

# Ground Delay Program Planning Under Uncertainty in Airport Capacity

Avijit Mukherjee\*

*University Affiliated Research Center, University of California at Santa Cruz*

Mark Hansen†

*Department of Civil and Environmental Engineering, University of California at Berkeley*

Shon Grabbe‡

*NASA Ames Research Center*

**This paper presents an algorithm that can assign flight departure delays under probabilistic airport capacity. The algorithm dynamically adapts to weather forecasts by revising, if necessary, departure delays. The information required by the algorithm is considerably less than that required by existing stochastic dynamic optimization models. The proposed algorithm leverages state-of-the-art optimization techniques that have appeared in recent literature. It is a viable approach for planning ground delay programs at airports where probabilistic information on airport capacity are available. As a case study, the algorithm is applied to assigning departure delays to flights scheduled to arrive at San Francisco International Airport in the presence of uncertainty in the fog clearance time. The cumulative distribution function of fog clearance time was estimated from historical observations on 387 days in 2004-2007. When probabilistic weather forecasts were used to update the probabilities of fog clearance times, the expected delays obtained from the algorithm were reduced by approximately 7% compared to delays when the forecasts were not utilized. Experimental results also indicate that if the proposed algorithm is applied to assign ground delays to flights inbound at San Francisco International airport, overall delays could be reduced up to 20% compared to current level.**

## I. INTRODUCTION

In the United States, the Federal Aviation Administration implements a ground delay program (GDP) at an airport when arrival demand exceeds capacity. Such situations typically occur when adverse weather conditions reduces the maximum throughput, i.e., capacity, of an airport. When a GDP is implemented, a subset of flights scheduled to arrive at the airport are assigned departure delays. These are commonly known as ground delays. Flights that receive ground delays arrive later than their original scheduled arrival times. This results in reduction of arrival demand at the airport during certain time-periods. Delaying flights before departure is less expensive than letting them take-off at their scheduled times and encounter airborne delays at or near their destination. One of the primary objectives of a GDP is to maximize throughput of the impacted airport, and hence, to reduce or eliminate any unnecessary delays<sup>1</sup>. Uncertainty in weather forecasts poses a significant challenge towards minimizing delays. Inaccurate forecasts make it impossible to know the airport arrival capacity in advance and to determine the necessary departure delays of aircraft. Along with the quality of weather forecasts, algorithms used to plan a GDP can have significant impact on delays<sup>2-6</sup>.

Over the past decade, research has led to the advancement of decision models for GDP planning under uncertainty in airport capacity<sup>2, 3, 4, 5, 10, 11, 13</sup>. A key input to these models is a probability distribution function of airport capacity. In the models proposed in Ref. 3 and Ref. 4 ground delays are not revised after they are assigned. The output of these models is a set of landing slots, which could be assigned to aircraft. Ref. 2 proposed efficient and equitable algorithms for slot allocation. From the computational standpoint, models proposed in Ref. 3 and 4 are

---

\* Associate Project Scientist, MS 210-8, Moffett Field, CA 94035, avijit@ucsc.edu

† Professor, 114 McLaughlin Hall, U.C. Berkeley, CA 94720, mhansen@ce.berkeley.edu

‡ Research Scientist, MS 210-15, Moffett Field, CA 94035, Shon.R.Grabbe@nasa.gov, Senior Member of AIAA

easily solvable. Ref. 5 proposed a dynamic programming based model for assigning ground delays and revising those in response to updated forecasts. Along with a distribution of airport capacity, the model in Ref. 5 requires as input, a decision tree whose branches reflect updates on airport capacity as time progresses<sup>10</sup>. Such intensive data requirement makes it hard to implement a dynamic programming model in practice.

This paper presents an algorithm that can utilize probabilistic capacity forecasts to decide on flight departure delays. The algorithm applies the static stochastic optimization model, proposed in Ref. 4, at multiple stages to optimize the number of aircraft planned to arrive at an airport, and an algorithm proposed in Ref. 2 to allocate departure times to individual flights. While being computationally easy, the proposed algorithm incorporates updated weather forecasts to dynamically revise flight departure times. As a case study, the algorithm is applied to assign departure delays to flights scheduled to arrive at San Francisco International Airport (SFO) under uncertainty in the clearance time of fog. The probabilistic distribution of fog clearance times is constructed using historical data. On any given day the probabilities are updated based on forecasts generated by the National Weather Service, located in Monterey, California. The results from the proposed algorithm are compared with those from a dynamic stochastic optimization model<sup>5</sup>. In theory, the expected total delay from the dynamic optimization model will always be less than that from the proposed algorithm. However, there are certain advantages of using the latter. The proposed algorithm requires far less data. The individual modules of the algorithm are computationally simple and generate solutions in real-time. Also, its steps are similar to planning ground delay programs in today's system.

The outline of this paper is as follows. Section II provides a brief description of the key parameters involved in planning and implementing ground delay programs. Section II presents a literature review of existing optimization models addressing this problem. Section III presents an algorithm for assigning ground delays to aircraft under uncertainty. The algorithm is applied to decide ground delays for flight arriving at SFO, and the results are presented in Section IV. Section V concludes the paper followed by acknowledgements and references.

## **II. GROUND DELAY PROGRAMS – PLANNING, IMPLEMENTATION, AND REVISION**

The decision support tool that is used to plan and implement a GDP at an U.S. airport is known as the Flight Schedule Monitor (FSM)<sup>7</sup>. There are three main parameters associated with any GDP: (1) planning horizon (i.e., length of the program), (2) airport acceptance rate during various time-periods within the planning horizon, and (3) the set of flights that are included in the program (commonly known as the scope.) Anytime a GDP is implemented, these parameters are set based on the projected arrival demand and airport capacity. The planning horizon, which is the difference between end and start times of the GDP, typically coincides with weather-induced period of reduced arrival capacity.

The airport acceptance rate (AAR), which is defined as the number of flights allowed to land in an hour, is set based on the anticipated severity of weather. Based on the AARs, a set of landing slots are created, and each flight included in the program is assigned one such slot. The difference between the landing slot assigned to a flight and its scheduled arrival time amounts to ground delay.

When a GDP is implemented, a subset of flights may be exempted from being assigned ground delays even if they are scheduled to arrive within the planning horizon. Typically, these are the flights that are either airborne at the time when GDP is implemented or that originate from airports located beyond certain distance from the destination airport. The primary motivation behind such distance-based exemptions is to prevent long-haul flights from facing unnecessary delays if weather conditions improve earlier than anticipated. The subset of flights left is a ground-based 'inventory' of short-haul flights whose departure times can be revised. If weather improves earlier than anticipated, short-haul flights could be released with lower delays in order to utilize increased airport capacity. If the weather conditions worsen or persist longer, ground delays could be extended for those flights. Thus, distance-based exemptions not only prevent long-haul flights from facing unnecessary delays, but also provide additional flexibility to respond to unexpected capacity changes by controlling the departure times of flights that have not yet departed.

Following exemptions, the set of flights included in the program are assigned departure delays using the Ration-by-Schedule (RBS) algorithm, which is based on the first-scheduled-first-served principle. RBS is viewed as an equitable method of slot allocation. Previous research has proved that RBS minimizes the maximum delay imposed on a flight<sup>8</sup>. In a recent study it was proved that a new algorithm, Ration-by-Distance (RBD), maximizes airport throughput if weather clears earlier than anticipated<sup>2</sup>. Like RBS, RBD is a greedy heuristic where flights are prioritized by their distance from the destination airport. However, RBD could lead to severe delays of short-haul flights and cause inequity in slot assignment. Ref. 2 proposed a variant of the RBD algorithm, which was named as the Equity-based RBD (E-RBD) algorithm, where the landing slot of a flight would not exceed the arrival time under RBS allocation by certain pre-determined amount.

Under CDM, airlines are allowed to substitute one flight for another in a landing slot they own. This process is called intra-airline substitution. Airlines may also cancel some flights. After airline substitutions and cancellations the FAA runs the Compression algorithm to re-assign any slot that was vacated due to cancellations<sup>7</sup>.

A GDP planning and control process is both stochastic and dynamic in nature. While the stochastic aspect is mainly due to uncertainty in weather forecasts, the dynamic aspect is related to early termination or extension of the program in response to changing weather conditions. In both cases, revising ground delays of flights is warranted. At any time during a GDP, the ability to revise various parameters of the program depends on the decisions made during earlier time-periods. For instance, if many flights were originally exempted and weather conditions worsen, it may become necessary to impose more ground delays on flights that are still on ground. If, on the other hand, a lot of flights were assigned ground delays and weather conditions improve earlier than anticipated, it may not be possible to recover the unnecessary delays imposed on some flights. Assigning ground delays to flights in the face of uncertainty is, therefore, a challenging problem often posed as a stochastic integer programming (IP) model. The next sub-section summarizes the existing research literature on this problem.

### III. A DYNAMIC GROUND DELAY ASSIGNMENT ALGORITHM

This section presents a new algorithm that could be applied to plan a GDP under uncertainty in airport capacity. From hereon the algorithm is termed as the Dynamic Stochastic Ground Holding (DSGH) algorithm. There are two main components of the proposed algorithm: (1) determining the optimum number of landing slots during a time-period within the GDP planning horizon and (2) assigning the landing slots to flights. Whenever there is an update in weather forecasts these two steps could be repeated and ground delays of flights could be revised.

Figure 1 illustrates the various steps of planning a ground delay program using the DSGH algorithm. The primary inputs to the algorithm are the scheduled arrival times of flights and a set of airport capacity scenarios with their respective probabilities. As mentioned earlier, capacity scenarios can be constructed from past observations of airport capacity or from the weather forecasts. Using these input on arrival demand and capacity, a static stochastic optimization model, presented below, is applied to output the optimum time-varying “planned airport arrival rates” (PAAR). The primary difference between the model presented below and that in Ref. 4 is the inclusion of the exempted flights in the proposed model.

#### 1. Notations

$T$  : number of discrete time-periods of equal duration that constitute the planning horizon,

$Q$  : number of capacity scenarios, each of which depicting a possible time-varying airport arrival capacity,

$p_q$  : probability of occurrence of scenario  $q$ ,

$M_t^q$  : airport arrival capacity during time-period  $t$  under the scenario  $q$ ,

$D_t$  : number of flights, which are not exempted, scheduled to arrive during time-period  $t$ ,

$E_t$  : number of flights, which are exempted from being assigned any ground delay, scheduled to arrive during time-period  $t$ ,

$\lambda$  : cost-ratio between unit airborne and ground delay of any flight.

#### 2. Decision Variables

$A_t$  : number of flights rescheduled to arrive during time-period  $t$  (i.e., the PAARs),

$G_t$  : number of flights that are delayed on ground from time-period  $t$  to  $t+1$ ,

$W_t^q$  : number of flights airborne delayed between  $t$  and  $t+1$ , under scenario  $q$ .

#### 3. Objective Function

$$\text{Min. } \sum_{t=1}^T G_t + \sum_{q=1}^Q p_q \sum_{t=1}^T \lambda W_t^q \quad (1)$$

#### 4. Constraints

$$A_t - G_{t-1} + G_t = D_t; t = 1, \dots, T+1; (G_0 = G_{T+1} = 0) \quad (2)$$

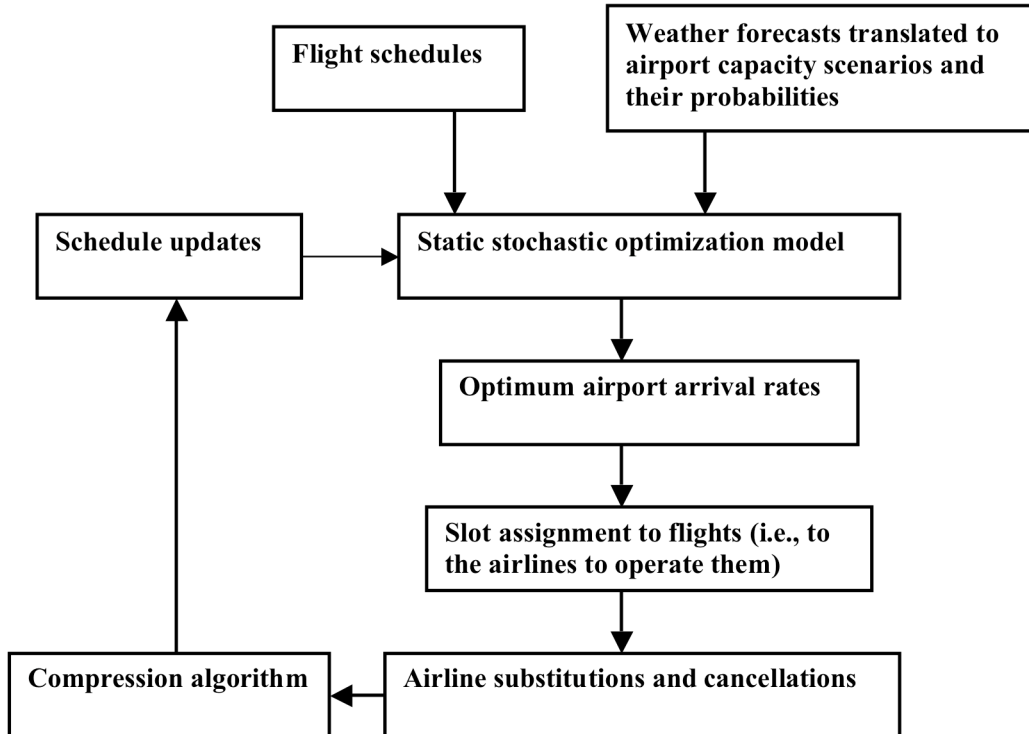
$$A_t + E_t + W_{t-1}^q - W_t^q \leq M_t^q \quad (3)$$

$$A_t, G_t, W_t^q \geq 0 \text{ and integer} \quad (4)$$

The objective function given by expression (1) minimizes the expected total delay cost, where an unit of airborne delay is weighted by a cost factor of  $\lambda$  compared to unit ground delay. Constraint set (2) implies that the difference between cumulative scheduled and planned arrivals amounts to total ground delay. Constraint set (3) imposes upper

limit on the number of flights that could actually land under a given capacity scenario. Any difference between planned and actual landings results in airborne delays.

After determining the optimum PAARs, a set of landing slots are created and all flights scheduled to arrive at the destination airport are assigned one such slot. This is done by applying a priority-based algorithm such as the RBS or the RBD. As mentioned earlier, these algorithms generate certain amount of equity and efficiency in slot allocation. Following slot assignment, airlines are allowed to perform flight substitutions and cancellations just as it is done in today's system. Thereafter, the Compression Algorithm is invoked to utilize slots vacated by cancelled flights. Intra-airline flight substitutions and application of the Compression Algorithm result in schedule changes. The overall GDP planning and implementation process is repeated at multiple stages while utilizing updated information on flight schedules and weather forecasts. The DSGH algorithm is formally presented below.



**Figure 1: Components of the Dynamic Stochastic Ground Holding Algorithm**

The DSGH Algorithm

1. At time  $t$ , obtain a list of flights whose scheduled or previously rescheduled arrival times are later than  $t$ . Let  $F_G$  be the set of flights whose departure times are later than  $t$ . Similarly, let  $F_A$  be the set of flights which are already airborne as of time  $t$ .
2. Divide the planning horizon into a set of  $T$  time-periods of equal duration and generate aggregate arrival demand,  $D_i$ , during time-period  $i$  based on arrival schedule of ground-based  $F_G$ . Similarly, generate the arrival demand,  $E_i$ , based on flights that are already airborne at  $t$  (i.e.,  $F_A$ ).
3. Obtain capacity scenarios and their probabilities based on weather forecasts at time  $t$ . Let  $C_i^q$  denote the airport arrival capacity during time-period  $i$  under the scenario  $q$  ( $q \in \{1, \dots, Q\}$ ), and  $p_q$  denote its probability of occurrence
4. Solve the static stochastic optimization model for the GHP (Ball et al., 2003)<sup>4</sup> using the inputs  $D_i$ ,  $E_i$ ,  $M_i^q$ ,  $p_q$ , and a chosen value of  $\lambda$ . Obtain the set of optimum PAAR, i.e.,  $A_i$ .

5. In each time-period  $i$ , generate  $A_i$  landing slots of equal duration. Assign one landing slot to each flight  $f \in F_G$  based on a priority rule such as RBS or RBD.
6. Allow intra-airline flight substitutions and cancellations.
7. Execute the Compression algorithm.
8. At time  $t' = t + \Delta t$  obtained revised schedules and updated capacity forecasts. If weather has cleared by time  $t'$  then go to step 9. Otherwise, repeat steps 1-7.
9. Generate landing slots based on fair weather capacity of the airport.
10. Assign airborne flights  $f \in F_A$  the earliest possible landing slot. Note that some airborne flight may face airborne holding due to unavailability of its desired slot. After assigning slots to airborne flights, assign each flight  $f \in F_G$  an earliest possible landing slot without violating airport capacity under fair weather conditions.
11. End algorithm.

The steps of the DSGH algorithm are similar to current-day GDP planning and implementation procedure. There are, however, two main differences between current practice and the proposed algorithm. First, the PAARs are decided using an optimization model which accounts for uncertainty in capacity forecasts. Second is the dynamic aspect of the algorithm. Steps 1-7 of the DSGH algorithm are repeated at multiple stages utilizing updates on flight schedules and weather forecasts. Such sequential application of the algorithm makes it possible to revise ground delays of flights in response to changing conditions. The parameter  $\Delta t$ , which is the time difference between successive applications of the algorithm, depends on the frequency of weather forecast updates and the required duration of collaborative decision making described in steps 6 and 7.

#### IV. DYNAMIC GDP PLANNING AT SAN FRANCISCO INTERNATIONAL AIRPORT (SFO) UNDER UNCERTAINTY IN FOG CLERANCE TIME

A GDP is implemented at SFO on a typical day when fog clears late. The marine stratus conditions effectively eliminate side-by-side landings, thereby reducing the AAR from approximately 60 flights per hour to 30 flights per hour. The purpose of this section is to illustrate how the DSGH algorithm could be applied to mitigate demand-capacity imbalance caused by such adverse weather conditions.

##### A. Capacity Scenarios and their Probabilities

As mentioned earlier in Section II, the static stochastic optimization model for GHP (Ball et al., 2003)<sup>4</sup> requires as input a finite set of scenarios of airport capacity and their respective probabilities. Each scenario depicts a time-varying profile of airport capacity. The arrival capacity profile of SFO before and after fog clearance time could be represented by a simple step function as shown in Figure 2. Before the fog clears (i.e., until time  $\tau$ ) the landing capacity of the airport is 30 aircraft per hour, and after it clears the capacity rises to 60 aircraft per hour.

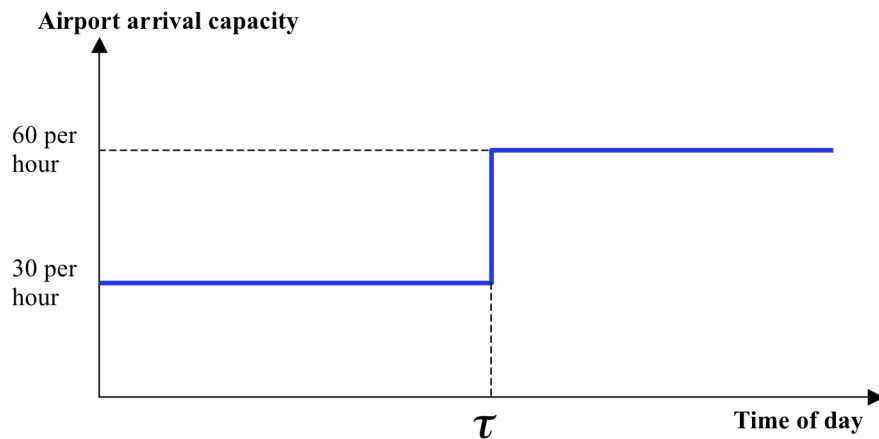
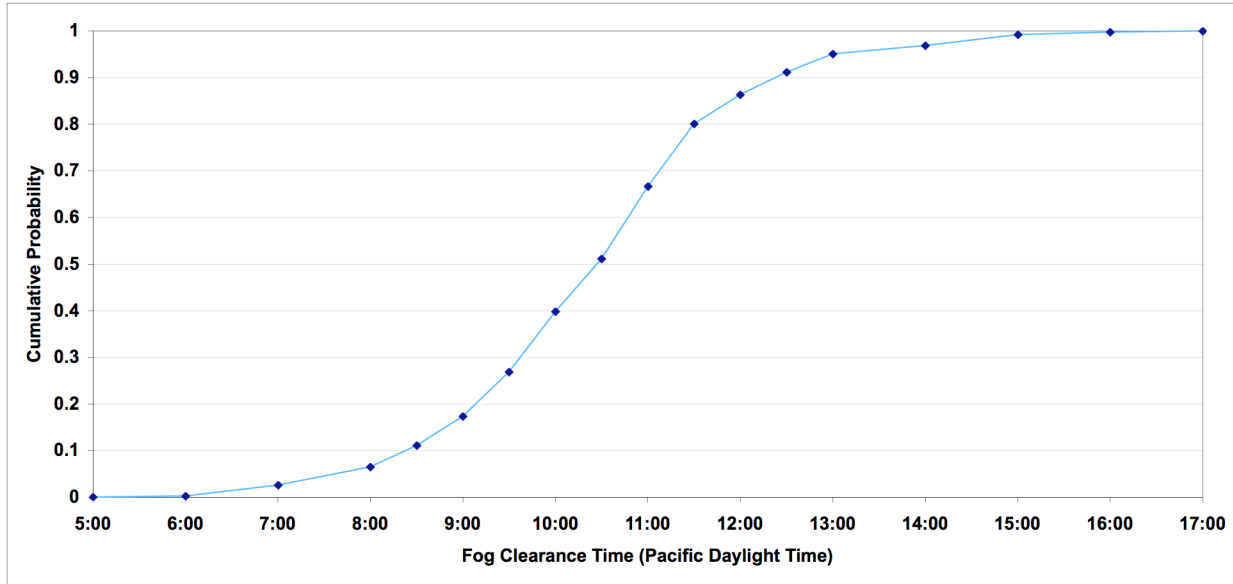


Figure 2: SFO Arrival Capacity Profile under Fog Clearance Time  $\tau$

Since the fog clearance time,  $\tau$ , is not known with certainty, it is necessary to consider a finite set of possible values of  $\tau$ . Corresponding to each value of  $\tau$  there would be a capacity scenario whose profile is similar to the one shown in Figure 2, and whose probability of occurrence is equal to the probability of  $\tau$  assuming that particular value. Figure 3 shows the cumulative probabilities distribution of  $\tau$  as estimated from observed fog clearance times on 387 summer days in 2004-2007. The time of day shown on the abscissa is in Pacific Daylight Time (PDT). From this distribution, a set of 17 capacity scenarios, each corresponding to a particular value of  $\tau$ , is provided as input to the static stochastic optimization model in step 3 of the DSGH algorithm. The clearance time associated with each scenario, denoted by  $\tau_q$ , and their probabilities are presented in Table 1.



**Figure 3: Cumulative Probability Distribution of Fog Clearance Time at SFO**

**Table 1: Initial Set of Capacity Scenarios and their Probabilities**

Scenario ( $q$ )	Scenario-specific fog clearance time in UTC ( $\tau_q$ )	Probability of occurrence ( $p_q$ )
1	6:00	0.0026
2	7:00	0.0233
3	8:00	0.0388
4	8:30	0.0465
5	9:00	0.0620
6	9:30	0.0956
7	10:00	0.1292
8	10:30	0.1137
9	11:00	0.1550
10	11:30	0.1344
11	12:00	0.0620
12	12:30	0.0491
13	13:00	0.0388
14	14:00	0.0181
15	15:00	0.0233
16	16:00	0.0052
17	17:00	0.0026

At time instant  $t$  within the GDP planning horizon the conditional probability of any scenario changes depending on whether or not the fog has cleared by  $t$ . For instance, if on any given day, the fog has cleared between 9:00 and 9:30 AM, the conditional probabilities of all scenarios associated with clearance times later than 9:30 AM becomes zero. Thus, when the DSGH algorithm is applied at multiple stages, the number of future scenarios and their conditional probabilities are updated and provided as input to the static model in step 3. On any day, if the fog has not cleared by time  $t$ , set of scenarios is updated to contain only those whose clearance times are later than  $t$ , and their probabilities are updated as follows:

$$\hat{p}_q = \frac{p_q}{\sum_{k:\tau_k > t} p_k}, \quad q \in \{1, \dots, Q\} : \tau_q > t \quad (5)$$

### B. Arrival Demand at SFO

For comparing performance of the DSGH algorithm and a dynamic stochastic optimization model, flights schedules on a representative summer day in 2005 were used to compute the arrival demand at SFO. The flight schedules were obtained from the FAA – Aviation System Performance Metrics database. Figure 4 shows the hourly arrival demand of domestic flights at SFO between 5:00 and 17:00 PDT. As shown in the figure, the arrival demand at SFO during morning hours exceeds the reduced airport arrival capacity in presence of fog, which is 30 landings per hour. Therefore, on any day when the fog doesn't clear before 9:00 AM it becomes necessary to implement a GDP to mitigate this demand-capacity imbalance.

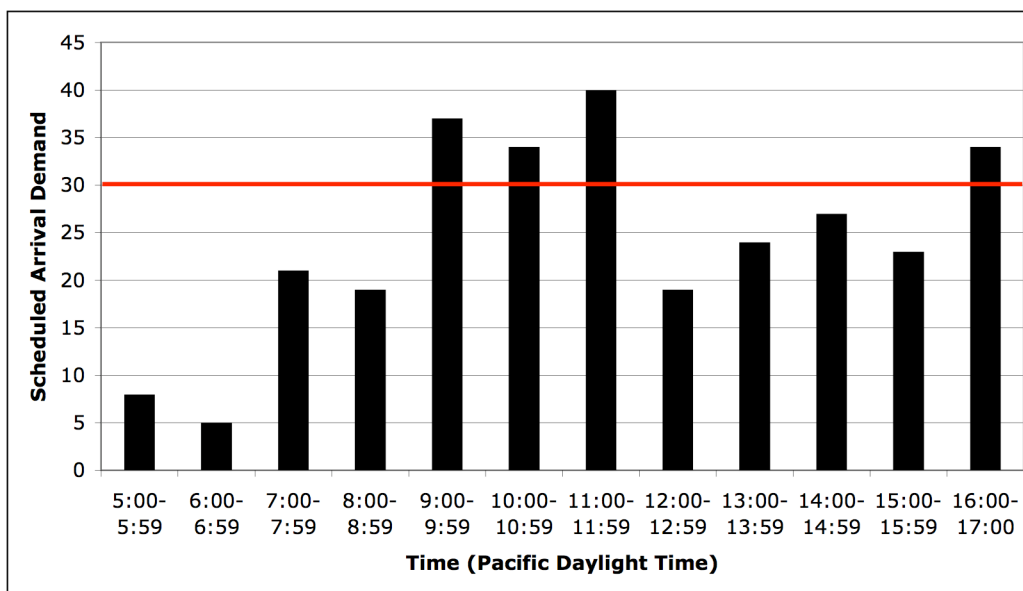


Figure 4: Hourly Arrival Demand at SFO on Aug-11-2005

### C. DSGH Algorithm Performance

The DSGH algorithm was applied to assign departure times to flights in response to low airport capacity at SFO. Airborne delays could result if flights could not land due to inadequate capacity. The scenario-specific delays and the total expected delays obtained from the DSGH algorithm were compared with those from Mukherjee-Hansen (2007)<sup>5</sup> stochastic dynamic optimization model. The results are presented here.

Figure 5 shows the expected ground and airborne delays from the DSGH Algorithm and the Mukherjee-Hansen optimization model when the cost-ratio  $\lambda$  was set to 2. Airborne delays could occur if flights are released with low ground delay and the airport capacity remains low for extended periods of time. It can be easily observed that the expected airborne delays obtained from the DSGH algorithm and the Mukherjee-Hansen model are almost same. When RBD is used to allocate slots to individual flights in step 5 of the DSGH algorithm, the total expected delay is approximately 2% higher than the Mukherjee-Hansen model. When RBS is used instead, the total expected delay from the DSGH model is about 8% higher. This is because under RBS slot allocation, the chance of recovering

flight delays when fog clears early is lower than that under RBD. In fact, it was proved in Ref. 2 that RBD allocation minimizes total ground delays if airport capacity increases earlier than anticipated. Thus, from an efficiency standpoint, RBD outperforms RBS, which is evident from the results shown in Fig. 5. Similar trends in expected delays are observed when the cost ratio  $\lambda$  is set to a high value of 100 (see Fig. 6). Under high cost-ratio, the DSGH algorithm with RBD slot allocation generates the same ground and airborne delays under various scenarios as the Mukherjee-Hansen model. Total expected delay under DSGH algorithm with RBS slot allocation is approximately 43% higher than the delay under RBD allocation.

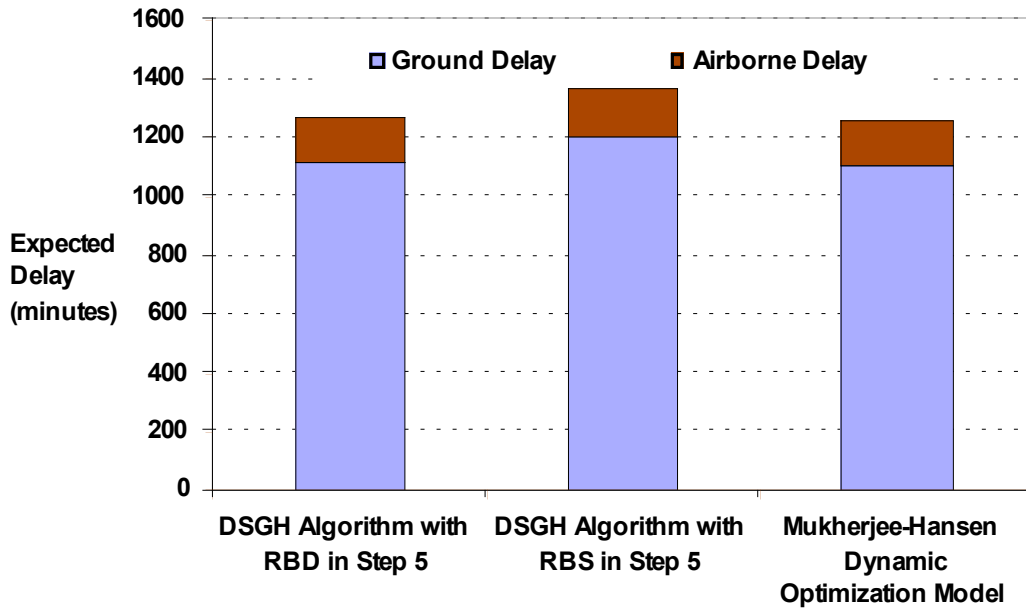


Figure 5: Expected Delays from DSGH Algorithm and Mukherjee-Hansen Model for Cost-Ratio  $\lambda = 2$

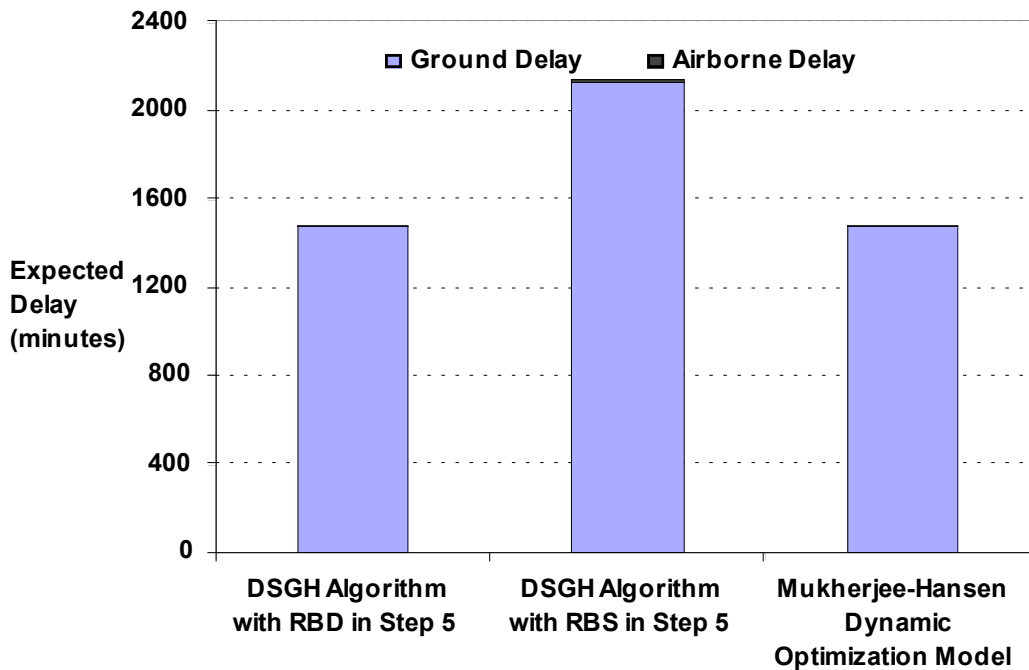


Figure 6: Expected Delays from DSGH Algorithm and Mukherjee-Hansen Model for Cost-Ratio  $\lambda = 100$



Total delay depends on the fog clearance time. Figure 7 shows the scenario-specific delays obtained from the DSGH algorithm and the Mukherjee-Hansen model when cost ratio  $\lambda$  was set to 2. The dynamic optimization model generates lower delays compared to the DSGH algorithm under almost all possible fog clearance times. Comparing RBD versus RBS allocation in step 5 of the DSGH algorithm, the total delays are almost equal when fog clears late. However, for early clearance times, total delay under RBD is generally lower than RBS.

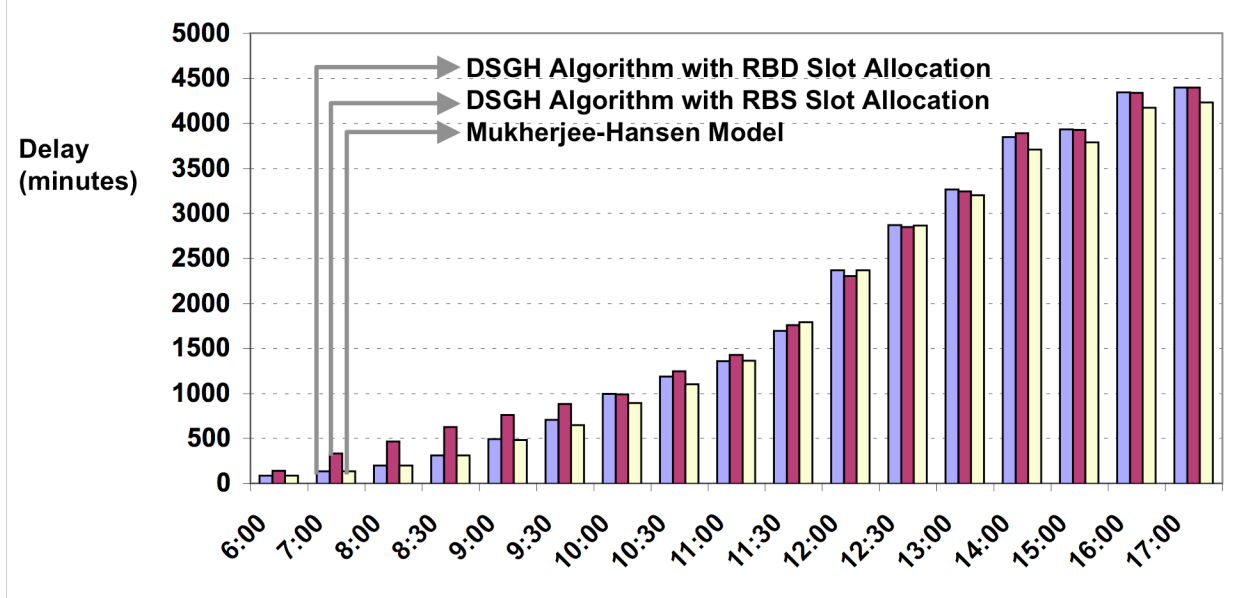


Figure 7: Scenario-Specific Delays from DSGH Algorithm and Mukherjee-Hansen Model for Cost-Ratio  $\lambda = 2$

#### D. Utilizing Weather Forecasts in the DSGH Algorithm

The National Weather Service provides cumulative probability of fog clearance at SFO by 10:00, 11:00, 12:00, and 13:00 PDT on each day during the summer months. The forecasts are generated at 4:00, 6:00, 8:00, 9:00, and 10:00 PDT. On a few days, when fog clears late, forecasts are also available at 11:00 and 12:00 PDT.

The cumulative probabilities provided by the weather forecasts could be used to recalculate the probabilities of scenarios. For example, on a given day, let 0.6 be the probability of fog clearance by 10:00 AM based on the 4:00 AM forecast. The cumulative probability of fog clearance by 10:00 AM without taking into account the forecast is approximately 0.4 (see Fig. 3). To take the weather forecast into account, the probabilities of a scenario  $q$ ,

corresponding to fog clearance times at 10:00 AM or earlier, is updated as follows:  $p'_q = \frac{0.6}{0.4} p_q = 1.5 p_q$ .

In general, if  $P'_{10:00}$  is the cumulative probability of fog clearance by 10:00 AM according to weather forecast, the probability of a scenario  $q$ , such that  $\tau_q \leq 10:00$ , is recomputed as  $p'_q = \frac{P'_{10:00}}{P_{10:00}} p_q$ , where  $P_{10:00}$  is the

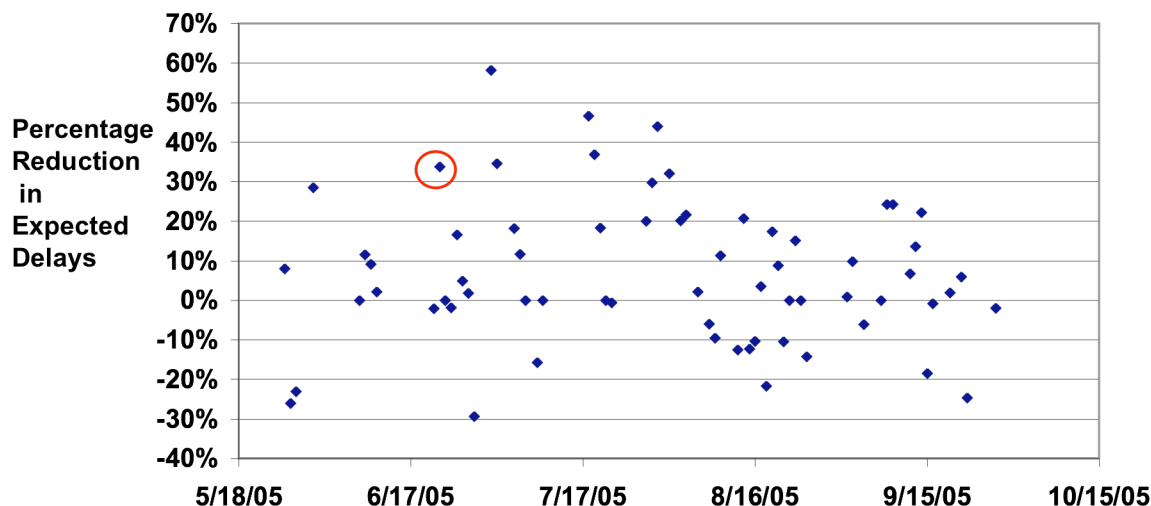
cumulative probability clearance by 10:00 AM computed from historical data (i.e. based on the values provided Figure 3). The scenario probabilities for  $q \in \{1, \dots, Q\}$ , such that  $10:00 \leq \tau_q \leq 11:00$ , are readjusted

as  $p'_q = \frac{P'_{11:00} - P'_{10:00}}{P_{11:00} - P_{10:00}} p_q$ , where  $P_{11:00}$  and  $P'_{11:00}$  are the cumulative probability of fog clearance by 11:00 AM

with and without weather forecast. The probabilities of scenarios corresponding to clearance time later than 11:00 AM are recalculated similarly. The conditional probabilities of scenarios are updated at any time  $t$  by utilizing both weather forecasts, if available, and by eliminating from possibility those scenarios whose clearance times were before  $t$ , as described earlier in Equation (5).

Forecasts from the National Weather Services were obtained for 67 days in the summer of 2005 and the DSGH algorithm along with RBD procedure for slot allocation was applied to assign flight departure delays. Figure 8 shows the reduction in expected delays, expressed in percentages, when the scenario-specific probabilities were updated using the forecasts compared to when they were not. For example, on 6/22/05 (highlighted as red circle in

the figure), utilizing weather forecasts to recomputed probability of fog clearance times resulted in 33% less total delay compared to when the weather forecasts were not used. The percentage delay reduction in Fig. 8, therefore, provides the value of utilizing the weather forecasts. On 19 out of 67 days this value is negative, which means that expected delay increases when scenario probabilities are updated using weather forecasts. Typically, on these days the weather forecasts are either overly optimistic about fog clearance times, often leading to airborne delays, or they are overly pessimistic, in which case there is significant unnecessary ground delays. On an average, however, the reduction in expected delay by utilizing weather forecasts is about 7%.



**Figure 8: Value of Fog Clearance Time Forecasts**

**E. Performance of the DSGH Algorithm Compared with Simulated Ground Delay Programs**

Delays obtained from the DSGH algorithm were compared with those from simulated GDPs on 67 summer days in 2005. In the simulations, the GDP parameters were set based on a set of guidelines, described below, which are similar to those adopted by the FAA when GDPs are implemented at SFO in response to marine stratus<sup>15, 16</sup>. The goal of this exercise is to analyze the potential delay savings that could be achieved by applying the DSGH algorithm to implement GDPs at SFO compared to what is done in today’s system.

*Step 1: Setting the planning horizon.* On each of the 67 days, the predicted fog clearance time at SFO was obtained from the forecasts generated by the National Weather Service at 4:00 AM. If due to some reason 4:00 PDT forecast was not available 6:00 PDT forecast was used instead. On each day, a GDP was implemented with a start time of 6:00 PDT and an initial end time being 2-hours later than the predicted fog clearance time based on available forecast. The 2-hour buffer was applied as a hedging strategy against potential late fog clearance time than what was forecasted.

*Step 2: Setting the airport capacity.* The airport acceptance rate during GDP was set to 30 arrivals-per-hour, and 60 arrivals/hour after the program cancelled.

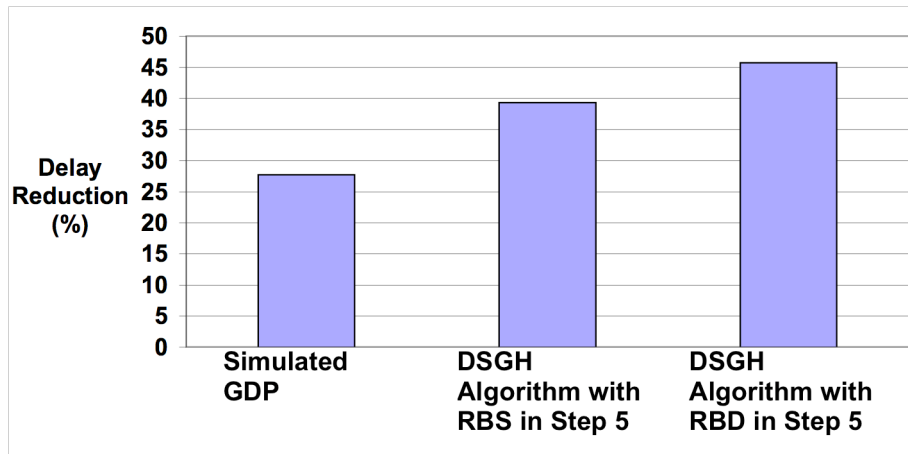
*Step 3: Setting the scope of GDP.* The scope of the GDP on a given day was set based on the confidence of the forecast clearance times. The exemption distance was set to 1000 nautical-miles if the confidence of the 4:00 PDT forecast (or 6:00 PDT forecast if the 4:00 PDT forecast was unavailable) was “High”, or if the predicted clearance time based on the forecast was no later than 11:00 PDT. The exemption distance was set to 1500 nautical-miles if the forecast confidence was “Low” and the predicted fog clearance time was between 11:00 and 14:00 PDT. The scope was set to 2000 nautical-miles if the predicted fog clearance time was later than 14:00 PDT.

*Step 4: Slot allocation to flights.* Flights that originated outside the exemption distance received no delays. Also, flights already airborne at the time of GDP implementation were exempted. Ration-by-schedule (RBS) algorithm was applied to allocate landing slots to non-exempt flights.

*Step 5: Revision.* If, on a given day, the fog cleared 2-hours before initial end time of GDP then the airport capacity was set to 60 arrivals/hour from the time of clearance. Departure delays of flights still on the ground were revised accordingly. If, however, the fog did not clear 2-hours prior to the initially planned end time of GDP, the

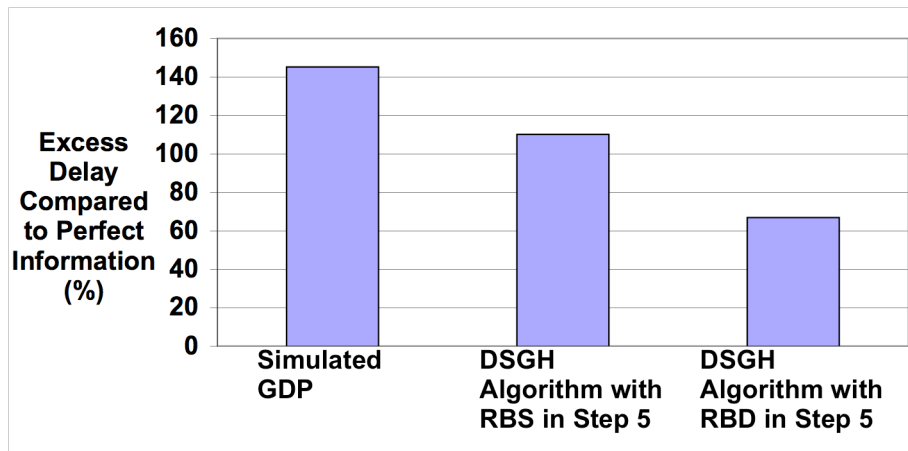
program was extended and the end time is reset to 17:00 PDT and all ground-based flights were included (i.e., the scope was extended to capture all airports within U.S.) The GDP was revised again once the fog actually clears.

Delays obtained from the DSGH algorithm and those from the GDPs simulated based on the above guidelines are compared with delays from a very conservative strategy where, on each of the 67 days, GDPs are implemented with initial end time set to 23:59 UTC, and the scope set to include all airports in the U.S. The program is revised only when fog actually clears on each day. Figure 9 shows the reduction in delays obtained from the DSGH algorithm and simulated GDP based on above guidelines compared to the conservative strategy.



**Figure 9: Reduction in Total Delay, Compared to a Conservative Strategy, By Applying Various Algorithms**

Delays obtained from GDPs simulated based on the above guidelines are, on average, 28% lower than those obtained from the conservative strategy. When the DSGH algorithm is applied with RBS slot allocation the delays are about 10% lower than those from the simulated GDPs. When RBD is applied to allocate landing slots in the DSGH algorithm the delays further reduce by 8%. These experimental results indicate that, on average, 10-20% reduction in delays could be achieved by applying the DSGH algorithm to implement GDPs at SFO compared to how they are implemented in today’s system.



**Figure 10: Excess Delays, due to Imperfect Information, from the DSGH Algorithm and Simulated GDPs**

Figure 10 shows the excess delays, compared to those when perfect information on fog clearance time is available in advance, from the DSGH algorithm and GDPs simulated based on guidelines states earlier in this section. Thus, Fig. 10 shows the excess delays due to imperfect information on fog clearance times at SFO. As evident from the results, the excess delays from the DSGH algorithm, compared to those under perfect information, ranges between 65 – 110%. The delays from simulated GDPs are, on an average, 145% greater than that could be achieved if perfect information on fog clearance times were available in advance. Thus, while there are excess

delays faced when GDPs are planned under uncertainty, applying an advanced algorithm, such as the DSGH algorithm, could potentially reduce the loss.

## V. CONCLUSIONS

This paper presented the Dynamic Stochastic Ground Holding (DSGH) algorithm, which could be applied to plan and control a GDP under uncertainty in airport capacity. Various steps within the DSGH algorithm are repeated in order to make use of, and hence, dynamically respond to, updated information on airport conditions. The steps of the algorithm are similar to the GDP planning and implementation process in today's system. However, the algorithm applies some of the latest techniques in making ground delay decisions under uncertainty. Computationally, the proposed algorithm is efficient, and therefore, could be applied in real-time. Due to its simplicity and relatively smaller input data requirements, the algorithm could be easily incorporated within decision support tools to plan and control GDPs at airports where probabilistic weather forecasts are available.

The performance of the DSGH algorithm was compared to an existing dynamic stochastic optimization model for assigning departure delays to flights. The expected total delay obtained from the algorithm was greater than the dynamic stochastic optimization model by approximately 2%. The choice of slot allocation method within the DSGH algorithm impacted overall delays. Applying Ration-by-Distance resulted in 6% delay reduction than Ration-by-Schedule. Overall delays generated by the algorithm reduced further when the daily forecasts on fog clearance time were utilized. On average, delays reduced by approximately 7% when the forecasts were used to recompute probabilities of capacity scenarios in the DSGH algorithm. The performance of the DSGH algorithm was compared to GDPs, simulated based on guidelines which are similar to current practice. Based on the experiments, it is concluded that, on an average, the DSGH algorithm could reduce delays by 10-20% compared to those at current level.

## VI. ACKNOWLEDGEMENTS

Authors acknowledge the thoughtful suggestions provided by Ms. Lara Cook at Mosaic ATM Inc. The probabilistic weather forecast data was provided by the National Weather Service, Monterey, CA.

## VII. REFERENCES

- <sup>1</sup>Wambsganss, M., "Collaborative Decision Making through Dynamic Information Transfer," *Air Traffic Control Quarterly*, Vol. 4, 1996, pp. 107-123.
- <sup>2</sup>Hoffman, R., Ball, M.O., and Mukherjee, A., "Ration-by-Distance with Equity Guarantees: A New Approach to Ground Delay Program Planning and Control," *Proceedings of 7<sup>th</sup> USA/Europe Air Traffic Management R&D Seminar*, Barcelona, Spain, 2007.
- <sup>3</sup>Richetta, O., and Odoni, A.R., "Solving Optimally the Static Ground-Holding Problem in Air Traffic Control," *Transportation Science*, Vol. 27, 1993, pp. 228-238.
- <sup>4</sup>Ball, M.O., Hoffman, R., Odoni, A.R., and Rifkin, R., "A Stochastic Integer Program with Dual Network Structure and its Application to the Ground-Holding Problem," *Operations Research*, Vol. 51, 2003, pp. 167 – 171.
- <sup>5</sup>Mukherjee, A., and Hansen, M., "A Dynamic Stochastic Model for the Single Airport Ground Holding Problem," *Transportation Science*, Vol. 41, 2007, pp. 444-456.
- <sup>6</sup>Joint Planning and Development Office, "Concept of Operations for the Next Generation Air Transportation System," Version 0.2, URL: <http://techanger.jpdp.aero/> [Cited Jan 25, 2007].
- <sup>7</sup>Federal Aviation Administration, "Collaborative Decision Making," URL: <http://cdm.fly.faa.gov/index.html>.
- <sup>8</sup>Vossen, T., and Ball, M.O., "Optimization and Mediated Bartering Models for Ground Delay Programs," *Naval Research Logistics*, Vol. 51, 2006, pp. 75-90.
- <sup>9</sup>Odoni, A.R., "The Flow Management Problem in Air Traffic Control," *Flow Control of Congested Networks*, Edited by A.R. Odoni, L. Bianco, and G. Szego, Springer-Verlag, Berlin, 1987, pp. 269-288.
- <sup>10</sup>Liu, P.-c, Hansen, M., and Mukherjee, A., "Scenario-Based Air Traffic Flow Management: From Theory to Practice," *Transportation Research Part-B*, Vol. 42, 2008, pp. 685-702.
- <sup>11</sup>Kotnyek, B., and Richetta, O., "Equitable Models for the Stochastic Ground Holding Problem under Collaborative Decision Making," *Transportation Science*, Vol. 40, pp. 133-146.
- <sup>12</sup>Ahuja, R.K., Magnanti, T.L., and Orlin, J.B., *Network Flow: Theory, Algorithms, and Applications*, Prentice Hall, New Jersey, 1993.
- <sup>13</sup>Richetta, O., and Odoni, A.R., "Dynamic Solution to the Ground-Holding Problem in Air Traffic Control," *Transportation Research Part-A*, Vol. 28, 1994, pp. 167-185.

<sup>14</sup>Brige, J.R., and Louveaux, F., *Introduction to Stochastic Programming*, Springer, New York, 1998.

<sup>15</sup>Cook, L., and Wood, B., "A Model for Determining Ground Delay Program Parameters Using Probabilistic Forecast of Stratus Clearing," *Proceedings of 8<sup>th</sup> USA/Europe Air Traffic Management R&D Seminar*, California, USA, 2009.

<sup>16</sup>Artist, M., "SFO Ground Delay Program Guidelines," FAA ATCSCC Memorandum, 2005.