

# A Data Analysis Approach for Simulations of Urban Air Mobility Operations

Kushal A. Moolchandani  
Universities Space Research  
Association  
at NASA Ames Research Center  
Moffett Field, CA, USA  
[kushal.a.moolchandani@nasa.gov](mailto:kushal.a.moolchandani@nasa.gov)

Hanbong Lee  
Aviation Systems Division  
NASA Ames Research Center  
Moffett Field, CA, USA  
[hanbong.lee@nasa.gov](mailto:hanbong.lee@nasa.gov)

Heather Arneson  
Aviation Systems Division  
NASA Ames Research Center  
Moffett Field, CA, USA  
[heather.arneson@nasa.gov](mailto:heather.arneson@nasa.gov)

Annie Cheng  
Aeronautics Projects Office  
NASA Ames Research Center  
Moffett Field, CA, USA  
[annie.w.cheng@nasa.gov](mailto:annie.w.cheng@nasa.gov)

**Abstract**—For the Urban Air Mobility (UAM) industry, NASA has defined a series of UAM Maturity Levels (UML) corresponding to increasingly more complex and operationally dense UAM operations. In support of the gradual progression towards higher UML levels, NASA is currently conducting a set of UAM air traffic simulations—collectively referred to as X4. This paper describes a set of system effectiveness measures, and their associated metrics, for data analysis of X4 simulations. The descriptions, rationales, and calculation procedures for two metrics to be used in data analysis of simulation results, the number of predicted demand-capacity imbalances and the pre-departure delays, are described. Results from data analysis of one set of simulation runs are presented to demonstrate how these metrics support the assessment of performance of the system architecture for X4 simulations and the verification of experiment requirements.

**Keywords**—Urban Air Mobility (UAM), simulations, data analysis, metrics

## I. INTRODUCTION

Urban Air Mobility (UAM) refers to an emerging aviation market that provides air transportation services in and around urban areas with the support of highly automated air traffic management services. For the UAM industry, NASA has defined a series of UAM Maturity Levels (UML) corresponding to increasingly more complex and operationally dense UAM operations [1]. NASA’s overarching goal is to “evolve the airspace towards UML-4”, and the objective is to “evolve and develop the notional UAM architecture for early airspace UML traffic management and ensure it is extensible to higher UMLs.” At higher levels of maturity, FAA’s Concept of Operations (ConOps) for UAM [2] envisions dense flight operations within designated metropolitan and surrounding airspaces supported by selected Community Based Rules (CBRs) and high levels of automation both in airspace services and aircraft capabilities.

In the air traffic management research, various simulations, including fast-time and real-time simulations, have been performed to evaluate the new concept of operation or the changes of existing operational procedures, systems, and infrastructure before conducting field tests and demonstrations [3], [4]. These simulations can also provide standards bodies

with some guidance on decision-making for the development of future system architecture of new types of air transportation services such as UAM and Advanced Air Mobility (AAM). To assess the benefits and costs of the new ConOps and Use Cases like FAA’s ConOps for UAM from the simulation activities, we need to have a systematic approach to managing and analyzing the simulation output data. This data analysis approach includes the collection, mediation, storage, and analysis of the data obtained during the simulation. Further, detailed data analysis requires that all selected metrics are evaluated in parallel to avoid biases in derived insights. In this paper, we will discuss how the simulation data for UAM related research and development are collected and stored and describe how those data can be analyzed systematically. Before describing the data analysis approach, we present some background on the set of simulation activities being conducted by NASA in support of UAM industry maturation.

### A. Background on X-Series Simulations for UAM Operations

To support the gradual progression of UAM market towards higher UML levels, NASA has organized a series of test activities under the “Advanced Air Mobility (AAM) National Campaign (NC)” banner, involving collaboration between government and industry. These test activities are intended to provide insights into the evolving regulatory, operational, and safety environment of new aviation markets, including UAM. In turn, the insights generated by these tests are necessary to enable the envisioned UAM concept of operations while promoting public confidence in safety. In support of these test activities, NASA has been conducting a series of simulation events to help integrate the software components developed by airspace service provider partners and establish a framework for the necessary foundational research into airspace structure design and air traffic management.

The simulation events being conducted by NASA, collectively called the X-series simulations, started with “X1” simulations during 2017-18, where the goal was to explore and evaluate the roles and responsibilities and information exchange requirements of UAM stakeholders during both nominal and off-nominal conditions [5]. These were followed by “X2”, during 2018-19, which investigated whether the information exchange architecture developed for Unmanned

Aircraft System (UAS) Traffic Management (UTM) could support UAM operations in shared airspace [6]. The next such activity, completed in December 2020 and referred to as “X3”, provided the initial opportunity to assess the NC airspace system developed by the UAM Sub-Project under NASA’s Air Traffic Management – eXploration (ATM-X) project and the capabilities provided by airspace partners [7], [8].

The latest in the X-series of simulation activities, referred to as “X4” simulations, are currently ongoing and focus on the strategic conflict management service for UAM operations [9], including an initial implementation and testing of Demand Capacity Balancing (DCB) of UAM operations. In this implementation, all operators have to develop (or procure from an external source) a service that strategically schedules operations to ensure that the total demand at each of the constrained resources remains at or below its capacity. The providers of this service are responsible for ensuring submitted operational plans meet all applicable capacity constraints.

In this paper, we focus on one run of the X4 simulation and describe the results obtained from NASA’s implementation of a DCB algorithm; the experiment setup and testing are described in detail in Sec. III. We describe the selection of a set of system effectiveness measures that evaluate the success of the system architecture utilized for X4 simulations. We also discuss the selection and calculation of a set of selected metrics that characterize the system effectiveness measures. Finally, we discuss the importance of selecting an appropriate set of metrics to the derivation of insights on system architecture.

## II. EVALUATING THE RESULTS OF SIMULATIONS

To measure outcomes and performance as the UAM airspace research and development progresses and the airspace structure is defined, we need to select a set of system effectiveness measures for the UAM system architecture. These system effectiveness measures, in turn, are characterized by one or more metrics which quantify the associated measures. In the following subsections, we discuss the selection of system effectiveness measures and associated metrics that help assess the performance of the X4 system developed with initial strategic conflict management capabilities.

### A. Selection of System Effectiveness Measures for System Performance Evaluation

The X4 simulation architecture aligns with the aforementioned FAA ConOps [2]. As part of development of this system architecture, a set of system requirements is defined pertaining to the capabilities of a simulation platform along with the services necessary to execute and collect data during simulations. The system-level requirements are further decomposed and allocated to each of the subsystems, i.e., the software components of the simulation architecture. To measure the effectiveness of the proposed X4 system architecture, we need a set of system effectiveness measures. These effectiveness measures should measure system attributes such that they help verify that the system meets the stated requirements. In other words, these effectiveness measures should evaluate how well the proposed architecture performs

against system-level requirements. These effectiveness measures must be stated quantitatively and may be correlated so that they provide insights on specific system characteristics [10].

For example, we want to ensure that the proposed system architecture supports safe operations. System safety can be characterized with multiple system effectiveness measures, for instance, “Maintain resource demand below capacity” and “Maintain safe separation between airborne flights.” The former can be quantitatively stated that the provided airspace services should be able to plan flight operations such that the number of aircraft occupying or using any given resource in a specified time frame should be at or below a threshold value; in Sec. IV we will demonstrate how a demand-capacity imbalance management service can maintain demand at vertiports at or below a specified rate.

### B. Selection of Metrics

At an even lower level, a set of metrics measures attributes of system elements to assess the satisfaction of system requirements [10]. Metrics are quantitative in nature, generally derived from the system effectiveness measures, and may be expressed as maximum, minimum, or even threshold targets [11]. They help compare differences between actual and planned performance, identify and reduce risks, and compare effects of design decisions on solution outcomes, among other things [10], [11]. In the context of X4 simulation experiments, metrics are used to assess the success of a given run of a simulation experiment by identifying if the events expected in the experiment occurred, if the received data was as expected, and whether the airspace partners were able to perform the capabilities needed by the scenarios. The updates to lower-level metrics and targeted thresholds also allow for the tracking and management of technical progress by monitoring technical capability advancement within the UML framework to better meet stakeholder expectations. An example of a lower-level metric measured during X4 simulations is a count of predicted demand-capacity imbalances, including a breakdown into the number of predicted imbalances that were either resolved or left unresolved by the demand-capacity imbalance management services; as mentioned before, we will further discuss this metric in Sec. IV.

Fig. 1 represents how we assess the safety of the X4 system with a set of effectiveness measures and associated metrics. Safety of the UAM operations can be ensured if the system architecture can support conflict management functions in ensuring the separation between flights. Maintaining demand at or below resource capacity is one way that the separation between operations can be maintained, which means that the conflict management functions should be able to resolve all predicted instances of excess demand over capacity at a resource. This effectiveness measure can be further characterized by the metric which measures the number of predicted demand-capacity imbalances along with the number of such imbalances that were resolved.

Table I lists a subset of system effectiveness measures and some examples of metrics that are of relevance to X4. Among

Effectively support UAM operations staying safely separated through multiple layers of conflict management

Resolve all predicted instances of excess demand over capacity at all vertiports

0 unresolved demand-capacity imbalances

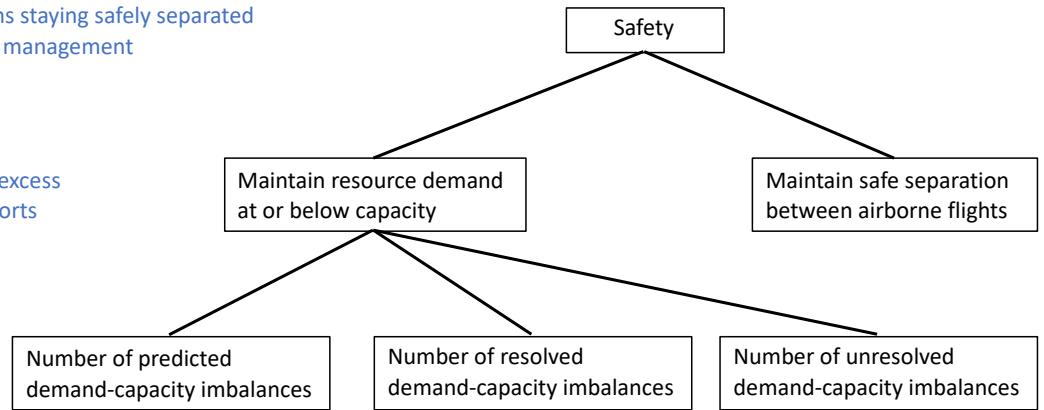


Fig. 1. Flow down from “Safety” MOE to a selected set of TPMs.

the effectiveness measures identified in this table, we will discuss those that characterize system safety, especially a count of total demand-capacity imbalances identified and resolved since these are the primary criteria for the fulfillment of X4 requirements. Alongside, the metric calculating assigned delays to aircraft will give more context for operations under specified scenarios.

### III. SIMULATING UAM OPERATIONS AND ANALYZING DATA

#### A. Airspace Services and Experiment Setup

In ICAO’s air traffic management concept, conflict management is one of seven concept components, and it is further divided into three layers: strategic conflict management, separation provision, and collision avoidance. The Strategic Conflict Management (SCM) layer, in turn, includes airspace organization and management, demand-capacity balancing, and traffic synchronization [12]. SCM’s role is to “reduce the need for separation provision to a designation level” [12]. The focus of X4 simulations is on the development and integration of a strategic conflict management layer for UAM operations; the X4 architecture does not include the other two layers of conflict management. In the following discussion, Demand Capacity Balancing (DCB) is a sub-service of SCM. We developed, implemented, and tested a DCB algorithm; [13] gives the full details of NASA’s DCB algorithm including a pseudo-code of its implementation in X4 simulations.

In X4, participating operators have their own Provider of Services for UAM (PSU), and they go through a series of “sprints” in order of increasing complexity. In this paper, we describe the simulation where the PSUs have demonstrated basic data exchange and conformance monitoring capabilities, and the objective is to demonstrate demand-capacity balancing capabilities. A requirement for all operators is that they modify an operation plan, if necessary, to resolve any predicted demand-capacity imbalances associated with the use of planned resources at the proposed times. This requirement exercises the set of defined Community Based Rules (CBRs)

on resource capacity and usage and is in addition to the requirement to ensure that the flights remain in conformance with the operational intent. It is assumed that all operators use the same vehicle model and cruise speeds.

We define a traffic scenario as an input that includes a total of 40 flights shared between two operators; in the results presented in Sec. IV, NASA plays the role of both operators. The traffic scenario specifies the origin and destination vertiports, a recommended route for each flight, and an original desired departure time for each operation specified as a delta (in seconds) from the simulation start time. Together, the routes form a network with five vertiports and ten routes in the Dallas/Fort Worth metropolitan area; Fig. 2 shows this route network, with the vertiports shown as black circles.

The operators propose flights in accordance with the given scenario, six minutes prior to the desired departure time so that the scheduling happens in the order of the desired departure time. Briefly, for each operation, the PSU submits an operation

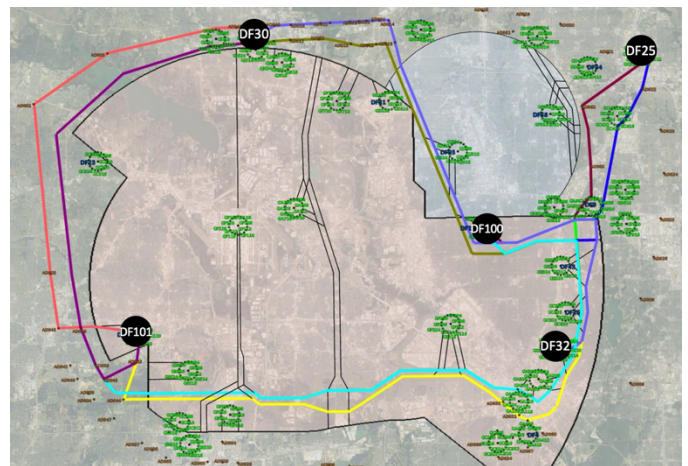


Fig. 2. Route network in Dallas/Fort Worth urban area.

TABLE I. SELECTED SYSTEM EFFECTIVENESS MEASURES AND METRICS FOR X4

System Effectiveness Measure	Description	Selected Metrics
<b>Scalability.</b> Measure the ability of the UAM system architecture to accommodate increasing levels of traffic as operations mature over time.		
Operation Density	Counts the total number of operations within a given airspace over a given interval of time	Total number of airborne operations per route; Running count of simultaneous airborne operations
Services' Messages Throughput	Measures the number of requests that pass through UAM services	Services' messages processing rate
<b>Efficiency.</b> Measure the efficiency of UAM operations that maximizes the use of the airspace. In X4, we measure resource utilization for all operational scenarios.		
Utilization	Evaluates the difference between capacity and demand and measures how effectively the capacity of the airspace is utilized	Throughput of UAM routes; actual arrival and departure rates at vertiports
<b>Predictability.</b> Measure the ability of UAM operators and service providers to deliver consistent and dependable levels of performance.		
Delay	Calculates the gap between the scheduled times and actual times of arrival	Total ground delay assigned; number of aircraft delayed
Trajectory Conformance	Evaluates how well the actual flown trajectory meets the specified trajectory conformance requirements	Trajectory conformance to defined procedures; percentage of operations conforming to operational intent
<b>Safety.</b> Measure whether the system architecture effectively supports UAM operations staying safely separated through multiple layers of conflict management. In X4, we especially evaluate the effectiveness of strategic conflict management in mitigating potential conflicts.		
Rate of Safe Operations	Calculates the percentage of operations that did not have any conflicts (i.e., those that meet all applicable separation minima)	Separation at specified waypoints
Count of Demand-Capacity Imbalances	Counts the number of operations that had a demand capacity imbalance, including those that were resolved versus those that remained unresolved	Number of predicted demand capacity imbalances resolved / unresolved
<b>Reliability.</b> Measure the ability of the UAM services to function without failure under nominal conditions.		
UAM Services Latency	Calculates the total time it takes from when a service makes a request until they receive a response	PSU-PSU Communication Latency
Uam Services Response Time	Calculates the time difference between when a service receives a request and sends a response	PSU-PSU response time
<b>Responsiveness.</b> Measure whether the UAM architecture provides the infrastructure for operators to react to unplanned events quickly.		
Dynamic Replan Rate	Evaluates the operations that successfully re-plan in response to dynamic airspace changes (e.g., airspace constraints)	Number of operations re-planned in response to airspace constraint; time between constraint announcement and re-plan

plan to a Discovery and Synchronization Service (DSS) and receives a list of PSUs to notify, i.e., the list of other PSUs that will be sharing its airspace and resources during an operation. The DSS is a service that enables a PSU to discover other PSUs operating in the shared airspace and facilitates automated data exchanges in the PSU network. Then, the PSU notifies the other PSUs identified by the DSS about its new operation plan and obtains authorization to “activate” an operation. Once activated, the operator flies the aircraft as per the operational intent and finally “closes” the operation upon landing. Note that, even though the X4 simulations do not include a tactical conflict management service, it is required that all flights remain in conformance with their operational intents throughout the mission.

*B. Data Collection and Storage*

Both during the simulation and after an operation is closed, vehicle telemetry and related data pertaining to flight operations are collected and stored for post-simulation analysis by a data collection service. Fig. 3 shows the interface between software components of the simulation system and elements of

the data storage system. On the left are the UAM subsystems including the PSUs, an Airspace Structure Definition Service (ASDS), which provides the adaptation data such as airspace structure and performance requirements, a DSS, which allows PSUs to discover other PSUs operating in the shared airspace, and a Flight Information Management System Authorization (FIMS-AZ) service, which provides authentication and authorization services to the PSUs. These subsystems provide the software components developed to demonstrate the capabilities defined in the X4 simulation scenarios.

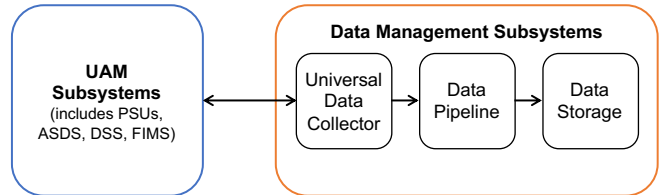


Fig. 3. Interface between UAM simulation components and data storage subsystems.

On the right are the components of the data collection environment, including components for collecting PSU exchange data during simulation and storing these data for post-sim data analysis. All simulation data are collected by a Universal Data Collector (UDC) via the endpoints defined in the PSU Application Programming Interfaces (API). These data are forwarded to the Data Pipeline, which validates all messages received for conformance to the baselined X4 APIs and further forwards them to data storage, which are secure repositories-of-record utilized to store and recall both real-time and post-operations data.

The data stored in the database is accessed with PostgreSQL queries, which apply the requisite filters and perform the necessary associations / transformations to obtain the metric results. In the next section, we describe some of the metrics along with their calculation approaches. Because successful demand-capacity balancing was the primary requirement, we focus on those metrics.

#### IV. DATA ANALYSIS AND RESULTS

We will now discuss two metrics that characterize the safety of X4 system: the number of predicted demand-capacity imbalances that were resolved and the amount of delay assigned to operations for resolving those demand-capacity imbalances. The latter metric is useful because, while there are a variety of ways demand-capacity imbalances can be resolved including assignment of departure delay, re-routing airborne aircraft, path stretching, speed changes, etc., we restrict our DCB algorithm to only perform departure delay to resolve DCB imbalances at both the departure and arrival vertiports. Along with the results presented, we will discuss how calculation of these metrics can inform future decision-making on the design and integration of airspace services.

##### A. Predicted demand-capacity imbalances resolved

The first metric we will discuss counts the number of flight operations at each vertiport in a given unit of time and compares this number with the pre-specified capacity of the vertiports. The unit of time we use, a “time bin”, is an interval of duration 12 minutes starting from the “top of the hour” of simulation start time. For example, if a simulation starts between 0900 and 1000 hours, the time bins for that run are [9:00, 9:12), [9:12, 9:24), ..., [9:48, 10:00). Notice that the time bin intervals are closed at the start time and open at the end.

In the simulations described in this paper, we assume that each vertiport can safely accommodate only two operations in each time bin. It is the responsibility of the DCB algorithm to ensure that the addition of a new operation does not cause a demand-capacity imbalance at the origin or destination vertiports during the time bins associated with its planned departure and arrival, respectively. Thus, this metric is used to evaluate the efficacy of the DCB algorithm in performing pre-departure strategic conflict management. However, as defined in ICAO’s air traffic management concept [12], neither DCB nor SCM is designed to eliminate the need for separation provision, but instead to reduce the need for it and create manageable problems for separation provision to resolve. The

DCB algorithm used in these simulations will always resolve predicted DCB imbalances, even if it needs to assign large delays to do so. Since large delays are undesirable, we calculate this metric in the next subsection.

The data collection API specifies that each operator must submit a “log set”, from which we get the “initial operational intent” that contains the details of the originally proposed flight trajectory. Thus, from the initial operational intent, we get the originally planned times of operation at both the origin and destination vertiports for each flight in the scenario. We then assign these flights to the appropriate time bins and increment the demand count at all vertiports in each time bin to calculate predicted demand-capacity imbalances prior to DCB.

During a simulation, two tables called “Operations” and “Trajectory” record the actual operation times for each operation. This includes the timestamps indicating when a flight was at a given position. From these two tables, we can identify the actual time bins of operation at all vertiports for all operations. Fig. 4 shows the flowchart of the above process. This figure shows the calculation of the number of predicted demand-capacity imbalances and the number of resolved / unresolved imbalances, as described in this section.

Fig. 5 shows the comparison of data obtained from one such simulation run. On the left is the heatmap showing the original demand profile in each time bin at all vertiports. This demand is specified as an input in the scenario and includes excess demand in some time bins to test the DCB algorithm. On the right of this figure is the heatmap showing the modified demand profile after the DCB algorithm re-plans operations by delaying some departures. In the next subsection, we will further discuss the distribution of assigned ground delays.

##### B. Ground Delays

NASA’s DCB algorithm resolves predicted demand-capacity imbalances by delaying aircraft prior to departure. Ground delays improve safety by reducing traffic density, but they can also reduce efficiency. Hence, for a given traffic demand scenario, calculating the delays assigned to aircraft is useful in

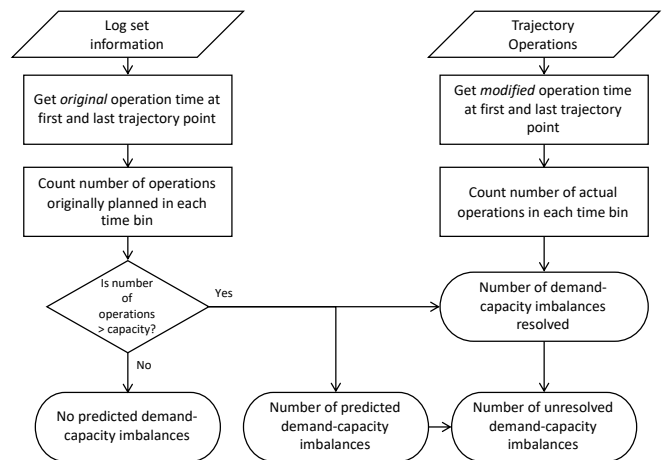


Fig. 4. Flowchart for calculating demand-capacity imbalances.

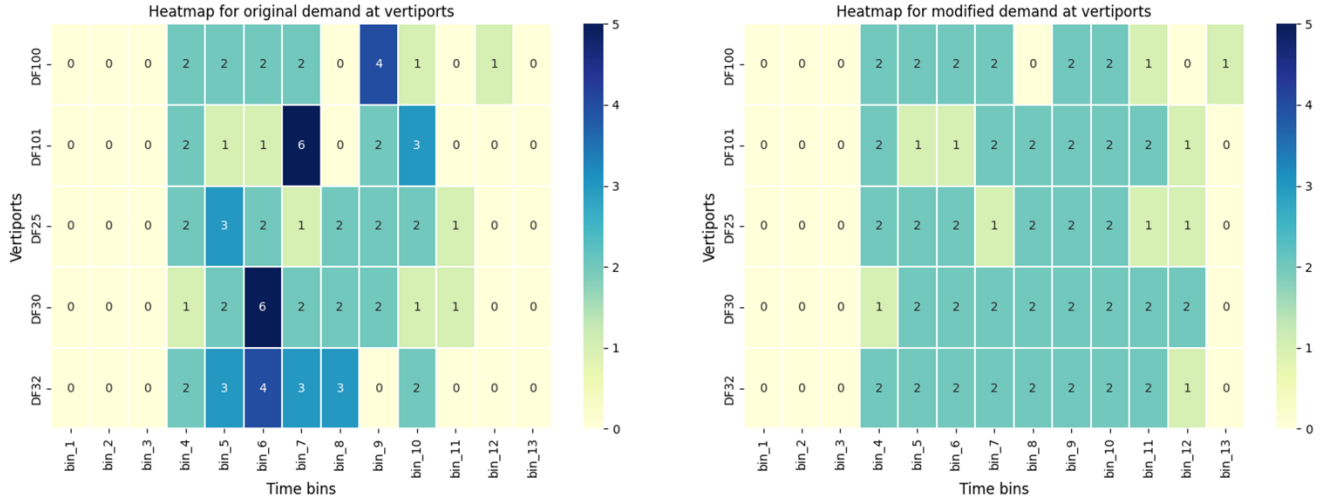


Fig. 5. Heatmap for original and modified demand at vertiports.

comparing the trade-off between safety and efficiency of operations. Furthermore, measuring how many aircraft are delayed, in addition to how much each aircraft is delayed, is also a measure of system capacity – a high number of delayed aircraft indicates that there are more operations than the system can safely accommodate.

To calculate assigned ground delay, we use the same set of tables as those used to count demand-capacity imbalances and resolutions. From the log set tables, we use the initial operational intent to get the original departure times for all flights. Likewise, from the operations table, we get the actual departure times post re-planning by the DCB algorithm. The difference between the original and actual operation times is the amount of ground delay assigned. Additionally, we can also count the number of aircraft that were delayed in a given scenario. Fig. 6 shows the process for calculating assigned ground delays.

Fig. 7 shows a histogram of delayed operations. Assigned delays range from just over two minutes (128 seconds) to over 29 minutes (1,776 seconds); note that this figure only shows

those aircraft that were assigned delays. Out of the 39 operations that were activated in this scenario, 23 operations were assigned delays.

### C. Insights from Data Analysis

Since the focus of our data analysis was on assessing the performance of a DCB algorithm, we presented two metrics that provide the desired insights. From the discussion in Sec. IV.A and as shown in Fig. 5, we see that the DCB algorithm developed by NASA for this simulation performs as expected. The excess demand over capacity, for example in bin 7 at vertiport DF101, was scripted in the scenario. During simulation, the DCB algorithm reduces the demand in bin 7 at vertiport DF101 from 6 operations per time bin to 2 operations per time bin in accordance with the capacity constraint, by delaying several of their departure times. The resulting ground delays are a tradeoff that needs to be considered when evaluating the other metrics. The average delay assigned to the 23 aircraft that were delayed in the given simulation was

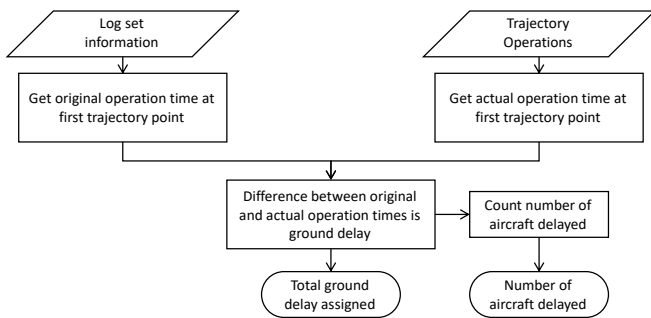


Fig. 6. Flowchart for calculating ground delays assigned by DCB service.

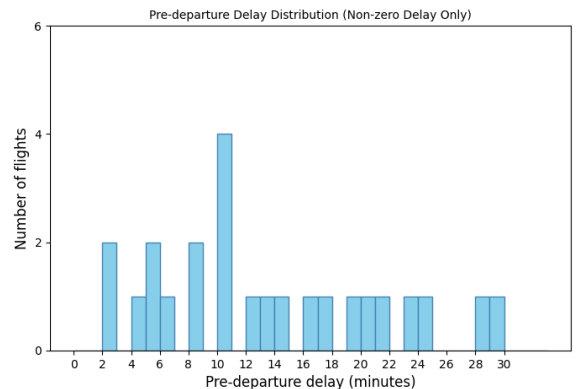


Fig. 7. Distribution of pre-departure delay assigned to flights.

13.35 minutes (800 seconds) and the average flight time for the same set of aircraft was 15.13 minutes (908 seconds). In this case, ground delays doubled the total travel time, which is clearly undesirable. Ground delays reduce traffic density, which, if applied too liberally, may unnecessarily throttle system throughput. If we allow for greater flexibility to resolve demand-capacity imbalances (e.g., by allowing re-routing or speed changes), then we may be able to balance demand and capacity with less onerous pre-departure delays. This indicates a need for a more sophisticated DCB algorithm and SCM service, not just to maintain safety but also to improve the scalability and efficiency of the system. For example, in its current form, the DCB algorithm only handles demand management at vertiports; future versions of this algorithm can be made to deal with other airspace resources like UAM corridor entry and exit points and intersection waypoints for crossing and/or merging.

Another consideration in analysis of the above metrics is that the presented simulations were conducted under deterministic conditions. If uncertainties had been modeled, SCM may not have been sufficient to resolve all instances of demand-capacity imbalances. Wind effects, for example, would have altered observed flight speeds which, in turn, would have resulted in earlier or later arrival times at the destination vertiports, leading to different demand from that predicted by the SCM service.

Finally, the X4 simulation architecture is being developed to meet the Minimum Viable Product (MVP) development requirements. An MVP provides no guarantees on functionality of the final system architecture. Ongoing X4 simulations are investigating the integration of DCB algorithms from multiple operators to ensure that, even in a collaborative environment, strategic conflict management can resolve the predicted demand-capacity imbalances. More advanced simulation experiments can explore additional features of SCM services, for example, its ability to handle uncertainties with the possibility of using airborne deconfliction maneuvers.

## V. CONCLUSIONS

We have presented an approach to the selection and evaluation of system effectiveness measures and associated metrics for the assessment of urban air mobility simulations. We described the considerations involved in the selection of these effectiveness measures and metrics and demonstrated how one aspect of system performance can be decomposed into multiple metrics. The selection of an appropriate set of metrics influences design decisions and the solution outcomes. Detailed analysis of simulation data requires that all selected metrics be evaluated in parallel to avoid biases in derived insights.

We also discussed the setup and execution of X4 simulation experiments, which are currently ongoing with participation between NASA and industry partners. The focus of X4 simulations is on the development of a strategic conflict management service. To demonstrate how data analysis can

support the development of this service, we presented results from one simulation test. Results from this test included the calculation of the number of predicted demand-capacity imbalances and the pre-departure delays assigned to aircraft. Additional metrics will be calculated at the conclusion of the X4 simulations, and the lessons learned from this simulation activity will be used to guide future development of the UAM system architecture. The same data analysis approach will be used for the future series of simulations that NASA is planning to conduct for the Advanced Air Mobility research and development.

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