h,k}(t) \le D_t^{h,k} \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T}\setminus\{T\},\ \forall s\in\mathcal{S}. \tag{2}$$

$$d_s^{h,k}(T) = D_T^{h,k} \qquad \forall k,h\in\mathcal{K},\ \forall s\in\mathcal{S}. \tag{3}$$

$$d_s^{h,k}(t) = d_{s'}^{h,k}(t) \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T},\ \forall s\in\mathcal{S}\ \forall s'\in\mathcal{B}_s^t. \tag{4}$$

$$a_s^{h,k}(t) \le d_s^{h,k}(t - FT_s^{h,k}) \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T}\setminus\{T\}\ \forall s\in\mathcal{S}. \tag{5}$$

$$a_s^{h,k}(T) = d_s^{h,k}(T - FT_s^{h,k}) \qquad \forall k,h\in\mathcal{K},\ \forall s\in\mathcal{S}. \tag{6}$$

$$a_s^{h,k}(t) \ge= a_s^{h,k}(t-1) \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T}\ \forall s\in\mathcal{S}. \tag{7}$$

$$d_s^{h,k}(t) \ge= d_s^{h,k}(t-1) \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T}\ \forall s\in\mathcal{S}. \tag{8}$$

$$d_s^{h,k}(t), a_s^{h,k}(t) \in \mathcal{Z}^+ \qquad \forall k,h\in\mathcal{K},\ \forall t\in\mathcal{T},\ \forall s\in\mathcal{S}. \tag{9}$$

where $\mathcal{B}_t^s$ represents the set or bundle of scenarios that are indistinguishable from scenario s at time t, i.e. all scenarios u for which $\omega_\tau^u = \omega_\tau^s$ for all $\tau = 1,\ldots,t$. Therefore, for each node n of the scenario tree $\Im$ uniquely defined by the scenario s and time t, the bundle of scenarios is the set of all the scenarios, i.e. root-leave paths passing through the node $n \in \Im$.

The first set of constraints represent capacity constraints, where the first term on the left hand side equals the total number of flights in arrival while the second term equals the total number of departures at the considered airport h in the specified time period t. We here suppose that the airport capacity is unbounded at the last time period T in order to assure problem feasibility. The set of constraints 2 and 3 states that all of the flight demand must be satisfied by means of flight delays. Constraint 4 represents the non-anticipativity requirement. Constraints 5 and 6 are the *coupling* constraints. These constraints explicitly "link" together the arrival and departure variables, where the connection follows from the flights demand. Constraints 7 and 8 state that decision variables are time-periods non-decreasing functions. Finally, the integer requirements on the decision variables are stated.

As in all stochastic programming problems, the non-anticipativity constraints state that decisions depend only on information revealed in the past and not in the future, i.e. all scenarios with same history until the t-th stage should result in the same decisions until this stage. Therefore, we make decisions before realizing the random outcomes of airport capacity and origin-destination flight times.

We recall that the stochastic programming formulation presented above, with respect to its deterministic counterpart ([10]) does also formalize the assignment of airborne holding delay as a control action. Therefore a trade off exists between the assignment of ground delay, which is certain, and the possible assignment of airborne holding delay, which is uncertain and imposed only in case of a capacity reduction. Varying the ratio c_a/c_g, a wide range of operational "situations" can be defined. For big values of the ratio ($c_a >> c_g$), the problem is equivalent to a formulation (OGH model) where the ground delay is the only control action, as opposed to the case with $c_a \leq c_g$ where the only one control action would be the assignment of airborne holding. Obviously, this last operational situation is rather unrealistic while the former one leads to too conservative solutions based on the worst scenario (in terms od capacity evolution).

Finally, note that our approach could also accommodate, at least in principle, uncertainty in the flight times $FT^{h,k}$. This would more accurately reflect ATFM operations. More specifically, it will be useful to address issues related to sector congestion which are of particular relevance within the European ATFM context. However, this extension is not pursued here.

4 Settings for experimental analysis

For our experimental analysis, we consider a small network of Italian airports composed of two hubs, Rome Fiumicino and Milano Malpensa, and a set of spokes. We are going to simulate different operational conditions. Data on the arrivals and departures airports' demand and traffic flows, have been provided by ENAV, while the capacity envelopes have been generated based on simulation using the aircraft-sequencing model described in [7]. We focused on these two airports because they represent a typical instance we want to consider.

The capacity envelope is represented in the model as random variable, in order to capture its uncertain evolution over time. Since few data are available at the moment, we use randomly generated instances. In particular, we consider the case where only one airport has uncertain capacity while the capacity of the other airport takes on deterministic values. In our analysis, we have also assumed that the capacity envelopes do not change over time up to a scale factor. A possible evolution of the scale factors is represented by a scenario. The scenario tree used in our computational analysis, is schematically depicted in Figure 1.

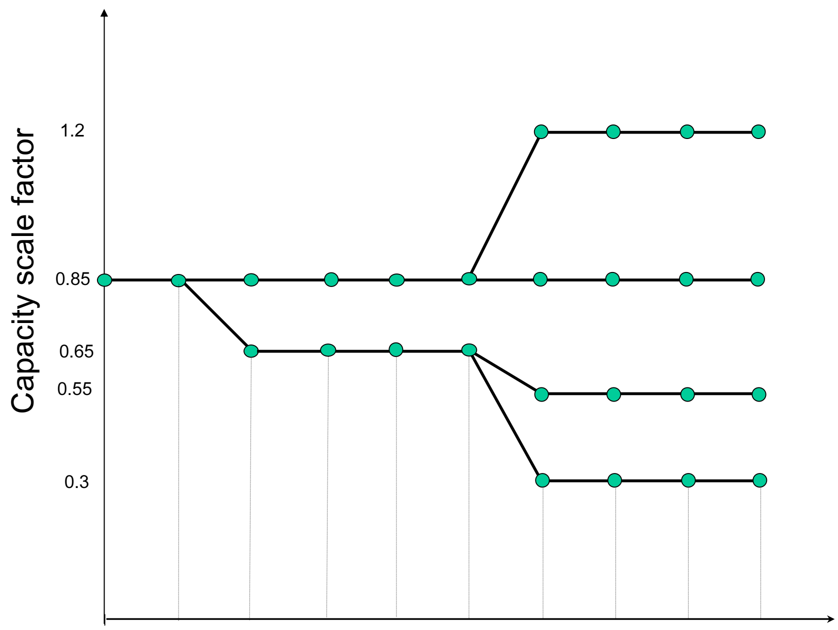

Figure 1: *Scenario Tree.*

In particular, the conditional probability for any branch is denoted by p_n, so that the other branch has conditional probability $1 - p_n$, where n denotes a node of the tree. p_n is randomly chosen from the uniform [0,1] distribution. By choosing alternative values of p_n, as well as various values of the capacity scale factor, we generated different problem instances.

4.1 Computational Experience

In this section we show the potential benefits of hedged solutions with respect to deterministic counterpart. To solve both the stochastic formulation and its deterministic counterpart we used CPLEX 7.0 Branch and Bound method (CPLEX-MIP), implemented using AMPL as the modelling language. A CPLEX default relative tolerance of 0.0001 is set. We run our experiments on a two-processor, 1 GB RAM SUN Ultra 80 workstation.

The stochastic model computes here-and-now decisions, i.e. decisions that are implemented before the realizations of the random variable becoming known. Decisions depend only on the history of the system, that is, on the values assumed by the random variables in the previous stages (time periods). We here introduce two measures to gauge the value of stochastic programming: the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS). These are standard measures to evaluate the benefits of taking into account uncertainty, see Birge and Louveaux [5]. The EVPI measures the maximum amount a decision maker would be ready to pay in return for complete and accurate information about the future. Having perfect knowledge of airport capacity would enable the decision maker to devise appropriate (best) decision policies. We can quantify its value to see the importance of having accurate weather forecast and consequently airport capacity estimations. The VSS measures the cost of ignoring uncertainty in making a planning decision. This value is computed comparing the value obtained by solving the stochastic program with the "expected value" of the deterministic solution, obtained by plugging the deterministic solution of the program which replaces all the random variables with their expected values, into the original probabilistic model.

We run several computational tests, using different demand patterns (named $d1, \cdots, d5$) and two different discrete probability distributions, one with more equiprobable scenarios ($p1$) and the other with the following probabilities for each scenario: 0.12, 0.48, 0.225 and 0.175. Moreover, the evolution of airport capacities is modelled by a capacity scale factor whose evolution in represented by the scenario tree depicted in Figure 1. The final values of the airport capacity factor, for each scenario, are: 1.2 for the first scenario, 0.85 for the second scenario, 0.55 and 0.3 for the third and the fourth scenario respectively.

We summarized the results in the following table where we report the instance, the value of the stochastic solution (Stoc), the solution value (Det) of the deterministic program which replaces all the random variables with their expected values, the perfect information solution (PIS), the expected value solution (EVS) and finally the expected value of perfect information (EVPI) and the value of stochastic solution (VSS). Note that, the deterministic program, from now on, is the mathematical program which replaces all the random variables with their expect value.

The value of the stochastic solution is here always larger than the value of the corresponding deterministic solution. This is because the unit cost of airborne holding delay is higher than the unit cost of ground delay (the ratio c_a/c_g was set to 1.2).

The values on which we should focus more are the VSS values. This statistic gives a measure of the benefits of the solution of the stochastic program. Even though such values are modest, 5.74 % on average for the instance reported in Table 1, the benefits could be significant given the delays assigned every year; its annual cost was quantified by IATA in Euro 5.73 billion (year 1999).

We here give some more insights on the stochastic program solution, describing into details the solution of the $d2p2$ instance.

Figure 2 and Figure 3 depict the stochastic solutions for the two airports (hubs)

Instance	Stoc	Det	PIS	EVS	EVPI	VSS
d1 p1	879	720	760	918	15,7	4,3
d2 p1	1050	916	910	1108	15,4	5,2
d3 p1	857	758	761	886	12,6	3,3
d4 p1	844	732	742	905	13,7	6,7
d5 p1	1073	916	910	1155	17,9	7,1
d1 p2	934	751	800	977	16,8	4,4
d2 p2	1167	893	971	1253	20,2	6,9
d3 p2	940	793	817	976	15,1	3,7
d4 p2	923	769	795	998	16,1	7,5
d5 p2	1159	953	971	1264	19,4	8,3

Table 1: EVPI and VSS statistics

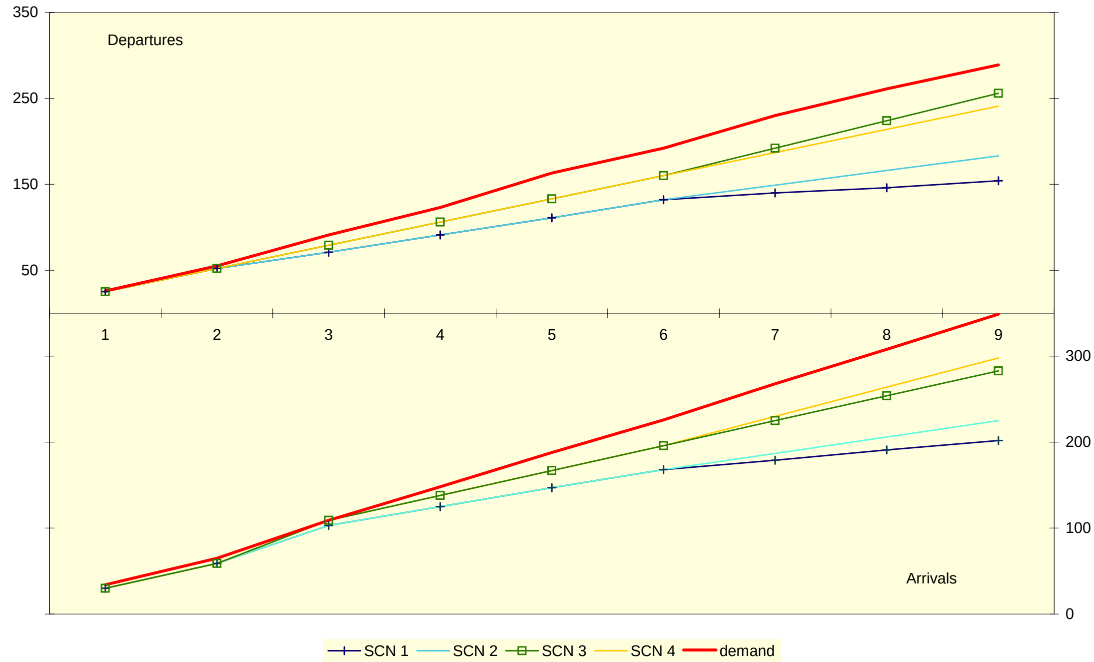

Figure 2: *Departures and Arrivals at airport 1 (stochastic solution).*

we are considering. The upper histograms show the cumulative departures while the lower histograms depict the cumulative arrivals. The red thicker line represents the cumulative demand. The other colored lines represent scenario solutions, according to the legend reported below the histogram. For any time period (reported on the x-axis), the difference between the demand and the solution represents the number of delayed flights at that period of time. For instance, at time period 5 (stage 5) at airport 1 we have 52 (41) departures (arrivals) delayed in case scenario 1 and 2 unfold and 30 (21) departures (arrivals) delayed otherwise.

We recall that, only the capacity of airport 1 is affected by uncertainty, while capacity of airport 2 is deterministic. However, due to the connection (in terms of exchange of flows of flights) between the two airports, airport 2 solution is correlated to the scenario that is unfolding in airport 1. Therefore, also airport 2 has scenario solutions, even though there is much less variability among them.

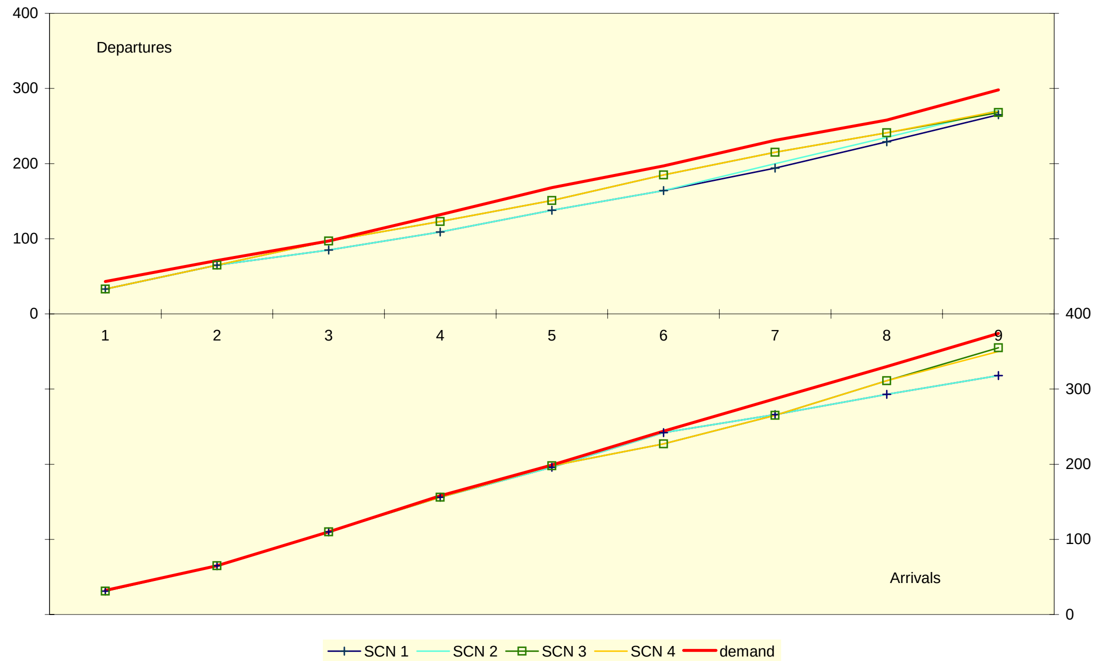

Figure 3: *Departures and Arrivals at airport 2 (stochastic solution).*

In the following table, we compare the stochastic solution and the deterministic solution. We report the departures (Dep) and the arrivals (Arr) for both the stochastic (S) and the deterministic (D) solutions in the first two time periods. We report only the first two time periods because those are the here-and-now solutions for the stochastic program.

First of all, at airport 2 the stochastic solution suggests a higher number of departures with respect to the deterministic counterpart. Indeed, some of these flights may incur in an airborne holding delay if scenarios which represent a capacity reduction unfold. On the other hand, if a scenario with enough capacity actually occurs, all the capacity is going to be used. In other words, the scope of a greater number of departures, in the stochastic framework, is to have a reservoir of incoming flights in

	Airport 1				Airport 2			
Time period	Dep D	Dep S	Arr D	Arr S	Dep D	Dep S	Arr D	Arr S
1	23	25	31	30	32	34	33	31
2	23	27	31	29	32	33	33	32

Table 2: Stochastic vs deterministic solution (for the first two time periods)

order to avoid that some capacity is going to be wasted. Analogously, at airport 1, the stochastic solution suggests a higher number of departures with respect to the deterministic solution. Therefore, first stage stochastic solution is less restrictive, in terms of ground delay assignment, than the corresponding deterministic solution. This represents a way of hedging against uncertainty. Of course, even though this is quite general, we cannot conclude that this is always the case, since it depends on the cost structure, demand patterns, airport capacities and their evolution over time.

4.2 Effect of Strategic Aircraft Flow Re-allocation

The stochastic model proposed in §3 is envisioned within the framework of Air Traffic Flow Management in order to detect strategies to solve or reduce periods of congestion. However, the model can be used to evaluate the effect/benefit of possible reallocation of flows of flights. The scope would be a more efficient use of available resources and the consequent alleviation of airport congestion. Obviously, delay reduction at one airport comes at a cost, which can be the increase of congestion at the other airport. Such reallocation of flights can take place even within the same airlines, especially for the case study we are considering, i.e., two national hubs. Through the following example, we show the benefits of moving a certain number of flights from one hub airport to the other one. In Figure 4 and Figure 5, we depict the stochastic solution for the instance $d2p2$, where we reallocate 20% of flights from airport 1 to airport 2. The reallocation of flights induces delays at airport 2 but drastically reduce those at airport 1.

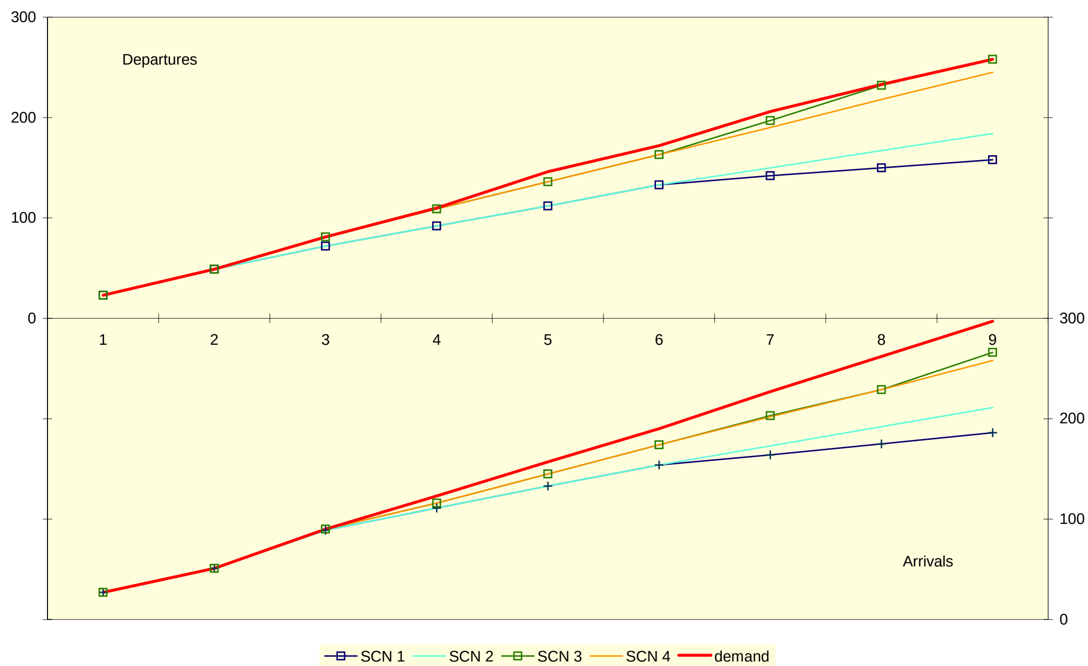

Figure 4: *Departures and Arrivals at airport 1 after aircraft flow re-allocation.*

More specifically, at airport 1 the number of delayed departures (arrivals) reduces from 36.4 (36.9) to 20.2 (26.3) flights per period, while at airport 2 the number of delayed departures (arrivals) increases from 16.6 (14.7) to 33.2 (14.4). These values are on average computed across all the time periods. Even though the number of delayed arrivals at airport 2 increases substantially, the net reduction in the

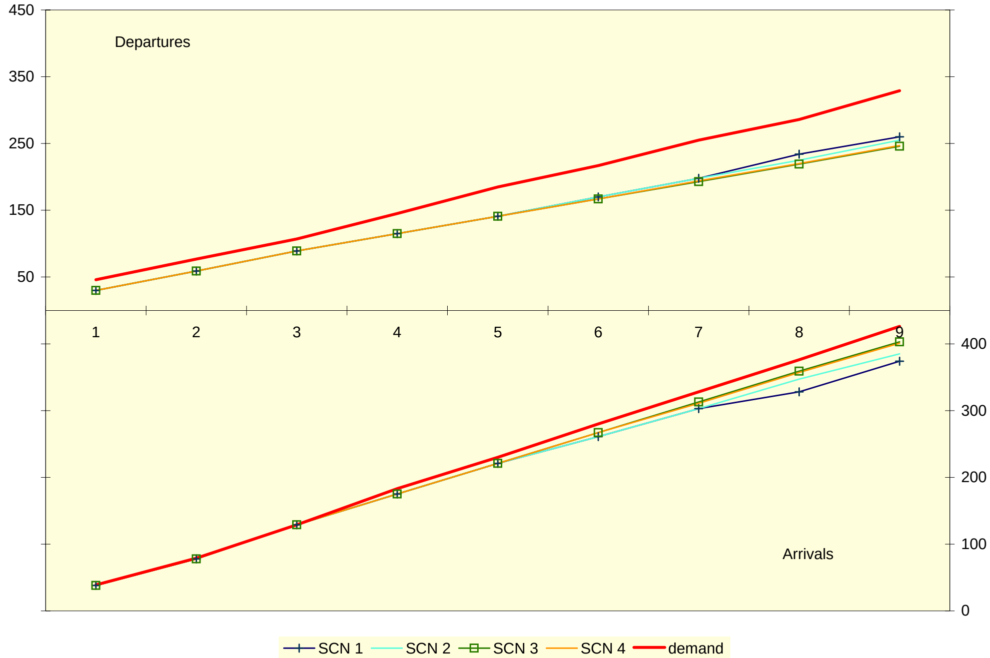

Figure 5: *Departures and Arrivals at airport 2 after aircraft flow re-allocation.*

number of delayed flights is positive, about 9% in this case. The decision on the amount of flights to move from one hub to the other can be formalized as a one parameter optimization problem. To give an idea, in Figure 6 we plot the stochastic solution value (on the y-axis) for the $d2p2$ instance for different percentage of flights reallocation (reported on the x-axis).

Finally, we have also to note that moving flights from airport 1, whose capacity is uncertain, to airport 2 whose capacity is deterministically known helps in hedging against uncertainty. Indeed, the effects od uncertainty are attenuated as it can be verified by comparing both the values of the expected value of perfect information (EVPI) and of the value of stochastic solution (VSS) before and after the flights reallocation. Before moving flights to airport 2, the EVPI and the VSS are 20.6% and 6.9% respectively which are reduced to 15.6% and 4.4% after the reallocation.

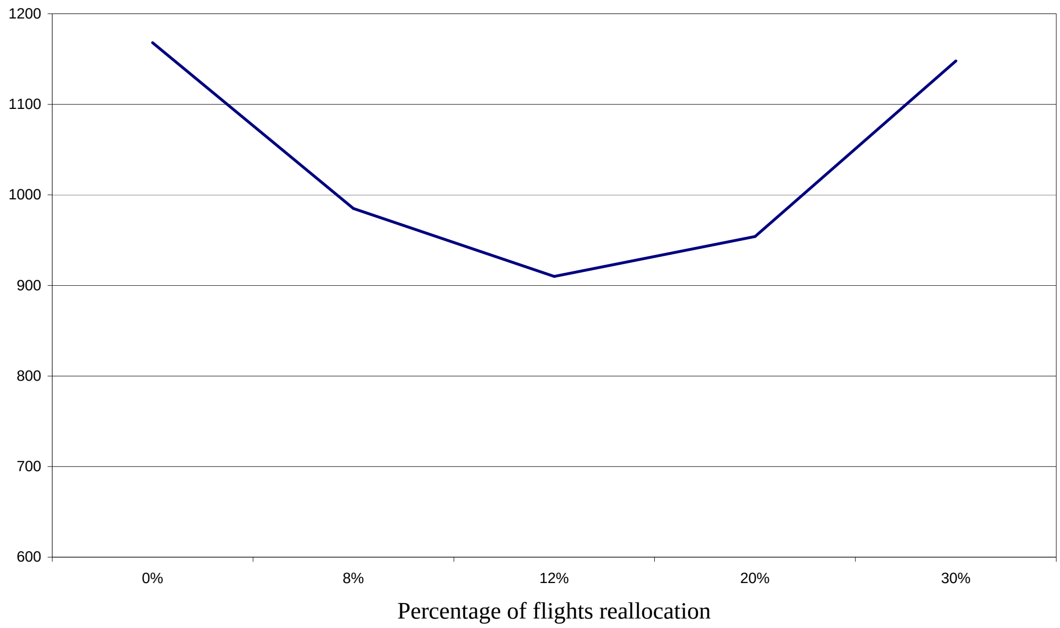

Figure 6: *Reallocation benefits.*

5 Conclusions

In this paper we addressed several issues within the domain of Air Traffic Management. First of all, we developed a stochastic programming model, named Stochastic Multi-airport Capacity Allocation Model, which extends previous Air Traffic Flow Management approaches in several directions. The proposed model takes into account three important issues: (i) the model explicitly incorporates uncertainty in the airport capacities using scenarios; (ii) it also considers the trade-off between airport arrivals and departures, crucial issue in any hub airport; and (iii) it takes into account the interactions between airports.

This last issue is of particular interest in Europe, where several countries have their flag carriers which typically connect national airports to major foreign airports using a couple of national hubs. In this cases, especially if one of the hub airport often experiences congestion due to airport capacity restrictions, then, beyond adopting the necessary air traffic flow management measures, it is advisable to redirect some demand from the more congested airport to the less congested one. The developed model has been used to give a quantitative measure of the overall capacity gain to be achieved through reallocation of demand.

Form our computational analysis, the benefits coming from explicitly modelling uncertainty are evident. Moreover, it clearly appears that strategic aircraft flow re-allocation is another possible control action, in addition to those proposed by the ATFM stochastic model, which helps in hedging against uncertainty.

References

[1] Adams M., Kolitz S., Milner J., Odoni A.R. Evolutionary concepts for Decentralized Air Traffic Flow Management. Air Traffic Control Quarterly 1997, **4**:281-306.

[2] Andreatta G., Brunetta L. Multiairport Ground Holding Problem: A Computational Evaluation of Exact Algorithm. Operations Research 1998, **46**:57-64.

[3] Ball M.O., Hoffman R., Odoni A.R., Rifkin R. A Stochastic Integer Program with Dual Network Structure and its Application to the Ground-Holding Problem. Operations Research 2003, **51**:161-171.

[4] Bianco L., P. Dell'Olmo, S. Giordani, G. Lulli, "Models and Algorithms for Multi-airport Traffic Flow Coordination In *Proceedings of Advanced Workshop ATM 2002*, G. Galati and A. Zellweger eds., Capri 2002.

[5] Birge, J.R. and F. Louveaux. *Introduction to Stochastic Programming.* Springer-Verlag, New-York, 1997.

[6] Bertsimas D.J., Stock S. The Air Traffic Management Problem with Enroute Capacities. Operations Research 1998, **46**:406-422.

[7] Bianco L., Dell'Olmo P., Giordani S. "Coordination of Traffic Flows in the TMA." In *New Concepts and Methods in Air Traffic Management*, L.Bianco, P.Dell'Olmo, A.R.Odoni, eds., Springer Verlag, 2002.

[8] *Collaborative Decision Making in Aviation Transportation* Web Pages, http://cdm.metronaviation.com/.

[9] Dell'Olmo P., Lulli G. The airport capacity allocation problem: a dynamic programming approach. IMA Journal of Management Mathematics 2003, **14**: 235-249.

[10] Dell'Olmo P., Lulli G. "Models and Algorithms for the Airport Capacity Allocation Problem." In *OR is Space and Air*, T. Ciriani et al. eds., Kluwer Academic Publisher 2002.

[11] Fan T.P. , Odoni A.R. "Airport Demand Management Policies." In *Proceedings of Advanced Workshop ATM 2002*, G. Galati and A. Zellweger eds., Capri 2002.

[12] Gilbo E.P. Airport Capacity: Representation, Estimation Optimization. IEEE Transaction on Control Systems Technology 1993, **1**:144-154.

[13] Gilbo E.P. Optimizing Airport Capacity Utilization in Air Traffic Flow Management Subject to Constraints at Arrival and Departure Fixes. IEEE Transaction on Control Systems Technology 1997, **5**:490-503.

[14] Grether D., Isaac M., Plott C., The Allocation of Scarce Resources: Experimental Economics and the Problem of Allocating Airport Slots, Westview Press, 1989.

[15] Hall W.D. Efficient Capacity Allocation in a Collaborative Air Transportation System. PhD dissertation, MIT, 1999.

[16] Hoffman R.L., Ball M.O. A Comparison of Formulations for the Single Airport Ground Holding Problem with Banking Constraints. Operations Research 2000, **48**:578-590.

[17] T. Niznik , Optimizing the Airline Response to Ground Delay Programs, Proceedings of AGIFORS Airline Operations Meeting, 2001.

[18] A. Odoni, The Flow Management Problem in Air Traffic Control, in *Flow Control of Congested Networks*, eds. A.R. Odoni, L. Bianco and G. Szego, pp. 269-288, Springer-Verlag, Berlin, 1987.

[19] Taaffe K. "Single Airport Ground Holding Problem - Benefits of Modeling Uncertenty and Risk. In *Supply Chain and Finance*, P.M. Pardalos, A. Migdalas, and G. Baourakis eds., World Scientific 2004.

[20] Terrab M., Odoni A.R. Strategic Flow Management for Air Traffic Control. Operations Research 1993, **41**:138-152.

[21] Vranas P.B., Bertsimas D.J., Odoni A.R. The Multi-Airport Ground Holding Problem in Air Traffic Control. Operations Research 1994, **42**:249-261.