

Collaborative Optimization of Airport Arrival and Departure Traffic Flow Management Strategies for CDM

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Abstract

The Collaborative Decision-Making (CDM) Ground Delay Program Enhancement (GDP-E) activity has focused on solving airport arrival problems during congested periods when the airport arrival capacity, or airport acceptance rate (AAR), decreases due to weather events. The Flight Schedule Monitor (FSM) uses hourly AARs provided by the FAA and predicted arrival demand to determine GDP strategies. This paper proposes a next step to advance CDM GDP-E: Collaborative Optimization. Under Collaborative Optimization, arrivals and departures are considered jointly and are treated as interdependent operations. When arrival capacity can be traded for departure capacity, Collaborative Optimization provides the best allocation of capacity to arrivals and departures to maximize the airport throughput and minimize delays. Furthermore, Collaborative Optimization uses flight priorities from airlines and other users in the optimization model. The resulting solutions provide the best capacity allocation strategies that take into account user priorities (e.g., preserving integrity of banks at hub airports). The presented optimization model can be used as a decision support tool for solving TFM problems at airports. In the current system, the optimal varying AARs can be used in FSM to generate more efficient strategies for Ground Delay Programs. Numerical examples illustrate the potential benefits of Collaborative Optimization.

1. Introduction

The FAA's Traffic Flow Management (TFM) system manages and controls air traffic and

provides the operational resources, or capacity, to serve the traffic. In this sense, the FAA is considered as a service provider. The airlines and other users of the National Air Space (NAS) resources create the traffic demand that can be satisfied (served) without any delay if it does not exceed available capacity. If demand exceeds capacity, some flights will be delayed. TFM strategies attempt to resolve conflicts between demand and capacity, providing smooth traffic flow that is compatible with capacity. Strategic TFM decisions are made for some hours in the future (up to 15 hours) on the basis of comparison of predicted traffic demand and capacity.

Severe congestion problems can occur at airports when capacity substantially decreases due to weather deterioration. If the local TFM specialists cannot resolve the problem within their constraints, the FAA's Air Traffic Control System Command Center (ATCSCC) takes actions of a wider scale, generally involving many airports and Air Route Traffic Control Centers (ARTCC). For solving airport arrival problems, the ATCSCC often uses a Ground Delay Program (GDP). A GDP is a strategy that releases flights from the ground in a manner that will not greatly exceed the airport arrival capacity, and therefore cause significant airborne holding.

In 1995, the CDM program started as a cooperative effort between NAS users and FAA to make the GDP system work better for all parties involved. The fundamentals of the CDM approach are:

- 1) Create a common view of the problem that is shared between FAA and users,

- 2) Create the opportunity and incentive for users to mitigate problems through their own actions and notify FAA of their intentions,
- 3) Give the users flexibility to satisfy their own priorities within the context of an FAA-initiated TFM constraints,
- 4) Allow the users to participate in the determination of TFM policies and procedures.

A major accomplishment of the CDM program is the development and implementation of enhanced collaborative procedures and tools for GDPs.

A CDM GDP works as follows. Users provide FAA with a continuous data stream updating their operating plans on a flight-by-flight basis. FAA combines the user data with other TFM data to provide an aggregate arrival demand list (ADL) for the airport. The ADL is shared with users and FAA TFM specialists. The ATCSCC establishes the hourly AAR (also shared with the users), which along with the ADL is input to the Flight Schedule Monitor (FSM) algorithms. Based on the data, FSM computes a GDP strategy that determines what flights should be delayed and for how long. The FAA then issues the flight-specific delays to the users as controlled times of departure (CTDs). There are two main control procedures used in the FSM to determine CTDs: ration-by-schedule and compression [1].

FSM currently solves arrival problems at airports without taking into account departure operations at the same airports. It is well known, however, that significant number of airports, such as BOS, DCA, JFK, LAX, SFO, STL, practice a trade-off between arrival and departure capacity. At these airports, arrivals and departures are interdependent processes and generally cannot be considered independently. The degree of the interaction varies from airport to airport, and even within an airport it may vary for various runway configurations. In the case of substantial interaction between arrivals and departures, the airport arrival and departure capacities vary when the arrival/departure mix varies. Under given weather conditions (or operational category), a runway configuration may have several different values of arrival and departure capacities depending on arrival/departure mix. For each arrival/departure mix, there is a pair of values: arrival capacity and corresponding departure capacity.

Graphically, the airport capacity can be represented on an “arrival capacity – departure capacity” plane by the airport capacity curve [2] (see. Fig.1). The arrival/departure capacity curve reflects a

functional relationship $v = \varphi(u)$ between these two capacities in the entire range of arrival/departure ratios.

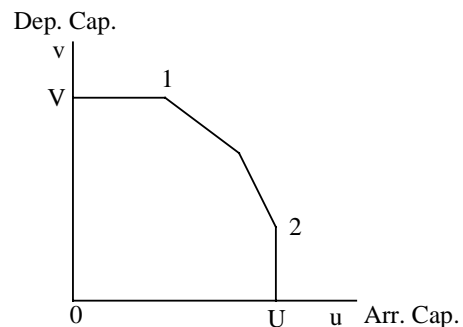


Fig. 1. Airport Arrival/Departure Capacity Curve

In Fig. 1, vertex 1 determines the airport’s operational limits with maximum departure capacity V and minimum arrival capacity. Vertex 2 corresponds to maximum arrival capacity U and minimum departure capacity.

The segment between points 1 and 2 shows the trade-off area between arrival and departure capacities. In this area, arrival capacity can be increased at the expense of decreasing departure capacity and vice versa. The question then arises: if a range of arrival/departure capacities is available for each time interval, what is the best set of choices to accommodate the traffic demand over a given time period?

An answer to this question has been given in the papers [2] and [3], where optimization problems were formulated to determine the best allocation of airport arrival/departure capacities during periods of congestion at airports. These solutions were based on the goals of minimizing overall delays and maximizing overall throughput, and assume that all flights are of equal priority. However, optimal strategies that maximize efficiency of NAS utilization (the major objective for the service provider) are not necessarily optimal or even acceptable to users.

Each user creates its own schedule in accordance with its specific multi-criteria objectives and optimization procedures. The cost of delaying one flight may vary greatly from the cost of giving another flight the same delay. At the hub airports, for example, an airline may operate in banks, and may assign a higher cost to delays for flights in the banks. Another airline may assign higher costs to delays for flights making international connections. Whatever the criteria, it is clear that the TFM strategies generated by the FAA cannot be considered optimal for the users if they do not include the users’ objectives explicitly.

This paper expands the arrival/departure capacity optimization model that was first presented in [2] and applies it to the CDM environment. It first re-introduces joint consideration of arrivals and departures at an airport during a GDP. This makes it possible for more strategic and more efficient assignment of AARs during a GDP. Next, this paper proposes an arrival/departure optimization model that is capable to take into account users' priorities in their traffic demand when allocating airport capacities.

To take a full benefit of this model, additional ADL input data from users is needed. The new data includes the number of first priority (i.e., high cost of delay) arrival and departure slots in the total user demand at each 15-minute interval. First priority demand is treated in the model as exempt. The model aggregates the first priority demands from all users in a subset of the overall demand, both for arrivals and departures. This subset is called the priority demand. The priority demand is used as additional constraints when allocating the arrival and departure capacity at each 15-minute interval. These additional constraints may affect the allocation of arrival and departure capacity and, hence, may allow the airlines an opportunity to reduce or eliminate the delays from their first priority flights, at the possible expense of more delays to their other flights.

The objective of this model is not to alter the manner in which delays are assigned to individual flights. Airlines might object if FAA is trying to second-guess their intentions by altering the order of the flights in the airline schedule. Rather, the user priority constraints are used solely in the allocation of the available capacity between arrival and departure demand. This approach can perhaps provide each user with the number of arrival and departure slots necessary to best satisfy their own goals during a GDP. Once the slots have been allocated, the airlines will fill the slots with specific flights using the existing CDM GDP procedures.

The paper has been organized as follows. Mathematical formulation of optimization problem is presented in Section 2. Illustrative, numerical examples are given in Section 3. Section 4 contains conclusive remarks.

2. Mathematical formulation

2.1 Notation

T – time period of interest, consisting of N discrete-time intervals of length Δ (e.g., $\Delta = 15$ min); $T = N\Delta$

$I = \{1, 2, \dots, N\}$ – a set of time intervals

$\Phi = \{\varphi^{(1)}(u), \varphi^{(2)}(u), \dots, \varphi^{(M)}(u)\}$ – a set of M airport arrival-departure capacity curves that represent the operational limits for each available runway configuration under various operational (e.g., weather) conditions

$\Pi = \{1, 2, \dots, P\}$ – a set of airport users (e.g., airlines)

a_i – airport total arrival demand for the i th time interval, $i \in I$

d_i – airport total departure demand for the i th time interval, $i \in I$

$a_{i,r}$ – first priority arrival demand of the r th user for the i th time interval, $i \in I, r \in \Pi$

$d_{i,r}$ – first priority departure demand of the r th user for the i th time interval, $i \in I, r \in \Pi$

$a_i^{(s)}$ – total first priority arrival demand for the i th time interval, $i \in I$; $a_i^{(s)} \leq a_i$

$d_i^{(s)}$ – total first priority departure demand for the i th time interval, $i \in I$; $d_i^{(s)} \leq d_i$

X_i – airport arrival queue at the beginning of i th time interval, $i = 1, 2, \dots, N+1$

Y_i – airport departure queue at the beginning of i th time interval, $i = 1, 2, \dots, N+1$

u_i – airport arrival capacity at the i th time interval, $i \in I$

$v_i = \varphi_i(u_i)$ – airport departure capacity at the i th time interval, $i \in I, \varphi_i(u_i) \in \Phi$

2.2 Uncontrollable flights

There is a fraction of traffic demand, both arrival and departure that cannot be delayed and must be served at the scheduled slots. These flights are called uncontrollable and comprise an uncontrollable fraction of traffic demand. Those include airborne flights with long en route time, flights with special status, such as international, military, etc. The flights in the first priority demand identified by the users are also considered as uncontrollable flights.

Let $a_{i,r}$ and $d_{i,r}$ be the first priority arrival and departure demand of the r th user for the i th time interval, respectively. Then by summing first priority demands over all P users, we can determine total priority fraction of arrival and departure demand for the i th interval, respectively:

$$a_i^{(s)} = \sum_{r=1}^P a_{i,r}; \quad d_i^{(s)} = \sum_{r=1}^P d_{i,r}, \quad i \in I \quad (1)$$

If the priority demand does not exceed airport capacity constraints at all N time intervals, i.e., the points $(a_i^{(s)}, d_i^{(s)})$ are under or on the capacity curve (see Fig. 1), then the priority demand is called a feasible demand and can be completely satisfied without any delay.

If $a_i^{(s)}$ or/and $d_i^{(s)}$ exceed airport capacity constraints at least in one of N intervals, then the priority demand cannot be completely satisfied. This demand is non-feasible. In this case, a feasible priority demand will be created by delaying some of the priority flights from the original slots. After that the optimization model will provide the best solution that satisfies the modified users' priority demand.

2.3 Optimization model

Now we can present the optimization model that provides the best allocation of arrival and departure capacities (u_i, v_i) over N intervals of period T ($i = 1, 2, \dots, N$).

First, determine arrival and departure queues at the beginning of $(i+1)$ th interval by the following recurrent equations:

$$X_{i+1} = (X_i + a_i - u_i)^+, \quad X_1 = X^0, \quad i \in I, \quad (2)$$

$$Y_{i+1} = (Y_i + d_i - v_i)^+, \quad Y_1 = Y^0, \quad i \in I, \quad (3)$$

where X^0 and Y^0 are initial conditions that represent residual queues left from the previous time period; symbol $(A)^+$ denotes:

$$(A)^+ = \begin{cases} A, & A \geq 0 \\ 0, & A < 0 \end{cases}$$

Equations (2) and (3) reflect the evolution of arrival and departure queues at each time interval, respectively. In particular, the queue at the beginning of the $(i+1)$ th interval is equal to the sum of the queue at the beginning of the i th interval left from the preceding intervals and traffic demand for the i th interval minus airport capacity.

The regions for arrival and departure capacities are determined by the following inequalities:

$$a_i^{(s)} \leq u_i \leq U_i, \quad (4)$$

$$d_i^{(s)} \leq v_i = \varphi_i(u_i), \quad (5)$$

where $a_i^{(s)}$ and $d_i^{(s)}$ are uncontrollable fractions of arrival and departure demands for the i th interval, respectively, that are determined by (1); U_i is maximum arrival capacity at the i th interval (see Fig. 1).

As an optimization criterion, consider a minimum weighted sum of cumulative arrival and departure queues $\sum_{i=1}^N X_{i+1}$ and $\sum_{i=1}^N Y_{i+1}$, respectively:

$$\text{minimize}_{u, v} \sum_{i=1}^N [\alpha X_{i+1} + (1-\alpha) Y_{i+1}]; \quad 0 \leq \alpha \leq 1, \quad (6)$$

where α is a weight coefficient; $u = (u_1, u_2, \dots, u_N)$ and $v = (v_1, v_2, \dots, v_N)$ are vectors comprising consecutive values of arrival and departure capacities, respectively.

It is not difficult to show that if the traffic demand has been completely satisfied within the time period T , then the cumulative queue over a period T is equal to a number of time intervals Δ (e.g., 15-minute intervals) in the total aircraft flight delay. Therefore, criterion (6) corresponds to minimum weighted total arrival and departure delay. In [3], it is also shown that criterion (6) is equivalent to maximizing weighted sum of total arrival and departure traffic flow (i.e., throughput) at the airport.

Note that (6) is a special case of more general criterion

$$\text{minimize}_{u, v} \sum_{i=1}^N [\alpha_i X_{i+1} + (1-\alpha_i) Y_{i+1}]; \quad 0 \leq \alpha_i \leq 1, \quad (7)$$

with variable weights α_i at each time interval i , which was introduced in [2] and [3].

In this paper, we consider criterion (6).

Then the optimal sequence of arrival and departure capacity pairs (u_i, v_i) at each interval $i = 1, 2, \dots, N$ can be found as a solution of the following optimization problem:

$$\underset{u, v}{\text{minimize}} \sum_{i=1}^N [\alpha X_{i+1} + (1-\alpha)Y_{i+1}]; 0 \leq \alpha \leq 1, \quad (8)$$

subject to

$$X_{i+1} = (X_i + a_i - u_i)^+, \quad X_1 = X^0, \quad i \in I, \quad (9)$$

$$Y_{i+1} = (Y_i + d_i - v_i)^+, \quad Y_1 = Y^0, \quad i \in I, \quad (10)$$

$$a_i^{(s)} \leq u_i \leq U_i, \quad (11)$$

$$d_i^{(s)} \leq v_i = \varphi_i(u_i), \quad (12)$$

where u_i and v_i are integer.

After optimal airport capacities have been determined, the optimal number of arrivals w_i and departures z_i that are accommodated at each time interval (we call it traffic flow) can be calculated as follows:

$$w_i = X_i + a_i - X_{i+1}, \quad i \in I, \quad (13)$$

$$z_i = Y_i + d_i - Y_{i+1}, \quad i \in I, \quad (14)$$

Constraints (11) and (12) guarantee that at least the first priority flights will be served at their requested intervals.

The optimization model contains parameter α that determines relative impact of arrivals and departures in the optimization criterion. The

parameter may be interpreted as a relative priority rate for arrivals in total airport operations. Allocation of weights between the two components in the objective function affects the optimal solution making it more favorable to arrivals or departures. Traffic management specialists can use this parameter as a control parameter for generating alternative strategies of allocation of arrival and departure operations at each 15-minute interval. By varying the parameter, a TFM specialist and other participants in the collaborative optimization process can perform “what if” experiments to find mutually acceptable TFM strategies.

3. Numerical examples

Numerical examples in this section are based on March 3, 2000 historical data for Newark International Airport (EWR).

That day, there was a GDP for EWR that was initiated at 1716 and lasted from 2000 to 2300. (Note: time in this section is Zulu time.) Hourly AAR's during the GDP were 40 flights per hour.

Examples in this section will be calculated for a time period from 1945 to 0245, which includes three hours of GDP and four hours post-GDP.

Table 1 shows arrival and departure demand predicted at 1700 for each 15-minute interval from 1945 to 0245. For both arrivals and departures, there are separate columns for total demand and priority demand for each 15-minute interval.

Table 1. Predicted Demand

TIME	DEMAND				TIME	DEMAND			
	Total		First Priority			Total		First Priority	
	arrival	depart	arrival	depart		arrival	depart	arrival	depart
1945 – 2000	17	9	14	8	2315 – 2330	9	16	9	12
2000 – 2015	9	10	9	10	2330 – 2345	15	8	13	8
2015 – 2030	9	3	9	3	2345 – 0000	6	9	6	9
2030 – 2045	14	14	11	11	0000 – 0015	15	9	14	8
2045 – 2100	15	11	14	8	0015 – 0030	8	12	8	8
2100 – 2115	10	15	8	13	0030 – 0045	4	10	4	10
2115 – 2130	9	10	9	10	0045 – 0100	13	5	13	5
2130 – 2145	20	12	10	12	0100 – 0115	7	11	7	11
2145 – 2200	10	9	10	9	0115 – 0130	10	13	10	12
2200 – 2215	12	8	12	8	0130 – 0145	16	12	13	10
2215 – 2230	6	14	6	14	0145 – 0200	5	12	5	12
2230 – 2245	10	14	10	12	0200 – 0215	6	9	6	9
2245 – 2300	9	8	9	7	0215 – 0230	5	11	5	11
2300 – 2315	11	13	11	11	0230 – 0245	11	6	11	6
TOTAL:						291	293	266	267

During the time period, there was low visibility and ceiling that determined the IFR conditions at the airport. Single runway 4L/4R was used for both arrivals and departures. The fifteen-minute arrival/departure capacity curve for this runway configuration under IFR conditions is shown in Fig. 2.

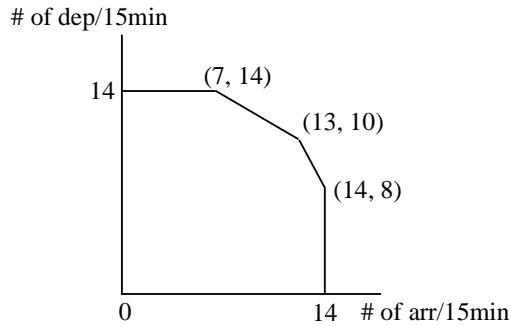


Fig. 2. EWR Arrival/Departure Capacity Curve

The coordinates of the vertices in Fig. 2 clarify the scale of the capacity curve.

According to the curve, the trade-off area comprises six arrival/departure capacity pairs: (7, 14), (8, 13), (10, 12), (11, 11), (13, 10), and (14, 8). Thus, under maximum arrival capacity of 14 flights per 15-minute there is minimum departure capacity equal to 8 flights per 15-minute interval. Under maximum departure capacity of 14

flights per 15-minute, there is minimum arrival capacity equal to 7 flights per 15-minute interval. There are also four arrival/departure capacity pairs of intermediate values available that can be realized at the runway configuration.

The optimization problem (8) – (12) was solved for the predicted traffic demand from Table 1 and the airport capacity curve from Fig. 2 using various values of arrival priority rate α .

Some of the results are shown in Tables 2 - 5. The tables contain the optimal values of arrival and departure capacities, the number of arrivals and departures accommodated in each 15-minute interval, and the size of queue at the end of each interval. The tables also show total traffic and cumulative arrival and departure queues over the period from 1945 to 0245.

Tables 2 and 3 represent the optimization results obtained for $\alpha = 0.5$ and 0.4 , respectively, without taking into account the users' priorities in the predicted demand, i.e., for $a_i^{(s)} = 0$ and $d_i^{(s)} = 0$, $i \in I$.

In the case of equal priority for arrivals and departures ($\alpha = 0.5$), the optimal solution provided cumulative queues of 40 arrival and 106 departure flights with total arrival and departure cumulative queue of 146 flights. It can be interpreted that 40

Table 2. Optimal Solutions without Users' Priorities ($\alpha = 0.5$)

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	13	10	13	9	4	0	2315 – 2330	10	12	10	12	0	10
2000 – 2015	13	10	13	10	0	0	2330 – 2345	13	10	13	10	2	8
2015 – 2030	14	8	9	3	0	0	2345 – 0000	8	13	8	13	0	4
2030 – 2045	13	10	13	10	1	4	0000 – 0015	13	10	13	10	2	3
2045 – 2100	13	10	13	10	3	5	0015 – 0030	10	12	10	12	0	3
2100 – 2115	13	10	13	10	0	10	0030 – 0045	8	13	4	13	0	0
2115 – 2130	7	14	7	14	2	6	0045 – 0100	14	8	13	5	0	0
2130 – 2145	13	10	13	10	9	8	0100 – 0115	11	11	7	11	0	0
2145 – 2200	13	10	13	10	6	7	0115 – 0130	10	12	10	12	0	1
2200 – 2215	13	10	13	10	5	5	0130 – 0145	13	10	13	10	3	3
2215 – 2230	10	12	10	12	1	7	0145 – 0200	8	13	8	13	0	2
2230 – 2245	10	12	10	12	1	9	0200 – 0215	11	11	6	11	0	0
2245 – 2300	10	12	10	12	0	5	0215 – 0230	11	11	5	11	0	0
2300 – 2315	10	12	10	12	1	6	0230 – 0245	14	8	11	6	0	0
TOTAL:										291	293	40	106

arrival flights and 106 departure flights were moved (delayed) from one 15-minute interval to another. (Note: the optimization model deals with 15-minute counts and does not consider flight delays within a 15-minute interval). It is interesting to notice that in spite of almost equal total demands for arrival and departures (291 and 293, respectively) and equal priority ($\alpha = 0.5$) for arrivals and departures, the optimization model provided the strategy much more favorable to arrivals. This happens due to the specific arrival and departure demand profiles over the period of interest.

Table 3 shows that reducing arrival priority rate from 0.5 to 0.4 changed the allocation of arrival and departure capacities so that total arrival queue increased from 40 to 53 flights and total departure queue decreased from 106 to 96 flights. This made the strategy more balanced in terms of number of arrival and departure flights delayed, though the sum of total arrival and departure queues increased slightly from 146 to 149.

Different allocation of arrival and departure capacities for $\alpha = 0.5$ and $\alpha = 0.4$ resulted also in different times of complete recovery from congestion. The complete recovery occurs at the 15-minute interval after which there is no queue. For $\alpha = 0.5$, the complete recovery for arrivals occurred earlier than for $\alpha = 0.4$ (at 0145 as

opposed to 0200). The departure problem in both cases was resolved at the same time interval, 0200.

Now one can determine whether the optimal solutions satisfy the hypothetical first priority flights in the total traffic demand. This can be done by comparing the number of arrivals and departures accommodated by the optimal strategies in each 15-minute interval (from column "Traffic Flow" in Tables 2 and 3) with corresponding values of priority demands from Table 1.

It appeared that neither of the optimal solutions completely satisfies the priority demand and some of them would be delayed. For $\alpha = 0.5$, priority arrival demand was not satisfied at five intervals and priority departure demand was not satisfied at four intervals.

For $\alpha = 0.4$, priority arrival demand was not satisfied at six intervals and priority departure demand was not satisfied at three intervals.

The optimization problem (8) – (12) was then solved using the values of first priority demand in constraints (11) and (12) taken from Table 1. Optimal solutions for $\alpha = 0.5$ are presented in Table 4. As one can see, the priority demand is completely satisfied. The price, however, for making it happen is a substantial deviation from the optimal solution of Table 2: both arrival and

Table 3. Optimal Solutions without Users' Priorities ($\alpha = 0.4$)

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	13	10	13	9	4	0	2315 – 2330	10	12	10	12	0	10
2000 – 2015	13	10	13	10	0	0	2330 – 2345	10	12	10	12	5	6
2015 – 2030	14	8	9	3	0	0	2345 – 0000	10	12	10	12	1	3
2030 – 2045	13	10	13	10	1	4	0000 – 0015	13	10	13	10	3	2
2045 – 2100	13	10	13	10	3	5	0015 – 0030	10	12	10	12	1	2
2100 – 2115	7	14	7	14	6	6	0030 – 0045	10	12	5	12	0	0
2115 – 2130	13	10	13	10	2	6	0045 – 0100	14	8	13	5	0	0
2130 – 2145	13	10	13	10	9	8	0100 – 0115	11	11	7	11	0	0
2145 – 2200	13	10	13	10	6	7	0115 – 0130	10	12	10	12	0	1
2200 – 2215	13	10	13	10	5	5	0130 – 0145	13	10	13	10	3	3
2215 – 2230	10	12	10	12	1	7	0145 – 0200	7	14	7	14	1	1
2230 – 2245	10	12	10	12	1	9	0200 – 0215	13	10	7	10	0	0
2245 – 2300	10	12	10	12	0	5	0215 – 0230	11	11	5	11	0	0
2300 – 2315	10	12	10	12	1	6	0230 – 0245	14	8	11	6	0	0
TOTAL:										291	293	53	96

departure cumulative queues are increased (from 40 to 79 flights for arrivals and from 106 to 117 flights for departures). The sum of cumulative arrival and departure queues increased from 146 to 196, i.e. 34% increase. Note that no other strategy can provide smaller sum of cumulative arrival and departure queues (and therefore total delay) than the one obtained for $\alpha = 0.5$ without additional

constraints for priority demand. In spite of increase in queues and delays, the users might be happy because their first priority flights in the traffic demand were satisfied.

The optimal results with users' priorities for $\alpha = 0.4$ are shown in Table 5.

Table 4. Optimal Solutions with Users' Priorities ($\alpha = 0.5$)

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	14	8	14	8	3	1	2315 – 2330	10	12	10	12	2	11
2000 – 2015	11	11	11	11	1	0	2330 – 2345	13	10	13	10	4	9
2015 – 2030	14	8	10	3	0	0	2345 – 0000	10	12	10	12	0	6
2030 – 2045	11	11	11	11	3	3	0000 – 0015	14	8	14	8	1	7
2045 – 2100	14	8	14	8	4	6	0015 – 0030	8	13	8	13	1	6
2100 – 2115	8	13	8	13	6	8	0030 – 0045	7	14	5	14	0	2
2115 – 2130	13	10	13	10	2	8	0045 – 0100	14	8	13	7	0	0
2130 – 2145	10	12	10	12	12	8	0100 – 0115	11	11	7	11	0	0
2145 – 2200	13	10	13	10	9	7	0115 – 0130	10	12	10	12	0	1
2200 – 2215	13	10	13	10	8	5	0130 – 0145	13	10	13	10	3	3
2215 – 2230	7	14	7	14	7	5	0145 – 0200	8	13	8	13	0	2
2230 – 2245	10	12	10	12	7	7	0200 – 0215	11	11	6	11	0	0
2245 – 2300	13	10	13	10	3	5	0215 – 0230	11	11	5	11	0	0
2300 – 2315	11	11	11	11	3	7	0230 – 0245		8	11	6	0	0
TOTAL:									291	293	79	117	

Table 5. Optimal Solutions with Users' Priorities ($\alpha = 0.4$)

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	14	8	14	8	3	1	2315 – 2330	10	12	10	12	2	11
2000 – 2015	11	11	11	11	1	0	2330 – 2345	13	10	13	10	4	9
2015 – 2030	14	8	10	3	0	0	2345 – 0000	10	12	10	12	0	6
2030 – 2045	11	11	11	11	3	3	0000 – 0015	14	8	14	8	1	7
2045 – 2100	14	8	14	8	4	6	0015 – 0030	8	13	8	13	1	6
2100 – 2115	8	13	8	13	6	8	0030 – 0045	7	14	5	14	0	2
2115 – 2130	13	10	13	10	2	8	0045 – 0100	14	8	13	7	0	0
2130 – 2145	10	12	10	12	12	8	0100 – 0115	11	11	7	11	0	0
2145 – 2200	13	10	13	10	9	7	0115 – 0130	10	12	10	12	0	1
2200 – 2215	13	10	13	10	8	5	0130 – 0145	13	10	13	10	3	3
2215 – 2230	7	14	7	14	7	5	0145 – 0200	7	14	7	14	1	1
2230 – 2245	10	12	10	12	7	7	0200 – 0215	11	11	7	10	0	0
2245 – 2300	13	10	13	10	3	5	0215 – 0230	11	11	5	11	0	0
2300 – 2315	11	11	11	11	3	7	0230 – 0245	14	8	11	6	0	0
TOTAL:									291	293	80	116	

Any of the optimization results were much better than results obtained when the trade-off between arrival and departure capacity was not utilized. For a constant arrival rate of 13 flights and departure rate of 10 flights per 15-minute (this corresponds to maximum total capacity of 23 flights per 15 minute) the cumulative arrival queue is 29 flights and cumulative departure queue is 429 flights (see Table 6). Moreover, 21 departure flights were not

served within the time period considered and were left in outstanding queue for service after 0245. In this case, without using the trade-off, arrival capacity was underutilized in many time intervals because of insufficient demand. At the same time, departure demand was high enough so that departure capacity of 10 flights per 15 minutes was consistently insufficient.

Table 6. Solutions without Trade-Off for Constant Airport Capacity: 13/10

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	13	10	13	9	4	0	2315 – 2330	13	10	9	10	0	24
2000 – 2015	13	10	13	10	0	0	2330 – 2345	13	10	13	10	2	22
2015 – 2030	13	10	9	3	0	0	2345 – 0000	13	10	8	10	0	21
2030 – 2045	13	10	13	10	1	4	0000 – 0015	13	10	13	10	2	20
2045 – 2100	13	10	13	10	3	5	0015 – 0030	13	10	10	10	0	22
2100 – 2115	13	10	13	10	0	10	0030 – 0045	13	10	4	10	0	22
2115 – 2130	13	10	9	10	0	10	0045 – 0100	13	10	13	10	0	17
2130 – 2145	13	10	13	10	7	12	0100 – 0115	13	10	7	10	0	18
2145 – 2200	13	10	13	10	4	11	0115 – 0130	13	10	10	10	0	21
2200 – 2215	13	10	13	10	3	9	0130 – 0145	13	10	13	10	3	23
2215 – 2230	13	10	9	10	0	13	0145 – 0200	13	10	8	10	0	25
2230 – 2245	13	10	10	10	0	17	0200 – 0215	13	10	6	10	0	24
2245 – 2300	13	10	9	10	0	15	0215 – 0230	13	10	5	10	0	25
2300 – 2315	13	10	11	10	0	18	0230 – 0245	13	10	11	10	0	21
TOTAL:										291	272	29	429

Table 7. Solutions without Trade-Off for Constant Airport Capacity: 11/11

TIME	Airport Capacity		Traffic Flow		Queue		TIME	Airport Capacity		Traffic Flow		Queue	
	arr	dep	arr	dep	arr	dep		arr	dep	arr	dep	arr	dep
1945 – 2000	11	11	11	9	6	0	2315 – 2330	11	11	11	11	5	12
2000 – 2015	11	11	11	10	4	0	2330 – 2345	11	11	11	11	9	9
2015 – 2030	11	11	11	3	2	0	2345 – 0000	11	11	11	11	4	7
2030 – 2045	11	11	11	11	5	3	0000 – 0015	11	11	11	11	8	5
2045 – 2100	11	11	11	11	9	3	0015 – 0030	11	11	11	11	5	6
2100 – 2115	11	11	11	11	8	7	0030 – 0045	11	11	9	11	0	5
2115 – 2130	11	11	11	11	6	6	0045 – 0100	11	11	11	10	2	0
2130 – 2145	11	11	11	11	15	7	0100 – 0115	11	11	9	11	0	0
2145 – 2200	11	11	11	11	14	5	0115 – 0130	11	11	10	11	0	2
2200 – 2215	11	11	11	11	15	2	0130 – 0145	11	11	11	11	5	3
2215 – 2230	11	11	11	11	10	5	0145 – 0200	11	11	10	11	0	4
2230 – 2245	11	11	11	11	9	8	0200 – 0215	11	11	6	11	0	2
2245 – 2300	11	11	11	11	7	5	0215 – 0230	11	11	5	11	0	2
2300 – 2315	11	11	11	11	7	7	0230 – 0245	11	11	11	8	0	0
TOTAL:										291	293	155	115

In the case of constant arrival and departure capacity of 11 flights per 15-minute each during the whole time period, cumulative arrival and departure queues are equal to 155 and 115 flights, respectively, with the sum of these queues equal to 270 flights (see Table 7). This is much worse than any of the optimal trade-off solutions.

To estimate the potential benefits of optimal arrival/departure trade off for the CDM GDPs, the optimal arrival rates for each solution were incorporated into the FSM algorithms and applied to the March 3rd data using the reply feature of FSM. (Note: FSM does not currently control departures). In the case without taking into account the users' priority and for $\alpha = 0.5$, the total delay is 1129 minutes. The optimal arrival rates that reflect the users' priority provided the total arrival delay of 1737 minutes, i.e., 54% increase. This is the price for satisfying the users' priority in their traffic demand.

Without a trade off, for constant airport arrival rate of 11 flights per 15-minute (or hourly AAR of 44 flights), the FSM algorithms provided a total arrival delay of 4054 minutes. This is 133% higher than for optimal AARs with users' priorities and 259% higher than for optimal AARs without users' priorities in case of $\alpha = 0.5$.

The examples clearly illustrate the potential benefits from Collaborative Optimization and show how it could upgrade the level of collaboration between the FAA and NAS users within the CDM program. Collaborative Optimization offers more efficient arrival/departure strategies and better utilization of existing airport capacity in combination with users' participation in TFM decision making.

4. Conclusions

This paper introduces a new concept, Collaborative Optimization, that could advance the CDM GDP procedures and algorithms, improve efficiency of GDP and offer a constructive approach for optimizing utilization of airport capacity while simultaneously solving arrival and departure congestion problems at airports in the CDM environment.

The core element of the concept is joint consideration of arrivals and departures and optimization of trade-off between arrival and departure capacity at the airport during GDP. It provides more strategic and more efficient assignment of AARs during GDP. Additionally, it makes it possible for more efficient departure planning at airports that are subject to GDP.

The paper also proposed an optimization model that is capable to take into account users' priorities in their arrival and departure traffic demand. Optimal solution provides more efficient TFM strategies at airports with minimum delays and maximum airport throughput that could be achieved while satisfying users' priorities.

The Collaborative Optimization approach and the underlying optimization model can be used as a basic addition to CDM decision-making processes and decision support tools to improve their efficiency and expand their functionality and applications.

Numerical examples, presented in the paper, illustrate the benefits that Collaborative Optimization would provide to advance the CDM procedures and enhance their efficiency and level of collaboration between the FAA and NAS users.

References

1. Wambsganns, M., "Collaborative Decision Making Through Dynamic Information Transfer", *Air Traffic Control Quarterly*, Vol. 4(2), pp. 109 – 125, 1997
2. Gilbo, E. P., "Airport Capacity: Representation, Estimation, Optimization," *IEEE Transactions on Control Systems Technology*, Vol. 1, pp. 144 – 154, 1993
3. Gilbo, E. P., "Optimizing Airport Capacity Utilization in Air Traffic Flow Management Subject to Constraints at Arrival and Departure Fixes," *IEEE Transactions on Control Systems Technology*, Vol. 5, pp. 490 – 503, 1997

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