Quantifying Effects of Departure and Flight Time Uncertainty on Urban Air Mobility Operations

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***Abstract*— Demand capacity balancing is a key mechanism for maintaining safe and efficient Urban Air Mobility (UAM) operations. However, uncertainties such as departure delays and flight time variation may reduce the effectiveness of algorithms used for balancing and detrimentally impact the safety and efficiency of UAM operations. In this paper, the effects of these uncertainties on UAM operations are quantified by modeling a distribution of departure and flight time errors. A route network in the Dallas/Fort Worth metropolitan area was used to simulate traffic demand with and without uncertainty. Simulations were conducted with three main models of uncertainty – first uncertainty in departure time delay resulting in late takeoffs, second with uncertainty in flight times in addition to departure delays, and finally, uncertainty in departure times that cause either late or early takeoffs. Each of these simulations were performed using varied standard deviations to fully understand the effects of uncertainties. Results from these simulations were compared to a baseline simulation using the same parameters, but without any uncertainty. The results suggest that both safety and efficiency are significantly impacted by uncertainty even with relatively low uncertainty introduced. These results work towards quantifying the effects of uncertainty in flight scheduling for UAM. They will also aid in the further development of the demand capacity balancing algorithms for UAM operations and associated air traffic management.**

I. Introduction

Forecasts for the next few years predict that there will be a substantial number of aerial systems including unmanned aircraft systems (UAS) and various types of other small aircraft such as electric vertical takeoff and landing (eVTOL) vehicles operating in cities all over the world [1]. Existing infrastructure and air traffic management (ATM) procedures were designed to accommodate demand from commercial aviation and general aviation. As the National Airspace System (NAS) continues to experience increasing demand coming from new types of aerial systems, these current systems will be difficult to scale, making them insufficient to meet this expected demand. This was demonstrated through simulations performed by NASA referred to as the X-Series simulations [2,3,4] . To meet this demand, a new system to manage air traffic of this type, beyond what the current ATM system can offer, needs to be developed.

The Advanced Air Mobility (AAM) initiative has been envisioned by the Federal Aviation Administration (FAA), National Aeronautics and Space Administration (NASA), and industry partners to meet the demand and new challenges posed by integrating all these vehicles into the current ATM system. The goal of the AAM initiative is to develop an air transportation system that moves cargo and people between local, regional, and urban locations that have not been served or have been underserved by aviation using modern aircraft, technologies, and operations [5]. UAM is one of the AAM air transportation service concepts to carry passengers or cargo in and around metropolitan areas. The future of UAM market is envisioned with low cost, efficient, and high-density transportation in urban areas using new technologies, autonomy, and operational procedures [5]. Currently, development of the UAM ecosystem is moving at a swift pace with dozens of companies designing, building, and testing vehicles for commercial use.

In support of one of the AAM missions to accelerate the integration of UAM operations in the NAS, NASA planned a series of test activities focused on flight tests and simulations called the National Campaign (NC) [6]. The flight test series were intended to guide the collective community and stakeholders through a series of scenario-based test activities that involve vehicles and airspace management services operating in a live test environment. The Urban Air Mobility (UAM) subproject of NASA's Air Traffic Management – eXploration (ATM-X) project supported the NC flight test activities by conducting simulation test activities with NC airspace partners each of whom demonstrated their airspace services' capabilities prior to NC flight activities [7].

To handle the proposed density of operations, UAM architectures have been proposed by many organizations and industry partners around the world [5]. Each system has both merits and downsides. However, they all have key features in common. They all contain vertiports to handle the physical air traffic. They also utilize strategic deconfliction to manage demand for a given capacity at airspace resources, as well as supporting services needed for safe and efficient UAM operations. Vertiports are like airports for UAM flights which are strategically placed in cities at designated areas that allow eVTOL aircraft to land and takeoff. Strategic deconfliction algorithms determine how to manage traffic throughout the entire route network to reduce the need of tactical separation provisions and increase adherence to safety constraints, while maintaining traffic flow volume. Lastly, the supporting services allow flights to be scheduled and be given clearance for takeoff and landing at vertiports.

Research and development work on these systems is ongoing, including work on the development of new airspace services for UAM operations. Work on the airspace services includes efforts toward the development of strategic conflict management of operations. However, there is a significant gap in current studies of airspace services of incorporating operational uncertainties. Operational uncertainties can be observed in all areas of transportation including commercial aviation. In UAM operations, uncertainties can include pre-departure delays that may occur due to late arriving passengers, technical issues, passenger boarding delays, communication delays, and even traffic congestion at the vertiport They also include flight time variation which can be caused by wind or other environmental factors, resulting in a change in the aircraft predicted flight time. These delays negatively impact the safety and efficiency of air traffic, and can lead to conflicts, if not managed properly. Therefore, the strategic conflict management algorithms for UAM will need to account for these operational uncertainties to mitigate expected effects. However, how to incorporate these delays in an accurate manner within existing UAM architecture is still an open question. Effects of this uncertainty need to be incorporated into flight planning and strategic deconfliction to accurately quantify their affects.

This research study aims to quantify the impact of departure time uncertainty and flight time uncertainty on the safety and efficiency of UAM operations. Departure time uncertainty is the variance between the time at which aircraft depart and their expected departure times while flight time uncertainty is the variance in expected flight times on the different segments of a mission profile. The insights from this study can help aid further development of UAM services and operational capabilities.

Section II of this paper provides an overview of relevant work in this area thus far. Section III explains the simulation architecture used to conduct the study and details on its implementation. Section IV gives an overview of the approach and methodology of this study. Finally, Section V will present the fast-time simulation results for uncertainty. Section VI will provide a brief discussion of these results.

II. Background

Flight scheduling and planning has been studied extensively for several years [3,4,5]. Researchers have proposed methods of studying uncertainty in the form of departure time delays and airborne delays. One method proposed to understand uncertainty for cases with limited real-world data is by modeling uncertainties using normal distributions [8]. These authors studied uncertainty for UAM departure error (delays before takeoff) by modeling takeoff time deviations using a normal distribution with a mean of zero and standard deviation varied between 0 to 5 minutes. The authors of [8] conducted this uncertainty study using a scenario of the San Francisco Bay Area to quantify the impact of departure and airborne delays on early-stage demand levels. They estimated the impact of uncertainty by adding departure error to the flight after it was scheduled to simulate real life conditions. This delay was added under multiple variations of traffic demand. The scenario consisted of a simplified network of three vertiports at early-stage UAM demand levels and once uncertainty was added they ran each simulation 10 times.

This paper aims to extend this work by building on the shortcomings of that work. This includes simulating a larger urban network of seven vertiports all around a single city and running each scenario simulation 100 times rather than 10 to provide more reliable results. The paper will also focus on the effects of uncertainty at peak network traffic to compare the real-life limitations of the network with the theoretical limits without uncertainty.

The simulations presented in this paper use a fast-time simulation tool that NASA has been developing to support the testing and verification of new airspace services and platforms that may be used in UAM operations. This simulation capability is necessary due to the lack of real-world performance data for UAM operations. The UAM Simulation Tool for Airspace services Research (USTAR) is a Python-based object-oriented fast-time simulation tool. Each of the components of the UAM system such as fleet operators, airspace services, and demand capacity balancing services are defined as separate classes. This allows users to separately test any new system or capability. The developers envisioned the next step in the development of this simulation tool to be the capability to model uncertainty in UAM operational environments. This will create the capability to quantify the effects of uncertainty on scheduling and performance of the system and assess how to accommodate for these uncertainties during operations planning. The next section presents a brief overview of the simulation tool.

III. A Fast-time Simulation Tool: USTAR

This section provides an overview of USTAR, the tool used for uncertainty modeling and simulation. USTAR has three components that are important for this study: Fleet Operator (FO), Provider of Services for UAM (PSU), and Demand-Capacity Balancing (DCB) algorithm. Below are definitions of these components.

A. Fleet Operator (FO)

This component selects flights to propose to the PSU and then performs dispatch duties for the final schedule confirmed by the PSU. The proposed flights have a predetermined flight plan which consists of a set of waypoints the flight passes through to reach its destination.

B. Provider of Services for UAM (PSU)

This component supports the scheduling of flights by assigning estimated times of arrival at vertiports along the given route for each flight. Then, it calls the DCB algorithm to resolve any imbalances between capacity and the demand at those vertiports. If too many flights are planned at a vertiport during a certain time interval, the algorithm delays flights to alleviate this congestion. The final flight plan is then returned to the FO for execution.

C. Demand-Capacity Balancing (DCB)

The length of time for each scenario tested in this study can be evenly divided into a certain number of time bins. Each time bin has a maximum number of operations that are assumed to be handled safely. The demand-capacity balancing component contains an algorithm that delays a flight if there are too many flights projected to be operating at a certain waypoint or vertiport within a specific time bin. This allows safety assumptions to be met.

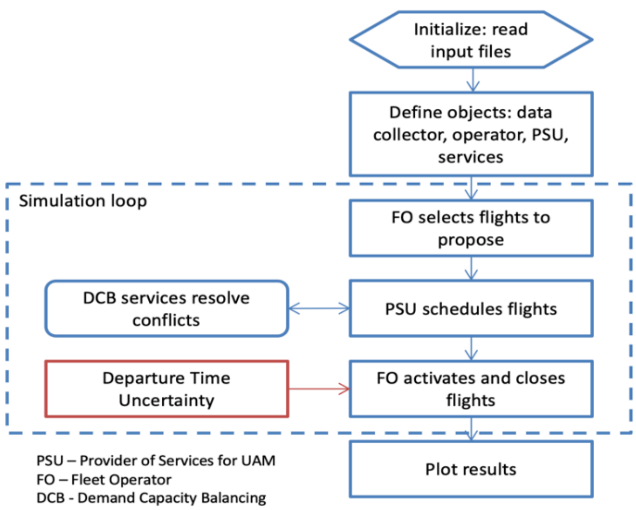


Fig. 1. USTAR Simulation Flowchart

Fig. 1 shows how these components work together during a simulation. Note that the brief descriptions given above are of the current implementation with USTAR, and they continue to evolve as the tool is under active development. Additional details of the tool will be published in subsequent technical reviews that are currently in writing [9].

IV. APPROACH

In real-world operations, flights do not take off at the exact proposed departure time due to a variety of factors such as weather, late passengers, and technical issues. This section describes how operations uncertainties have been modeled in the USTAR environment, especially, the modeling of departure time and flight time uncertainty in UAM operations.

Departure time uncertainty occurs when flights are unable to take off at their designated time. Commercial aircraft have flight times of the order of a few hours. Meanwhile, UAM flights are typically on the order of tens of minutes. This means delays of just several minutes can significantly impact UAM operations. For example, a 10-minute flight delayed by just 5 minutes is effectively delayed by 50% of its flight time. Flight time uncertainty may be caused by wind, precipitation, or other environmental factors. This can lead to slight increases or decreases in total flight time. To quantify the impact of these uncertainties on safety and efficiency of UAM operations, efficiency is measured by total departure delay and safety by demand capacity imbalances observed in the simulation results.

Uncertainty is added to the model after the PSU has provided the Fleet Operator with the final schedule to execute (see red box in Fig. 1). This uncertainty is modeled by a normal distribution with a standard deviation dependent on the average flight length of the flights within the scenario. A normal distribution is most commonly used when there is very limited data to model uncertainty [10,11]. Since UAM operations are not occurring today, no data is available that can be used to describe the nature of these uncertainties, though it may be possible to use data from other forms of transportation and extrapolate it for use in UAM scenarios. Normal distributions are widely used for modeling continuous data and are an effective way of modeling departure delays, especially when there are no significant external factors causing those delays. Fig. 2 shows an example normal distribution observed in our final trial with a mean of 0 and standard deviation of 120 seconds.

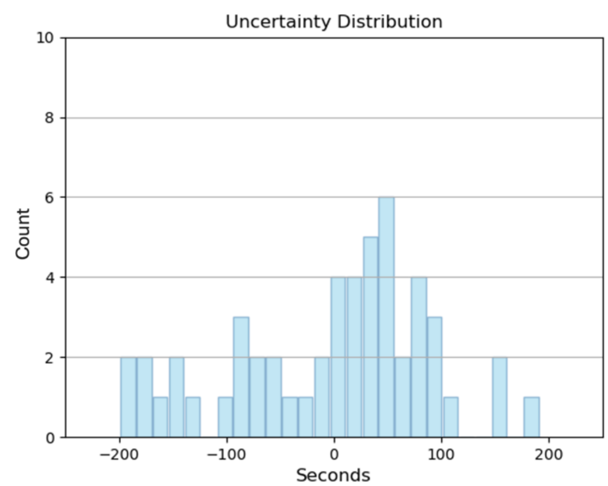


Fig. 2. Distribution of Departure Time Deviations from Final Trial.

To model uncertainties for flight time delays, a uniform distribution was used ranging from 0% to 5% of the flight time. This resulted in increasing or decreasing each flight time to within 5% of its original time. The motivation behind using 5% is that the proposed UAM flights are typically 20 minutes at most. Therefore, flight delays due to wind and aircraft type expected to be relatively small.

To quantify the effect of uncertainty on efficiency and safety a scenario with predetermined flights, waypoints, and vertiports was created. The scenario was designed for the

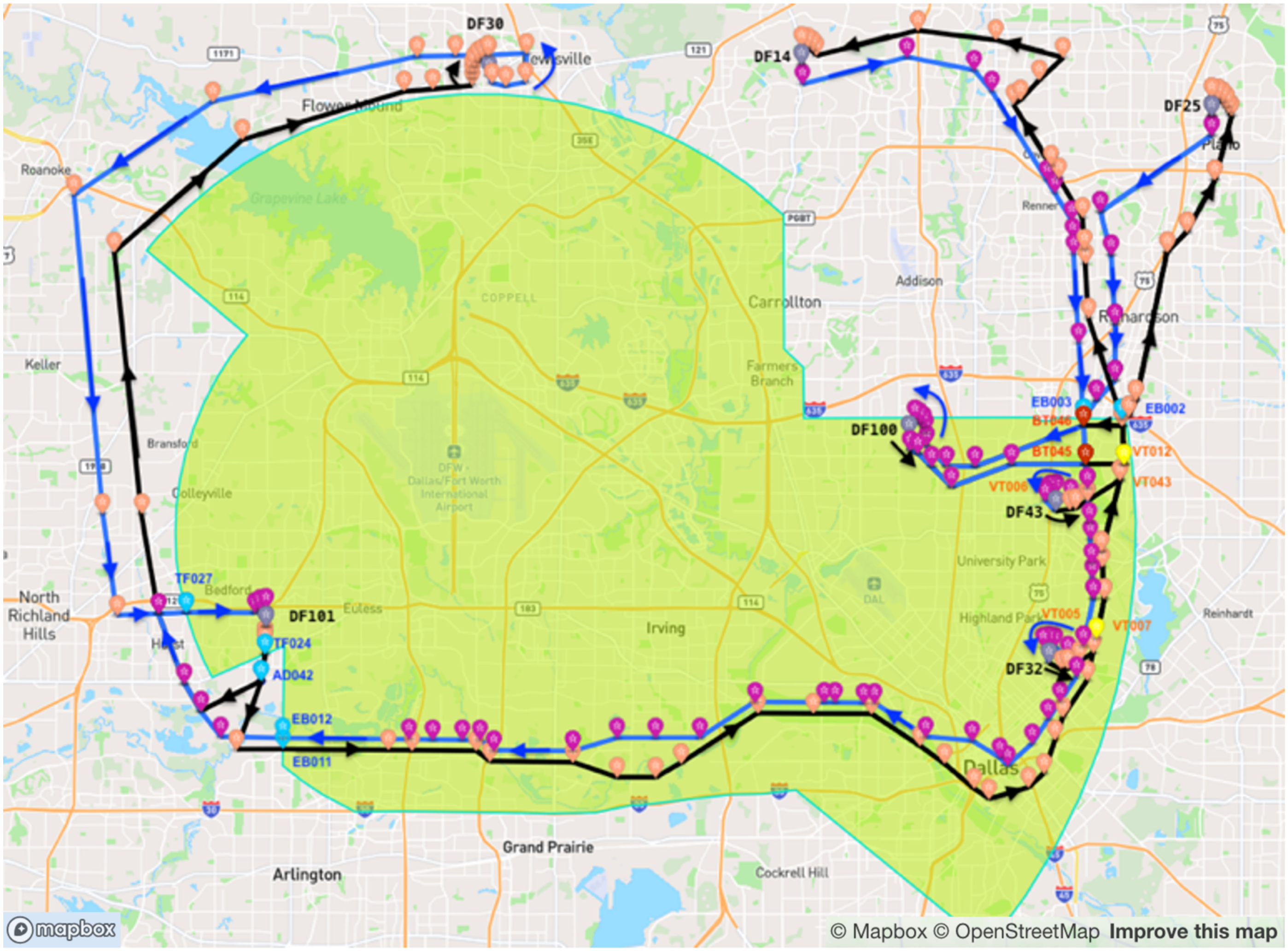


Fig. 3. Scenario Map of Dallas-Fort Worth Area

Dallas/Fort Worth Area which consisted of 7 vertiports, 10 Origin-Destination routes, 5 crossing/merging waypoints, 8 entry/exit waypoints into/out of controlled airspace shown – this is illustrated in Fig. 3. The scenario length was 120 minutes with 61 flights distributed over the route network. Each vertiport had a capacity of 2 flights per time bin and each waypoint had a maximum capacity of 4 flights per time bin. A time bin is defined as a period of 12 minutes with the 2-hour long scenario consisting of 10 time bins.

The number of flights in the scenario, 61, is based off the number of vertiports, seven, multiplied by the nine time bins (only nine since flights are not added flights at the very end of the scenario). Then two flights were removed due excessive scheduling conflicts. These flights were created to model a realistic scenario of high demand during morning or evening rush hour – more flights were scheduled in the beginning of the scenario and the amount tapers off towards the end of scenario. The traffic demand is illustrated in Fig. 4. The intention of this scenario is to evaluate the performance of the DCB algorithm in presence of uncertainty by inducing demand capacity imbalances. To provoke this situation, many flights were scheduled at a few vertiports. This concentrated flight demand is expected during peak travel times in metropolitan areas. Fig. 5 shows the demand distribution heatmaps before and after the DCB algorithm is applied. In the heatmaps, the horizontal axis

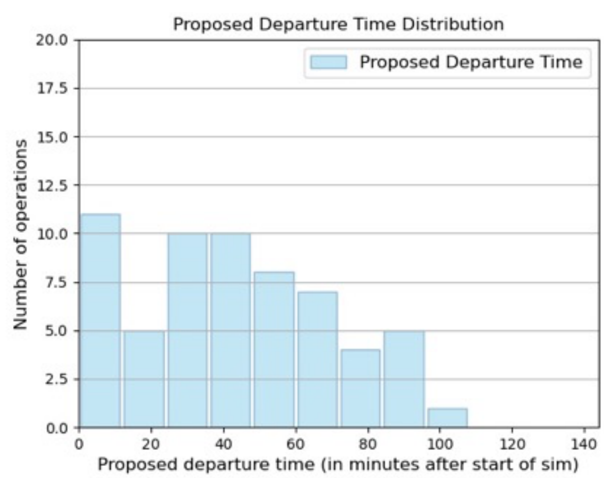


Fig. 4. Scenario Demand Over Time

axis shows 12 time bins, where each bin represents a 12-minute interval, and the vertical axis shows vertiports. It is important to note this scenario was originally 2 hours long, with 10 time bins of 12 minute length. 12 time bins are shown because DCB resulted in delaying flights, lengthening the entire scenario. The number in each cell shows the number of flights assigned to a specific vertiport in each time bin. Once the scenario had a maximum number of flights that could be scheduled without causing demand capacity imbalances, added uncertainty was incorporated into the scenario. This approach provides significant insight into better understanding how uncertainty can affect high density routes. Another approach used to induce demand-capacity imbalances was by setting departure times near the end of each time bin. This caused the original flights to be pushed into to the next time bin when a departure time delay was added, resulting in a cascading affect throughout the scenario, which is the basis for this study. Collectively, these approaches allow for the study of how well the DCB algorithm can handle delays.

The same traffic scenario described earlier was used to simulate many different variations of uncertainty. The first set of simulations modeled the delay by implementing a departure time uncertainty using a one-sided normal distribution with a mean of 0 seconds and a standard deviation of 60, 90, or 120. A one-sided normal distribution was used to avoid early departures (which correspond to negative delay) and any negative values were set to zero (i.e., no delay). Each of these three scenarios were run 100 times and averaged out. The next set of simulations modeled the delay using a two-sided normal distribution using the same parameters which were also run 100 times each. To be explicit, in this set of simulations, early departures were included (which correspond to negative delays). Early departures can occur because flights can be ready for take-off earlier than their scheduled departure times if all passengers and cargo are loaded early. It is necessary to understand if early departures could also create demand capacity imbalances and the magnitude of those affects as compared to no early departures. Finally, the last set of simulations involved including flight time uncertainty modeled by the uniform distributions and departure delays modeled by a two-sided normal distribution.

V. Results

Fig. 5(b) is the base scenario without uncertainty to which all the new simulation results are compared. All factors remain the same except for varying uncertainty in the following simulations. For Figs. 6-8, each of the 3 heatmaps in each figure represent the average traffic of 100 simulations.

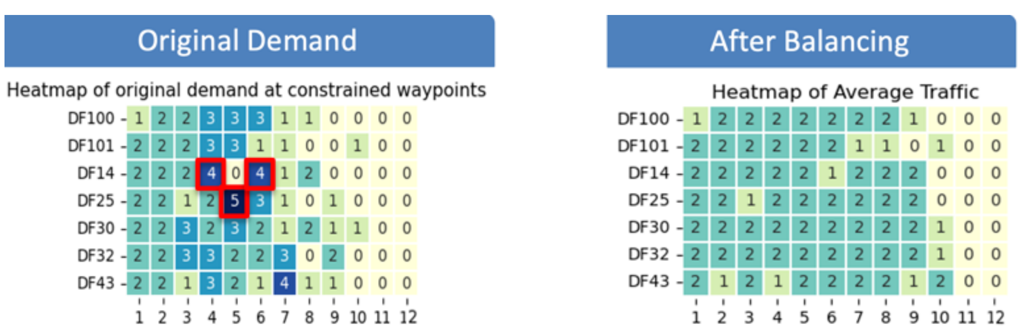
A. Baseline case with no uncertainties

Fig. 5(a) shows the initial demand distribution of the scenario before scheduling where all vertiports are overcapacity in at least one time bin; some of the overcapacity time bins are shown highlighted with red borders. Note that the vertiport capacity is assumed to be 2 vehicles per time bin. Fig. 5(b) shows the demand distribution after DCB is applied and delays certain flight before takeoff. This limits the number of vehicles at each vertiport to 2 for each time bin. From Fig. 5(b), we can see that the DCB algorithm successfully resolved all predicted imbalances, such that there are no overcapacity time bins post demand-capacity imbalance resolution.

B. Departure time uncertainty with no early takeoff allowed

For these simulations, departure time uncertainty was incorporated by adding a delay value resulting from a one-sided normal distribution with a mean of zero and standard deviations of 60, 90, and 120 seconds and any negative departure values were set to zero (no delay).

Fig. 6 shows the average traffic distributions in each of the simulations after 100 runs. Comparing the vertiports in the base scenario, Fig. 5(b), and Fig. 6, there are clear demand capacity imbalances in the latter figure. Since each vertiport can only handle at most 2 operations within a time bin, multiple demand capacity imbalances are seen and highlighted in red. For the 60 second standard deviation, there is a 11.16% increase in total delay due to uncertainty itself using the average experimental delay aggregated from 100 trials. There is a 15.55% increase in delay when standard deviation in delay uncertainty was 90 seconds and 19.25% increase in delay when the standard deviation was 120 seconds.



(a) (b)

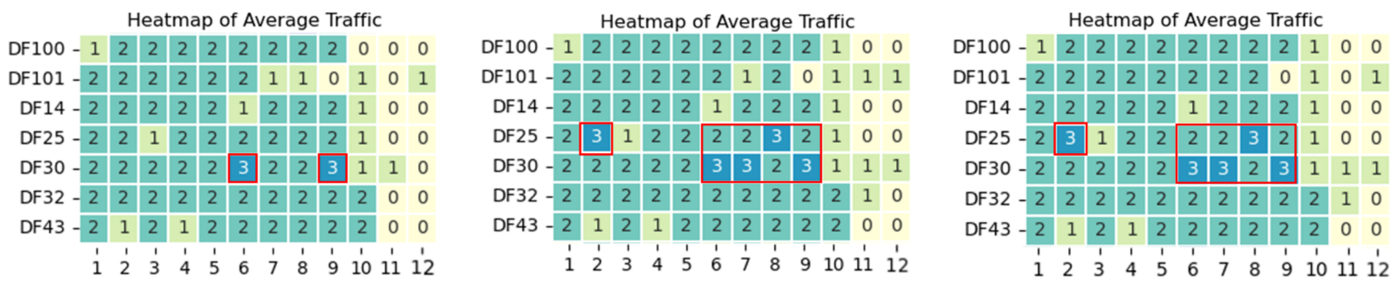
Fig. 5. Heatmaps showing the traffic distribution within each bin at each vertiport. (a) Original Distribution before balancing, (b) Distribution after balancing.

C. Departure time uncertainty with early takeoff allowed

In the next set of simulations, departure time uncertainty was incorporated using a two-sided normal distribution using the same parameters (mean zero and standard deviation values of 60, 90, and 120 seconds). Using a two-sided distribution implies that early departures were permitted. Fig. 7 shows the heatmaps for these trials with demand-capacity imbalances. Compared to the previous set of simulations discussed in Sec. V.A, they seem to appear at different locations and time bins. Moreover, compared with the baseline metrics without uncertainty from Fig. 5(b), there was an 8.67% increase in total delay from the 60 second standard deviation, 15.76% for 90 seconds, and 22.15% for 120 seconds. It may seem counterintuitive that total delay increased, even when early departures were permitted. It is possible ignoring negative delays in the previous set of simulations lessened the variance in departure flight times. Since these effects can cascade, even variance from permitting early departures can affect scheduling of future flights and consequently, impact the total delay.

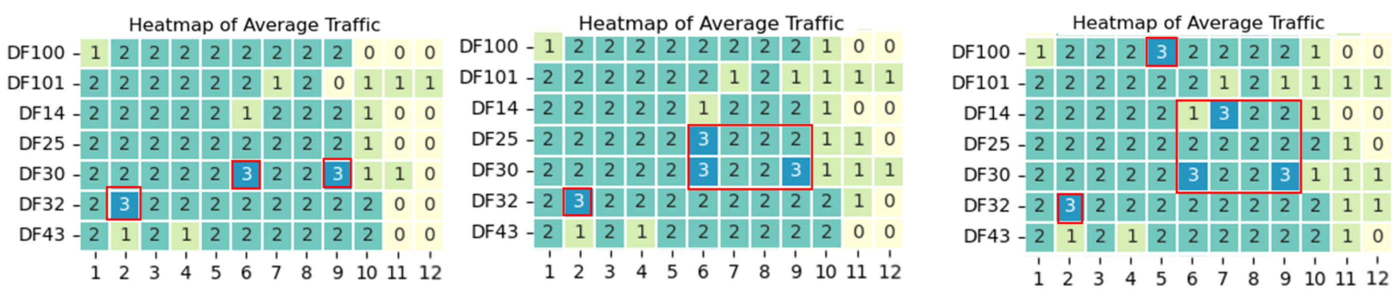
D. Flight time uncertainty

These last set of simulations incorporated flight time uncertainties. The results of these simulations are shown in Fig. 8. As compared with the baseline metrics without uncertainty from Fig. 5(b), there was a 9.97% increase in total delay from the 60 second standard deviation 14.83% for 90 seconds and 21.01% for 120 seconds for these trials. A similar amount of demand capacity imbalances is seen at the vertiports to the simulations from subsection B. This suggests that modeling flight time uncertainty in this way may only have a minimal impact on flights as compared with departure time delay.



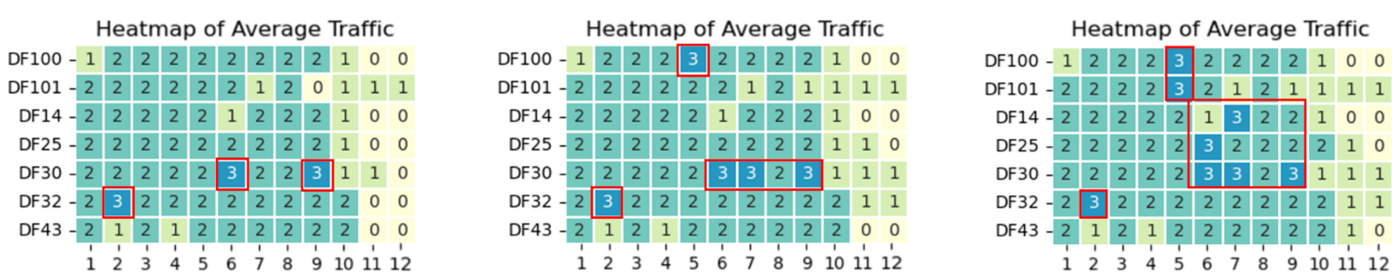
(a) (b) (c)

Fig.6 Heatmap of average observed demand with **no** early departures: (a) Standard deviation of 60 seconds, (b) Standard deviation of 90 seconds, (c) Standard deviation of 120 seconds



(a) (b) (c)

Fig.7 Heatmap of average observed demand with early departures: (a) Standard deviation of 60 seconds, (b) Standard deviation of 90 seconds, (c) Standard deviation of 120 seconds



(a) (b) (c)

Fig.8 Heatmap of average observed demand with early departures and flight time uncertainty: (a) Standard deviation of 60 seconds, (b) Standard deviation of 90 seconds, (c) Standard deviation of 120 seconds

The results from this trial show a decrease in total delay for the 60 and 90 second standard deviation as compared to our initial trial with no early departures.

This seemingly inconsistent finding is due to the large range of values computed within each of the 100 trials. For the scenario with no early delays the range is only about 105 minutes, with a minimum of 410 minutes and maximum of 515 minutes. However, the scenario with flight and departure time uncertainty has a range of about 255 minutes with a minimum of 380 minutes and maximum of 635 minutes. This highlights that the standard deviation for the trials with departure and flight time uncertainty are substantially higher as compared with the trials with no early departures, as shown in Table II below. This suggests that the final scenario presents even more challenges as the variance in outcomes is very large. Another reason for this finding is that positive departure time delay and reduced flight time would mitigate the impact of each other and vice versa.

Focusing on the trials a standard deviation of 120, Fig. 9 describes the variance in the total delay from each of the 100 runs of the scenario. This variance highlights how much of an impact uncertainty has on nominal operations of UAM. In the trial with no early departures (green), the highest total delay value is around 510 minutes. Whereas, for the trial with both departure and flight time delay (blue) it is around 640 minutes. A one-way analysis of variance (ANOVA) test was done to identify if there were differences between the average delays observed in each of the three cases. Assuming that the three cases had similar average delay as the null hypothesis, the test failed to reject this null hypothesis at the 5% significance level, with a calculated p-value of 0.464. It is also important to note that the one-sided normal distribution from the first round of simulations reduces the number of flights directly delayed due to uncertainty.

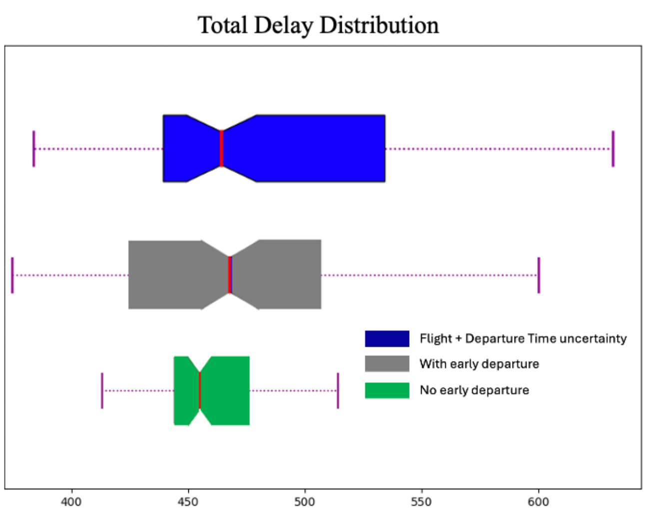


Fig.9 Distribution of Total Delay from Each Trial with Standard Deviation of 120 seconds

Table I shows the first trial from each set of 100 simulations that were run from all the different uncertainty types. It shows that the number of flights assigned uncertainty was greatly reduced with the one-sided normal distribution compared with the other 2 uncertainty types where negative values were included. The mean delay here is calculated by dividing the total delay by the number of flights delayed in the scenario. The number of flights delayed includes all delayed flights, not just flights that were directly assigned delay.

TABLE I. DELAY STATISTICS FOR UNCERTAINTY

Statistics for the First Simulation of Each Scenario with 120 second Standard Deviation			
Data	Departure Time Uncertainty (no early departures)	Departure Time Uncertainty (with early departures)	Departure + Flight Time Uncertainty
Number of Flights Directly Affected by Uncertainty	26	52	53
Total Delay (minutes)	462.45	459.16	479.91
Mean Delay (minutes)	10.05	8.35	8.73

Table II is a summary of the results from the simulation studies and shows the impact of uncertainty on performance. As compared with the baseline case (no uncertainties) where the total delay was 387.066 minutes, these cases with uncertainty took between 8 and 22% longer. Not only this, but this extra delay forces the scenario to continue running for two extra time bins as shown in Figs. 6, 7, and 8 as compared to the only 10 time bins initially needed as shown in Fig. 5(b).

Our results have quantified the uncertainty as a measure of total delay and show the magnitude of these effects through demand capacity imbalances. The results show how, as the variance in delay is increased, even if the average delay times are similar the standard deviations are very different. This shear range of possibilities needs to be planned for in UAM operations.

VI. CONCLUSIONS

Operational uncertainties in the form of departure delays and flight time variation can be caused by early/late arriving passengers, communication errors, or environmental factors (i.e. wind). These uncertainties have the potential to cause problems for existing ATM algorithms. The research conducted quantifies the effects of these operational uncertainties resulting from departure time delay and flight time variation. Through multiple simulations, departure time delay was modeled as a one-sided or two-sided normal distribution and flight time variation was modeled as a uniform distribution. Incorporating these operational uncertainties provides insight into better understanding how they affect the safety and efficiency of UAM operations.

The departure and flight time uncertainty models can more closely capture the behavior of a realistic UAM architecture. Our results showed that both total delays and demand-capacity imbalances increased by the addition of

TABLE II. RESULTS SUMMARY

Results of Departure Time Error Simulations						
Description	Simulation	Standard Deviation (seconds)	With Negatives	Mean of Total Delay (minutes)	Standard Deviation of Delay (minutes)	Increase in Total Delay
No Uncertainty	Base Scenario	N/A	N/A	387.066	N/A	N/A
Departure Time Uncertainty (no early departures)	#1	60	No	430.28	18.832	11.16%
	#2	90	No	447.257	23.676	15.55%
	#3	120	No	461.591	28.865	19.25%
Departure Time Uncertainty (with early departures)	#4	60	Yes	420.627	24.36	8.67%
	#5	90	Yes	448.079	46.752	15.76%
	#6	120	Yes	472.797	56.463	22.15%
Departure + Flight Time Uncertainty	#7	60	Yes	425.681	27.434	9.97%
	#8	90	Yes	444.458	43.559	14.83%
	#9	120	Yes	468.383	60.943	21.01%

uncertainty to the model. Our results showed that efficiency, as measured by total delay, was significantly decreased in the presence of uncertainty. The decrease in efficiency will lead to higher costs of operation, longer wait times, and lower capacity. Our results showed that safety, measured by demand capacity imbalances, was also affected in the presence of uncertainty. These results work towards quantifying the effects of uncertainty in flight scheduling and allow for a better understanding of the impact of uncertainties in the form of departure time delay and flight variation on UAM operations. This research contributes towards improving current solutions to mitigate these effects and improving overall UAM simulation capabilities.

The next step of this study is using these results to propose, test, and implement mitigation strategies to help resolve efficiency and safety issues caused by departure time delays and flight time variation. For example, one possible mitigation strategy is En Route Conflict Management which can provide flights in transit with real-time information. This information can be used by flights to adjust their speed along the trajectory to satisfy demand capacity balancing requirements.

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