Agent-Based Modeling of Uncrewed Aircraft System Flight Planning for Airspace Fairness

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June 2023

ICP-2023-U-035811-1Rev
Approved for public release

CNA | Center for Data Management and Analytics

DOI: 10.2514/6.2023-3554

https://arc.aiaa.org/doi/10.2514/6.2023-3554

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AGENT-BASED MODELING OF UNCREWED AIRCRAFT SYSTEM
Flight Planning for Airspace Fairness

The number of uncrewed aircraft systems (UAS) and corresponding UAS operations is expected to increase dramatically soon. Regulatory agencies are currently designing and piloting UAS traffic management concepts that rely on federated protocols and a cooperative, community-based approach. As demand increases, the need to ensure fair usage of airspace among operators will be an important challenge. Currently, there are no widely agreed upon definitions or guidelines for UAS airspace fairness. The objective of this work was to evaluate the fairness implications of using a first-filed-first-served protocol for flight planning. We developed UAS Cooperative Airspace Traffic Simulation (UCATS™), an agent-based modeling simulation tool, to evaluate different UAS package delivery scenarios using a first-filed-first-served approach to UAS flight planning. We defined key metrics to measure fairness, including average delay, maximum delay, and percentages of flights as planned, replanned, and canceled. Our results showed that a first-filed-first-served approach may cause flights having a departure time later in the day and flights that are filed with less advanced time have a higher probability of experiencing more negative flight outcomes. We also evaluated the sensitivity of fairness metrics to different traffic levels, different flight densities, and the addition of food delivery operations.

Contents

Introduction

As demand for uncrewed aircraft systems (UAS) operations increases, regulatory agencies must develop concepts for managing widespread UAS operations. In the US, future UAS traffic management (UTM) will be community based and cooperative [1]. This approach differs from traditional crewed air traffic management, which relies on the Federal Aviation Administration (FAA) to provide centralized traffic management. In UTM, the FAA will establish "rules of the road," but the operators and third-party UAS service providers will be responsible for coordination, execution, and management of operations [1].

UCATS™

UAS COOPERATIVE AIRSPACE TRAFFIC SIMULATION

With the decentralization of UTM, competing operators should work together to ensure that all have fair access to the airspace. The FAA will need to ensure that UTM is implemented fairly, despite the competing interests and unequal market shares among operators. Currently, however, the FAA has yet to formally define what fair access to airspace entails.

In this work, CNA developed UAS Cooperative Airspace Traffic Simulation (UCATS™) as a tool to investigate UAS airspace fairness with the intent of providing insight into future decision-making for UTM. UCATS™ is an agent-based modeling (ABM) tool that simulates UAS flight planning scenarios to provide insights into usage of airspace, including metrics to measure fairness. Industry and government stakeholders can use this tool to assess future high-density UAS operations and resulting fairness toward UAS operators.

PRIOR WORK

There are limited studies of airspace fairness for UAS operations. Evans et al. (2020) simulated UAS scenarios where two operators served in overlapping regions [2]. The study used a first-come-first-served allocation of resources with de-confliction by departure time and determined an optimized solution set based on the cost of delay to the operator. The study found that significant imbalances in delays occurred due to shorter file-ahead times and higher traffic levels.

Sacharny et al. (2020) compared the efficiency of two UTM strategic deconfliction scenarios: a gridded approach, where the airspace is defined into grids that each must be deconflicted independently, versus a lane-based approach where deconfliction only occurs on predefined lanes of traffic [3]. The study used a series of computational experiments to determine relative metrics of average and maximum delay, flight time, and computational deconfliction time to determine that the lane-based approach outperformed the gridded approach.

Finally, Chin et al. conducted a series of studies on efficiency and fairness for future UAS operations. The first study simulated the problem of four package delivery operators making overlapping deliveries with different fairness metrics [4]. The study found that total delay was a more effective metric than departure reversals. The second study expanded this problem to consider operator preferences, airborne-to-ground delay cost ratios, and market shares and found similar results as the previous study [5]. A third study computed optimized solution sets based on queuing and lane-based fairness protocols for air taxis and ranked each by the resultant system delays [6].

Each of these studies has advanced the field of UAS airspace fairness; however, our study fills technical gaps in the body of work by considering a non-homogenous set of operators that differ in file-ahead time and peak time of delivery, including the reality of flight cancelations, and conducting sensitivity analyses of different traffic levels and allowable flight densities. We were able to incorporate these new considerations into an UAS simulation because of our use of ABM and the flexibility that such a modeling approach provides.

ABM APPROACH

ABM is a bottom-up computational approach used to analyze the effects of autonomous interacting agents on the overall system [7]. Agents are given predetermined properties and interact with each other and their environments using predefined rules. ABM can simulate heterogeneous systems where the behavior of each agent contributes to the overall outcome. In our approach, the UAS operators are the agents, who are autonomous and interact with each other. The operators also follow defined behaviors regarding the flight planning process, eligible trajectories, and conflict detection and resolution procedures.

ABM has been used to simulate a variety of environments, including those related to UAS. Recent studies have addressed specific problems without an explicit focus on fairness, such as last-mile delivery [8]. In a 2019 literature review of ABM applications for unmanned aircraft vehicles, the authors reviewed 42 papers that addressed a variety of UAS topics, none of which directly address strategic flight planning or airspace fairness [9]. We addressed this gap by using an ABM approach that considers the sensitivity of UAS parameters that contribute to strategic flight planning.

OBJECTIVES

Our goal was to develop an ABM tool that simulates flight planning for small UAS delivery operations and use its derived statistical metrics to evaluate airspace usage fairness. This work focuses on two research questions.

First, how can airspace fairness be measured for small UAS package delivery operations? Metrics such as the average delay and number of flight cancelations per day are helpful in determining how often operations are being completed as planned. Moreover, a relatively fair airspace would have low percentages of cancelations and delays because operators would complete their flights with minimal conflicts.

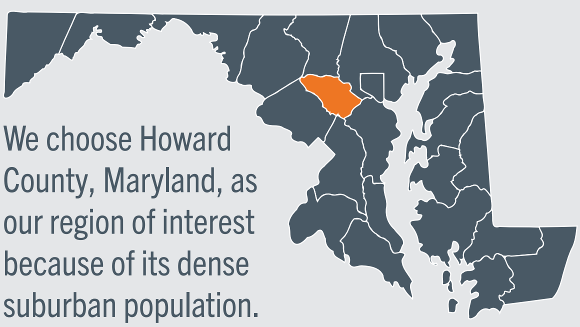
Second, how will prioritizing flights using a first-filed-first-served (FFFS) method affect airspace fairness? Within this scope, we aimed to quantify how different levels of traffic and types of UAS operations will affect a fair approach to traffic management planning. Eventually, operations will reach a traffic threshold at which an increase in cancelations and delays occurs. Introducing different types of UAS operations, such as food delivery (which naturally operates on a different demand schedule), influences both traffic level and package delivery filing. These variables would impact our metrics for airspace fairness under the FFFS method.

ASSUMPTIONS

The following assumptions were made for our scenarios and analyses.

Location

Our first assumption was based on the location that would be used for the small UAS delivery operations. We chose Howard County, Maryland, as our region of interest because of its dense suburban population. We choose two hypothetical package warehouse locations in the eastern part of the county based on existing warehouse locations and major surface transportation routes. For simplicity, we did not consider the effect of flight-restricted areas such as those near hospitals or airports.



We choose Howard County, Maryland, as our region of interest because of its dense suburban population.

UAS Operations

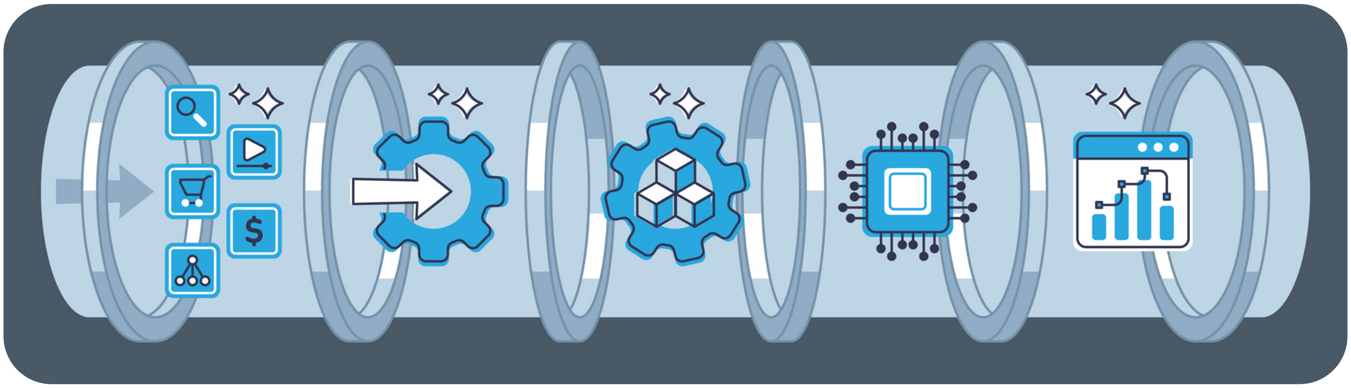
We assumed clear and optimal weather and flying conditions for all UAS operations. The UAS will comply with Washington, DC, Metropolitan Area Flight Rules: total UAS weight less than 55 pounds, package weight less than 10 pounds (i.e., small packages only), and flights remaining below 400 feet in altitude. These restrictions limit UAS delivery speed to 50 miles per hour and flight ranges to 20 miles based on existing battery life and specifications of current commercial uncrewed aircraft. The UAS delivered one package at a time and used the same trajectory for delivery and return. Once the UAS reached the destination address, it paused to deliver its package and then immediately used the reverse path to return, which limited the delivery radius of a distribution location to 10 miles. We assumed each UAS will require 300 feet of separation in any direction from other UAS. For simplicity, UAS are assumed to fly at the same altitude to avoid violating vertical separation requirements. Finally, our scenarios did not consider the effect of interference from emergency or crewed operations.

Year

We assumed the year 2035 to calculate the expected population in Howard County and the corresponding number of deliveries for the simulations. The percentage of the population to receive UAS package deliveries in any given day was determined based on methods from two 2017 studies [10][11]. Using the studies, we estimated that Howard County would have a total of 102,029 combined residential and commercial addresses that would be eligible for package delivery. With two operators and one distribution location for each operator, the volume of UAS launches at each location was high, and we assumed that each operator had access to unlimited UAS.

Model

To capture uncertainty around delivery patterns, we used a stochastic approach to randomly assign deliveries to each operator. Each scenario was run for 1,000 iterations, which we assumed was sufficient to process a range of possible outcomes. UCATS™ simulates the flight planning process of future UAS flights, not the physical flights of the operations themselves. Thus, we assumed that the actual operations would occur as planned.



Methodology

After completing a thorough literature review, narrowing the scope of our problem statement, and defining our assumptions, we completed our work with the following phases: data collection, data processing, model algorithm, and scenario generation.

DATA COLLECTION

We used existing residential and commercial addresses to represent all possible delivery locations in Howard County, Maryland. We imported the address data from the Department of Transportation's National Address Database [12]. We also obtained county boundary data from the State of Maryland's Geographical Information Systems [13]. Then, we used ArcGIS to filter, visualize, and export the addresses within our defined radius of each origin (e.g., warehouse).

DATA PROCESSING

Two parts of our solution development required data processing: sector approach and shortest path.

Sector Approach

We divided the geographical region of interest into 300-by-300-foot sectors to represent the physical separation required for UAS based on our assumptions. We standardized spatial and temporal units by defining s to represent the sectors and t to represent a 5-second time unit (i.e., the approximate time it takes for the UAS to traverse a sector at 50 miles per hour). For sectors that contained addresses, the approximate housing density per occupied sector was 5 to 10 single family homes, 10 to 15 townhomes, or 20-plus apartments. This step of processing used spatial data from the Maryland GIS Data Catalog that was visualized in ArcGIS.

Shortest Path

To reduce the computational effort of the model, we pre-generated one trajectory for each possible delivery address–origin distribution pair. The trajectories were calculated using a shortest path approach from Python's

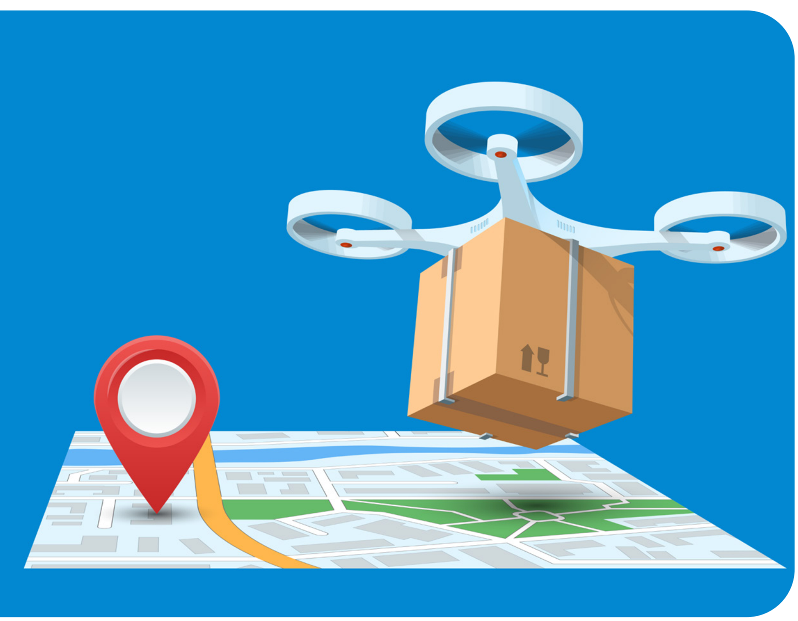
NetworkX package [14] before running the model simulations. We defined a graph in which nodes are the sector centers and edges are the distance between centers. Our shortest path algorithm allowed for both diagonal and orthogonal movement between sectors but assumed the cost (i.e., distance) between them is the same.

MODEL ALGORITHM

The UAS operators were the autonomous interacting agents of the ABM and their behaviors were dictated by their flight plans, trajectories, and conflict detection and resolution procedures.

Flight Plans

The delivery destinations of the flight plans were randomly assigned for each operator. The departure and file-ahead times were also randomly assigned to each flight plan. The departure times were selected between 8 am and 8 pm in time intervals t. The allowable file-ahead times were 24 hours, 12 hours, 6 hours, and 1 hour before departure time. To align with the FFFS approach mentioned earlier, flights are ordered by their actual filed time, which is derived from the departure time minus the file-ahead time. A single flight plan can be traced back to its trajectory, filed time, and original departure time.



Conflicts

We defined a conflict as when an operator submitted a plan that included one or more instances in which the UAS would be in the same sector s at the same time t at any point during the operation (i.e., delivering and returning trajectories) as another UAS whose plan had already been submitted and approved. This definition assumed that all UAS operated at a single altitude. To allow for multiple launches and maneuvering from the distribution location, no conflicts were considered within a four-sector buffer around the distribution location sector.

Deconfliction

Our deconfliction protocol followed an FFFS approach, where flights were considered in the order that they were filed. Operators submit their desired flight plan and must deconflict with any filed flight plans before their flight plan is successfully filed. Thus, deconfliction was managed at the preflight or planning stage. In addition, all deconfliction occurred at the ground (not air) level before takeoff from the distribution location. The only acceptable method of deconfliction was to ground (delay) the flight plan for as many time steps t as needed until no conflicts remained with any other filed flight plans. Flights were canceled if they were delayed past the last available departure time or an operator's defined tolerance (i.e., for time-sensitive operations). Directional changes to flight trajectories and airborne holdings were not considered as deconfliction strategies.

SCENARIO GENERATION

To evaluate airspace fairness for future UAS operations, we ran a total of four scenarios using UCATS™, each addressing some part of our problem statement. The four scenarios were: Scenario I: Baseline, Scenario II: Differing Traffic Levels, Scenario III: Differing Traffic Levels, and Scenario IV: Adding Fast Food Operations. A report with calculated descriptive statistics was generated at the end of each scenario to be analyzed. The four scenarios are summarized in Figure 1 and described in the subsequent subsections.

Figure 1. Summary of the Four Scenarios

	Scenario I Baseline	Scenario II Differing Traffic Levels	Scenario III Differing Traffic Levels	Scenario IV Adding Fast Food Operations
Agent / Operator	2 package warehouses	2 package warehouses	2 package warehouses	2 package warehouses 3 fast food locations
Total Daily Deliveries	12,000	6,000 to 24,000	12,000	15,150
UAS Allowed per Sector	1	1	2 to 3	1
Delivery Distribution	Uniformly throughout the day (8am–8pm)	Uniformly throughout the day (8am–8pm)	Uniformly throughout the day (8am–8pm)	Uniformly throughout the day; 11am–2pm for food

Scenario I: Baseline

Our first scenario provided the basis of evaluation for future scenarios. We ran a series of simulations with two package delivery operators (agents) at two different distribution locations (i.e., warehouses). Each operator delivers 6,000 packages randomly over the course of 12 hours, for a total of 12,000 daily deliveries.

Scenario II: Differing Traffic Levels

Our baseline assumption of 12,000 flights per day was based on UAS and population forecasts; however, future traffic levels may differ from the baseline assumption. We ran a series of simulations with total traffic levels of 6,000, 9,000, 12,000 (baseline), 15,000, 18,000, 21,000, and 24,000 to capture a range of possible levels. All other baseline assumptions remained the same.

Scenario III: Differing Sector Density

Our baseline scenario allows only one flight per sector based on assumptions that every UAS needed 300 feet of separation. However, future UAS may have improved tactical deconfliction capabilities, decreasing the separation requirements for UAS and thus, in our model, increasing the number of flights allowed per sector. In addition, future UAS operations may allow vertical deconfliction and multiple UAS within the same horizontal sector at different altitudes. We ran two additional simulations allowing up to two flights per sector and then three flights per sector. All other baseline assumptions remained the same.

Scenario IV: Food Delivery

In the final scenario, we evaluated the effect of adding new types of UAS delivery operations. The baseline scenario considers only package deliveries that can be filed up to 24 hours ahead of time and delivered in a 10-mile radius. In this scenario, we added three new distribution locations for fast food delivery over lunchtime hours. These locations can deliver in a 3-mile radius and receive their orders 30 minutes ahead of time. In addition, because of the time sensitivity of the orders, flights are canceled if they are delayed more than an hour. We purposely chose the locations to overlap with each other and with the two existing package delivery services. The locations also correspond with actual food establishment hubs that serve surrounding residents in Howard County, Maryland.

Based on existing literature, we assume that 47 percent of the eligible addresses order food at least once per week [15]. We divide this percentage by 7 to obtain the assumption that 6.7 percent of addresses order once per day. We assume that the food orders all occur during lunchtime hours from 11 am to 2 pm. Thus, along with the 12,000 daily deliveries expected from the warehouse agents, there are an additional 3,150 food deliveries for a total of 15,150 daily deliveries for this scenario. The fast food agent breakdown per day is as follows: 1,500 deliveries for Fast Food 1,950 deliveries for Fast Food 2, and 700 deliveries for Fast Food 3.

Results

We ran each scenario for 1,000 iterations to capture a range of outcomes based on the randomization of each delivery's details (i.e., delivery address, departure time, file-ahead time, and origin distribution location). The stochastic nature of UCATS™ considers the uncertainty in the behavior of the deliveries based on customer needs. In this study, we measured fairness by the comparability of planned flight outcomes for UAS operations. The key metrics we defined are:

- **Average delay in minutes**: the mean of the delays experienced by any replanned flights,
- **Maximum delay in minutes:** the greatest delay experienced in any replanned flight throughout the day,
- **Percentage of as-planned flights:** the percentage of flights that depart at their original desired departure times when filed,
- **Percentage of replanned flights:** the percentage of flights that depart after their original desired departure times,
- **Percentage of canceled flights:** the percentage of flights that would be delayed beyond the 8 pm limit (or beyond the delay tolerance of the operator) and are considered terminated.

SCENARIO I: BASELINE

The key metrics for the 1,000 iterations of the baseline scenario are found in Table 1, where 69.1 percent of the 12,000 flights (i.e., 7,878 flights) experience some length of delay.

Table 1. Key metrics for Scenario I: Baseline

Key Metric	Average (± Standard Deviation)
Average Delay	60 minutes (± 6)
Maximum Delay	563 minutes (± 80)
Percentage As-Planned Flights	22.1 percent (± 0.5)
Percentage Replanned Flights	69.1 percent (± 0.7)
Percentage Canceled Flights	8.8 percent (± 1.0)

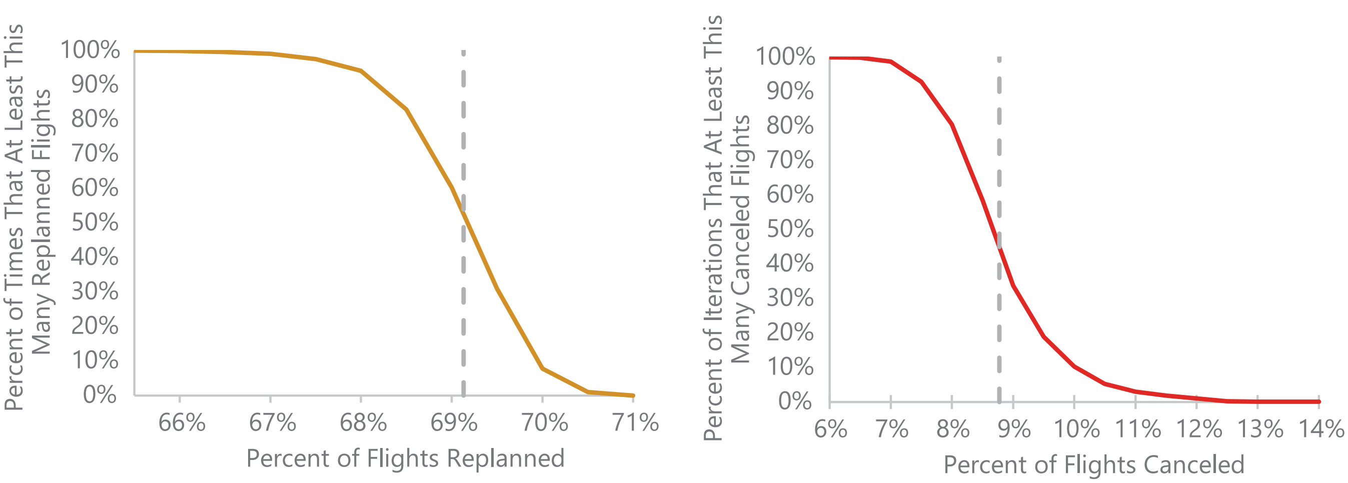
FFFS

FIRST-FILED-FIRST-SERVED DELIVERY METHOD

Because of the stochastic nature of UCATS™, it is also useful to look at the range of possible outcomes of the iterations, including best case and worst-case outcomes. The worst-case outcomes represent instances when conflicts are more likely to occur (e.g., when a surge of deliveries are requested within a short amount of time or by addresses along the same delivery route). In Figure 2, we see that the range of replanned flights is smaller and more consistent than the range of canceled flights. In 75 percent of the iterations run, at least 68.7 percent (8,249) of flights are replanned and at least 8.1 percent (976) of flights are canceled. In extreme cases, the number of replanned flights can be as high as 8,505 (70.9 percent) and the number of canceled flights can be as high as 1,681 (14.0 percent).

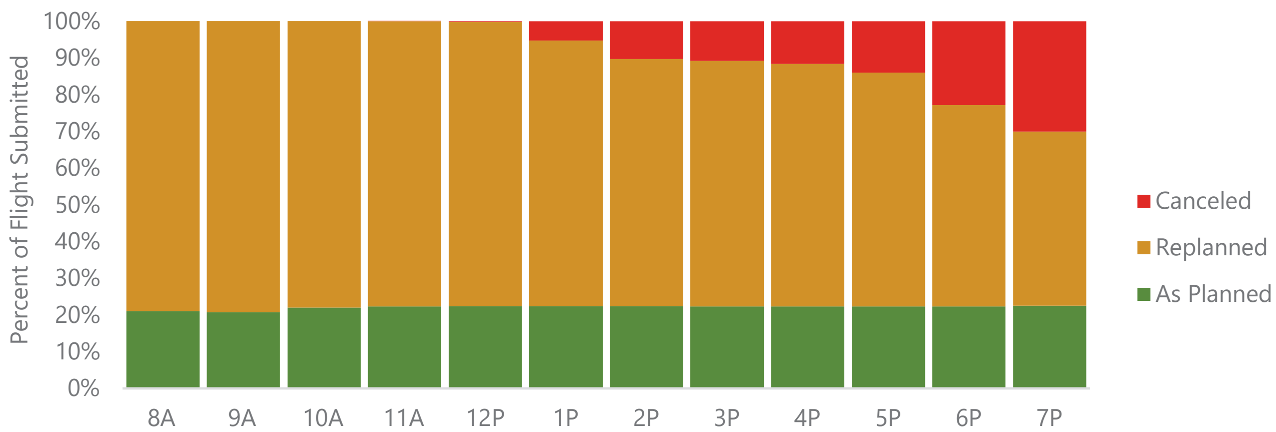
The results can be broken down further to look at the proportion of flight outcomes by original desired departure time of the flight as seen in Figure 3. Later departing flights are canceled more often because of a domino effect in which earlier flights are delayed, causing conflicts with later flights. Flights are canceled if they are delayed past 8 pm (the time representing the final allowable departure time and the maximum operator delay tolerance), so late departure flights have less time available for replanning. On average, flights departing in the morning hours can be delayed but typically are not subject to cancelation. In an FFFS prioritization approach, earlier departing flights have a higher probability of obtaining a more positive flight outcome if they encounter conflicts during flight planning. The discrepancy in outcomes from using the FFFS approach may be less fair to time-restricted flights that must depart later, which are more likely to have a less positive flight outcome if they are not able to file ahead and then encounter conflicts. However, we also observe that the percentage of as-planned flights is similar

Figure 2. Distribution of flights that were (a) replanned and (b) canceled over all iterations



(a) (b)

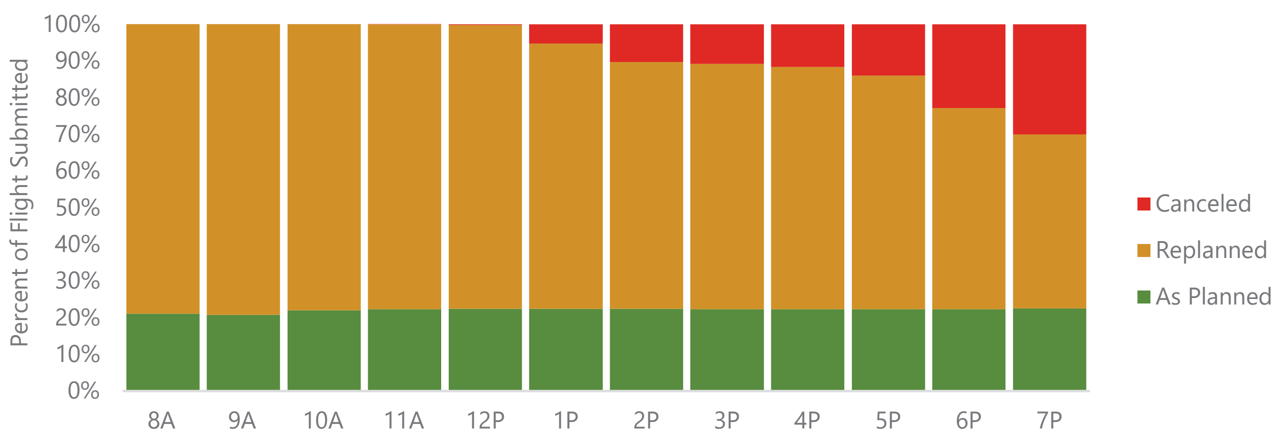
Figure 3. Breakdown of flight plan outcomes by original departure time



for all departure times, at around 20 percent. This finding occurs because flights planned far in advance (e.g., 12 or 24 hours) are evenly distributed throughout the day.

We can also view the flight outcomes by file-ahead time as shown in Figure 4. Flights planned farther in advance have a clear advantage over flights planned closer to departure. No flights planned 12 or 24 hours ahead were canceled in any of the 1,000 iterations. As such, operations that can be filed hours or days before departure have a higher probability of obtaining a more positive flight outcome in an FFFS prioritization approach. The discrepancy in flight outcomes from using a FFFS approach may be less fair to more urgent flights that must be scheduled with shorter advance notice. However, we also observe that next-day deliveries still have a 60 percent chance of being delayed, albeit not by much time (i.e., on average, 48 seconds).

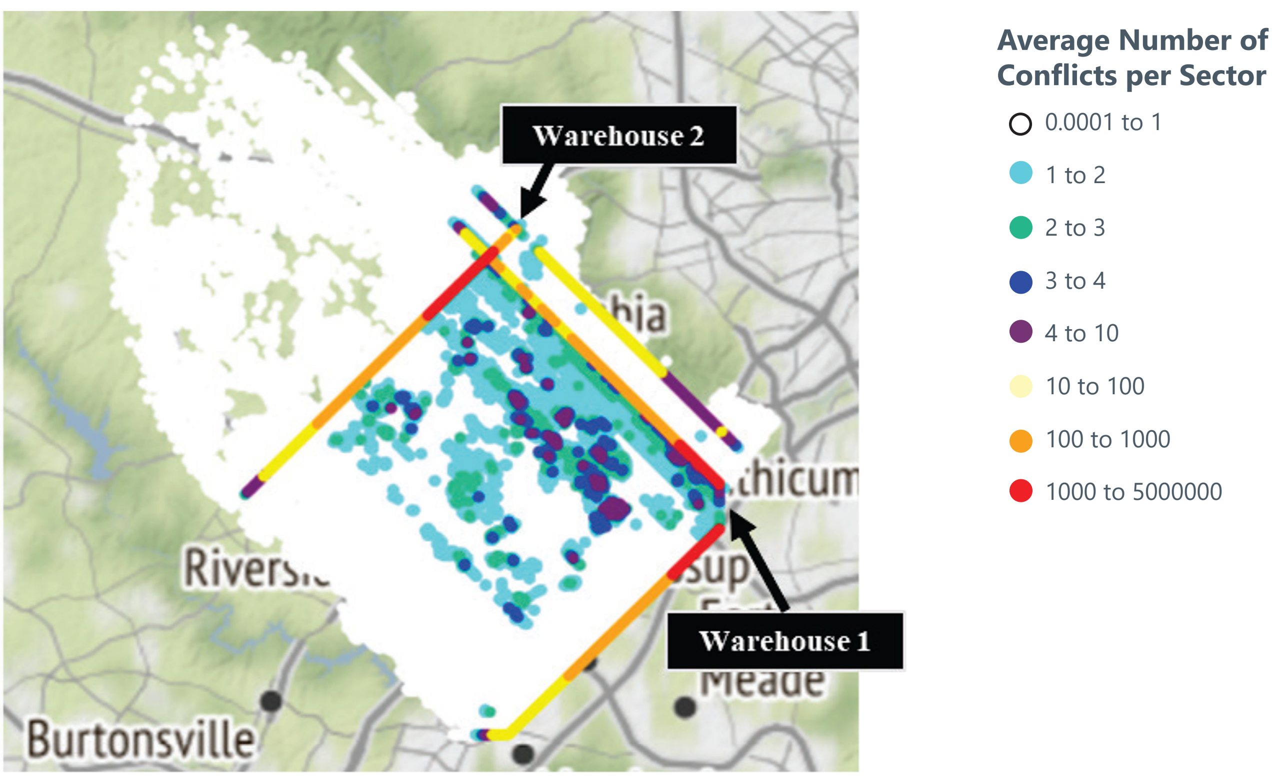
Figure 4. Breakdown of flight plan outcomes by file-ahead time

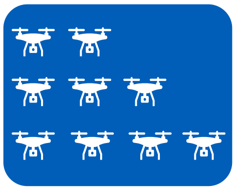


Finally, we can break down the results based on which sectors are experiencing the most conflicts. UCATS™ processes the trajectory for each flight plan in the order that it was filed. If an attempt to file a plan fails because an earlier filed flight already occupies the same sector at the same time, a conflict is recorded for that sector. The map in Figure 5 shows the average number of conflicts per sector for all iterations.

We observe that 20 percent of all sectors recorded at least one conflict. There are approximately 150,000 total sectors in the grid and more than 100,000 addresses that are randomly selected for delivery, so some addresses or sectors may have been randomly selected only a few times in the 1,000 iterations. Thus, most sectors are in the lowest (0.001 to 1, white) range of the legend. However, we also note that 95 percent of conflicts occurred in the same five sectors located near the warehouses because of congestion of flights leaving and returning (red range of the legend, 1,000 to 5 million). The five sectors with the highest number of conflicts claimed 60 percent, 29 percent, 2.5 percent, 2.5 percent, and 1 percent of all conflicts, respectively, whereas all others claimed the remaining 4.9 percent. This result is supported by the finding that conflicts occur largely between flights from the same operator (97 percent) versus flights from different operators (3 percent). Possible mitigations for conflicts near the warehouses could include alternate or more regulated departure and landing approaches. Finally, we also see that patterns in conflicts occur in popular "corridors" leaving the warehouses, especially those at perpendicular angles to the warehouse locations. We attribute this finding to our use of the gridded approach and shortest path algorithm, which limit the flights to diagonal and orthogonal movements based on 300-by-300-foot sectors. The patterns are consistent with existing initial concepts of designating corridors for air taxis.

Figure 5 Average number of conflicts per sector for 12,000 deliveries

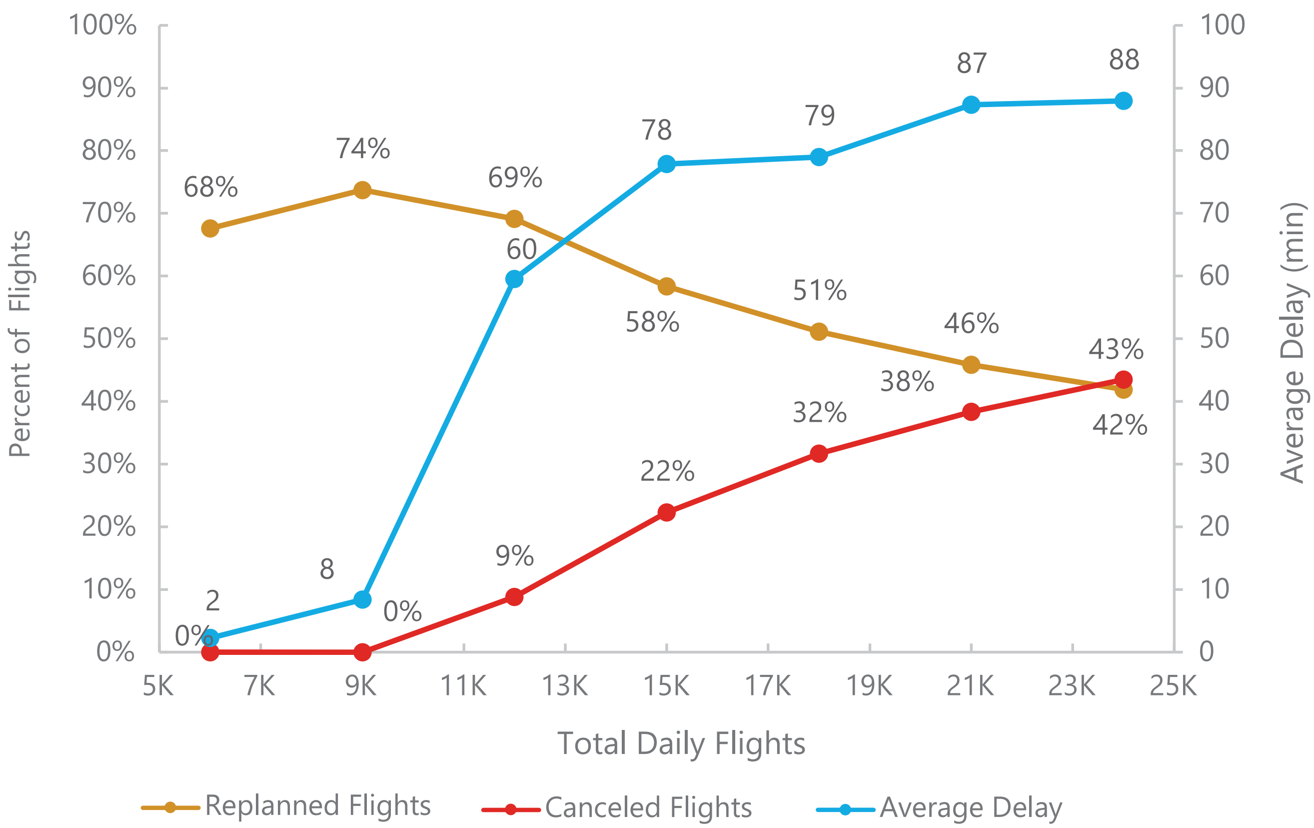


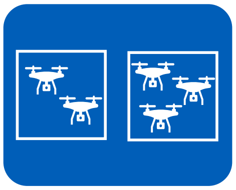


SCENARIO II: DIFFERING TRAFFIC

In the second scenario, we evaluated the effect of traffic levels from 9,000 to 24,000 flights. The results in Figure 6 show inflection points and patterns. At fewer than 9,000 flights, flight delays are minimal and flights are not canceled. At 9,000 flights, the number of replanned flights increases slightly as the system reaches its capacity to manage delays before flight cancelations begin. At more than 24,000 flights, more flights will be canceled than will be completed. In general, the percentage of canceled flights increases with higher traffic levels while the percentage of replanned flights decreases with higher traffic levels because flights that would be replanned instead become canceled.

Figure 6. Flight plan outcomes for different traffic levels

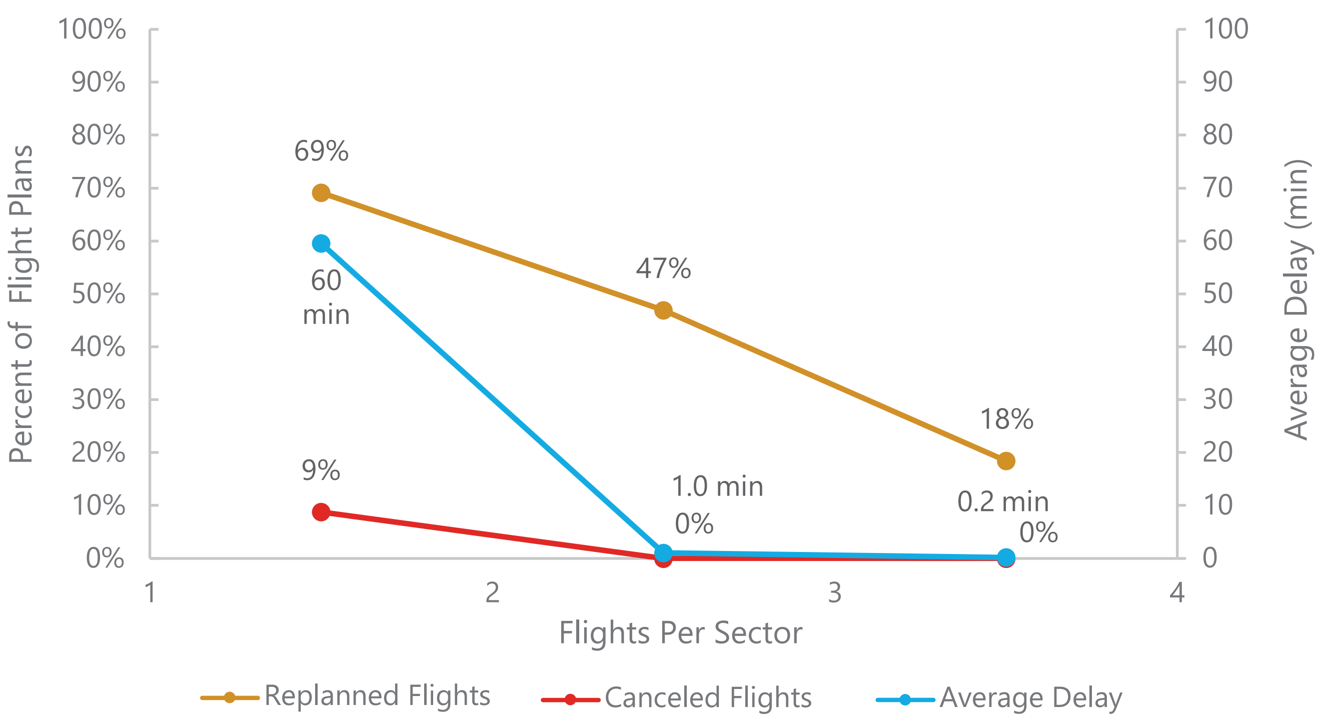




SCENARIO III: DIFFERENT DENSITY

In the third scenario, we evaluated the effect of increasing the number of flights allowed from one per sector to two per sector and three per sector. The results are shown in Figure 7. As expected, the flight outcomes improve immediately with increased density because the number of conflicts is directly reduced. The percentage of replanned flights decreases linearly with increased allowable density; however, the average delay of the flights decreases sharply. With the 12,000 daily baseline flights, canceled flights and average delay have the potential to be almost eliminated with a density of two flights per sector.

Figure 7 Flight plan outcomes for different flight densities per sector



SCENARIO IV: FOOD DELIVERY

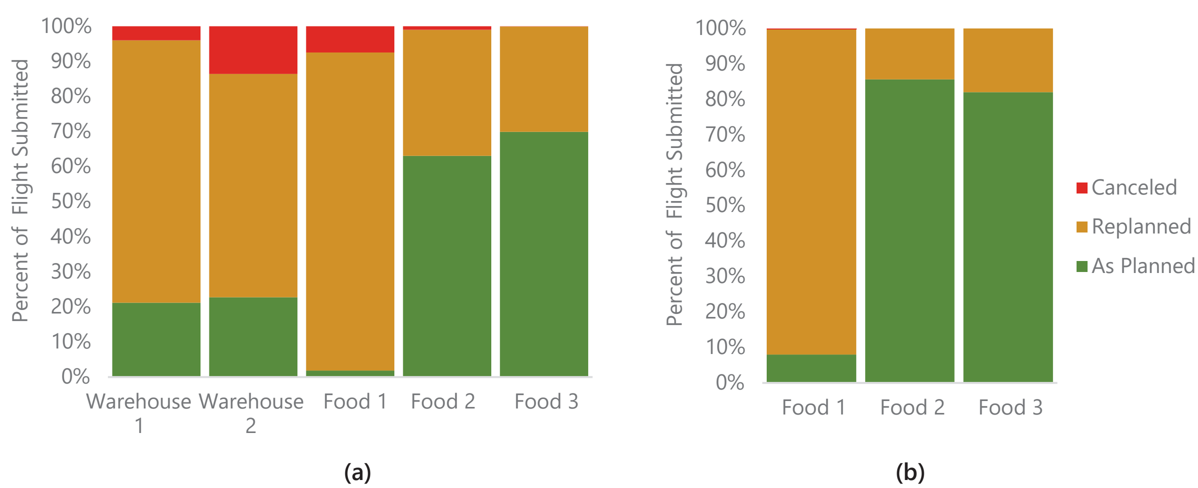
The key metrics for the 1,000 iterations of the food delivery scenario are found in Table 2. Averaged over all operators and flights, we observe that the average delay, number of canceled flights, and number of replanned flights are similar to the baseline scenario with only package delivery operations. However, from the individual operator perspective, the individual food delivery metrics are overshadowed by the more numerous package delivery metrics.

Table 2. Key metrics for Scenario IV: Food Delivery

Key Metric	Average (± Standard Deviation)
Average Delay	52 minutes (± 6)
Maximum Delay	569 minutes (± 82)
Percentage As-Planned Flights	24.8 percent (± 0.4)
Percentage Replanned Flights	67.4 percent (± 0.7)
Percentage Canceled Flights	7.8 percent (± 0.9)

Food deliveries can file only 0.5 hours ahead, so package deliveries always take priority. This prioritization is shown when we view the results by operator and not as a whole. We then simulated the effect of considering only food deliveries (no package deliveries) to compare the difference in flight outcomes. As shown in Figure 8, we found that in simulations without package deliveries, the food operators experience fewer delayed flights, almost no canceled flights, and less delay. Thus, a segregated airspace may help improve equity among operators that have short file-ahead times, such as fast food delivery services.

Figure 8. Comparison of flight outcomes by operation with (a) food and package deliveries and (b) food deliveries only.



MODEL LIMITATIONS

The results from the four scenarios provided in this paper provide a proof of concept for using ABM to simulate future UAS operations and measure airspace fairness. However, UCATS™ has several major limitations that should be addressed in future work to further improve and mature the model itself, as well as the data and assumptions used in the scenarios. These limitations include the following:

1. UCATS™ is driven by assumptions used in the model algorithm and on scenario parameters and should be validated with stakeholder and additional subject matter expertise.
2. The flight paths are all predetermined and do not allow for dynamic deconfliction. Further expansion of UCATS™ can optimize flight trajectories, allow for alternative trajectories, or allow for air-based deconfliction (e.g., holding).
3. The agents (i.e., UAS operators) have limited interaction with each other. Further work can define more behavior protocols, such as negotiation between agents.
4. Only trajectory-based package and food delivery operations are considered, and all operations are considered with equal priority. Further expansions may add more types of operations, such as area-based operations and prioritized public safety operations.
5. Only up to five distribution locations are considered in the scenarios, which led to many internal conflicts near launch. Further work may add more locations or change locations for each operator.

Acknowledgments

This work was funded by an internal CNA research grant. The authors would like to acknowledge review and guidance by the following CNA analysts and researchers: Adam Monsalve, Addam Jordan, Aparna Calambur, Ashish Khatta, Ben Sugg, Kasia Jaskowska, Marina Rozenblat, and Vincent Bauer.

Conclusion

In this study, we evaluated how airspace fairness may be measured for future UAS operations and how a FFFS flight planning method might affect airspace fairness. We measured airspace fairness by developing an ABM tool, UCATS™, to simulate four different flight planning scenarios and analyze key metrics. We found that when prioritizing flights using a FFFS method, flights that are unable to participate in advanced file-ahead times and flights that depart late in the day are disadvantaged. This inequity may be further evaluated in UCATS™ by studying the feasibility of non-FFFS prioritization schemes (e.g., such as those based on specific operator preferences or package priorities). We also identified high congestion areas around the distribution locations and along popular corridors. To further investigate these phenomena, UCATS™ can be used to assess different design factors, such as number and placement of distribution locations and the effect of designated air corridors. Other opportunities for further expansion and application of UCATS™ include assessing additional deconfliction schemes, estimating airspace operational capacities, and examining the effect of prioritized operations on UAS flight planning.

Overall, this effort showed that UCATS™ has potential to provide informative insights to industry and government stakeholders. Because of its agent-based design, UCATS™ is highly customizable and can be used to model different UAS operations and environments. The scenarios developed in this proof of concept demonstrate initial insights that a more mature UCATS™ could expand on. UCATS™ can be used in numerous applications to provide decision-makers with data-driven information.

Key Take Aways

UCATS™ HAS POTENTIAL TO PROVIDE INFORMATIVE, DATA-DRIVEN INSIGHTS TO HELP INDUSTRY AND GOVERNMENT STAKEHOLDERS PLAN FOR THE FAIR USAGE OF UAS AIRSPACE.

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