Noise Estimation for future large-scale small UAS Operations

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***Abstract*—This paper provides estimates for ambient noise levels that may be generated by future unmanned air traffic in low-altitude uncontrolled urban airspace. It is motivated by the need to assess the aural impact on communities from such large-scale close proximity unmanned aircraft operations. We simulate unmanned traffic over urban areas and estimate the noise footprint generated over a day. We compute four metrics namely L_{eq} (the long term Average dB level), L_n (dB level exceeded n% of the time over a location for n = 10, 50, 90), A_{55} (Area affected by noise above 55dB) and P_{55} (population affected by noise above 55dB). The effect of increasing traffic density, varying source noise and different operation altitudes on the measured noise levels is also captured. The estimates show that noise levels alone will not be a nuisance especially with an expected altitude of high speed operations above 200ft. Future work should measure the spectral content of the sound and the auditory impact of specific frequencies.**

***Keywords*—Noise, Capacity, Airspace, unmanned aviation**

I. Introduction

The advent of civil unmanned aviation has changed the dynamics of interaction between aircraft and society. While small Unmanned Aircraft Systems (sUAS) (commonly known as drones) based applications show promise in the areas of package delivery[1], agriculture, infrastructure inspection, aerial mapping and so on, they have also raised several concerns regarding public safety, security, privacy and community noise. This exacerbates the existing negative public perception of the industry owing to the military history of unmanned aircraft. In addition, understanding the role of noise in airspace demand-capacity modeling stands out as one of the requests from UAV Traffic Management (UTM) developers to the avionics research community [2].

In this paper, we focus on addressing the community noise concern. What noise levels will be generated by large-scale low-altitude (below 500ft) sUAS operations in future? What proportion of the areas and population will be affected? These questions are important for regulators, operators and community alike. Hence, we seek to answer them by simulating the noise levels to quantify the aural impact of large-scale unmanned traffic operations.

Existing noise estimation approaches are derived primarily for manned civil aviation aircraft based on well researched source noise and sound propagation and transmission loss models for those aircraft. Since such detailed information is very limited for expected future sUAS[3], we assume the point source model for the sUAS and use the sound pressure level formula to compute the sound pressure at a distance. Despite its simplicity, our model agrees well with the measurements taken by NASA [4].

As many as thousands of low-altitude, high-speed unmanned flights a day may be expected in a metropolitan region [5]. We therefore simulate this sUAS traffic for two separate metropolitan regions, namely Norrköping municipality in Sweden and the San Francisco Bay Area in the US. We measure the net sound pressure produced at different points across the region and evaluate our noise metrics.

Section II discusses the role of noise estimation in aviation policy, the approaches to measure sUAS traffic noise impact so far and our selection of the model, in detail. It also presents reasons for the chosen metrics and traffic densities in our study. The simulation parameters, noise metric definitions and the detailed simulation methodology are described in section III.

Preliminary results show low community impact and are presented in section IV. Although the noise levels are low, the aural perception may still be substantial owing to the proximity of operations. A detailed discussion of this notion and proposed future extensions conclude this extended abstract in Section V.

II. Literature Review

Noise estimation has played an important role in the history of aviation policy [6]. Research has contributed towards the creation of standards for aircraft noise and development of regulations for minimizing impact of airport noise [7]. Standardized noise assessment models such as INM[8], now replaced by AEDT[9] have become a part of industry practice.

However, extending these standards and regulations to the unmanned traffic is not quite straightforward. First, the aero-acoustics of commercial and general aviation manned aircraft, incorporated in these models, have been studied and understood over the years. For future sUAS, such information is lacking, owing to the nascency of related research. Intratep et. al. [3], Herreman [10] and Cabell et. al. [4] present good examples of attempts in that direction. But the aircraft studied in their work are still a very small subset of sUAS that will

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

be used in future and hence not adequate enough.

Second, in the afore-mentioned models, airports are distinct zones of concentrated noise. Interaction between commercial aircraft and community, and their noise impact is localized to these zones. Hence, airport characteristics (runway location, orientation, etc.) and operational characteristics (approach and departure profiles, flight tracks, etc.) become necessary inputs to the models. For the rest of the flight, regulations keep the aircraft well above the populace. With respect to sUAS, this will change completely in future when, in the words of Dr. Kopardekar [11], "every home will have a drone and every home will serve as an aerodrome". The aircraft and community interaction will become much more dynamic and dispersed, and the models need to account for that.

We therefore use a basic model to produce a first order estimate of the ambient noise levels generated by sUAS traffic. We assume the aircraft to be point sources producing sound at a certain decibel (dB) level. The spectral characteristics would ideally vary with the type of aircraft. Since we only estimate the noise levels and not annoyance, which depends on the spectral characteristics, the type and model of aircraft can be ignored; instead, an average reference noise can be used for the estimation of the long-term mean of the noise pollution. Further, owing to the diversity in the nature of proposed operations, we follow the approach in [5], henceforth referred to as the Cal model, to generate sUAS traffic based on population density of the region and evaluate the noise footprints for the region.[1]

The most recent study from SESAR[12] found that regular service routes will be used by less than ten percent of the projected number of Unmanned Aircraft Systems (UAS). In addition, long range light load operations have the highest projected level of autonomy [12](p. 74). Last but not least, it is envisaged that in the low-altitude airspace, densely populated usage will account for almost 90% of mileage and about three-fourths of total hours flown [12](p. 38). This indicates that the majority of the traffic demand may actually follow the Cal model, which further estimates as many as 100,000 low-altitude, high-speed unmanned flights a day in a metropolitan region at maturity.

The noise footprints of unmanned aircraft for various traffic paradigms have been previously studied in [13] for mixed traffic of Personal Aerial Vehicles (PAV)(i.e. flying cars and buses) during the morning and evening hours when people massively move to and from the center of a futuristic city. Our study looks much closer into the future than [13]. We consider only sUAS that do not carry people and simulate traffic using layout of existing metropolitan regions (Norrköping municipality in Sweden and Bay Area in the US), using the Cal model based on the population density. In particular, existing and near-future sUAS operations have shorter flight ranges by nature in comparison to the distant-future PAVs and UAS used in [13]. This makes some of the paradigms from [13], such as radial paths, inapplicable for them.

[1]The name "Cal" is chosen for two reasons: from the fact that the model was introduced by researchers representing University of California Berkeley (going by Cal), and from the above-cited vision expressed by Dr. Parimal Koparderkar (representing California-based NASA Research Center).

Finally, to quantify the aural impact and the affected area and population, we use noise metrics that are based on outdoor noise limits as identified by the United States Environmental Protection Agency (EPA)[14]. EPA identified 55dB at outdoor locations as the noise limit requisite to protect public health and welfare. We assume the sUAS traffic operates only during the day and compute L_{eq} (the long term average dB level) and the n-percent exceeded noise levels L_n for the noisy hotspots (dB level exceeded n% of the time over a location for n = 10, 50, 90). Next, we estimate A_{55} (the area affected by noise above 55dB) and P_{55} (the population affected by noise above 55dB). We also build the contours for the areas with high long-term average noise exposure.

These metrics and the model we use are formally defined in the next section. The section also describes the simulation in detail, followed by the results presented in section IV.

III. Simulation

This section describes our setup: we recap the traffic generation in the Cal model and give definitions of the noise metrics used.

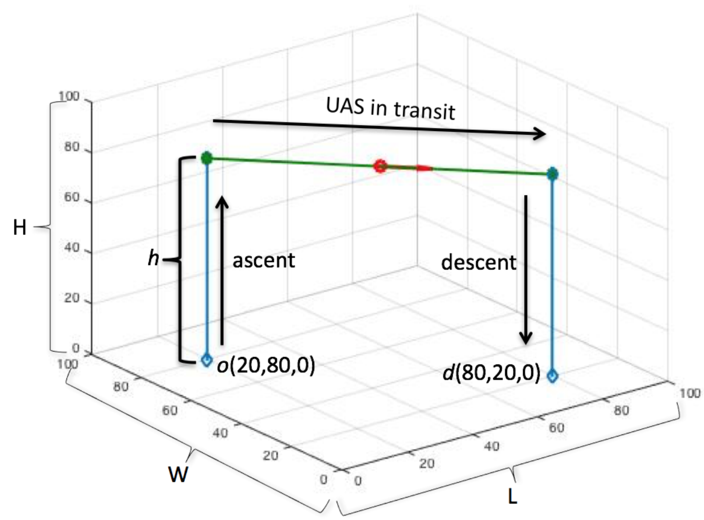

Fig. 1. A typical UAS flight path in the Cal model

A. Cal Model: Traffic Generation

We employ the model and approach introduced in [5]: The airspace is a cuboidal volume LWH defined by a rectangular area extruded to a given height H. sUAS have strictly vertical takeoff and landing, and fly on a fixed flight level h. A typical flight is shown in Figure 1. All aircraft are at the same level because with the restrictions on commercial sUAS operations[15], there is little room for multiple levels (see also [16] for the "horizontal-maneuvers" TCAS work for UTM). Thus, our setup is essentially two-dimensional. We experimented with two values of h: 50m and 75m (that is, we ran two series of experiments: in one all UAVs flew at h=50m, in the other all flew at 75m).

The flights' origins and destinations were generated randomly based on the population density over the rectangular area. This preserves the actual shape of the geographical area

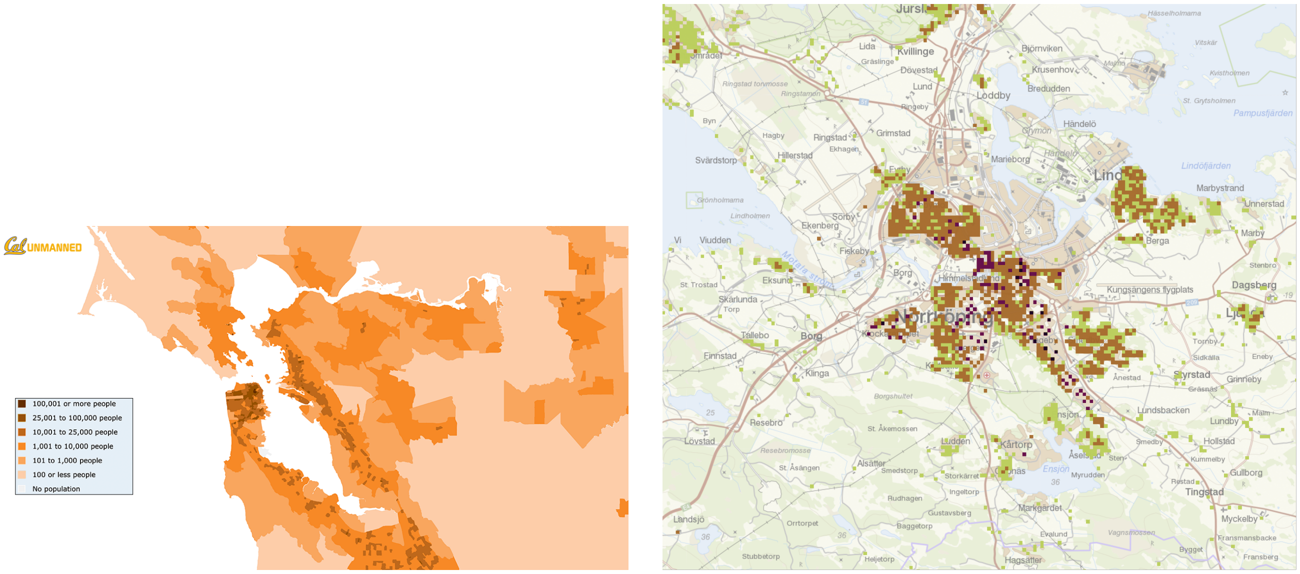

Fig. 2. Population Density Map. Left: the Bay Area [17]. Right: Norrköping municipality [18].

and the volume of airspace used. The total number N of flights expected during the day was given, and the intensity of the traffic starting or ending at a point ℓ of the domain was proportional to the population density at ℓ (that is, the starting times of the flights from ℓ form a Poisson process with the rate proportional to the density). The simulations were run in two regions: Bay Area in the US and Norrköping municipality in Sweden (see Figure 2). In each of the regions, we simulated 12 hours of traffic. For a statistically significant sample, we used $N = 5000$. Below we explain how the results for other N are obtained.

Cal model is an extension of what can be called *Dutch model*, used in PhD thesis of Hoekstra [19], developed by Jardin [20], and more recently explored within the Metropolis project by TU Delft [21]. In this model the aircraft are distributed *uniformly* in the given airspace. In the basic version of the Dutch model, the direction of flight is also uniformly distributed in 0...360; in [21], the different direction cones are separated by altitude. The simplicity of the model allows one to obtain exact formulas for conflict probabilities and other quantities, using a single parameter tuned to match the empirical data (in [19, p. 220] the parameter is the probability p_{c_a} of conflict in the air, estimated using real traffic observation; in [20] the parameter p_t is the ratio of the so called "element" to the area swept by an aircraft during the observation period).

B. Noise Calculation and Metrics Definition

Many factors influence sUAS sound level – vehicle weight and payload, speed, wind direction, etc. For calculating long-term average noise levels (our focus), we assume that any drone produces the same reference noise of L_h=55dB at the point directly under (i.e., at distance h from) the drone. That is, the square of the sound pressure at the point is

$$p_h^2 = p_0^2 \cdot 10^{L_h/10} \tag{1}$$

where $p_0 = 20\mu$Pa is the reference sound pressure [22, p. 240] (any arbitrary value of p_0 could alternatively be chosen:

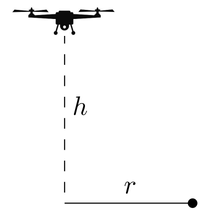

Fig. 3. The intensity (and the pressure square) follows the inverse-square laws (2) and (3).

this does not influence the results, as p_0 cancels out from formula (4)). Similarly, sound propagation depends on source directionality, atmospheric effects, ground effects, and many other things. A good first approximation of sound propagation is the spherical spreading (6 dB drop in sound level per doubling of distance from the source):

$$I(r) \sim \frac{1}{h^2 + r^2} \tag{2}$$

or

$$p^2(r) = \frac{p_h^2 h^2}{h^2 + r^2} \tag{3}$$

Here $I(r)$ is the sound intensity and $p(r)$ is the sound pressure at distance r from the point directly under the drone (Fig. 3). The sound from different vehicles is assumed uncorrelated, and the intensities are summed up (which corresponds, e.g., to 20dB per 100-fold increase in the number of vehicles). The above basic model has been confirmed in personal communication with the NASA Langley Research Center: we checked that the numbers and graphs that we obtain in simulations according to the above-outlined setup, agree with the experimental measurements reported by the center at Inter-Noise/Noise-Con 2016 [4] (Fig. 4).

We computed the following four metrics:

- L_{eq}: *long-term average noise level.* At every pixel ℓ of the domain, we take the average of the intensity during the

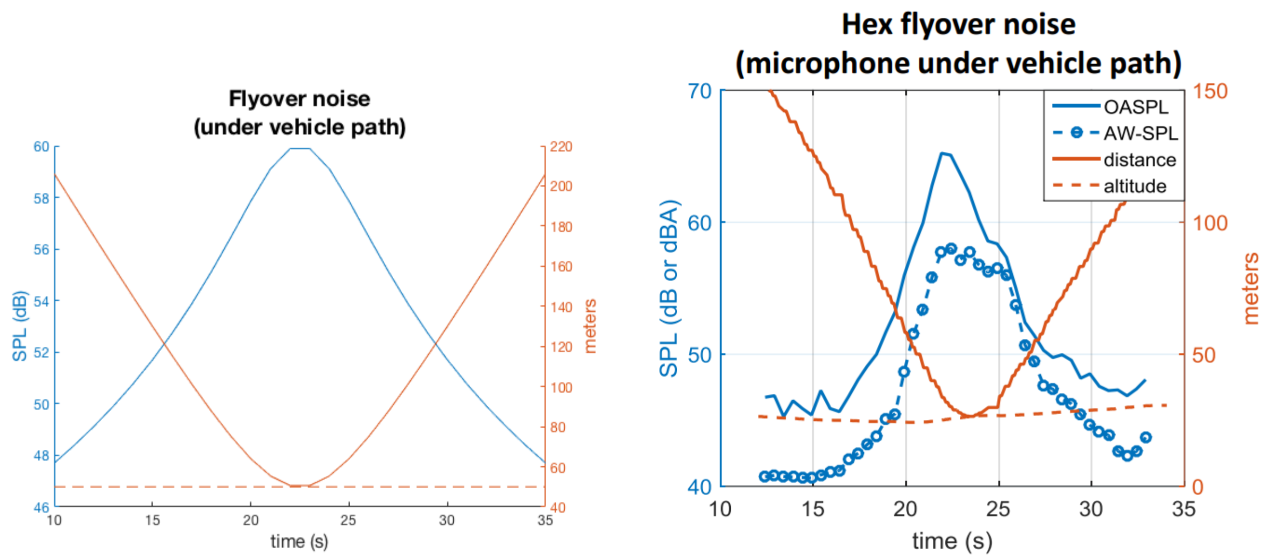

Fig. 4. The noise decay curve in our simulation has similar shape to the one measured experimentally. Left: Fly over a point under UAV path in our model. Right: A figure from the presentation of [4] (courtesy of NASA).

simulated day and convert it to dB [23]:

$$L_{eq}(\ell) = 10\log_{10}\frac{1}{12\text{hrs}}\int_0^{12\text{hrs}}\frac{p_\ell^2(t)}{p_0^2}\,dt \qquad (4)$$

where $p_\ell(t)$ is the sound pressure at ℓ at time t.

- L_n*: the n% exceeded level (for n = 10, 50, 90) over a noisy location.* L_n is the sound level exceeded for n percent of time. That is, we chose a pixel ℓ, and build the graph $L_\ell(t)$ of how the noise at the pixel changes with the time. Then, for a horizontal line running at some noise level L, we look at the total time $T(L)$ when $L_\ell(t) > L$. The function $T(L)$ is non-increasing: if $L = 0$, obviously $T(L) = 100\%$ of time; on the other hand, if $L = \infty$, then $T(L) = 0$. For any given n, there exists the level L such that $T(L) = n\%$ of the time – this is the level L_n.
- A_{55}*: area affected by noise above 55dB.* This is the area where $L_{eq} > 55$db – it can be directly obtained from the L_{eq} map: every pixel ℓ where $L_{eq}(\ell) > 55$dB, contributes one pixel area to A_{55}.
- P_{55}*: population affected by noise above 55dB.* This is similar to A_{55}, but the area is weighted by the population density: every pixel ℓ where $L_{eq}(\ell) > 55$d, contributes the population at ℓ to P_{55}.

IV. Results

The main output from our simulations is the noise footprint: Figure 5 shows L_{eq} maps for our default parameters $L_h =$ 60dB and $N = 5000$.

The other metrics are computed from the L_{eq} footprint (as described in the previous section). It is important to note that the results for other values of the reference UAV noise L_h and for other values of the traffic intensity N can be obtained from the L_{eq} maps for the default values $L_h = 60$dB and $N = 5000$ *without re-running the simulations.* The details follow.

Assume that L_h is changed to some new value $L'_h = L_h + \Delta L$ (ΔL can be larger or smaller than 0). We claim that this simply changes the L_{eq} value at each pixel by the difference ΔL. Indeed, by formulas (1) and (3), at any pixel ℓ the ratio $\frac{p_\ell'^2}{p_0^2}$ changes from $10^{L_h/10}$ to $10^{L'_h/10} = 10^{\Delta L/10}10^{L_h/10}$. That is, the integrand (and hence, the integral) in formula (4) is multiplied by $10^{\Delta L/10}$, implying that L_{eq} changes by ΔL, q.e.d. Thus, instead of rerunning the simulations, we simply uniformly change L_{eq} by Δ and recompute the other metrics. Similarly, if N is changed to N', the average noise L_{eq} changes by $10\log_{10}\frac{N'}{N}$ – this is because the integrand in (4) gets multiplied by a factor of N'/N. Again, we change L_{eq} accordingly and recompute the other metrics without redoing the simulations.

Figure 6 shows daily graphs of the noise over certain locations; the L_n noise levels for $n = 10, 50, 90$ are also drawn. The graphs are built for the default parameters $L_h = 60$dB and $N = 5000$. As explained above, the graphs for another reference noise L'_h are just shifted by $L'_h - L_h$. Consequently, the L_n's are also uniformly shifted up – this nonexciting behavior is depicted in Figure 7, left. Also as explained above, when $N = 5000$ changes to N', the noise is multiplied by $10\log_{10}\frac{N'}{N}$ – see Figure 7, right.

Figure 8, left shows A_{55}—the area polluted by noise above 55dB—as the function of the reference noise L_h. This time, the dependence cannot be given by any closed-form formula. To compute the metric, for every L'_h, the noise maps (Fig. 5) are shifted by $L'_h - L_h$ (at every pixel), and the affected area is recalculated. Similarly, the dependence of A_{55} on N is obtained by scaling the maps for every N' and recomputing the metric for each scaled map. Figure 8, right shows the results. We emphasize again that while the metrics are calculated separately for each L'_h and each N', the simulation is not rerun – the new maps are simply obtained by the shifting or the scaling.

Finally, Figure 9 shows the P_{55} metric – population affected by noise above 55dB. The metric is calculated similarly to A_{55}.

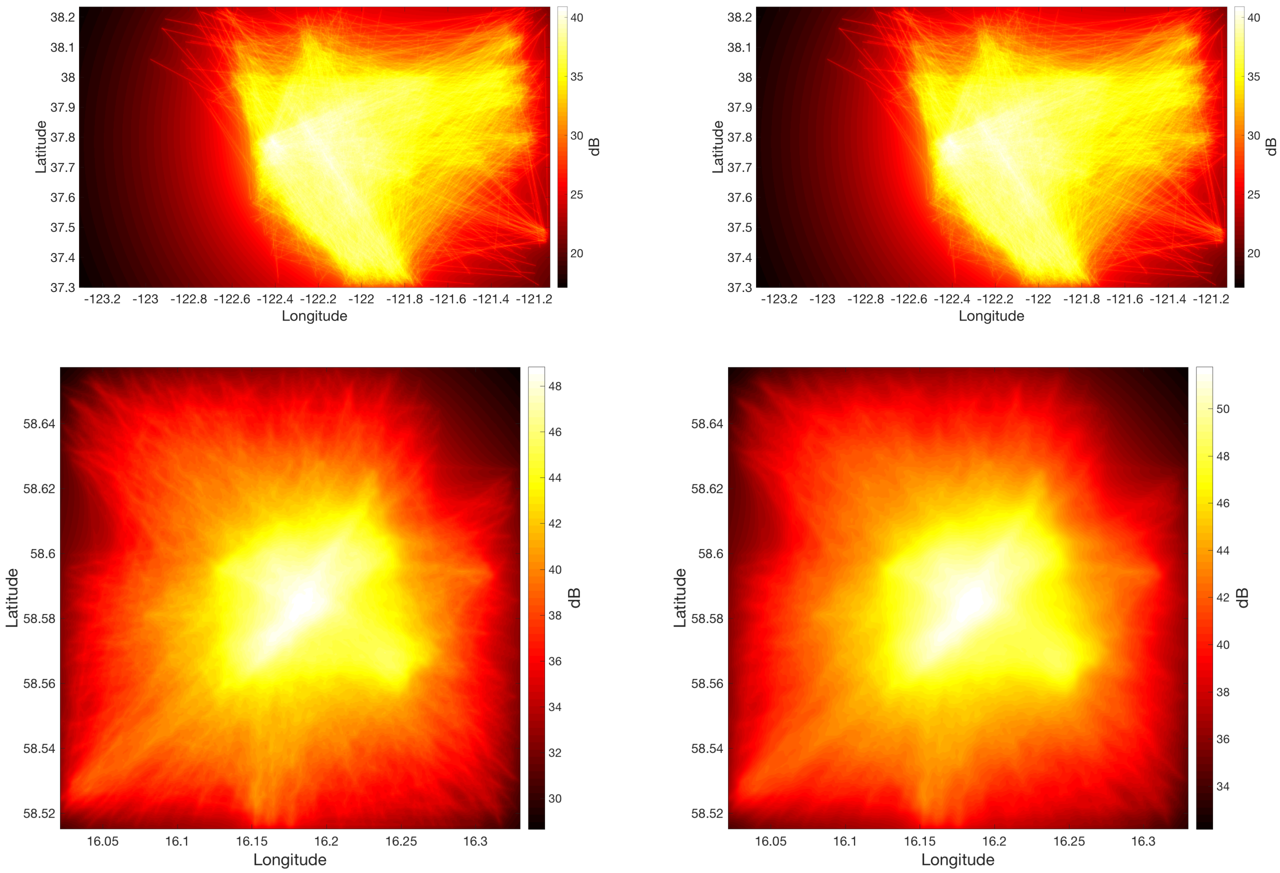

Fig. 5. The noise footprint. Top row: Bay Area. Bottom row: Norrköping municipality. Left: $h = 50$m. Right: $h = 75$m.

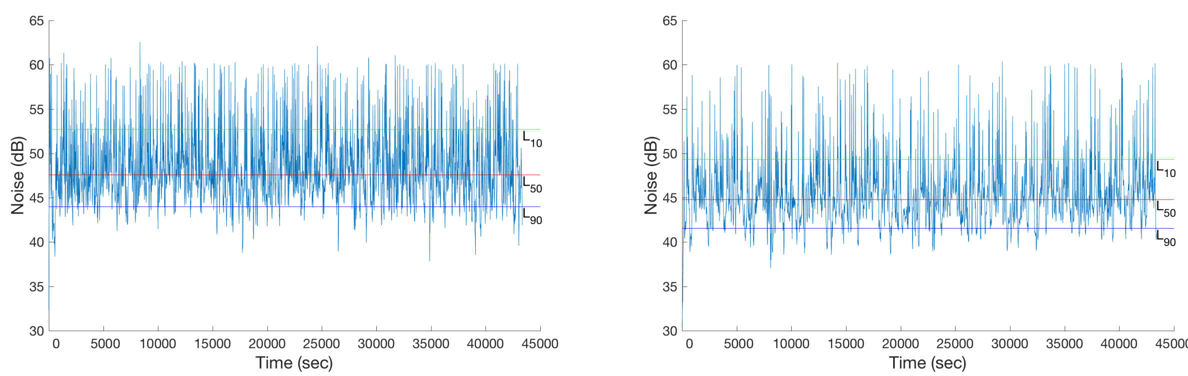

Fig. 6. Noise as a function of time at a location. Left: Bay Area. Right: Norrköping municipality. The horizontal lines show L_{10}, L_{50}, L_{90}

V. Conclusion and Future Work

We estimated noise footprint and associated noise pollution metrics for UAV operations in the very low level (VLL) airspace. We emphasize that we do not provide estimations of *annoyance* from the noise. This depends on the spectral variation of the frequency content of the noise (both observed and perceived). Because we are not aware of any research following Schultz [24] for UAS to measure any such psychoacoustic effects, we can only speculate that the dose–response curves for UAS traffic will lie even higher than for the airplanes (i.e., even more people will be annoyed with the same noise level). When such curves become available, our findings can be used to give lower bounds on traffic volumes when estimating the airspace capacity via potential societal effects of UAS operations.

This work continues the series of papers on capacity estimation for UTM (which, in its turn, is a continuation of the vast research on estimating airspace capacity in ATM [25]–[30]). In [31], the capacity was studied in terms of the UAVs deconfliction capabilities (the capacity limit was reached when non-resolvable conflicts were likely to emerge). It was observed that the transfer from conflict-free to unsafe regime exhibits *threshold* properties akin to phase transition (Fig. 10): small changes in the input parameters lead to drastic changes in the output. This is not the case with the noise: as explained

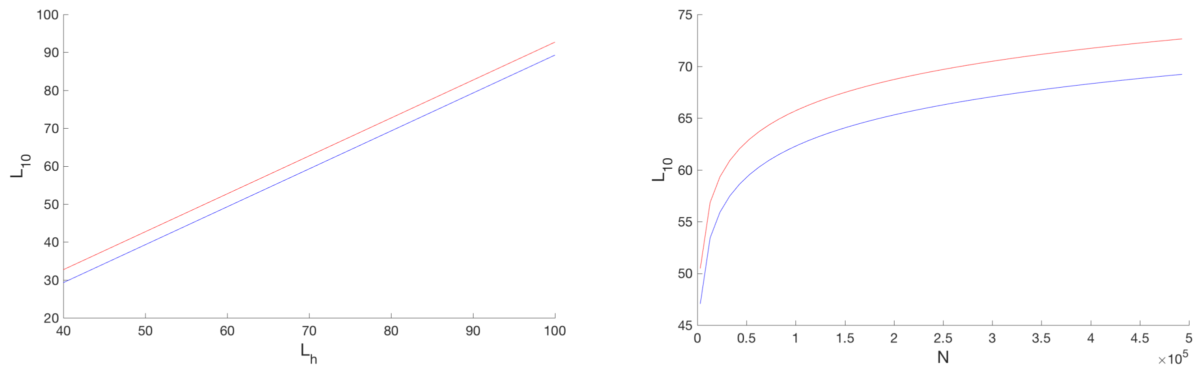

Fig. 7. Left: L_{10} linearly changes with the reference noise L_h. Blue: Norrköping municipality. Red: Bay Area. Right: The dependence of L_{10} on traffic intensity N is logarithmic.

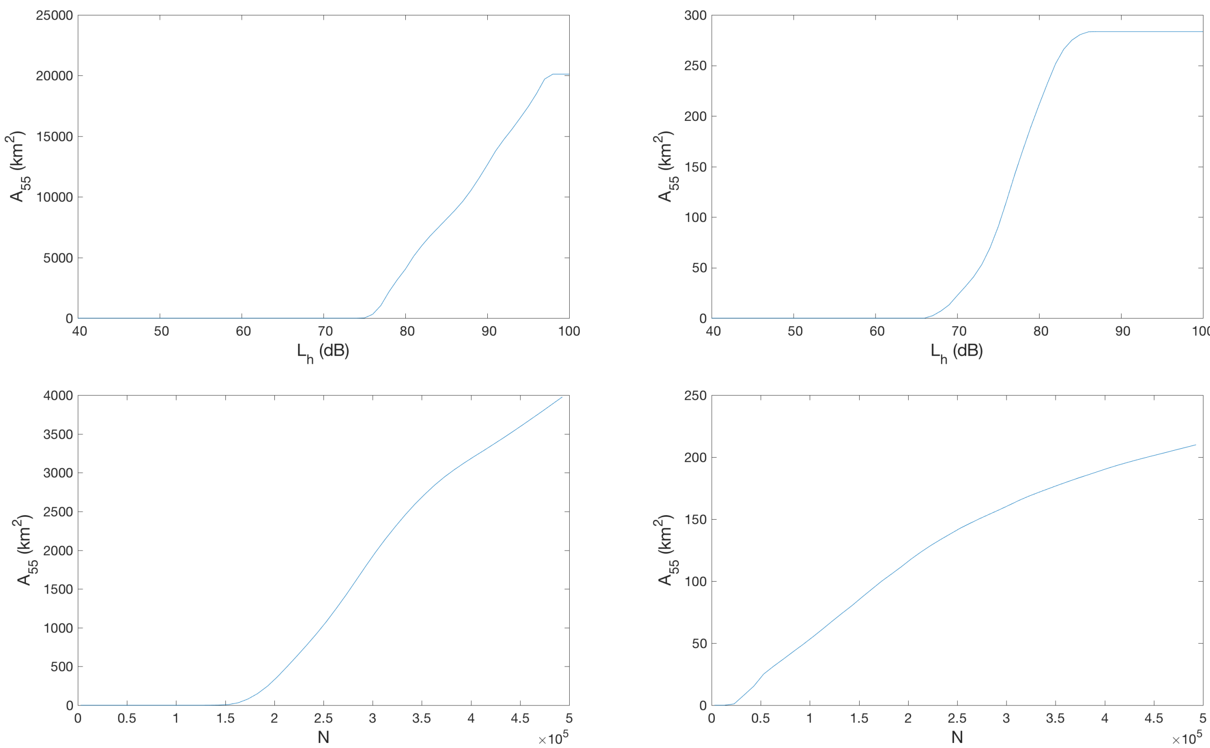

Fig. 8. Top row: A_{55} as the function of the reference noise L_h. Bottom row: A_{55} as the function of the traffic intensity N. Left: Bay Area. Right: Norrköping municipality.

above (and as confirmed by our results), when the UAV traffic density N and/or their reference noise level L_h changes, our noise pollution metrics change smoothly – small changes in the input imply small changes in the output. This sharp contrast between safety and noise as the capacity-limiting factors is worth keeping in mind when deciding the specifics of the UTM.

Further research:

- We suggest that other models—e.g., taking obstacle (geofences) avoidance into account—merit future investigations.
- It would also be of interest to estimate other noise metrics, such as e.g., the population affected by frequent noisy flyovers. One might consider UAVs using different flight levels as well, e.g., as studied in [29] for the conventional, manned aviation.
- We did not consider L_{DEN} (nor any other time-of-day combinations like L_{DN}). The reason is twofold: first, we assume that the drones operate during the day, and second, we are interested in understanding the basic picture. The necessary standard adjustments for the evening and/or night flights may be done straightforwardly.
- Last but not least, we believe that delineating the dose-response curves for UAVs noise pollution is of ultimate importance for assessing the societal impact of sUAS.

Acknowledgments

We express our sincere gratitude to Professor Raja Sengupta and Dr. Alex A. Kurzhanskiy from UC, Berkeley, Dr. Parimal H. Kopardekar from the NASA Ames Research Center, Randolph H. Cabell from the Structural Acoustics Lab at

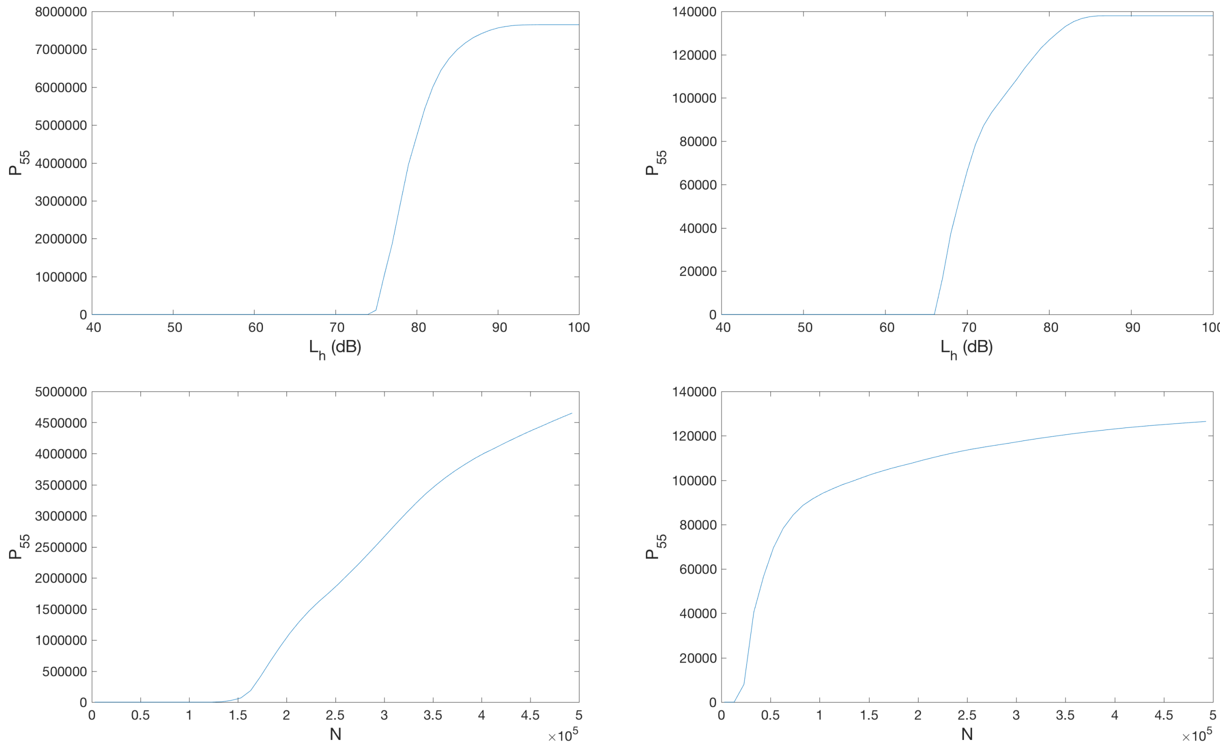

Fig. 9. Top row: P_{55} as the function of the reference noise L_h. Bottom row: P_{55} as the function of the traffic intensity N. Left: Bay Area. Right: Norrköping municipality.

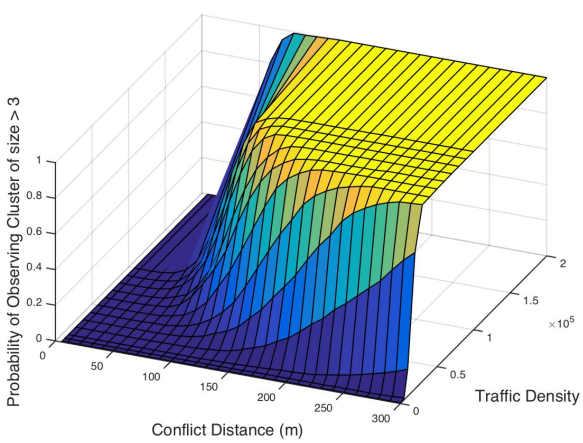

Fig. 10. Figure 9 from [31]: Probability of encountering a complicated conflict resolution event as a function of traffic intensity and loss-of-separation distance (simulation setup: the same, Cal model used in this paper) – the probability jumps sharply from almost 0 to almost 1, as any one of the parameters change.

NASA Langley Resrach Center, Dr. Eric Hoffman from EUROCONTROL, Professor Alon Efrat from the University of Arizona and Professor Jacco Hoekstra from TU Delft for valuable insights on the basic ideas and setup. We also acknowledge Mr. Frank Ketcham from Delta Airlines for teaching us about different air traffic management systems and existing aviation noise policies in the US. The work of LS and VP is part of the UTM-OK project supported by the Swedish Transport Administration (Trafikverket).

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