Urban Air Mobility Airspace Dynamic Density

Lilly Spirkovska*
NASA Ames Research Center, Moffett Field, CA, 94035

Chetan S. Kulkarni† and Jason Watkins‡
KBR Inc, NASA Ames Research Center, Moffett Field, CA, 94035

Lynne Martin§
NASA Ames Research Center, Moffett Field, CA, 94035

Effective flight planning requires information about a variety of potential threats, such as adverse weather or airspace restrictions, and about alternatives available if unforeseen events occur. Expected traffic along the route of flight is also essential to a safe outcome so that, for example, adequate fuel/energy supply can be loaded prior to flight. A dynamic density (DD) metric is introduced for the emerging urban air mobility (UAM) concept to predict airspace congestion that may lead to loss of separation between aircraft or less efficient operations. Using inspiration from dynamic density metric research for traditional air traffic management and a two-way highway analogy, we develop a dynamic density metric for a portion of airspace (a UAM corridor) that aggregates the impact from five factors: aircraft density, density of populous clusters, mean number of aircraft in populous clusters, mean distance between aircraft, and minimum distance between aircraft. This works describes our methodology, rationale, use cases, and visualization techniques to efficiently present the DD metric to an operator for informed decision making. We also present an approach for validating the metric. However, validation remains part of future work.

I. Nomenclature

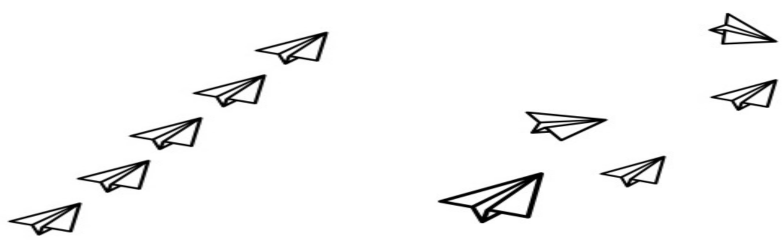
$aircraft\_density\_impact$	=	effect of aircraft density to DD
$area$	=	area of corridor
$cluster\_density\_impact$	=	effect of cluster density to DD
$cluster\_size\_impact$	=	effect of mean number of aircraft in cluster to DD
DD	=	dynamic density metric
i	=	time index during operational intent cloning
k	=	index of corridor
$mean\_cluster\_size$	=	mean number of aircraft in k
$mean\_distance\_impact$	=	effect of mean_prox to DD
$mean\_prox$	=	mean distance between nearest pairs of aircraft in k
$min\_distance\_impact$	=	effect of min_prox to DD
min_prox	=	distance between two closest aircraft in k
$num\_aircraft$	=	number of aircraft in k
$num\_clusters$	=	number of clusters in k
$offset$	=	start time of cloned operational intent
w	=	relative weight of importance of criterion

*Computer Engineer, Intelligent Systems Division, M/S 269-3.
†Scientist, Intelligent Systems Division, M/S 269-3, and AIAA Senior Member.
‡Software Engineer, Intelligent Systems Division, M/S 269-3
§Research Psychologist, Human Systems Integration Division, M/S 262-1.

II. Introduction

The air transportation system is expanding to accommodate a broad diversity and vast increase in air traffic[1–4]. New aircraft types are being introduced, ranging from very small unmanned aerial vehicles (sUAV) through supersonic transport aircraft. The piloting of these new operations is also changing from single- or multi-person crews, to remote pilots simultaneously flying one or more aircraft, to fully autonomous flight. And the type of operations are expanding from traditional general aviation and commercial flights to include package delivery by sUAV, cross-town transport of people, and providing autonomous rapid fire detection and suppression, among many others. These major changes in diversity of operations together with the expected vast increase in sheer number of operations requires new approaches to managing the new operations. Today's approach of relying on air traffic controllers is not scalable due to the workload required to safely and efficiently manage these new entrants .

Previous research focused on predicting the number of operations that one controller could effectively manage[5]. (See the Appendix for details.) The number of aircraft in a volume of airspace, i.e., density, is typically used to predict a controller's workload. The reliability of that metric is directly correlated with the potential for interaction between aircraft in a sector of airspace. That is, controlling a sector with few intersecting airways with flows of similar aircraft types requires less effort than controlling a sector with many intersecting flows of aircraft with widely differing performance, capabilities, and equipage, as shown in the two panels of Fig. 1. In sociology, the combination of population density and the amount of social interaction within that population is known as *dynamic density* (DD). The dynamic density of a sector, that is, the traffic and sector characteristics that are most relevant to accurately predicting controller workload, have been well studied and numerous combinations of factors have been found to have varying levels of predictive success[5].



(a) Low complexity operation. Aircraft of similar performance, capabilities, and direction of flight.

(b) High complexity operation. Aircraft of widely different performance, capabilities, and direction of flight, merging into one flow, for example, an airport traffic pattern.

Fig. 1 Numerous characteristics of airspace structure and aircraft flows determine operation complexity and thereby controller workload.

Our research objective is to explore how to define and validate a dynamic density metric that facilitates more autonomous and cooperative management of these new operations. In that context, controllers may be just one entity controlling traffic. Safety and efficiency of operations may additionally rely on a network of service providers and significantly increased ground and onboard automation. We propose airspace and traffic factors predictive of airspace congestion that may lead to loss of separation between aircraft or less efficient operations. We limit the scope to one rapidly-developing emerging airspace use case, that of urban air mobility (UAM), and use simulated traffic and expert judgment to evaluate the efficacy of the proposed metric.

The remainder of the paper is organized as follows. In Section III, we describe UAM and a notional airspace structure. In Section IV, we describe the DD metric, suggest several use cases of the metric in emerging operations, and present notional visualizations to facilitate its use. In Section V, we discuss experiments to validate the metric. Finally, in Section VI, we conclude with a summary of our work, discussion of how the DD metric may fit into the emerging air transportation system, and recommendations for future work.

III. Urban Air Mobility

NASA, FAA, and the aviation industry have been exploring alternatives to decrease the ground congestion that is clogging urban streets and highways, wasting people's time, and polluting the environment[6–9]. One alternative to address the ground congestion problem is urban air mobility (UAM)[10, 11]. The vision for UAM is to use highly automated, electric or hybrid-electric powered, vertical or short takeoff and landing aircraft to transport people and cargo over urban areas. UAM aircraft would fly between UAM airports, called *vertiports*, along UAM *corridors*[11]. Aircraft must meet performance requirements to operate within these corridors, and must operate under specific rules and procedures. UAM aircraft can also operate outside corridors where they must follow the rules applicable to the encompassing airspace.

NASA's Air Traffic Management eXploration (ATM-X) project is helping to develop the airspace concepts, technologies, and capabilities required for safe UAM operations through a series of simulations with industry partners[12–14]. To accommodate the scale of operations envisioned for UAM, ATM-X is leveraging NASA's Unmanned Aircraft Systems Traffic Management (UTM) system[15] which shifts some of the responsibility for air traffic control from FAA controllers to a network of third-party service providers. For UAM, these providers are referred to as Provider of Services for UAM (PSU). The ATM-X team is providing a virtual environment with simulated airspace, simulated aircraft, data visualizations, and realistic flight scenarios. The industry partners are assigned specific tasks to perform during a set of validation tests to evaluate a service-oriented architecture, PSU capabilities, and basic airspace/vehicle communication exchanges. Tasks could be as simple as requesting and receiving airspace data from an airspace structure definition service, to managing deconflicted departure times for multiple operations across multiple PSUs, to in-flight replanning due to a conflict. As described later in Section V, the DD metric is being applied to one of these simulations.

UAM is expected to mature in phases[16]. The initial phases will be characterized by low density, low operational complexity, and assistive automation. As technologies mature, density, complexity, and amount of automation will also increase. In the final phase, UAM operations will be ubiquitous; high density; highly complex; and rely on highly automated vehicles, airspace management, and system-wide optimization capabilities. The current simulation is of a fairly immature phase (UAS maturity level (UML) 3 as described in [16]) with low operational density and evolving PSU capabilities.

Airspace structure for the ATM-X simulations is derived from FAA NextGen UAM ConOps v1.0[11, 17]). Fig. 2 depicts a notional UAM airspace structure in the area of interest around Dallas-Ft. Worth, Texas. Each corridor contains *tracks*, a structural element to organize traffic, defined by a series of *waypoints*. Waypoints are simulation-specific named geographic points defined by latitude and longitude. Tracks may impose specific performance requirements on operations, such as speed or direction of flight. They provide access to vertiports – UAM airports where passengers would ingress/egress or cargo would be loaded/unloaded. Some vertiports may also be reached by routes outside of corridors, as shown in Fig. 2.

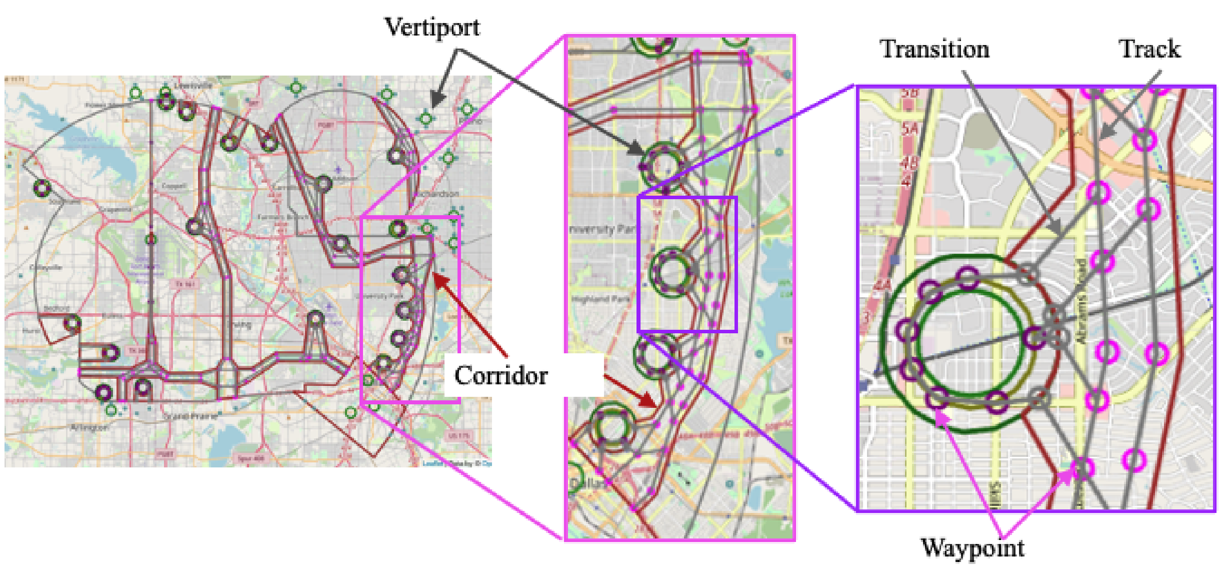


Fig. 2 Notional UAM airspace in area of interest. Corridors (brown polygons) contain tracks (gray lines) and transition tracks (gray lines). Tracks originate from and lead to vertiports (green circles) and are defined by waypoints (magenta and green small circles). Waypoints and vertiports may also be in uncontrolled (class G) or unstructured (outside corridors) airspace, where direct-to navigation is permissible.

Prior to takeoff, each operator must provide their *operational intent*. This is similar to traditional flight plans that provide route of flight, expected time of departure, estimated time of arrival (ETA), speed, altitude, type of aircraft, etc. Operational intent is more specific, however, requiring ETA, speed, and altitude at each waypoint along the route of flight. Predicting dynamic density requires more frequent aircraft position estimates to ensure traffic conflicts are not missed. Accordingly, the waypoint-to-waypoint route of flight is expanded into what we term a *full trajectory* by estimating aircraft position at 5 sec intervals (emulating simulation data) via linear interpolation between the given waypoints. Fig. 3 shows an example trajectory between two vertiports.

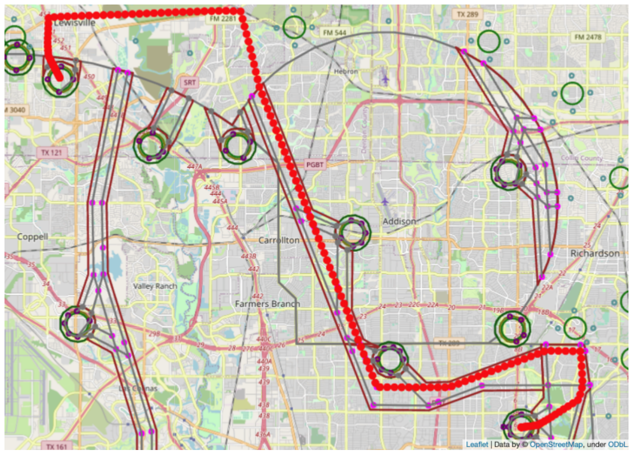


Fig. 3 Example trajectory between two vertiports.

IV. UAM Dynamic Density Metric

Dynamic density metrics have been explored in traditional air traffic management (ATM) to predict the workload of air traffic controllers. A controller is responsible for keeping aircraft well separated from each other and from any restricted airspace, while ensuring efficient flow of traffic. The number of aircraft within a controller's area of responsibility is a significant factor in their workload. The interaction between those aircraft is also highly relevant. The factors that are most relevant to accurately predicting controller workload have been well studied and numerous combinations have been empirically shown to have varying levels of predictive success[4-6]. Some of the important factors include the spectrum of aircraft types, the number and geography of crossing points and merges of flows of traffic, the difficulty of predicting aircraft conflicts due to the crossing geometry, and airspace restrictions due to presence of convective weather (see Appendix for more).

The DD metric may also be applicable to UAM traffic operating in corridors to ensure corridors are not saturated. Unlike traditional aviation, UAM operations will likely primarily be controlled by automated systems, not humans[15]. Thus, controller workload is not anticipated to be an issue (except perhaps during initial phases when humans may be much more involved). Conflicts between flights will remain an issue, however, and an excessive need for deconfliction may lead to an unsafe state due, e.g., to premature energy (battery) depletion from excessive maneuvering, or to an inability to remain within corridors. Additionally, the number of conflicts must remain within computationally-manageable levels. In short, whereas DD in traditional ATM is used to predict controller workload, UAM DD would instead predict situations that may lead to conflicts and excessive deconfliction. Saturated corridors may help the authorities open additional tracks or corridors. Also, as described below, operators may choose different routes based on the saturation of corridors predicted by the DD metric.

Much like in traditional ATM, considering only aircraft density may be insufficient. Even if the aircraft density in an area is low, the number of potential conflicts may be high if those aircraft are clustered in a small portion of that area, as shown in Fig. 1b. Alternatively, many aircraft may safely occupy an area if they are well separated and following similar flight paths, as shown in Fig. 1a.

The formulation of DD, paralleling UAM, is in its nascent phase. The list of important factors is expected to change as airspace structures change, vehicles and traffic management systems become more capable, and safety systems are fully vetted. Furthermore, the methodology used to determine importance of factors that contribute to DD will change as more flight data becomes available. With the sparsity of data currently available, we identify the characteristics that influence UAM dynamic density using analysis, domain knowledge, and conjecture. Data from more complex scenarios and simulations, combined with data and operational knowledge gained from actual UAM operations, would allow for a data driven or a hybrid approach, and may lead to improved conflict prediction accuracy. Additional data is also necessary to objectively validate the proposed metric, as discussed in Section V.

A. Dynamic Density Factors and Aggregation

We used a two-pronged approach for determining DD factors important in the UAM context. First, we evaluated the applicability of each of the factors that are important for predicting controller workload described in the Appendix. Some factors, such as coordination with other controllers, are clearly not a factor for UAM operations inside corridors where ATC will not provide services. Other factors, such as distance between aircraft, may apply. Second, we considered a two-lane highway traffic analogy and brainstormed factors that may lead to traffic accidents. We selected two-lane highways because they resemble the structure of bi-directional*, single-altitude UAM corridors used for this study.

In this first exploration, DD is computed only within corridors. Density of vertiport airspace and of unstructured airspace is outside the scope of the current work. As a further simplification that may result in an overestimate of DD†, altitude and speed were not considered because all aircraft cruise at the same altitude in the simulation. All aircraft also climb and descend with the same profile along well-specified transition routes.

An analysis of traditional DD work and the highway traffic analogy resulted in the following important factors (computed separately for each corridor):

1) Aircraft density
2) Density of populous clusters
3) Mean number of aircraft in populous clusters
4) Mean distance between aircraft
5) Minimum distance between aircraft

The impact of a factor on DD is determined using a heuristically-derived function, as described in detail for each factor below. A more rigorous approach to choosing a factor-to-impact function that assesses the resulting DD against multi-aircraft conflicts will be investigated in future work. The choice for distances (e.g., in cluster definition, negligible impact of mean/min factors, etc.) and the functions to map factors to DD impact are parameters to be estimated empirically. The choices will be influenced by a variety of considerations, such as the UAM operation rules and regulations, aircraft navigation system speed and precision, navigation facilities availability and capability, detect and avoid sensor capabilities, autonomy capabilities, etc. For example, the likelihood of loss of separation is lower if the required navigation performance[18] (RNP) in a corridor is 0.1 versus 1. In the former case (RNP 0.1), the aircraft navigation system must be able to calculate its position to within a circle with a radius of 0.1 nm, while in the latter (RNP 1), it is only required to calculate its position to within a circle with a radius of 1 nm. The positional uncertainty would need to be compensated for by a more conservative minimum standard separation distance between aircraft. By the same token, acceptable DD values depend on the positional uncertainty due to the strength of the GPS signal in an area. As a final example, a lower aircraft density in a corridor would be needed to compensate for aircraft with slow or less capable observe, orient, decide, act (OODA) decision making autonomy loops to provide enough time for the aircraft to detect a problem and determine a mitigation strategy before loss of separation occurs. In the following impact function and parameter choices, we assume RNP 0.1, single altitude operations inside bi-directional corridors, and fairly capable navigation and autonomy systems.

Aircraft density is the number of aircraft in an area (not volume, due to the same-altitude simplification stated above). It is reasonable to assume that dynamic density increases as aircraft density increases since there is more opportunity for interaction between more aircraft. Even in the situation of homogeneous aircraft in a well-constrained flow as shown in Fig. 1a, an aircraft system problem in a leading aircraft has an opportunity to affect more aircraft if it has more aircraft following it. We posit that the impact grows exponentially, making conflicts not just more likely but also more severe as the airspace becomes more saturated and avoidance paths become more limited. Therefore, the impact of aircraft density on DD is computed as follows:

$$aircraft\_density\_impact_k = 1.4^{num\_aircraft_k / area_k} - 1 \tag{1}$$

where $num\_aircraft_k$ and $area_k$ are the number of aircraft in and the area of corridor k, respectively. The 1.4 value, as is the case for values in subsequent equations, was chosen for its face validity.

*Corridors contain two opposing-direction tracks. Aircraft along a track fly in the same direction.

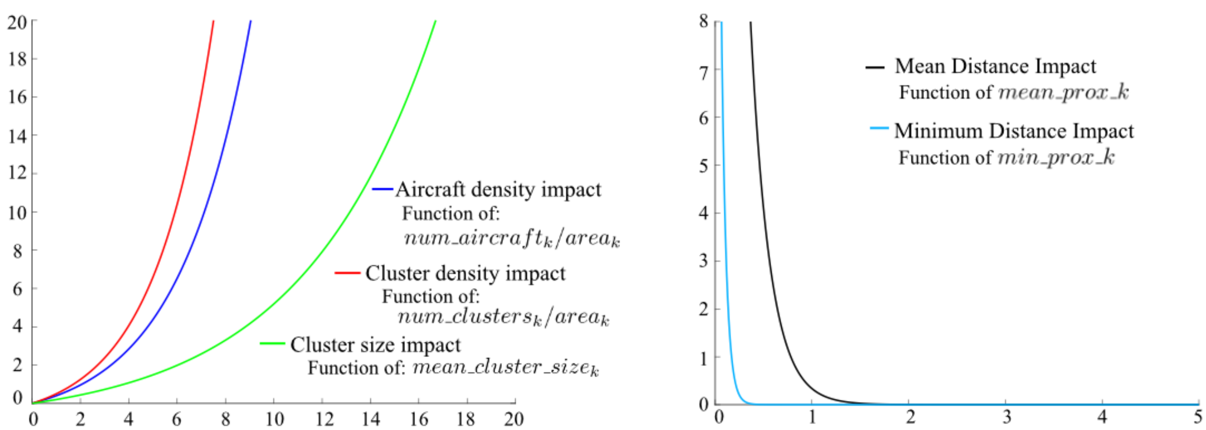
†As an example of overestimating DD due to ignoring altitude, consider aircraft that are laterally near each other but vertically separated. When projected onto a single altitude, they will appear to be in conflict but in fact would be well (vertically) separated.

We define a cluster as a set of aircraft that are within $3 * standard\_separation\_distance$ of another aircraft in that cluster, where $standard\_separation\_distance$ is set to 1250 ft, inspired by the minimum distance between tracks in a corridor (1500 ft). Given this definition, number of populous clusters and mean number of aircraft in populous clusters (mean cluster size) are computed. We posit that DD grows exponentially with these two factors. Our rationale is as follows. First, an unexpected maneuver of an aircraft is more likely to cause a disturbance in the flight path of a nearby aircraft than a more distant aircraft. Because the aircraft in a cluster are close to each other (by definition), there is greater likelihood that a disturbance will propagate to affect the other aircraft in the cluster. The more aircraft in a cluster, the more opportunity for interaction, and thereby higher DD. Moreover, the more clusters in an area, i.e., higher cluster density, the more cumulative likelihood for a disturbance. This follows from the probability of non-mutually exclusive independent events, i.e., $P(AorB) = P(A) + P(B) - P(A) * P(B)$. Finally, fewer maneuvering options are available to respond to a disturbance in corridors with higher cluster density and consequently less empty area. Based on this rationale, the impact to DD of cluster density and mean cluster size are computed as follows:

$$cluster\_density\_impact_k = 1.5^{num\_clusters_k/area_k} - 1 \tag{2}$$

$$cluster\_size\_impact_k = 1.2^{mean\_cluster\_size_k} - 1 \tag{3}$$

In future work, we will combine these two factors, with the rationale that many small clusters are not as likely to cause as much airspace disruption as a few large clusters. The curves in Fig. 4a graphically show the growing impact of $aircraft\_density$, $cluster\_density$, and $cluster\_size$.



(a) Growing impact to DD of aircraft_density, cluster_density, and cluster_size factors.

(b) Decaying impact to DD of mean_prox and min_prox factors.

Fig. 4 Direct and inverse contribution of factors to DD.

In contrast to the direct relationship between the above factors and their impact to DD, mean distance between aircraft and minimum distance between aircraft have an inverse relationship. The farther aircraft are from each other, the less likely it is that a disturbance of one would impact the operation of the other. If, on average, aircraft in a corridor are at least a certain distance apart, the likelihood of affecting each other is negligible. We set this distance to 1 nm. Considering only the mean distance between aircraft could potentially obscure pairs of aircraft that are much closer and are thus more susceptible to each other's disturbances. To account for this circumstance, we include the impact of the minimum distance between the closest aircraft in the DD computation. We posit that the effect is negligible unless the minimum distance is quite small and does not allow enough time for the other aircraft to execute an evasive maneuver. We set this distance to 0.25 nm. We hypothesize that both factors have an exponentially decaying impact. With this in mind, the impact to DD of the mean distance and minimum distance between aircraft in a corridor is computed as follows:

$$mean\_distance\_impact_k = 50 * e^{-5*mean\_prox\_k} \tag{4}$$

$$min\_distance\_impact_k = 30 * e^{-20*min\_prox\_k} \tag{5}$$

where $mean\_prox\_k$ is the mean distance between nearest pairs of aircraft (not the mean of the distance of each aircraft to all other aircraft in the corridor; both cases are shown in Fig. 5) and min_prox_k is distance between the two closest aircraft. The curves in Fig. 4b show the decaying impact effect graphically.

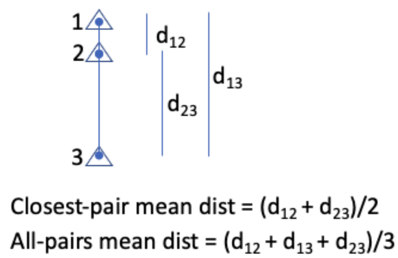


Fig. 5 Distinction between mean distance between nearest pairs (closest-pair) and mean distance between all other aircraft in the corridor (all-pairs).

DD for a corridor is then computed as:

$$\begin{aligned} DD_k =& w_1 * aircraft\_density\_impact_k \\ &+ w_2 * cluster\_density\_impact_k + w_3 * cluster\_size\_impact_k \\ &+ w_4 * mean\_distance\_impact_k + w_5 * min\_distance\_impact_k \end{aligned} \tag{6}$$

where w_i denote the relative weight of importance of each criterion. In future work, these weights can be learned from data as it becomes more available.

As new or updated operational intent is received, DD is predicted for a lookahead period, set by default to 15 min.[‡] Predicted DD for the entire airspace or for a specific trajectory can then be provided to an operator, as described in the use cases in Section IV.B. As aircraft position updates are received, a DD nowcast is computed. To reduce computational requirements, DD nowcasts are computed only every 1 sec (or 5 sec, configurable). All position updates received between DD updates are buffered and the most recently received position for each aircraft is used. DD produces a value between 0 and $infinity$. The numerical DD value is then categorized into four bins: negligible, low, moderate, and high. The thresholds delineating the bins are set empirically.

B. Use Cases and Visualization

DD can be used to facilitate UAM flight planning in the emerging ATM concepts that blend traditional ATC with a network of service providers and with significantly increased ground and onboard automation. We illustrate three use cases. First, during the initial planning stages, a 15-20 min[§] prediction of DD for the entire airspace can alert an operator of expected congestion areas. An operator can then either decide to avoid those areas by taking a different route, plan to takeoff with extra battery energy, or implement another business-appropriate mitigation strategy. Second, prior to finalizing operational intent, the operator can assess anticipated DD by visualizing the prediction along the planned trajectory. Third, once airborne, this trajectory-focused DD prediction can be monitored for change. Changes could occur for a variety of reasons, including the following:

- A newly airborne aircraft may increase the DD for a corridor to a higher category.
- Weather, an emergency vehicle, or other airspace disturbance may require widespread route replanning, increasing dynamic density in areas where it was previously acceptable.
- The subject aircraft itself may need to be rerouted. For example, ATC may need to close a corridor along the aircraft's path because an unexpected shift in wind direction requires reconfiguration of a nearby commercial airport.

If a reroute becomes necessary, an operator can once again scrutinize DD focused on the full airspace to determine the best mitigation strategy.

The actor in the above use cases does not need to be a human operator. An autonomous system can benefit from the same information, receiving that information in a machine-to-machine exchange rather than the visual representations

[‡]The lookahead period is configurable. By default, it is set to correspond with the expected duration of typical UAM flights.
[§]Corresponding to the anticipated length of typical UAM flights.

suggested below for human operators. For instance, thresholds can be set to alert an autonomous aircraft of congestion ahead so that it can enact a mitigation strategy without human assistance.

We developed one graphical display of current (nowcast) DD and two graphical displays of predicted DD, one focused on the airspace and the other focused on an individual aircraft's trajectory. DD nowcast is visualized by a color-coded representation of DD layered onto the UAM airspace, as shown in Fig. 6. For improved situational awareness, the most recent known position for all aircraft are also displayed.

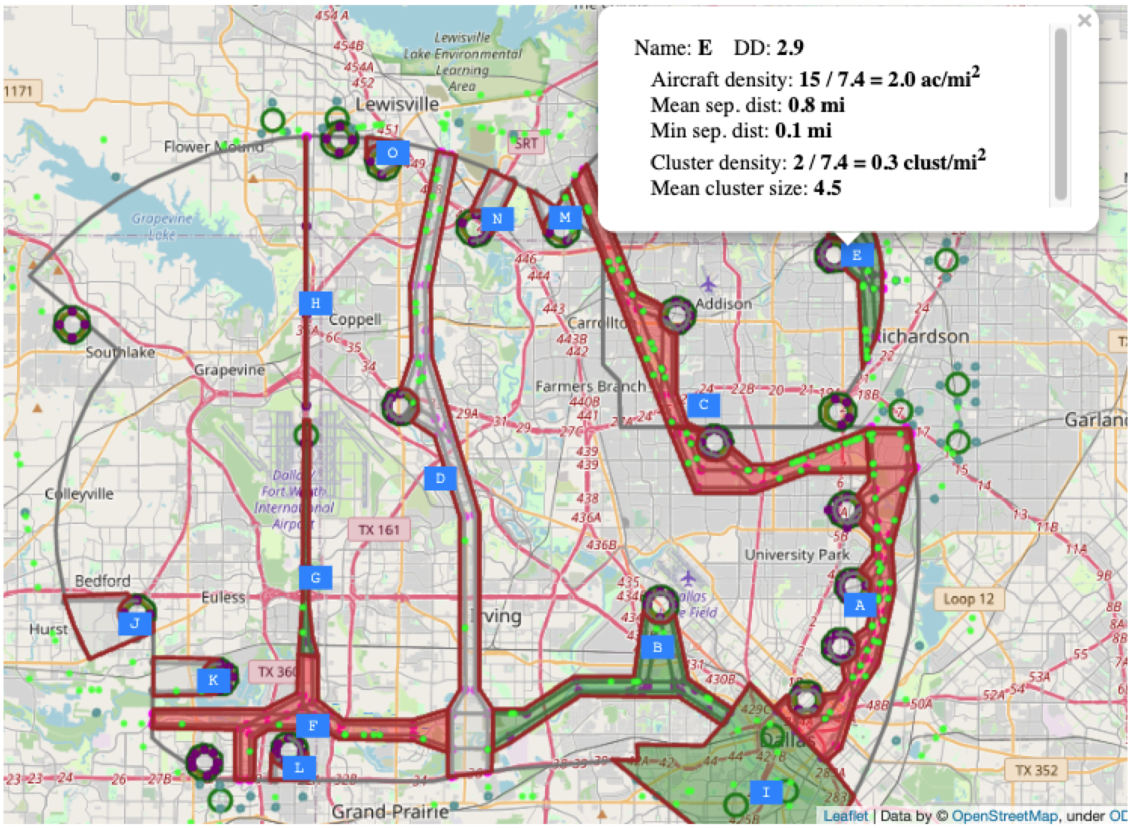


Fig. 6 Prototype display of DD for the current time, a nowcast. Bright green dots show most recent known positions of all aircraft. Corridors are color-coded for negligible (gray), low (green), moderate (yellow), and red (high) DD. Details are available on demand, as shown for corridor E.

A prototype visualization of a DD prediction with an airspace focus is shown in Fig. 7. The 15 min prediction is split into coarse timesteps (e.g., 20 sec bins) so that the full prediction can be displayed without scrolling. The maximum DD value in a bin is used to determine its color. In future prototypes, an operator could be given various configuration options, such as setting prediction lookahead and bin timestep size, and selecting from several functions for determining bin color. For example, bin color could be determined by the maximum DD value that persists for N samples. To reduce information overload, the operator may also prefer to specify the corridors of interest. An alternative approach to displaying how predicted DD changes over time is to add a time slider to the nowcast-type display. This requires more operator interaction and perhaps cognitive workload, but can provide more detailed data since coarse timesteps would not be required.

Prior to concluding route planning and submitting an operational intent to ATM, an operator may want to confirm DD along the flight's trajectory at a fine resolution, e.g., 5 sec intervals. The prototype visualizations of a DD prediction with a trajectory focus, shown in Fig. 8 and 9, could facilitate this task. The time-applicable DD for the enclosing corridor at that point is used to color code each location along the trajectory, providing an at-a-glance view of DDs that the aircraft is predicted to encounter. Because this is a prediction specific to an individual aircraft and would not be of interest to other operators, thus making a system-wide message undesirable, a what-if mode could be implemented that allows the operator to provide a proposed operational intent without officially submitting it.

Visual presentation of information often expedites interpretation. In some situations, however, simple textual

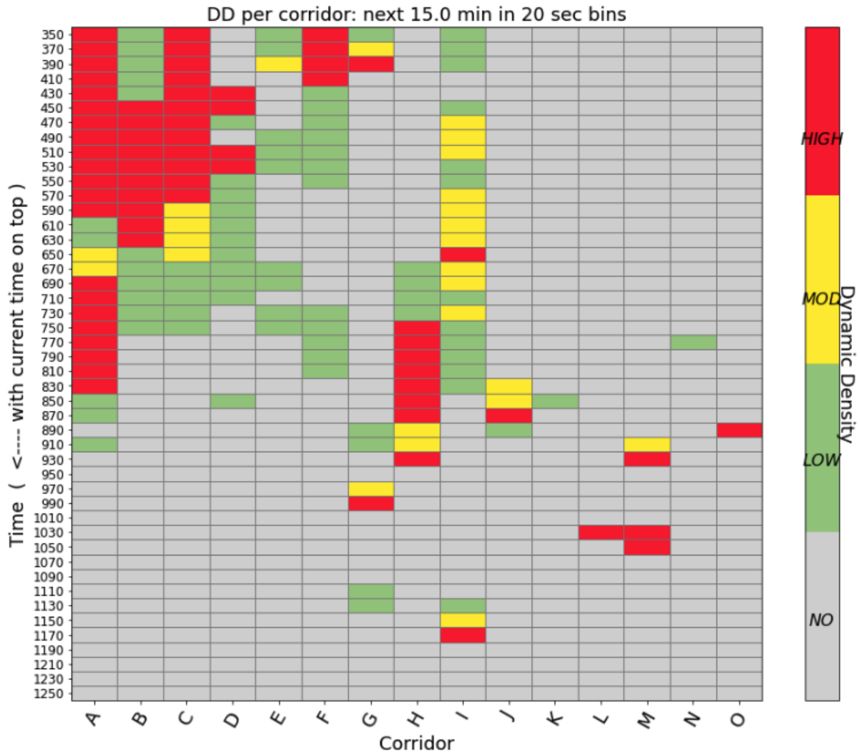


Fig. 7 Prototype display showing DD predicted for all corridors for the next 20 min in 20 sec bins. Each bin is color-coded based on the maximum DD. The top line shows the DD computed for the current time and matches the information shown in the nowcast display (Fig. 6).

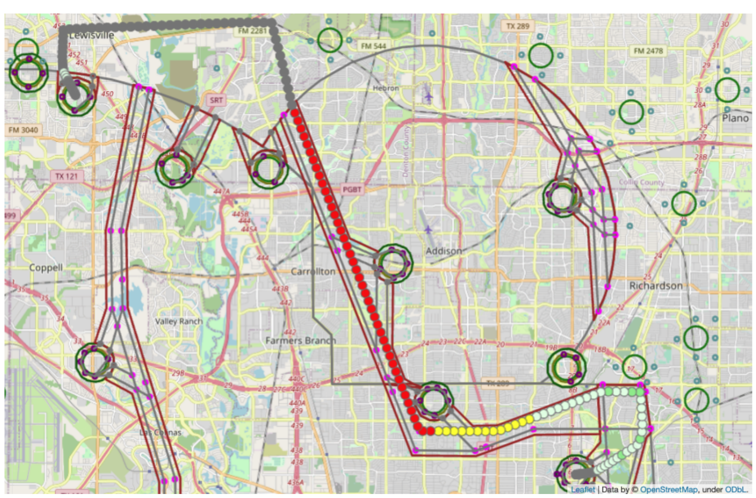


Fig. 8 Prototype display showing DD for an individual aircraft. Each trajectory point is color-coded based on the DD predicted to be encountered at the aircraft's arrival at that point. DD is computed only for corridors. Trajectory points outside a corridor are colored dark gray to signify lack of information for that point.

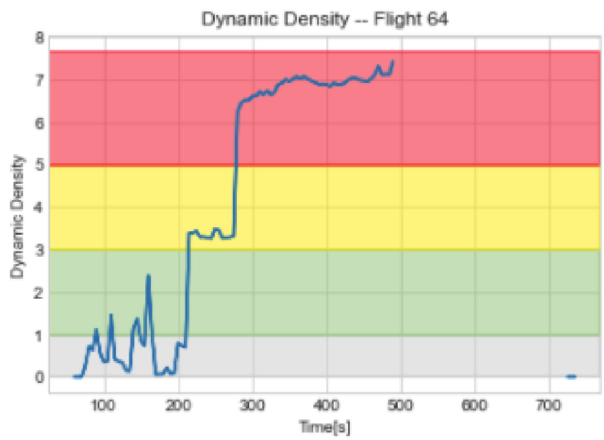


Fig. 9 Prototype display showing predicted DD against flight time. DD is computed only for corridors. Trajectory points outside a corridor result in a gap in the plot to signify lack of information for those points, such as the large gap from just before 500 sec (simulation time) to almost the end of the flight. The plot background is color-codes negligible (gray), low (green), medium (yellow), and high (red) DD.

presentation of targeted information, such as the following, could also be beneficial:

- Provide the operator (or autonomous system) with a list of times or corridors with moderate or high DD.
- Provide the percentage of flight time during which an aircraft is predicted to be in a moderate or high DD corridor.
- Provide only DD changes from the previous prediction rather than the full airspace/route prediction. This could help an operator more readily identify prediction updates.

A human-in-the-loop usability study could elicit additional options that can be explored in future simulations.

V. Validation

In this section, we discuss the critical aspect of validating the DD metric. We provide an overview of our approach and its constraints, and suggest alternatives.

A large set of traffic scenarios and an accurate method to categorize them (e.g., negligible, low, moderate, high) is necessary for selecting pertinent factors, and characterizing their impact on and contribution to DD. Similarly, a rigorous approach to validation also requires categorized (annotated) data, either from a high fidelity simulation or actual operations.

As previously stated, the DD metric is being developed in conjunction with NASA's ATM-X experiments. Simulated traffic was used in conjunction with domain knowledge and trial-and-error to select factors, determine their impact, and perform a sanity check of DD categorization on sample scenarios. The simulated traffic was mostly low corridor occupancy operations; that is, most corridors had only a few aircraft at any one time, as shown in Fig. 10. Moreover, those aircraft were mostly well separated. As expected, this resulted in low DD.

To increase corridor occupancy, we oversampled the simulated traffic. At regular (5 sec) intervals, we selected a random number of flights (between 0 and 10) that would takeoff. This became takeoff group i (i is incremented by 1 for each takeoff group). For each flight in the group, we selected (without replacement) a random operational intent from the original simulation, thereby giving each flight in that group a within-group-unique operational intent. That operational intent was cloned with the exception of the time field. The start time for each operation in a takeoff group was set to an offset defined as $offset_i = i * interval\_duration$, where i is the number of the group and $interval\_duration$ is 5 sec, the minimum time resolution of the simulation. Five sec was then added to the time for each subsequent trajectory point for each flight. For example, the start time for the first three points on the trajectory of a flight that is in the fifth takeoff group is set to 25 for the first point, 30 for the second point, 35 for the third. The pattern continues for the remaining trajectory points. For a flight in the seventh group, the time for the trajectory points are set to 35, 40, 45, etc. In effect, the cloned aircraft takes off later but flies the same exact route as its ancestor.

When all original operational intents were cloned (recall that selection was random without replacement), all original operational intents were replaced and cloned flights continued to be randomly created. This process was repeated until

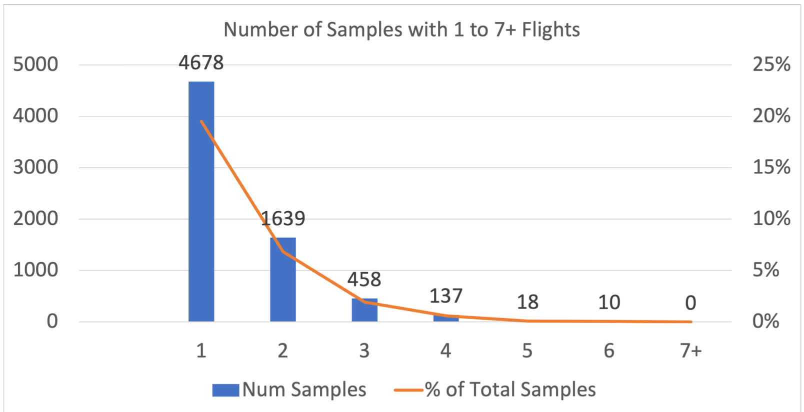


Fig. 10 Number of samples with 1 to 7 or more flights simultaneously in a corridor in the baseline simulated traffic. The total number of available samples (23955) is the product of the number of timesteps in the simulation (1597) and the number of corridors (15). Fewer than 3% of samples have at least 3 flights in a corridor. No corridor ever has 7 or more flights at one time.

the desired number of flights was met. The original set contained 136 aircraft. To create a simulation with, e.g., 500 flights, the original operational intents were cloned four times (but only 67% of the last set of clones was used).

This technique allowed us to create congested corridors with aircraft following approved routes along defined tracks to vertiports. Note that neither strategic (before takeoff) nor tactical (detect-and-avoid) conflict management was performed. As a result, aircraft sometimes flew in very tight formation with each other or even collided. This assumed limitation of the oversampling technique was beneficial to characterizing the impact to DD of the individual factors. The technique was also useful for determining the thresholds to categorize DD values into bins that had face validity.

The original data set and its oversampled clones were useful for development. The data can also be useful for validation. We have made only preliminary inroads toward this task.

Among the first steps toward objectively validating the DD metric is to define objective criteria against which to compare computed DD. The purpose of DD is to predict airspace congestion that may lead to loss of separation between aircraft or less efficient operations. This objective elicits two objective criteria: aircraft conflicts and operational delays. A future task is to determine how to automatically augment traffic scenarios with subsequent number of conflicts and seconds of delay and use this information to classify traffic scenarios using machine learning techniques.

Another future task is to automatically classify traffic scenarios from a training set of expert-annotated examples. Experts often develop an intuition about traffic scenarios that potentially cause problems (collisions or delays) that they cannot easily translate into a set of important characteristics. Although this is a less objective approach, it may be preferred by operators if it better reflects their experience and matches their expectations. A limitation to pursuing this approach is the lack of experts. It may become feasible after operators gain experience in the UAM system. In the meantime, we can adjust our sense of reasonableness by considering the operator feedback we receive during simulations and demonstrations.

VI. Conclusion

The main contributions of our work are the following: (1) Introduced a novel area of research: dynamic density metric to facilitate emerging UAM traffic management; (2) Developed a methodology and used it to prototype a DD metric; (3) Documented DD metric use cases and developed visualization alternatives to inform and expedite strategic and tactical flight planning by humans or autonomous systems; and (4) Suggested approaches for validation of the metric to measure how accurately it captures the relationship between traffic situations and subsequent loss of separation between aircraft or less efficient operations.

Federal aviation regulations [¶] require that a pilot in command, before beginning a flight, must become familiar with all available information concerning that flight, including weather reports and forecasts, fuel requirements, alternatives available if the planned flight cannot be completed, any known traffic delays, etc. Such information is essential to

[¶] 14 CFR § 91.103, 121.533, 121.599, 121.603, and others a safe outcome; UAM operators will likely also need to abide by similar regulations. Toward this end, the dynamic density metric contributes awareness of adverse traffic situations that may be encountered during a proposed flight. This information is useful for making informed decisions about when to takeoff, which route to fly, which alternative routes are feasible in case of unexpected events, and, critically, the expected energy usage and needed amount of energy reserves.

This may be the first body of work that has attempted to define a dynamic density metric for the emerging urban air mobility market. It is preliminary work that we hope motivates increased community attention and further progress. There are many opportunities to mature the methodology and improve prediction accuracy. Recommendations for future work have been included throughout the paper. A few other recommendations for future research are as follows:

- Perform a more rigorous analysis to study choice of impact function and determine parameters such as separation distance defining a cluster, exponents for growth/decay curves, etc. As additional high-fidelity simulated data or actual data becomes available, apply data-driven techniques as appropriate.
- Expand the airspace for which DD is computed to include vertiport airspace and unstructured (outside corridors/vertiports) airspace. We expect different factors will be needed to reflect the different operating procedures in the various airspace types.
- As discussed in Section V, verify performance against objective criteria.
- Conduct usability studies with operators to develop information and visualization requirements, evaluate prototype displays, and verify DD metric performance against expert (subjective) judgment.
- Expand the set of factors considered in the DD computation. In particular, the following factors may affect DD:
  - Traffic outside a corridor. Rationale: The initial prototype computes DD for each corridor independently of nearby traffic. Corridors are an organizational artifact, not a physical barrier. Conflicts can occur as easily between aircraft on either side of a boundary as within a corridor. The traffic may be in an adjacent corridor or in the airspace outside of the corridor/vertiport structure.
  - Aircraft speed. Rationale: The current simulation specifies a single cruise speed for all operations. It also specifies transition routes from vertiports to/from cruise tracks with identical climb/descent profiles for all aircraft. Future operations will be less homogeneous with differing climb/cruise/descent speeds necessitating passing, either at the same altitude or during climb/descent.
  - Aircraft altitude. Rationale: Similar to cruise speed, the current simulation specifies a single cruise altitude. Future operations may distribute corridor occupancy on vertically separated tracks. One advantage of this scenario is that a corridor can have higher aircraft density without a commensurate increase in potential interactions between aircraft. One disadvantage is that wake turbulence effects between a higher altitude aircraft and a closely following lower altitude aircraft must also be considered as a form of aircraft conflict.
  - Direction of flight. Rationale: Tracks now are separated by 1500 ft. It may be possible to treat bi-directional traffic independently for DD computation, depending on corridor RNP.
- As actual operations commence and UAM matures, augment factors that apply to the changing rules, regulations, procedures, vehicle capabilities, etc.

It is expected that commercial UAM operations will begin in 3 to 5 years[19, 20]. The DD metric may provide insight to airspace authorities and UAM operators to determine whether mitigation is required due to UAM corridor saturation and which mitigation options are feasible. We hope the work in progress described in this paper inspires additional research to answer the many questions that remain about how to compute DD, verify its accuracy, and effectively present the information. By conducting DD research as the UAM concept is maturing, the DD metric can be ready when the vehicles and the airspace are ready.

Appendix

Investigations of which factors are related to operational errors and controller workload have been ongoing since the late 1980s[21]. The early literature is summarized in [22]. The link between the sociology concept of dynamic density and its use as a controller workload metric was introduced in [23]. Researchers at NASA, FAA, Wyndemere, and related organizations expanded on the dynamic density concept to identify the characteristics that influence controller workload. The methods and findings of that research are summarized in [5]. To provide context for our work, Table 1 and Table 2 show some of the factors that contribute to controller workload. Table 1 lists factors derived from the complexity of the traffic and Table 2 lists factors derived from the structure of the airspace. These are just a few examples of the many factors previously studied.

Table 1 Air traffic related features affecting controller workload. From [23].

Heading Change (N > 15 deg in 2 min) (N = Number of aircraft)	Speed Change (N > 10 kts/0.02 Mach in 2 min)
Altitude Change (N > 750 ft in 2 min)	Conflict Predicted 0-25 nm (N predicted to be in conflict with another aircraft within 0-25 nm at end of 2 min)
Minimum Distance 0-5 nm (N within 0-5 nm to closest aircraft at end of 2 min)	Conflict Predicted 25-40 nm
Minimum Distance 5-10 nm	Conflict Predicted 40-70 nm

Table 2 Airspace related features derived from ATC site visits. From [24]. Items marked with a * are related to structural elements.

Airspace Factors	Traffic Factors	Operational Constraints
Sector dimensions* • Shape, physical size, • Effective "area of regard"	Density of aircraft • Clustering* • Sector-wide	Buffering capacity*
Spatial distribution of airways / Navigational aids*	Aircraft encounters • Number of, • Distance between aircraft, • Relative speed between aircraft, • Location of point of closest approach (near airspace boundary, merge points, etc)*, • Difficulty in identifying, • Sensitivity to controller's actions	Restrictions on available airspace • Presence of convective weather, • Activation of special use airspace, • Aircraft in holding patterns*
Number and position of standard ingress / egress points*	Ranges of aircraft performance • Aircraft types (747, Cessna) • Pilot abilities	Procedural restrictions • Noise abatement procedures* • Traffic management restrictions (e.g., miles-in-trail requirements)
Letters of agreement / Standardized procedures*	Sector transit time*	Communication limitations
Standard flows* • Number of, • Orientation relative to sector shape, • Trajectory complexity, Interactions between flows (crossing points, merges)	Number of aircraft in transition • Altitude, • Heading, • Speed	
Coordination with other controllers* • Point-outs • Hand-offs		

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