Unmanned Aviation: To Be Free or Not To Be Free?

A complexity based approach

Vishwanath Bulusu, Raja Sengupta and Zhilong Liu
The Cal Unmanned Aviation Lab
University of California
Berkeley, USA
vishwab@berkeley.edu, rajasengupta@berkeley.edu, lzl200102109@berkeley.edu

***Abstract*—This paper assesses the feasibility of organizing unmanned aviation as free flight. We do this by estimating the frequency of occurrence of large de-confliction problems. Statistics of these frequencies are measures of air traffic complexity appropriate for unmanned air traffic management. These complexity measures increase with air traffic density. Data suggests as many as 100,000 unmanned flights per day is realistic at maturity in a region such as the San Francisco Bay Area. We simulate 100 to 1,000,000 flights per day. Results suggest simple free unmanned flight is feasible up to 10,000 flights per day, but needs intelligent management thereafter. We also analyze a hypothetical unmanned airway network. The complexity reductions are large and optimistic.**

Keywords- unmanned aviation, ATM, complexity, deconfliction

I. INTRODUCTION

We seek to understand the nature of the air traffic control (ATC) problem for the next phase of small-unmanned aviation. In the current phase, small Unmanned Aircraft Systems (UAS) are mostly photography accessories, which come by car to a site, fly below five hundred feet taking pictures, and return by car. Flight management becomes an arrangement between photographer and landowner. This phase of unmanned aerial commerce is underway without airways, sectors, or air traffic controllers. What about phase two?

We think of the second phase as one in which the UAS flies itself from the premises of a service provider, to the site of service, and back. Such flights might be for the photography services of today, or for new purposes like the transport of small goods as contemplated by several large corporations [1][2]. No pilot would accompany the UAS by car or chase plane, making these Beyond-Line-Of-Sight (BLOS) flight operations as opposed to the Visual Line of Sight (VLOS) flights constituting the operations today. Can BLOS small-unmanned commerce also happen without airways, sectors, or air traffic controllers?

This paper approaches the question through the lens of de-confliction. For self-organizing free flight [3], the de-confliction of aircraft en-route must be solvable by software systems. In Visual Flight Rules (VFR) airspace today, simple right of way rules work when two pilots find themselves approaching each other [4]. For example, each can simply follow the rule to move right in a head-on conflict. However, these simple rules become inadequate if multiple aircraft are simultaneously in conflict. If one aircraft moves to the right to avoid a second, it might run into a third, a fourth, and so on. The free-flight multi-aircraft de-confliction problem has long been a subject of algorithmic research [5], [8]-[20].

Our thesis is as follows. If permitting free-flight results in the need to jointly de-conflict large numbers of aircraft, then the second phase of small-unmanned aviation cannot be free. We believe large de-confliction problems are difficult to solve in limited time and therefore hazardous in practice. Section II presents supporting arguments based on the mathematical literature and air transportation practice. Instead, the community must find some alternate organization of unmanned flight that reduces the need to jointly de-conflict large numbers of aircraft. Some potential ideas appear in [6] and [7].

Our research method is to estimate the densities of flight for the next phase of small-unmanned aviation, and derive the numbers of aircraft that need to be jointly de-conflicted as a function of these densities. Section III discusses traffic density estimation, section IV defines the size of a de-confliction problem, and section V describes the method mapping density to size. We think of the statistics describing the sizes of de-confliction problems as measures of air traffic complexity. These measures are 'intrinsic' in the sense of [7]. Size is defined as the number of vertices in a graph component. This makes it a well-understood graph theoretic concept. Section II argues that size also determines the computational complexity of de-confliction. This connects air traffic complexity to computational complexity by making the second a function of the first.

We estimate density by analyzing unmanned aviation at a metropolitan scale, because BLOS flights for purposes like package delivery or photography occur predominantly within a metropolitan region. We share this idea with the Metropolis project [7]. They build intuition based on the Paris region. We use the San Francisco Bay Area. We believe as many as 100,000 flights a day is viable at maturity for the bay area. The reasons are in section III. Metropolis stopped at 20,000 flights per day. Complexity remains reasonably stable up to 10,000 flights per day, but grows dramatically thereafter.

Research supported in part by NASA UARC Contract#: UCSCMCA-14-020 and NSF Contract#: CNS-1136141

Section VI presents de-confliction size statistics for free flight at different traffic densities. The results suggest small-unmanned aviation can be free in its initial growth phase but needs intelligent management at maturity. This motivates us to understand the best reductions in de-confliction size that might be achieved by having the aircraft operate in airways. This is the subject of section VII. The best looks promising, but this bound will have to be tight to be useful. This requires further research. Section VIII summarizes the findings of the paper.

II. Literature Review

We have hypothesized that if free unmanned flight results in de-confliction problems of large size, it cannot be free. We describe the theoretical and practical support for this below.

One part of the de-confliction literature formulates de-confliction as optimization problems minimizing the times or distances expended in de-confliction, while satisfying minimum vehicle separation constraints [8]-[17]. They then describe algorithms computing optimal or sub-optimal solutions that are correct in the sense of maintaining the separation. The computational results in these papers sometimes de-conflict as many as seven aircraft jointly [16]. Computation times vary. For example, [17] de-conflicts four aircraft sub-optimally in half a second, and take 540 seconds to do so optimally. These algorithms are based on mixed integer programming and have complexity exponential in the number of aircraft in conflict, namely Conflict Size - our measure of air traffic complexity. This makes computational complexity a function of this air traffic complexity.

Others propose a de-confliction strategy and prove it correct or argue both correctness and efficiency by simulation. We focus on the de-confliction strategies that are provably correct. [19] and [20] prove algorithms for n-aircraft and present simulations for 6 to 14 vehicles. [18] is an outlier. Hoffman and Tomlin [18] show the successful de-confliction of 200 aircraft by simulation, but prove the method correct for only two and three aircraft. If the community were to consider [18] practical and implementable, then this paper would find free unmanned flight viable even at very high traffic densities. The rest of the literature suggests that we consider conflict sizes outside the range of 6 to 14 large in the context of free unmanned flight.

Practice, in our understanding, tends to eliminate all free de-confliction problems involving more than three vehicles. Road transportation structures roads into lanes and intersections with stop signs or traffic lights for management, to ensure drivers mostly resolve conflict with only one other vehicle. We sometimes face a three-vehicle problem when merging into a highway, or when changing lanes into a gap and find another car trying the same. Aviation permits free operation in VFR airspace at very low traffic densities, but also structures airspace at airports into specific approach and descent paths, thereby imposing mostly two aircraft de-confliction problems, if any, on the pilot. Six or fourteen vehicle de-confliction problems are not seen in practice. Requiring unmanned aircraft software systems to freely de-conflict more than 3 aircraft would be a significant departure from practice. We go forward to the rest of the paper with free conflict sizes in excess of 3, or 6 to 14, as the two meanings of large.

III. Traffic Density Estimates

The second phase of unmanned aviation will entail BLOS flights from service provider to service consumer and back. Metropolitan regions typically hold both provider and consumer, making them the appropriate geographical scale for this analysis of unmanned aviation. For example, the UAS portion of goods transport is likely to be the last mile from hub to door, e.g., from the regional hub of the delivery company to the premises of the recipient. As a representative value, if Amazon were to deliver packages in the San Francisco Bay area by flying them directly from its fulfillment center to homes, the average flight length would be about 25 miles as per our computations (see Fig. 1). We focus on the San Francisco Bay Area to understand the future, just as the Metropolis project used Paris.

The various UAS airspace proposals by the FAA, NASA, and private corporations envisage unmanned flight near about 500 ft within class G airspace. Therefore we estimate current flight volumes in this airspace today by collecting data. On any given day, over bay area, there are roughly 60 helicopter flights and about 60 other recreational flight operations. Hence today's VFR air traffic below 1200 feet is nominally 100 flights per day. This is our lower limit traffic density.

Figure 1. Package delivery airways computed from Amazon Fullfilment Center avoiding high density popultion areas

Industries like package delivery [1][2] give us insight into the upper limits of traffic density. FedEx [21] and UPS [22] together deliver approximately 28 million packages every day in the US. If ten percent of that is delivered in California and only ten percent of that were to be delivered by UAS, California would see about 280,000 UAS flights per day. Since about half the state economy is in Northern California, we postulate 140,000 flights up north. Assuming 40,000 of that goes north of the Bay Area (sparsely populated), we obtain about 100,000 unmanned flights per day for package delivery in the Bay Area at maturity. Other UAS use sectors may add more leading us to postulate the highest order of Bay Area unmanned flight at between 100,000 and 1,000,000.

IV. COMPLEXITY MEASURES

Air traffic complexity measures such as dynamic density [23]-[25] or MAP [26][27] used by manned aviation today are extrinsic. They are definable only with reference to monitors, sectors, or airways – concepts other than the air traffic itself. We seek measures that are 'intrinsic' in the sense of Vidosavljevic[7] to analyze free unmanned flight [28].

We propose statistics of the numbers of aircraft simultaneously in conflict as the measures of air traffic complexity. Given a snapshot of airspace at any point in time, we derive these numbers from the pairs of aircraft in conflict, for which we turn to the aircraft de-confliction literature. Thus any choice of conflict definition bases the resulting complexity analyses on some component of the de-confliction literature. The later part of this section discusses our choice.

Our method of analysis of complexity follows the notion of a Cluster discussed in [31]. Given the pairs of aircraft in conflict in an airspace snapshot, the snapshot is abstracted as a graph as shown in Figure 2. The aircraft are vertices with an edge between each pair of aircraft in conflict. The evolution of airspace is then a trajectory of graphs. Each graph component represents a set of aircraft to be jointly de-conflicted. The cardinality of this set is the number of vertices in the component, and also the number of aircraft to be jointly de-conflicted. We call this number Conflict Cluster Size, informally shortened to Cluster Size.

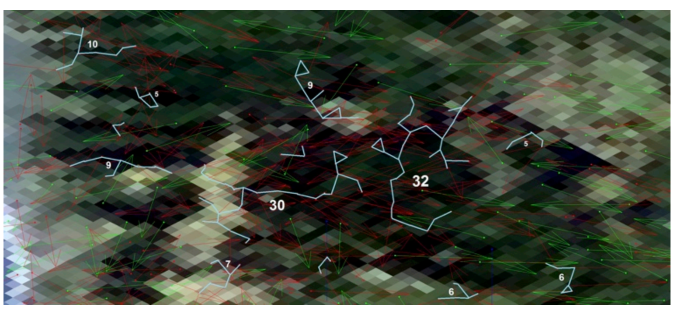

Figure 2. Abstraction of a snapshot from our simulation as a graph with cluster sizes indicated. (Aircraft pairs in conflict is connected by a white line)

Our computational method, which is a simulator, outputs all of the Conflict Cluster Sizes observed at each time step, which results in a size distribution at the time step. When the simulator is ergodic, as is ours, the distributions at each time step may be collapsed into one Cluster Size distribution for the entire simulation. The results in section VI focus on the tails of the distributions or the 99th percentile to emphasize the larger and more hazardous conflicts.

We define a second measure called 'Normalized Time Spent in Conflict (NTSC)' for each UAS. It is a measure of the percentage of flight time spent in conflict with another aircraft. We take a mean of the individual NTSC's of all UAS in the system and assign it as the system NTSC.

$$NTSC = \frac{Time\ in\ conflict\ with\ at\ least\ one\ other\ UAS}{Total\ Transit\ Duration\ of\ the\ \ UAS} \quad (1)$$

Our method rests on defining pairwise conflicts. The de-confliction literature is our source. Some pairwise conflict definitions are simple and kinematic, with other definitions being information rich. In this first investigation we define two aircraft to be in conflict at a time instant if their relative distance is below a threshold. We then run simulations with this threshold as 50, 100, 150, 200, 250, and 300 meters. For example, in the 50m simulation, all pairs of aircraft within 50m at a particular time step are counted as being in conflict at that time step. This simple definition enables a good laptop to simulate up to 100,000 aircraft per day, while still meeting the investigative purposes of this paper, i.e. - to observe order driven shifts in free air traffic complexity as we go from the 10^2 flights characterizing today, to the 10^5 flights at maturity.

Intuitively and as our results in section VI show, air traffic complexity should increase monotonically with the conflict threshold. Therefore, the 50m simulations produce the slowest complexity growth curve and the 300m simulation the fastest. The FAA permits small UAS to have speeds up to 45 m/s (100 mph) [30]. Most conflict definitions in the literature posit a space around an aircraft that cannot be violated by any other aircraft (for example the avoid set in [18]). We believe most of these definitions would find separations less than 50m to be unacceptable for aircraft at 45 m/s (1 second separation). Therefore, we present our 50m complexity curve as the one saying that reality will grow at least as fast.

On the other hand, most conflict models, would rarely consider two aircraft separated by 300m (over 6 second separation) to be in conflict. They would rely on shared information about intent [29], which would eliminate conflict between most aircraft at 300m based on relative heading. However, the worst-case is represented by the absence of intent information, in which case one aircraft is required to assume that the other might turn on a dime and head straight over at maximum speed. If two UAS fly at each other at 45 m/s and decelerate at 1g, they each require 100 meters to stop. We add the 50m unacceptable airspace violation to this and arrive at 250 meters. Therefore, we interpret our 300m complexity curve as the one saying reality will grow no faster. Future analyses based on richer conflict definitions would be expected to show complexity growth between the 50m and 300m curves.

V. SIMULATION

We built a Matlab simulation engine to estimate the Cluster Sizes and NTSC for an input traffic density. It has the following three components –

1. Parameter declaration and flight generation.

2. NTSC estimation.
3. Cluster Size estimation.

We first compute the conflict intervals for each UAS. Based on these intervals, the NTSCs are computed for each UAS and then used to compute the system NTSC. Then the flights are simulated. Flights enter the simulation at their start time, follow their trajectory and exit at the end of the flight. Cluster sizes are computed at each instant of time in the simulation. We simulate 5 days. The components of the simulator are explained in the next three sub-sections.

A. Parameter Declaration and Flight Generation

We model airspace as a cuboidal volume LWH defined by a rectangular area LW (L is length and W is width) extruded to a height H. UAS flights are generated in this area. Each flight is a quadruple (*o, d, h, t*) where *o* is the origin, *d* is the destination, *h* is the height at which the UAS travels from origin to destination and *t* is the flight start time. The UAS travels on the shortest path (essentially a straight line) and is considered to be in transit as it travels from origin to destination. A typical UAS flight is shown in Fig. 3.

The origins and destinations are generated based on a population distribution (Fig. 4) over the rectangular area. Since a geographical area is estimated as a rectangle, the population distribution preserves the actual shape of the metropolitan area and the volume of airspace used. The flights are modeled as Poisson processes and assigned start times consistent with exponentially distributed inter-arrival times.

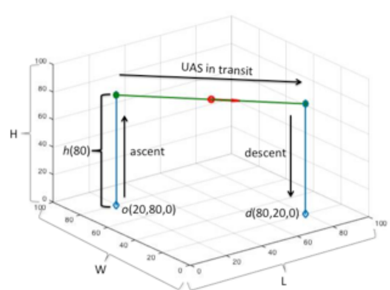

Figure 3. A typical UAS flight

Since we seek to understand free-flight complexity growth as function of growth in the order of traffic, we choose a simple flight model so as to simulate at scale. First, we assume vertical take off and landing, i.e. a UAS rises to height *h* at its origin, travels at the same height to its destination *d* and then descends. This excludes some unmanned aircraft like the fixed wings. FAA restricts UAS flights to below 500 feet limiting the flexibility of vertical separation. Hence, to measure the effects at the densities we chose, we assume all flight transit at the same altitude. Flights occur at uniform speed in the simulation. Flights are assumed to happen only for a twelve-hour period from 8a to 8p every day and uniformly distributed over the entire period with no peak UAS traffic times. Finally to distribute flights over the bay area, we follow a population density distribution shown in Fig. 4.

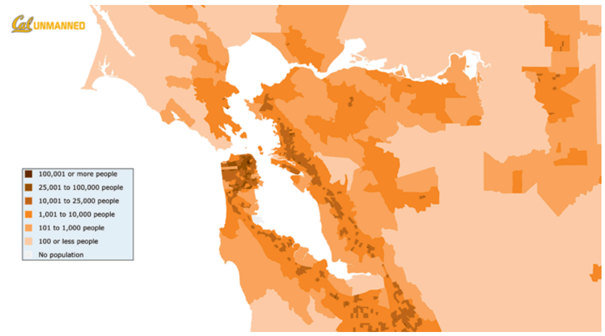

Figure 4. Population density map of the bay area
(Source: [ArcGIS USA Population Density Demographics](#))

Definitions and values used for the input parameters, required for flight generation and simulation, are listed below.

- λ - flight rate (number of flights per day) [varied from 100 to 1,000,000]
- W - width of the rectangular area [103700 km]
- α - ratio of length to width of rectangular area [1290/700]
- s - uniform speed of UAS flights [20m/s]
- *tol* - tolerance, conflict distance threshold [50m, 100m, 150m, 200m, 250m, 300m]

Width W is used to normalize all distance measures and make them dimensionless.

B. NTSC Estimation

Conflict intervals for each UAS are computed first. Every flight transits on a straight-line path from origin to destination. So the intersection of a pair of two flights can be computed analytically. Relevant quantities are defined as follows –

- t – simulation time
- T_{start} – simulation time instant at which the two flights begin to co-exist in simulator at the transit altitude
- T_{end} – simulation time instant at which the two flights stop co-existing at the transit altitude
- T – time measured from T_{start}
- T_i – i^{th} solution for time of conflict
- p_i – position vector of i^{th} UAS at time T
- p_{i0} – initial-position of i^{th} UAS at the start of the co-existing period
- v_i – velocity vector of i^{th} UAS
- δ – conflict distance or tolerance
- p_r – relative position of second UAS w.r.t. first
- p_{r0} – relative initial position of second UAS w.r.t. first
- v_r – relative velocity of second UAS w.r.t. first

The following equations describe the position vectors and the computation of the relative displacement.

$$p_1 = p_{10} + v_1 T \quad (2)$$
$$p_2 = p_{20} + v_2 T \quad (3)$$
$$p_2 - p_1 = p_{20} - p_{10} + (v_2 - v_1)T \quad (4)$$
$$p_r = p_{r0} + v_r T \quad (5)$$

Conflict happens if relative distance is within conflict distance.

$$\|p_r\| \leq \delta \quad (7)$$
$$\|p_r\|^2 \leq \delta^2 \quad (8)$$

or, $$\|v_r\|^2 T^2 + 2(p_{r0} \cdot v_r)T + \|p_{r0}\|^2 - \delta^2 \leq 0 \quad (9)$$

Considering the equality condition, this is a quadratic equation with two solutions for the actual simulation time.

$$T_1 = T_{\text{start}} + \frac{-(p_{r0} \cdot v_r) - \sqrt{(p_{r0} \cdot v_r)^2 - \|v_r\|^2\|p_{r0}\|^2 + \|v_r\|^2\delta^2}}{\|v_r\|^2}$$

$$T_2 = T_{\text{start}} + \frac{-(p_{r0} \cdot v_r) + \sqrt{(p_{r0} \cdot v_r)^2 - \|v_r\|^2\|p_{r0}\|^2 + \|v_r\|^2\delta^2}}{\|v_r\|^2}$$

The following two conditions must be satisfied for a real solution.

1. $\|v_r\|^2 \neq 0$
2. $(p_{r0} \cdot v_r)^2 - \|v_r\|^2\|p_{r0}\|^2 + \|v_r\|^2\delta^2 \geq 0$

Uniform speed implies condition 1 is violated when the flights are parallel. Condition 2 is violated when the flights are antiparallel (parallel but traveling in opposite directions) and the two paths are at a distance greater than the conflict distance. The above solutions work for all other conditions. However, they are for intersection of lines extending in both directions infinitely. The actual paths are only line segments. The solutions may therefore not produce the actual conflict intervals directly. The correct interval (T_{int1}, T_{int2}) in terms of the actual simulation time is computed as per Table 1.

TABLE 1. COMPUTING CORRECT CONFLICT INTERVAL

Conditions	**T_{int1}**	**T_{int2}**
$T_2 \leq T_{start}$ or $T_1 \geq T_{end}$	No Conflict	
$T_1 \leq T_{start}$ & $T_2 \geq T_{end}$	T_{start}	T_{end}
$T_1 \leq T_{start}$ & $T_{start} < T_2 < T_{end}$	T_{start}	T_2
$T_{start} < T_1 < T_{end}$ & $T_2 \geq T_{end}$	T_1	T_{end}
$T_{start} < T_1 < T_{end}$ & $T_{start} < T_2 < T_{end}$	T_1	T_2

We implement the exact analytical solutions and check all the conditions above. The computed conflict intervals are hence accurate. The only case ignored here is when two flights are parallel and within the conflict distance. We check for such flight pairs and calculate the conflict interval as the time period for which the two flights co-exist in the simulator. Finally, for each UAS, the total time spent in conflict with at least one other UAS is calculated as a union of all pairwise intervals.

C. *Cluster Size Estimation*

For each UAS, we store both the flight identification number of the other conflicting UAS in a pair and the conflict interval computed with it. While simulating the propagation of all UAS, at each instant, the simulator iterates through all conflicting UAS at that instant and computes a list of all clusters sizes produced.

VI. RESULTS

Our simulation data spans traffic densities varying from 100 to 100,000 flights per day for six conflict distance thresholds varying from 50m to 300m. Fig. 5 and 6 visualize the paradigm shift in complexity, as the traffic density increases by two orders of magnitude. Conflicting aircraft are marked red while the others are marked green. The arrows show the flight direction of the UAS. There is a dramatic rise in the number of conflicting UAS as large clusters begin to appear over densely populated areas, primarily over San Francisco city. In contrast, Fig. 5 drawn from a 1,000 flights per day simulation, shows only one conflict in the entire region. Both the figures are drawn from 300m simulations.

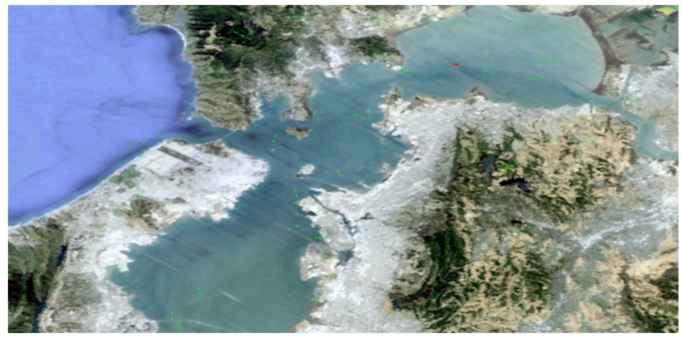

Figure 5. Zoomed perspective snapshot of conflicts at 1000 flights per day

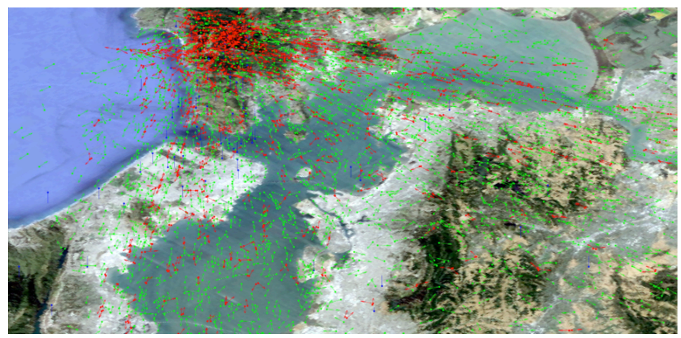

Figure 6. Zoomed perspective snapshot of conflicts at 100000 flights per day

The figures and tables in the rest of this section quantify the growth in complexity. We start by plotting the Normalized Time Spent in Conflict versus traffic density for the six conflict distance thresholds (Fig. 7). The NTSC lies between 0 and 1 due to normalization. Therefore, we expect this plot to look like an S-curve, flat at low and high traffic densities, while rising in some linear or non-linear fashion in between.

We simulated up to 10 million flights a day for the 300m conflict distance threshold to confirm this intuition (the fastest growing line in Fig. 7). As hypothesized in section IV, the complexity growth curves for the 50m and 300m conflict distance thresholds represent the slowest and fastest complexity growth. Real complexity growth should lie within these bounds based on the arguments in section IV. We did not simulate beyond 1 million flights per day for the other cases because the analyses in section III suggest UAS traffic will stay below that level even at maturity.

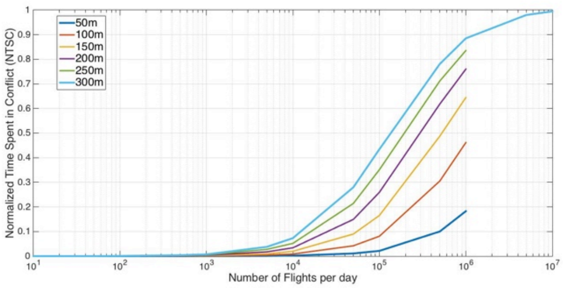

Figure 7. Growth of conflict coefficient with increasing flight rate and varying conflict distance

The NTSC complexity growth curves show transitions in the rate of complexity growth with air traffic density. Growth remains almost flat up to 1000 flights per day, and reasonably so even up to 10,000 flights per day. This already permits significant unmanned aviation growth with small change in complexity. However, there is a shift in the complexity growth between 10,000 and 100,000 flights per day, except in the slowest growth case (the 50m curve in Fig. 7). In this regime, complexity becomes sensitive to the volume of traffic. We believe high sensitivity means that beyond 10,000 flights per day, the system has to be designed to tolerate the complexity of the next order (100,000). There is a significant difference in NTSC between the best and worst cases at 100,000 flights. A UAS is expected to spend almost 45% of its transit time in close vicinity to another in the worst case and 2% in the best.

Next, we analyze the effect of traffic densities on conflict cluster sizes as defined in section IV. Fig. 8 shows the cluster size distributions. The three figures represent 1000, 10,000, and 100,000 flights per day respectively. Each figure has six curves, one for each conflict distance threshold. The horizontal axes are the cluster sizes and the vertical axes the number of occurrences of each size in our simulation dataset. The number of occurrences has a log scale to magnify the cluster sizes beyond the 99th percentile. The horizontal axis on the 1000 flight plot runs up to 3 because no greater conflict cluster is observed in our entire simulation dataset. In contrast, the axis for 100,000 flights runs up to conflict clusters with 100 aircraft needing to be jointly de-conflicted. The figures have no value for the cluster size 1 because an aircraft without conflict is given a size of 0. The next conflict size is 2, representing two aircraft in conflict. The three figures summarize our entire cluster size dataset.

Table 2 records the 99th percentile cluster size and the largest cluster size in each scenario. When the flight volume reaches 100,000 per day, the 99th percentile cluster size is 13 in the fastest complexity growth case (300m), but 2 in the slowest growth case (50m). Conflicts of size 2 are part of the daily business of free flight, while 13 would be outside the realm of possibility by most of the criteria in section II. The largest conflict clusters observed vary from 4 in best case, arguably negotiable by free unmanned flight, to 96 in worst-case, which would be a disaster. At 100m the largest conflict cluster is already 9 in 5 days of simulation. We read the shift from 4 to 9 as one goes from 50m to 100m at 100,000 flights, as signaling the infeasibility of simplest form of free unmanned flight (straight from origin to destination) at maturity. This case is worthy of further analysis with a richer conflict definition. We read the rest of table 2 as signaling the feasibility of free flight up to 10,000 flights per day.

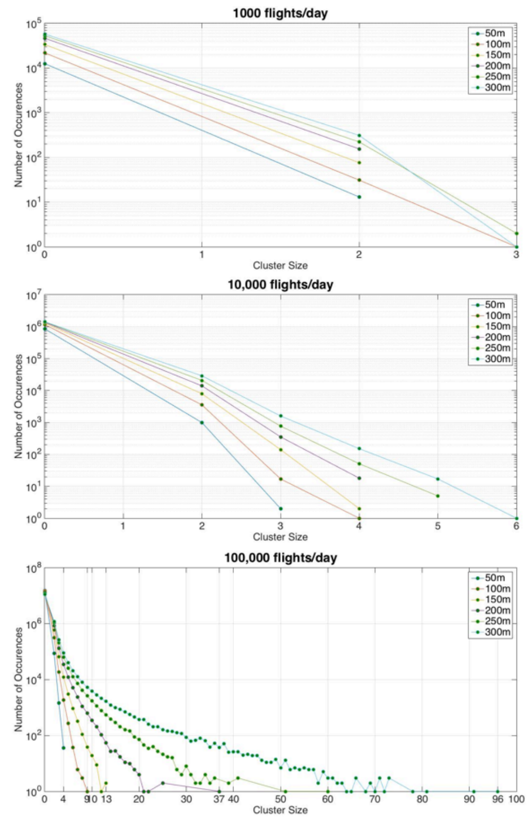

Figure 8. Cluster size distribution for varying flight densities and conflict distances

TABLE 2. CLUSTER SIZE DISTRIBUTION DATA

	(99th Percentile, Largest) Cluster Size					
Flight Rate (per day)	**50m**	**100m**	**150m**	**200m**	**250m**	**300m**
100	(0, 0)	(0, 0)	(0, 0)	(0, 2)	(0, 2)	(0, 2)
1000	(0, 2)	(0, 3)	(0, 2)	(0, 2)	(0, 3)	(2, 3)
10000	(0, 3)	(0, 4)	(2, 4)	(2, 4)	(2, 5)	(2, 6)
100000	(2, 4)	(2, 9)	(3, 13)	(4, 37)	(7, 60)	(13, 96)

Fig. 9 is our clearest representation of transitions in air traffic complexity with the growth of unmanned air traffic. The conflict distance threshold is 300m. It shows three stages of traffic growth. Below 100 flights per day, the 99th percentile is zero, meaning conflicts are statistically insignificant. From 500 to 10,000 flights per day, the statistically significant conflicts are between two aircraft even in the worst-case (300m). Finally, there is a very high-complexity regime beyond the 10,000 flights. The Metropolis analyses [7] suggest our intermediate 10,000 flight complexity regime should persist up to 20,000 flights. Fig. 9 looks consistent with their finding. The steep slope of the complexity curve, thereafter suggests the unmanned air traffic management architecture may have to move out of pure free flight near 10,000 flights per day.

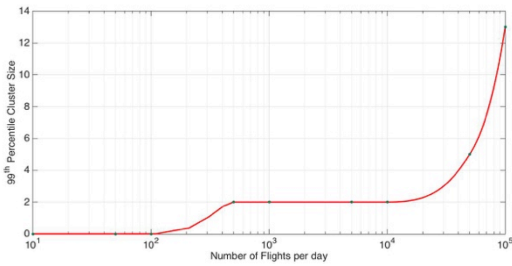

Figure 9. 99th percentile cluster sizes at 300m conflict distance

VII. A Simple Airway Complexity Analysis

We assumed a very simple airway network with a grid structure over the bay area. Every UAS flies to the nearest airway, follows it till the closest airway to its destination and then exits. While in the airway, the UAS are not in simple free flight any more but managed and controlled with new and emerging designs [6][7].

We apply our conflict criterion to the UAS outside the airways but not inside. The conflict paradigm inside is a new one to be modeled in new ways. Therefore we assign zero conflict to the aircraft inside the airways even though they would be packed at very high densities. Consequently, the results in this section can only be understood as a best possible reduction in complexity that might be achieved by imposing airways. Some conflict complexity should be added for the in-airway flight path for realism.

We simulate the airways at 100,000 flights per day. The conflict distance threshold is 300m. Fig. 10 shows a zoomed snapshot of the simulation. Unlike the free-flight case, most conflicts here are between parallel trajectories outside the airway within the conflict distance threshold. Conflicts due to intersecting flights are much lower. We observe a reduction in NTSC from 45% for free flight to 5% in this airway analysis. If we ignore the parallel flights by assuming shared heading information, the NTSC reduces further to 0.06%. The 99th percentile cluster size drops to 3 from 13 for free flight. The largest cluster observed is of size 10, down from 96 for free flight.

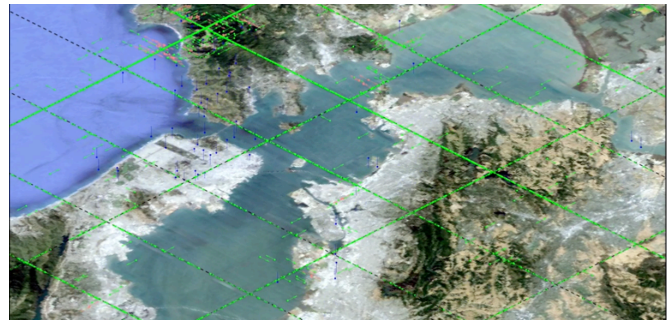

Figure 10. Snapshot of simulation with 100,000 flights directed through airways. Pink denotes UAS that are withinn 300m but on parallel trajectories.

VIII. Conclusions

Our aim has been to assess the feasibility of organizing unmanned aviation as free flight. Methodologically, we have done this by estimating the frequency of occurrence of large de-confliction problems and statistics therefrom. “Large” is based on the de-confliction literature and practice. The frequencies of occurrence are increasing functions of traffic density.

We collected data about low altitude flights in the San Francisco Bay Area to find the lower range of density, and analyzed the package delivery industry to obtain an upper range in excess of 100,000 flights per day. Our analyses have also led to a focus on metropolitan regions as the most appropriate scale for the study of the next phase of unmanned aviation. Hence we have derived our results by simulating a metropolitan region from 100 to 1,000,000 flights per day. The simulator considers the regional airspace a cuboidal volume with its actual shape emerging from its population density distribution. Simulation parameters have been picked to approximate the San Francisco Bay Area.

We have argued that the frequencies of occurrence of large de-confliction problems and statistics therefrom, are appropriate measures of air traffic complexity. Manned air traffic control complexity measures inform manned controller workload. Unmanned air traffic control complexity measures should inform the complexity imposed on software systems. Computational complexity is amongst the most widely understood measures for software. The number of aircraft to be jointly de-conflicted is a determinant of computational complexity in the de-confliction literature. Choosing this number as an air traffic complexity measure, makes computational complexity a function of air traffic complexity.

The simulation data shows the simplest form of unmanned free flight (straight from origin to destination) to be feasible up to 10000 flights a day even with the fastest complexity growth estimated by us. The largest de-confliction problems observed involve 6 aircraft, but the 99th percentile is 2. However, at 100,000 flights a day, simple free flight begins to break down. It seems to work in the slowest complexity growth scenario (50m), but breaks down even in the next growth scenario (100m) with 9 aircraft simultaneously in conflict in 5 days of simulation. This case merits further analysis with higher fidelity de-confliction models.

We also look at the Nominal Time Spent in Conflict as a complexity measure. It generates an S-curve as a function of traffic density. NTSC remains low up to about 10,000 flights per day, and then takes off in all but the slowest growth scenario. This is consistent with the Conflict Cluster Sizes. The cluster sizes reveal three complexity growth regimes – a zero conflict regime up to about 500 flights per day a two aircraft conflict regime from 500 to 10,000 flights per day, and a very high complexity growth regime thereafter. The intermediate traffic range is the feasible free flight range.

We applied our method to airways but assumed aircraft inside the airways are not in conflict even when densely packed. We only assume conflict in the free-flight regime outside the airways. The 99th percentile conflict size then drops to 2. Moreover most of these conflicts are between aircraft flying parallel trajectories, which means they could be eliminated by sharing intent. Further research into control designs for de-confliction inside airways such as [6] is suggested.

We have evaluated the simplest form of free flight where a UAS flies straight from origin to destination. Incorporating minimal en-route deviations may prevent large de-confliction problems and merits future investigation. Approaches such as the distributed decision making concepts developed by Green and Bilimoria [32] for manned free flight, need to be explored to enable such congestion sensitive unmanned free flight.

ACKNOWLEDGMENT

We express our sincere gratitude to Dr. Parimal H. Kopardekar and Dr. Thomas Prevot from the NASA Ames Research Center for valuable discussions on the basic ideas. We thank Mr. Frank Ketcham from Delta Airlines and Professor Michael Ball from the University of Maryland for teaching us air traffic management.

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