Demand Capacity Balancing at Vertiports for Initial Strategic Conflict Management of Urban Air Mobility Operations

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***Abstract*—Demand Capacity Balancing (DCB) can be applied in strategic conflict management for safe Urban Air Mobility (UAM) operations. Even when the operational tempo is low, traffic demand can locally exceed the capacity at airspace resources like vertiports. This paper proposes a DCB algorithm to manage the UAM traffic demand strategically, given the capacity at vertiports. The DCB algorithm is evaluated with traffic scenarios at Dallas/Fort Worth urban area in terms of various metrics such as demand distribution changes, pre-departure delay, and the number of simultaneous operations in the air. With the same experiment setup, more extended studies are also conducted to investigate how the UAM flight scheduling based on the DCB algorithm is affected by various conditions that can occur in a practical UAM environment, including vertiport capacity changes, a slot size parameter in capacity constraint, differences in operational policy between operators like lead time for flight plan submission and cruise flight speed, and uncertainties in actual departure and arrival times.**

Keywords—Urban Air Mobility (UAM), Strategic Conflict Management, Demand Capacity Balancing (DCB)

I. INTRODUCTION

Urban Air Mobility (UAM) is a new transportation concept that enables highly automated, cooperative, passenger or cargo-carrying air transportation services in and around urban areas [1, 2]. To achieve the high level of operational density and complexity desired by the UAM community, an airspace system that allows UAM operators to readily access and operate safely and efficiently in the airspace is needed. This airspace system will require air traffic management designed to reduce the risk of conflicts and loss of separation between UAM flights.

In air traffic management, strategic conflict management is generally considered as the first layer of conflict management for safe flight operations to condition the traffic to reduce the need for airborne separation provision, the second layer of conflict management [3]. Demand Capacity Balancing (DCB) is one of the concept components to achieve strategic conflict management, along with airspace organization and management and traffic synchronization components. For safe and efficient UAM operations, DCB strategically evaluates traffic demand and resource capacities to allow UAM operators to determine when, where and how they operate, while mitigating conflicting needs for airspace and vertiport capacity. The DCB can be applied whenever UAM demand exceeds the capacity in airspace or at vertiports where these facilities provide takeoff and landing areas and support other necessary services like maintenance and parking for UAM operations. As the UAM ecosystem evolves with advanced technologies and matured operational procedures, more complicated conflict management will likely be needed. However, even the UAM 'Concept of Operation (ConOps) 1.0' operational stage defined by the FAA [4] for low operational tempo needs the DCB to manage demand. Also, the vertiport capacity may become a bottleneck of growing UAM traffic as the airport runway is for traditional air traffic. Therefore, it is meaningful to explore the demand capacity balancing at vertiports only, as an initial strategic conflict management approach for UAM operations.

For this research, NASA has been developing a demand-capacity imbalance detection and resolution service for UAM. This DCB service identifies the demand from UAM operators and compares the demand to a given capacity at the shared resources (i.e., vertiports) over the upcoming time horizon which is divided into time bins having a constant interval. When a new flight plan is submitted, the algorithm embedded in the DCB service checks the available time bins based on the desired departure time and estimated arrival time at origin and destination vertiports, respectively. If the time bins for the originally desired times are already occupied by other flights (i.e., demand is at or above capacity), the algorithm finds the next available time bins for takeoff and landing and shifts the conflicting departure time to the earliest time that satisfies the capacity constraints at both origin and destination vertiports. The details of this DCB algorithm will be described in Section II.

When UAM flights are operated in urban areas, it is expected that many practical issues will arise. Due to many factors such as microclimate weather and facility conditions, vertiport capacity can change dynamically. Vertiport operators may adjust the parameters that define the capacity constraint like the slot size and the count of available operations in each slot. If the UAM ecosystem is built upon the federated system architecture with multiple operators, more complicated situations are expected to happen, which may require some Community Based Rules (CBRs) developed by stakeholders and approved by the FAA [4]. For example, UAM vehicles would fly at different flight speeds, depending on UAM vehicle models. While scheduling the same desired departure times, UAM operators may submit their flight plans in different timings by service type (e.g., regular shuttle service vs. on-demand service). Additionally, as in traditional flight operations, actual departure and arrival times can have large variations, compared to the schedule. Using the proposed DCB algorithm, we also investigate how the actual flight schedule and the DCB performance are affected by these practical considerations such as parameter changes in the vertiport capacity constraint, flight speed and lead time differences between operators, and actual departure and arrival time errors over the schedule.

This paper will describe the proposed DCB algorithm for UAM operations with a simple use case to explain how this algorithm works for flight schedule modification in Section II. After setting up the experiment environment with a route structure and a traffic scenario, the DCB algorithm is evaluated in Section III in terms of various metrics. Section IV provides the analytical results from the extended studies about the impacts of various practical considerations in UAM operations on the flight schedule and DCB performance. In Section V, conclusions and potential future work will be provided.

II. Demand Capacity Balancing Algorithm

Demand Capacity Balancing (DCB) consists of two parts: demand-capacity imbalance detection and its resolution. For the DCB implementation at vertiports in UAM operations, NASA has developed two services, which are Strategic Conflict Management Service (SCMS) and Demand-Capacity imBalance Detection service (DCBD). The objective of SCMS is to ensure that pre-departure flights have sufficient separation from other flights in the strategic planning phase. For this, SCMS coordinates with a UAM fleet operator to receive a new operational intent, asks DCBD whether any demand-capacity imbalances are observed if this new operation were to be scheduled at the desired time, resolve the imbalances, if any exist, and sends the modified operational intent back to the operator. DCBD is designed to detect any imbalances between demand and capacity at the shared airspace resources. DCBD keeps monitoring the existing demand from all the operators through the Provider of Services for UAM (PSU) network and receiving the latest capacity information. Per SCMS's request, DCBD checks the demand-capacity imbalance status at the airspace resources related to the new operational intent. If the new flight doesn't violate the DCB, SCMS doesn't need to modify its operational intent. On the contrary, if any airspace resource that the new flight plans to use is already at capacity, DCBD calculates the available capacity information at the current and future time horizon, comparing the given capacity with existing demand. The available capacity information (open slots) provided by DCBD is used by SCMS to find the best schedule that does not violate any capacity constraints at the shared resources. These services can be generally applied to all the shared airspace resources that UAM flights use during the entire flight phases such as origin/destination vertiports, entry/exit points of UAM corridors which are the UAM-specific performance-based airspace structures with defined dimensions [4], and crossing/merging waypoints in the UAM route structure. For the UAM ConOps 1.0 operations or the UAM Maturity Level (UML) 2 environment [5], however, we will focus on the DCB at origin/destination vertiports only.

Fig. 1 shows the flow chart for the proposed DCB algorithm. When the UAM operator gets a trip request, it creates a new operational intent, including origin, destination, desired departure time at origin vertiport, and estimated arrival time at destination. When SCMS receives this operational intent, it checks if this flight is new and still on the ground. For the new flight, SCMS requires DCBD to check if inserting this new flight would violate any capacity constraints at origin and destination vertiports. DCBD reads the latest vertiport capacity information related to this flight and identifies the relevant demand at the shared airspace resources (i.e., active or planned flights using the same vertiports). If the current demand is already at (or over) the given capacity, the new flight cannot use the assigned vertiport at the desired time. In that case, DCBD calculates the available capacity information (= capacity – demand) in the current and following planning horizon and sends the open slot information back to SCMS. If any demand-capacity imbalances with respect to the new flight are identified by DCBD, SCMS tries to resolve this imbalance by shifting its departure time to the next available slot until the imbalances are resolved. Note that SCMS should check the imbalances both at origin and destination vertiports. Once resolved, based on the modified departure time, SCMS will build four-dimensional trajectories (i.e., Expected Times of Arrivals at waypoints along the given route) and relevant operational volumes for safe operations, and send them back to UAM operator.

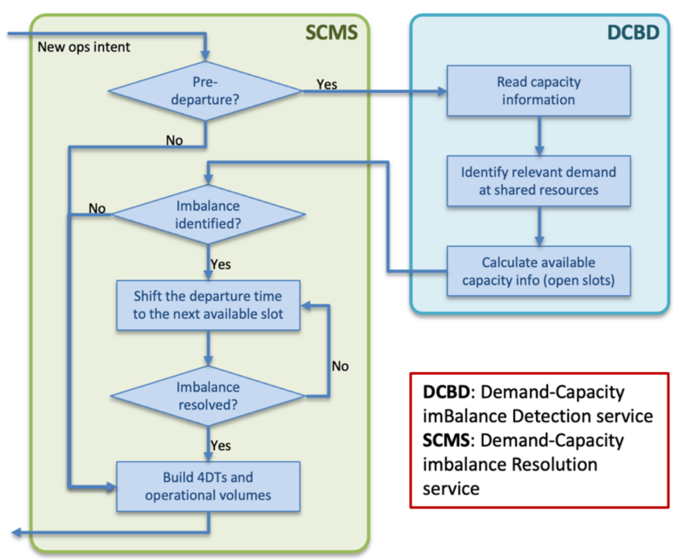

Fig. 1. Flow chart for demand capacity balancing services.

To help understand how the proposed DCB algorithm is working with an actual flight schedule, a simple use case is provided in Fig. 2. Suppose that a new flight shown as a red dot needs to be scheduled from vertiport A to vertiport Z with the desired departure time at 11:07 and the estimated arrival time at 11:21, as illustrated in Fig. 2. Assuming that only two operations are allowed in each 12-minute time slot as vertiport capacity, DCBD identifies which time bins at vertiports are already saturated with the existing demand. In Fig. 2, those blocked slots are marked as shaded boxes. Since the desired departure time of the new flight is within the blocked slot at origin vertiport A due to two existing flights illustrated as black dots, DCBD tells SCMS that there is a demand-capacity imbalance to be resolved. Then, SCMS shifts its departure time to the beginning of the next available time bin (open slot shown as a hollow box) in order to minimize the scheduled delay. In this example, the new departure time becomes 11:12, as shown as a blue dot in Fig. 2(b). However, it is found that the modified arrival time at destination vertiport Z is located within a blocked slot. Therefore, this flight is shifted to the next available time bin to satisfy the DCB conditions at both vertiports. Eventually, the new departure time is set to be 11:22, as shown as a green dot, with a 15-minute ground delay.

NASA is currently using these DCB services, DCBD and SCMS, to implement initial strategic conflict management in collaborative simulations with industry partners, called X4 simulation, of which the objective is to establish, develop, and test the Minimum Viable Product (MVP) for the PSU needed to ensure scalable UAM operations [6]. In this paper, the algorithms embedded in these services were integrated and simplified for easier applications to various experimental studies in Section IV. A pseudocode describing this DCB algorithm is shown in Fig. 3.

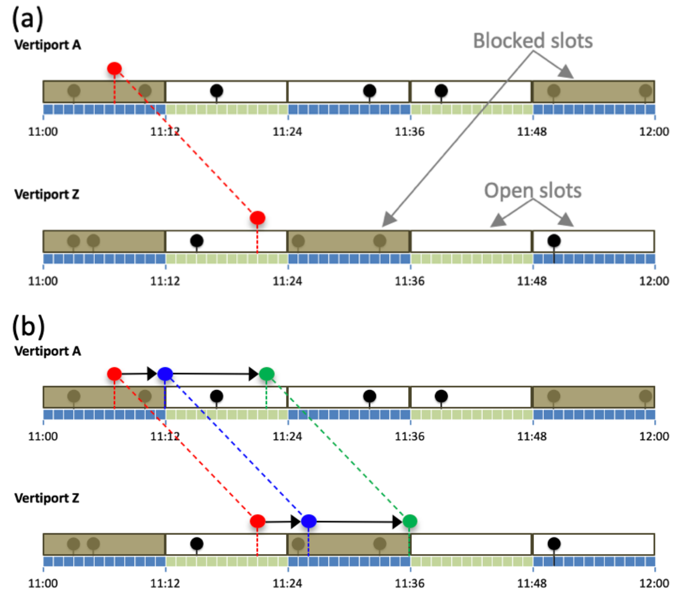

Fig. 2. Use case of demand capacity balancing algorithm.

Step 1. Initialization
bin = 12; # time bin size in minutes
c = 4; # capacity (ops/time bin)
demandDB = [,]; # database for existing demand count at [vertiport, time bin]
Step 2. Read the traffic scenario and capacity information
LOAD callsign, origin vertiport (v^x_{dep}), destination vertiport (v^x_{arr}), departure time (t^x_{dep}), arrival time (t^x_{arr}), etc. for all flights
$travelT^x = t^x_{arr} - t^x_{dep}$; # nominal travel time from Origin to Destination
$t^x_{dep,\ initial} = t^x_{dep}$; # initial departure time for delay calculation
Step 3. Receive a new operational intent and update 4-Dimensional Trajectory (4DT) data for demand capacity balancing
while a flight x for scheduling is remained from the traffic scenario (in the order of flight plan submission time),
j^o = QUOTIENT(t^x_{dep}, bin*60); t_{jo} = QUOTIENT(t^x_{dep}, bin*60)*bin*60; # At origin vertiport v^x_{dep}, $t_{jo} <= t^x_{dep} < t_{jo}$ + bin;
j^d = QUOTIENT(t^x_{arr}, bin*60); t_{jd} = QUOTIENT(t^x_{arr}, bin*60)*bin*60; # At destination vertiport v^x_{arr}, $t_{jd} <= t^x_{arr} < t_{jd}$ + bin;
dep_val = demandDB[v^x_{dep}, j^o]; # obtain existing demand at origin vertiport in the current time bin for desired departure time
arr_val = demandDB[v^x_{arr}, j^d]; # obtain existing demand at destination vertiport in the current time bin for estimated landing time
while (dep_val > = c) || (arr_val >= c) # repeat the while loop until finding an open time bin
if (dep_val > = c), # if the current time bin at origin vertiport is not available for takeoff,
$j^o = j^o + 1$; $t_{jo} = t_{jo}$ + bin; # move to the next time bin
$t^x_{dep} = t_{jo}$; # update the departure time to the start time of the next time bin
$t^x_{arr} = t^x_{dep}$ + travelT; # update the estimated arrival time
j^d = QUOTIENT(t^x_{arr}, bin*60); # update the j^dth time bin for arrival
dep_val = demandDB[v^x_{dep}, j^o]; arr_val = demandDB[v^x_{arr}, j^d]; # update dep_val and arr_val
else if (arr_val >= c), # if the current time bin at destination vertiport is not available for landing,
$j^d = j^d + 1$; $t_{jd} = t_{jd}$ + bin; # move to the next time bin
$t^x_{arr} = t_{jd}$; # update the arrival time to the start time of the next time bin
$t^x_{dep} = t^x_{arr} - travelT^x$; # update the departure time
t_{jo} = QUOTIENT(t^x_{dep}, bin*60)*bin*60; # update the start time of the departure time bin in which the new flight x will take off
j^o = QUOTIENT(t^x_{dep}, bin*60); # update the j^oth time bin for departure
dep_val = demandDB[v^x_{dep}, j^o]; arr_val = demandDB[v^x_{arr}, j^d]; # update dep_val and arr_val
end
end
demandDB[v^x_{dep}, j^o] = dep_val + 1; # update the existing demand database at origin vertiport with the current flight x
demandDB[v^x_{arr}, j^o] = arr_val + 1; # update the existing demand database at destination vertiport with the current flight x
$delay^x = t^x_{dep} - t^x_{dep,\ initial}$; # calculate pre-departure delay
$t^x_{wpt} = t^x_{wpt} + delay^x$; # update the Scheduled Times of Arrival at waypoints along the given route
RETURN the updated 4DT; # callsign, v^x_{dep}, v^x_{arr}, $t^x_{dep,initial}$, $t^x_{arr,initial}$, t^x_{dep}, t^x_{arr}, t^x_{wpt}, $delay^x$, etc.
end

Fig. 3. Pseudocode for demand capacity balancing algorithm.

III. DCB Algorithm Evaluation

In this section, the proposed algorithm for the DCB at vertiports is evaluated with traffic scenarios. The DCB algorithm is evaluated with a typical scenario first. Then, the same evaluation process is repeated for ten different traffic scenarios to obtain more general results in terms of various metrics.

A. Experiment Setup

We set up the experiment environment for the DCB algorithm evaluation. It is assumed that there are two UAM fleet operators sharing the traffic demand equally in the UAM network. We start with an assumption that these two operators use the same UAM vehicle model having identical performance (e.g., cruise speed, banked turn angle, and climb/descent gradient) and the same lead time from flight plan submission to desired departure time. To represent the UAM ConOps 1.0 operations environment, five vertiports and ten routes connecting those vertiports are considered in the Dallas/Fort Worth metropolitan area. Fig. 4 illustrates the route structure used in this experiment in which five vertiports starting with the “DF” tag are marked as black circles. All the vertiports and routes are shared between operators (i.e., no airspace resources are dedicated to a specific operator). For the vertiport capacity, up to 4 operations in the fixed 12-minute time bins are allowed at each vertiport, but simultaneous takeoffs and/or landings are allowed within the given capacity.

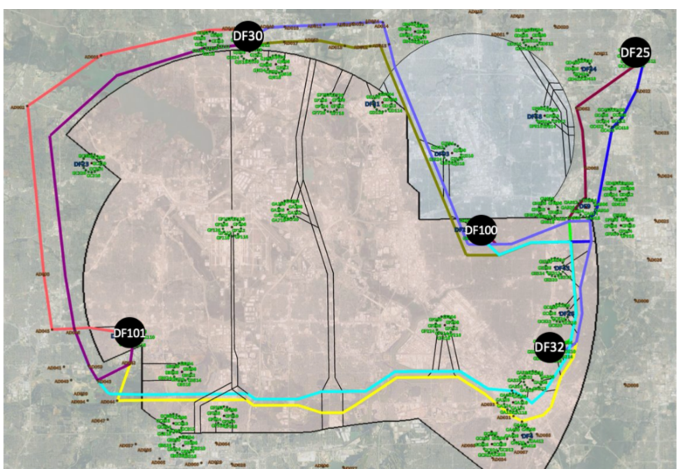

Fig. 4. Route network in Dallas/Fort Worth urban area.

For the traffic scenario, a two-hour long scenario with one peak is developed. Corresponding to the UML-2’s low density traffic, this scenario has 60 flights in total (30 flights for each operator), of which demand-capacity ratio is 60% as the demand is 120 operations (= 60 departures + 60 arrivals) and the vertiport capacity is 200 (= 4 ops/vertiport/time bin x 5 vertiports x 10 time bins/2hour). The departure times are properly distributed to have a peak in the middle of scenario, and demand is evenly distributed over ten routes (i.e., 3 flights per route from each operator). Then, the departure times and routes are randomly assigned to each flight. With the flight speed assumed to meet the performance requirements in the initial UAM corridors (e.g., 120knots for cruise speed), nominal flight times are computed for the given routes, as summarized in Table I. These flight times are used to estimate the landing times at destination vertiports.

TABLE I. Flight Times for nominal routes

No.	Origin	Destination	Flight Time (min)
1	DF100	DF25	11.2
2	DF100	DF101	24.7
3	DF101	DF30	15.3
4	DF101	DF100	25.4
5	DF25	DF100	10.5
6	DF25	DF32	10.6
7	DF30	DF101	16.5
8	DF30	DF32	15.8
9	DF32	DF25	10.7
10	DF32	DF30	17.0

B. Algorithm Evaluation for a Typical Scenario

Fig. 5 shows the traffic demand profile for a typical scenario developed in this experiment setup. Each stacked bar consists of departure demand (blue bars) and arrival demand (green bars) from two operators in each 12-min time bin.

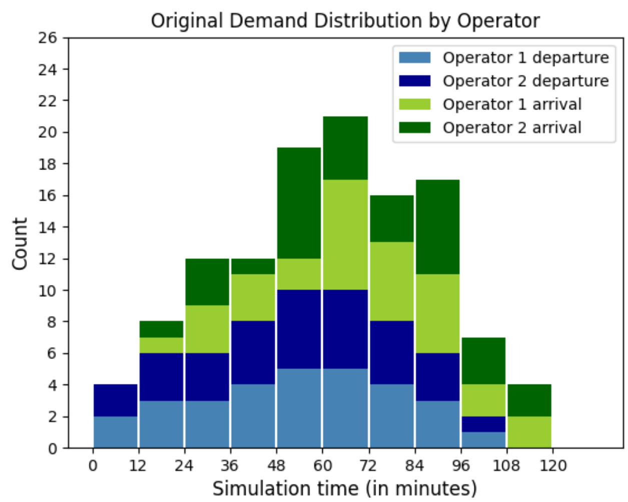

Fig. 5. Demand (departure and arrival) distribution by operator.

The proposed DCB algorithm was applied to resolve the demand-capacity imbalances that this traffic scenario would encounter. The comparison of the heatmaps in Fig. 6 shows how the DCB algorithm successfully mitigated the demand at vertiports. In the heatmaps, the horizontal axis shows ten time bins where each bin represents a 12-minute interval, and the vertical axis shows five vertiports. The number in each cell shows the number of operations, counting both departures and arrivals, at a specific vertiport in each time bin. For the given capacity of 4 operations/vertiport/bin, Fig. 6 shows that the original demand sometimes exceeds the capacity (e.g., 7 operations at DF100 in ‘bin4’), but the modified demand is reduced to the given capacity or lower after resolving demand-capacity imbalances.

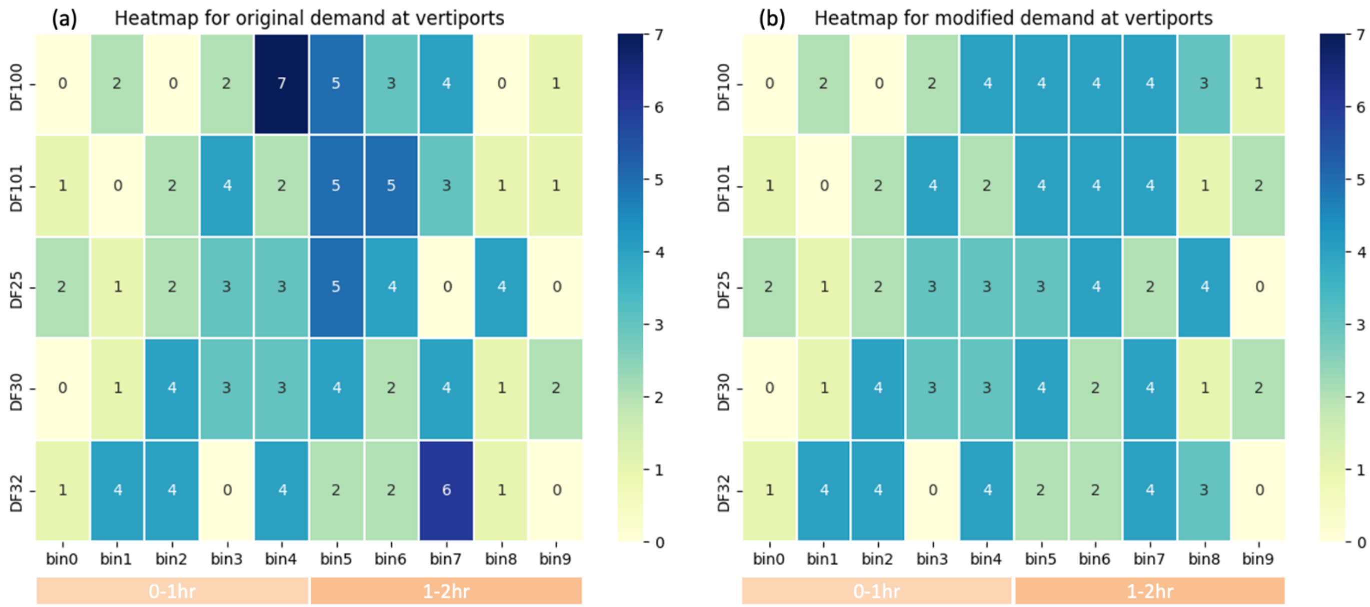

Fig. 6. Heatmaps for (a) original demand and (b) modified demand at five vertiports in each 12-min time bin.

In the strategic conflict management layer like the proposed DCB algorithm, the demand mitigation is achieved by assigning pre-departure delay. Fig. 7 compares the departure time distributions of original and modified flight schedules. Beyond 48 minutes, we can observe that the departure times of some flights are shifted to the later time bins to meet the capacity constraint at vertiports. The arrival time distributions also show a similar tendency because the same amount of time is shifted for each delayed flight. Fig. 8 shows the histogram for the pre-departure delay distribution by operator. In this scenario, 15 flights (25% of total flights) get delayed for the DCB. Those flights having positive delay values are delayed for 7.1min on average, with the maximum delay of 21.0min assigned to Operator 2's flight. The sum of delays is 55.5min (7 flights) and 51.5min (8 flights) for Operator 1 and 2, respectively, indicating that the scheduled delays are fairly distributed between operators in this case.

To measure the traffic density in the airspace, we also counted the number of simultaneous operations based on the modified schedule after DCB. Fig. 9 shows how the aircraft counts for each operator and in total change as the simulation time progresses. It is observed that the number of simultaneous flights reaches up to 15 flights in this scenario. As there are 10 routes available, that means more than one flight is flying along some of the individual routes during the peak.

C. Evaluation Metrics for Ten Traffic Scenarios

The evaluation has been repeated for ten different traffic scenarios in which the departure times and OD pairs are randomly assigned while keeping the same departure demand profile and demand distribution over the given ten routes. The main metrics measured are summarized in Table II. In most metrics, the average values from the ten random scenarios are similar to the ones for a typical scenario shown in Section III.B. Depending on the OD pair and departure time assignments in the given scenario, the delay distribution between operators can be varied, as shown in the large standard deviation values for the sum of delays by operator.

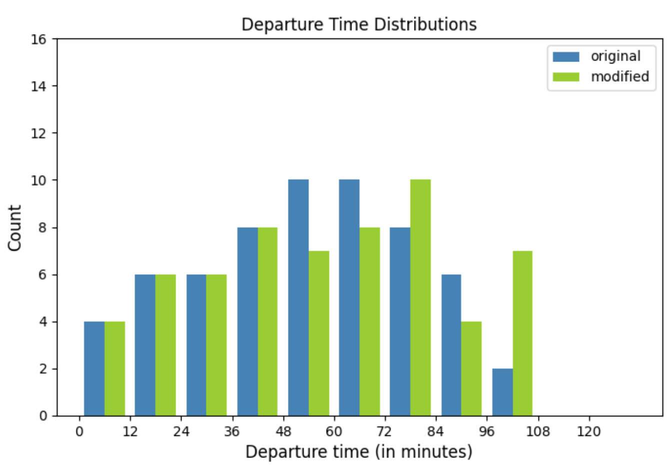

Fig. 7. Histogram for departure time changes before and after DCB.

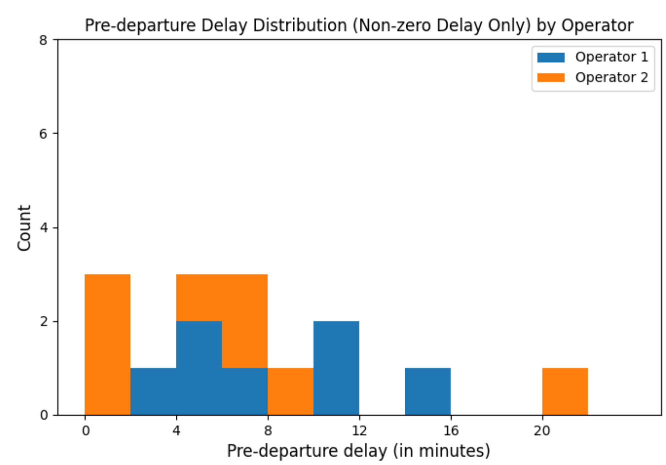

Fig. 8. Histogram for pre-departure delay distribution.

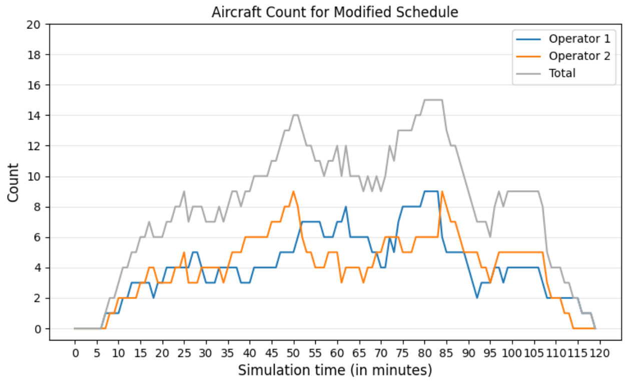

Fig. 9. Number of simultaneous flights over simulation time.

TABLE II. METRICS FOR EVALUATION FROM TEN RUNS

Measurement	Average	Standard Deviation
Number of flights delayed	15.7	4.2
Number of flights delayed [Operator 1 : Operator 2]	7.4 : 8.3	2.8 : 2.5
Number of flights delayed more than 5min	8.7	4.6
Mean delay (min)	1.95	0.85
Median delay (min)	0.00	0.00
Maximum delay (min)	16.50	4.01
Mean delay (nonzero only)	7.23	1.81
Median delay (nonzero only)	6.60	2.07
Sum of delays (min) [Operator 1 : Operator 2]	57.5 : 59.7	30.4 : 32.0

IV. EXTENDED STUDIES FOR PRACTICAL CONSIDERATIONS

There are various practical issues that should be considered when actual UAM flights are operated, which can affect the flight scheduling and DCB performance. Therefore, based on the same experiment setup using the proposed DCB algorithm and the traffic scenario in Dallas/Fort Worth urban area, we have conducted various experimental studies to see the impacts of practical concerns that can occur in actual UAM operations. These concerns include vertiport capacity changes (different demand-capacity ratios), a time bin size parameter (slot size) used in vertiport capacity constraint, lead time differences between operators for flight plan submission (fairness and prioritization issues in scheduling), flight speed differences between operators depending on the operating vehicle models, and uncertainties in actual departure/arrival times over the schedule.

A. Effects of Vertiport Capacity Constraint

The objective of the first extended study is to see the impact of vertiport capacity changes on traffic congestion and pre-departure delay. For a fixed demand level, vertiport capacity can be varied both in short and long terms. For example, the vertiport capacity can be temporarily reduced in daily operations due to adverse weather condition, vertiport facility issues, or resource shortage. On the other hand, the vertiport capacity can increase with additional vertipads (touchdown and liftoff (TLOF) areas), parking spaces, battery charging stations, and/or ground crew.

In this study, the experiment variable is the capacity value in the 12-min time bin at each vertiport, and ranges from 2ops/12min (equivalent to 120% of demand-capacity ratio) to 6ops/12min (equivalent to 40% of demand-capacity ratio). Note that the baseline capacity used in the example scenario and the following experiments is 4ops/12min at each vertiport, which corresponds to the demand-capacity ratio of 60% over capacity for the given traffic scenario.

Figs. 10-11 show the number of delayed flights and the mean delay for the given capacity values. In the figures, the bar chart shows the average values from 10 scenarios, while the whiskers represent the standard deviations. With the 4ops/12min vertiport capacity (baseline), 26% of flights are delayed for 7 minutes on average. When including flights that were not delayed, the mean delay goes down to 2 minutes, with zero for the median delay. The results in this study show that the higher vertiport capacity can accommodate the given demand with fewer delayed flights and lower delay. On the other hand, a capacity reduction that produces a demand-capacity ratio of 80% or higher may lead to passenger inconvenience with long delay. If the capacity constraint is reduced to 2ops/12min and 3ops/12min, the maximum ground delay can increase to 69 and 29 minutes, respectively, which may not be acceptable to the UAM transportation service users.

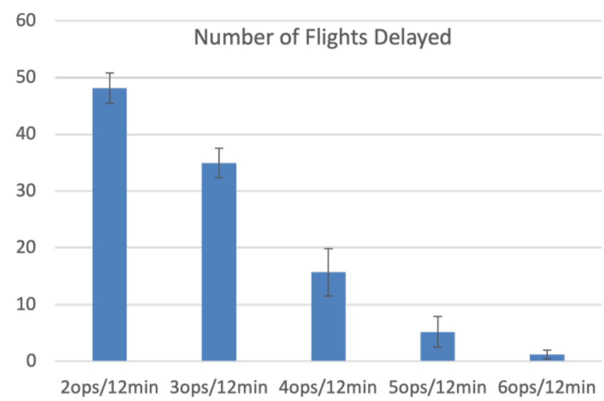

Fig. 10. Number of delayed flights for different vertiport capacity constraints.

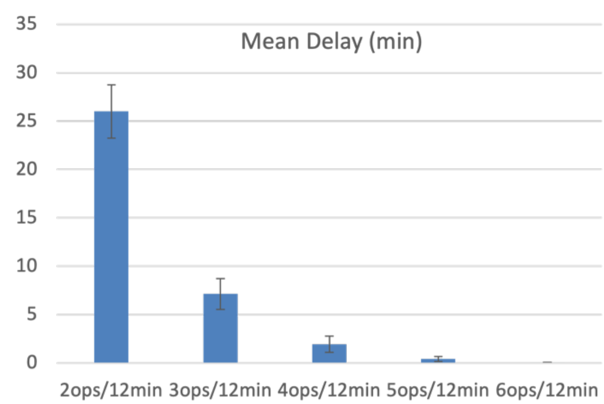

Fig. 11. Mean delay for different vertiport capacity constraints (all flights).

B. Effects of Time Bin Size in Capacity Constraint

Next, we investigate the impact of the time bin size (slot size) used in the vertiport capacity constraint on the assigned delay. As the baseline, we have assumed that the time bin size is 12 minutes for capacity constraints, but other time bin sizes can be used in the future UAM operations. In this study, we try various time bin sizes, ranging from 3min (1ops/3min) to 18min (6ops/18min), while keeping the same capacity rate (1operation every 3min).

Figs. 12-13 show the number of delayed flights and the mean delay for the different time bin sizes in the vertiport capacity constraint. As can be seen, the smaller capacity bin size can result in more delays with more delayed flights. When only one operation is allowed in 3min time bin at a vertiport, for instance, more than 60% of flights are delayed because of too tight capacity constraints. However, the large time bin size has a potential risk to increase the frequency of tactical separation provision in the air, which is the second layer in conflict management before collision avoidance, since the proposed strategic conflict management approach through DCB does not provide sufficient separation between consecutive departures. Also, with the large time bin size, the suggested approach cannot resolve the potential problem that the traffic may be concentrated at a specific time (i.e., many flights scheduled at the top of the hour), as in the typical flight schedule for legacy airlines operations.

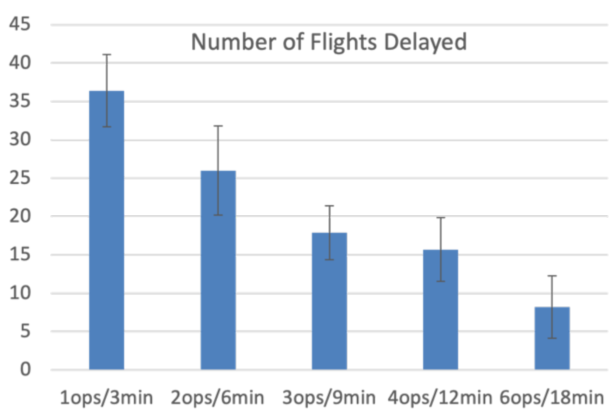

Fig. 12. Number of delayed flights for various bin sizes in capacity constraint.

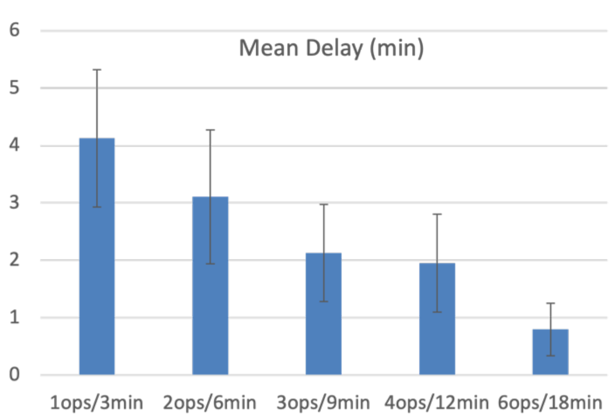

Fig. 13. Mean delay for various time bin sizes in capacity constraint (all flights).

C. Effects of Lead Time Differences

In this paper, we assume that the UAM flight scheduling is based on the First-Request, First-Served discipline. In this scheduling rule, the lead time for flight plan submission can affect the scheduling outcomes and assigned delays, as well as the fairness when there exist multiple operators in the UAM ecosystem. Therefore, we also investigate the impact of lead time differences between operators in this study. The lead time is defined as the time difference between flight plan submission and desired departure time. This lead time is required to go through the flight plan approval procedure, have an allocated UAM vehicle ready for this trip, and prepare the actual departure flight such as passenger boarding, ground movement to the assigned vertipad for takeoff, and takeoff clearance request and approval.

While the baseline case assumes two UAM operators use the same lead time of 6 minutes, different lead times between operators are explored in this study. As an extreme case, we test the case where one operator submits all the flight plans much earlier than the other operator's, for example, with 2-hour lead time. As another case for the competitive condition, we also test the case where one operator's lead time is 9 minutes, while the other operator's is still 6 minutes. Then, we measure the sum of scheduled delays by operator for comparison.

Figs. 14-15 show the number of delayed flights and the sum of delays by operator. Based on the First-Request, First-Service discipline, earlier flight plan submissions take the available capacity slots in advance, leading to fewer delayed flights and lower delays. For example, when all the flights from Operator 1 are submitted in advance with 2-hour lead time like a pre-scheduled shuttle service, Operator 1 is expected to have the minimum delay whereas Operator 2's flights providing ad hoc on-demand transportation service take most of delays because of few vertiport slots remained. Note that Operator 1 can still have some delays due to the demand-capacity imbalances induced by its own flights only. This result shows that the different lead time between operators can raise a fairness issue on scheduled delay distribution, which needs more research and the development of Community Based Rules (CBRs) in scheduling scheme and prioritization for UAM operations in the federated operating system.

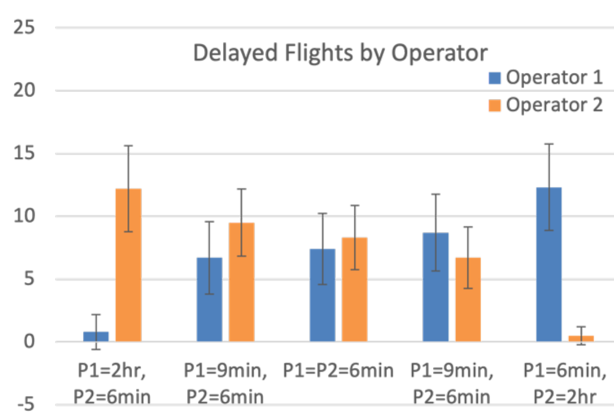

Fig. 14. Number of delayed flights by operator for different lead times.

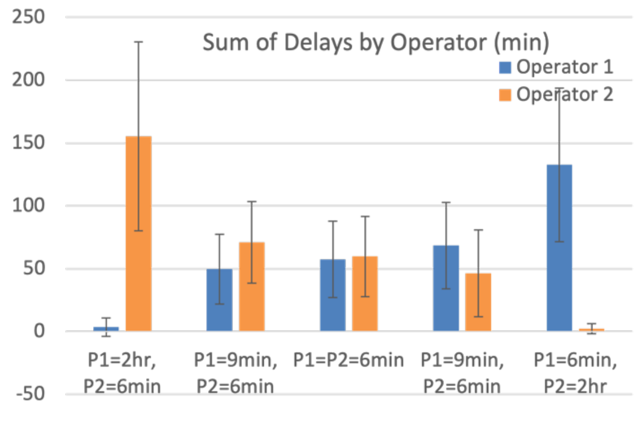

Fig. 15. Sum of delays by operator for different lead times.

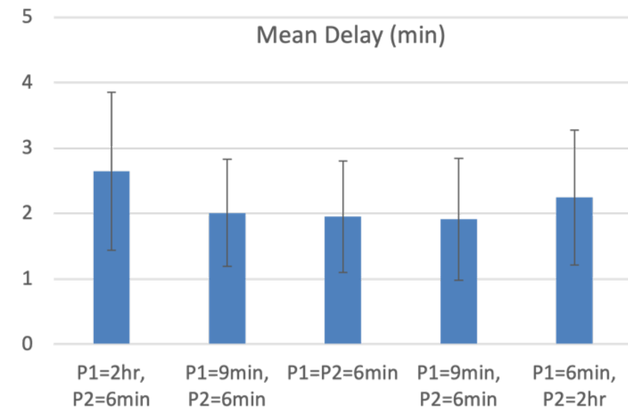

Fig. 17. Mean delay for different lead times (all flights).

Competitive vertiport slot assignment between multiple operators may help reduce the total delay in the whole system. Figs. 16-17 show the number of delayed flights and the mean delay for all the flights. Although the total number of delayed flights in the baseline case having the same lead time is higher than the extreme cases that one operator submits its flight plans very early, the bar graph shows that the mean delay (or the sum of delays) is lower in the baseline. If one operator (e.g., UAM shuttle service provider) pre-occupies the vertiport slots, then its flights are free from delay, leading to the reduce number of delayed flights in total. However, the other operator (e.g., on-demand UAM service provider) may get more delay penalty with more delayed flights and longer delay, resulting in a total delay that is even higher than the sum of delays from two operators when having the same lead time.

D. Effects of Flight Speed Differences

In the UAM ecosystem, it is expected that each operator operates different UAM vehicle models, which have different flight characteristics and performance. As one of the main vehicle performance characteristics, for instance, the cruise speed (or energy-efficient flight speed) can be varied by the vehicle models, which results in the different nominal flight times for the same origin-destination route between operators. In this subsection, we investigate the impact of the flight speed differences on the scheduled delay and the maximum number of simultaneous operations in the air.

The baseline case assumes that the two operators use the same flight speed. To differ the flight speed, four other cases assume that all the flights from Operator 1 fly faster or slower than Operator 2's by 10% and 20%.

Figs. 18-19 show the number of delayed flights and the mean delay for five different flight speeds of Operator 1, compared to the fixed flight speed of Operator 2. According to the results, various flight speeds between operators may induce the demand mitigation by shifting the arrival demand peak, resulting in fewer delayed flights and less delay, compared to the same flight speed case (baseline). However, the large variations are observed in individual runs, as indicated by the large standard deviations (whiskers in the bar graphs), which requires further investigation with more traffic scenarios in the future to find out what factors contribute to the scheduled delay when the flights are operated at different flight speeds.

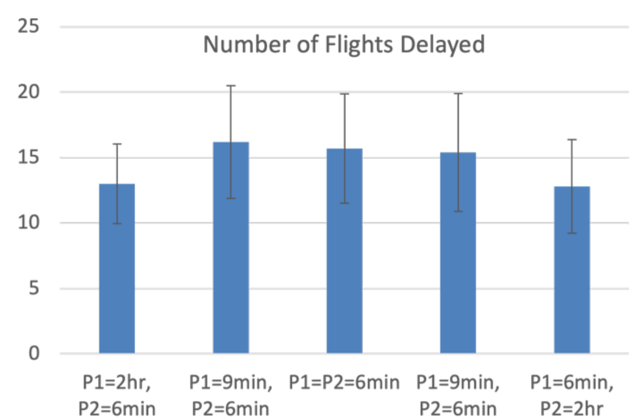

Fig. 16. Number of delayed flights for different lead times.

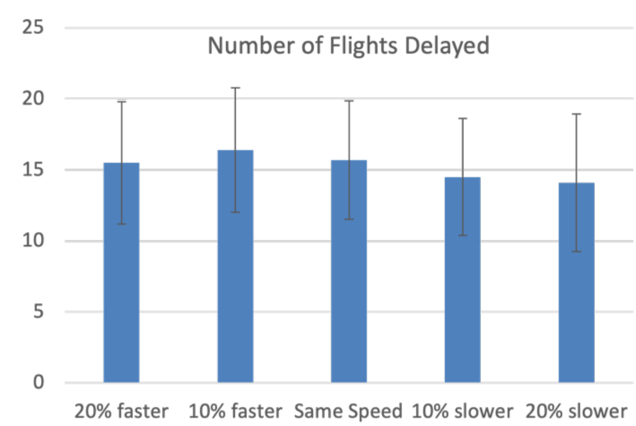

Fig. 18. Number of delayed flights when Operator 1 has different flight speeds.

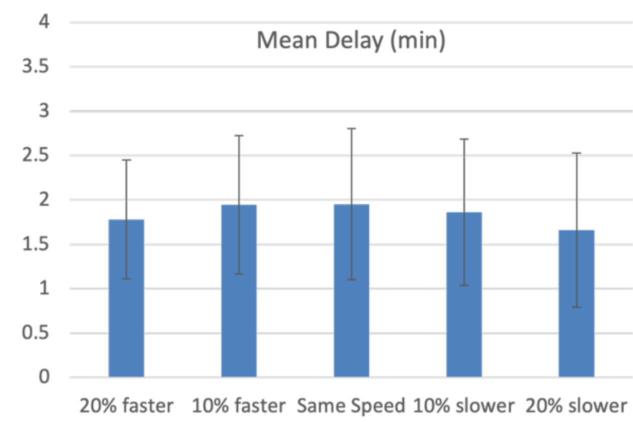

Fig. 19. Mean delay when Operator 1 has different flight speeds (all flights).

Flight speed can also affect the traffic density and throughput in the airspace. UAM flights flying at a slower speed will stay in the air for a longer time, leading to denser traffic. Fig. 20 shows the maximum number of simultaneous operations for Operators 1 and 2, as well as in total, based on the modified schedule after resolving demand-capacity imbalances. As expected, the maximum number of concurrent flights operated by Operator 1 in the given traffic scenario increases as its flight speed gets slower.

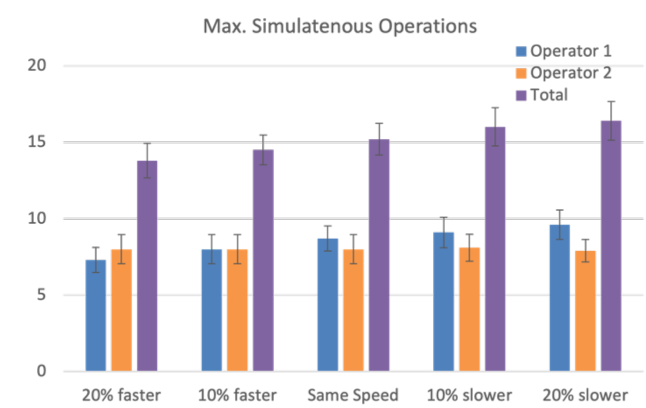

Fig. 20. Maximum number of simultaneous operations averaged from ten runs by operator and in total, when Operator 1 has different flight speeds.

If the UAM vehicles fly at different speeds in the shared airspace, there is a potential safety issue related to the overtaking case where a flight is moving faster than the other flights flying along the same route. In the experimental runs, a few cases were observed where a flight departing the origin vertiport later arrived at the destination earlier than the other flight having the same origin-destination route because of the flight speed difference. In future work, the proposed strategic conflict management needs to be improved to prevent flights from overtaking or tail-to-nose colliding in the air by considering additional constraints or introducing multi-lanes in the UAM corridors with sufficient lateral separations.

E. Effects of Departure & Arrival Time Errors

Lastly, we explore the impact of departure and arrival time errors from the schedule determined by the proposed DCB algorithm. As observed in the legacy airline industry, it is expected to have some levels of deviations in actual takeoff or landing times from the given schedule. For departures, actual takeoff time can be different from the schedule because of many reasons, including passenger's early/late arrival, pilot and aircraft readiness status, passenger boarding time delay, uncertainty in aircraft ground movement, communication delay with vertiport operator, and traffic congestion near vertipad. Similarly, actual arrival time at destination vertiport can have large deviations from the estimated landing time due to various uncertainties such as unexpected departure delay, convective weather along the route, localized wind impact, vehicle performance, and traffic congestion near and/or on vertiport. These errors do not only cause the adverse effects in aircraft scheduling like unscheduled delays and reduced throughput [7, 8], but also lead to violations in demand capacity balancing. In this study, we will focus on the DCB violations only. In the strategic conflict management phase, tactical rescheduling in a short time right before takeoff is not taken into consideration when detecting a DCB violation in actual operations.

To see the effects of departure time errors from the schedule, we implemented 10 runs for each scenario with different deviations, ranging from ±1min to ±5min errors, in which the actual departure times were randomly deviated from the scheduled departure times with a uniform distribution. Since there are 10 test scenarios in this study, we conducted 500 runs in total (= 10 scenarios x 5 deviation cases x 10 runs/case) and averaged the number of DCB violations for each deviation case.

The stacked bar chart in Fig. 21 shows the number of DCB violations at the given five vertiports, depending on the level of departure time errors from 1min to 5min. Note that the baseline case having no departure time errors is not shown in this graph because it has zero DCB violations. Even with the 1min deviation in departure time, more than 4 DCB violations are observed since the modified departure time for resolving a demand-capacity imbalance is assigned to the beginning of the next available time bin. The number of DCB violations also increases, as the departure time error increases from 1min to 5min. To mitigate these kinds of violations, we may assign the modified departure time to the middle of the next available time bin or add a buffer of 1 or 2 minutes to the next time bin start time. However, this mitigation plan will increase the scheduled delay up to 6min, if a 12min time bin is used. It is noted that there is a tradeoff between DCB violations and pre-departure scheduled delay in the DCB algorithm design, when considering the departure time uncertainty. Since the uncertainty is unavoidable in actual operations, on the other hand, the DCB violations in the strategic planning phase may be ignored by setting the capacity constraints with appropriate buffers such that there is still plenty of spacing in the demand for separation provision to deal with any potential conflicts.

Similar runs were executed to evaluate the impact of the arrival time errors. Fig. 22 illustrates the number of DCB violations for five different levels of arrival time errors. The bar chart shows that the number of DCB violations increases, as the arrival time error level increases from 1min to 5min. However, the DCB violations are relatively fewer, compared

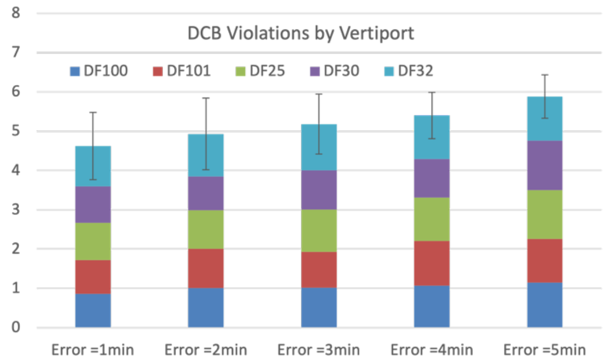

Fig. 21. DCB violation count for various departure time deviation levels.

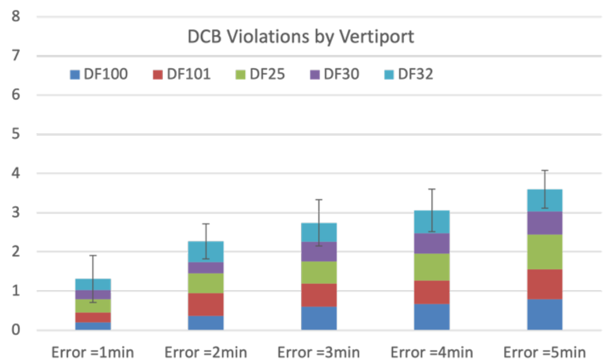

Fig. 22. DCB violation count for various arrival time deviation levels.

to the departure time error cases, because the departure time adjustment at origin vertiport is the main solution to resolve the demand-capacity imbalance. In most cases, the shifted arrival times after the DCB resolution can be located at any of the points in the given time bin, instead of the beginning of the next available time bin, depending on the nominal flight time.

V. Conclusions and Future Work

In this paper, the demand capacity balancing (DCB) at vertiports was explored to provide the UAM traffic with sufficient separation for takeoffs and landings in the strategic flight planning phase, aiming to reduce the need of tactical separation provision. Given the traffic scenarios in Dallas/Fort Worth urban area, we verified that the proposed DCB algorithm could work well to manage the demand effectively by assigning pre-departure delays. We also investigated how the flight schedule modified by DCB and the DCB performance would be affected by practical issues. The experiment results showed that the reduction in vertiport capacity could increase both the number of delayed flights and the mean delay significantly. Whereas the smaller time bin size in capacity constraint could result in more delays, the larger bin size might require more frequent tactical separation provisions in the air. In a competitive environment with multiple UAM operators, it was found that the difference in the lead time from flight plan submission to desired departure time would cause a fairness issue in terms of delay distribution between operators and that the difference in flight speed could not only affect the estimated arrival demand peak, but also change the traffic density in the UAM airspace. Lastly, we found that the uncertainty in actual departure and arrival times could bring about DCB violations at vertiports.

The experiment results about the DCB at vertiports shown in this paper provide a useful guideline for future research work with respect to the strategic conflict management for UAM operations. First, it is required to enhance the strategic conflict management approach to managing a higher operational tempo, taking the proposed DCB algorithm as a starting point. The current DCB has focused on the demand management at vertiports only, but it should deal with the other airspace resources like UAM corridor entry and exit points and intersection waypoints for crossing and/or merging. To reduce the need for tactical separation provision, more sophisticated aircraft control by assigning different flight speeds by route segment or providing the estimated times of arrival at significant waypoints may be needed in the strategic conflict management layer. Next, we need to consider the UAM operational conditions in the federated network system having multiple operators. As shown in Section IV.C, different operational rules between operators lead to the fairness and prioritization issues in the usage of shared airspace resources. It is required to develop appropriate scheduling disciplines (e.g., First-Come, First-Served vs. First-Request, First-Served) that can handle higher priority flights within and between UAM operators while satisfying all the stakeholders and to establish the relevant CBRs. Lastly, more realistic constraints in UAM operations should be considered in the DCB algorithm. These may include the maximum delay allowed, the possibility of flight cancellation, the minimum separation requirements between flights, freeze horizon for rescheduling, conformance requirements with the schedule, vehicle performance requirements within UAM corridors and near vertiports, the availability of vehicles, pilots, and ground crew resources at vertiports, and the integration with other traffic like helicopters and general aviation.

References

[1] D. P. Thipphvong, et al., “Urban Air Mobility airspace integration concepts and considerations,” AIAA 2018 Aviation Technology, Integration, and Operations Conference, Atlanta, GA, June 2018. doi: 10.2514/6.2018-3676

[2] National Aeronautics and Space Administration (NASA), “UAM vision Concept of Operations (ConOps) UAM Maturity Level (UML) 4,” December 2020.

[3] International Civil Aviation Organization (ICAO), “Global air traffic management operational concept,” ICAO, Doc 9854, First Edition, 2005.

[4] Federal Aviation Administration (FAA), “Urban Air Mobility: Concept of Operations v1.0,” version 1.0, June 2020.

[5] K. H. Goodrich and C. R. Theodore, “Description of the NASA Urban Air Mobility Maturity Level (UML) scale”, AIAA SciTech 2021 Forum, January 2021. doi: 10.2514/6.2021-1627

[6] H. Lee, “NASA’s Simulation Activities for Evaluating UAM Concept of Operations,” HorizonUAM Symposium 2021, September 2021.

[7] A. D. Evans, M. Egorov, and S. Campbell, “Accommodating operational uncertainty in Urban Air Mobility operations with strategic deconfliction,” AIAA Aviation 2021 Forum, August 2021. doi: 10.2514/6.2021-2333

[8] H. Lee, “Airport surface traffic optimization and simulation in the presence of uncertainties,” PhD thesis, Massachusetts Institute of Technology, Cambridge, MA, 2014.