Grand Rapids, MI
NOISE-CON 2017
2017 June 12-14

Noise Estimation for future large-scale small UAS Operations

Vishwanath Bulusu
Cal Unmanned Lab
CEE Department
University of California
Berkeley
CA, USA 94703
vishwanathb01@gmail.com

Leonid Sedov
Valentin Polishchuk
Communications & Transport Systems
ITN
Linköping University
Norrköping, Sweden

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 (~60m). Future work should measure the spectral content of the sound and the auditory impact of specific frequencies.

1. 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 2 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 3. Preliminary results show low community impact and are presented in section 4. 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 work in section 5.

2. 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 to the unmanned traffic is not quite straight forward. First, the aero-acoustics of 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 are still a very small subset of sUAS that will be used in future and hence not adequate enough. Second, 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-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. For 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. The aircraft are point sources producing sound at a certain decibel (dB) level. 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[1], to generate sUAS traffic based on population density and evaluate the noise footprints for the region.

The most recent study from SESAR[12] found that regular service routes will be used by less than 10% of the projected number of Unmanned Aircraft Systems (UAS). In addition, long range light load operations have the highest projected level of autonomy[12]. 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 75% of total hours flown[12]. This indicates that the majority of the traffic

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)

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 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[13]. Our study looks much closer into the future. We consider only sUAS that do not carry people and simulate traffic using layout of existing metropolitan, 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[13]. This makes some of the paradigms from [13], such as radial paths, inapplicable for them.

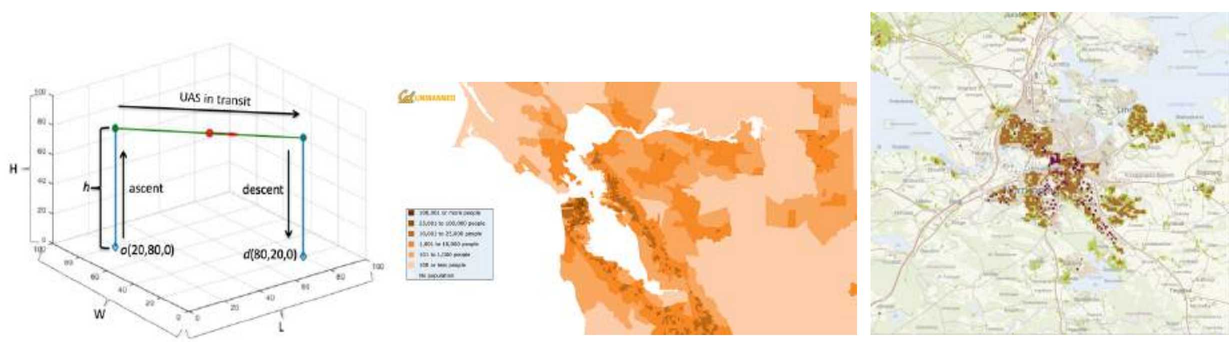
Finally, to quantify the aural impact and the affected area and population, we use noise metrics that are based on outdoor noise limits as identified by the United States Environmental Protection Agency (EPA)[14]. EPA identified 55dB at outdoor locations as the noise limit requisite to protect public 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.

3. SIMULATION

This section describes our setup: we briefly recap traffic generation in Cal model and define the noise metrics used.

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 1a. All aircraft are at the same level because with the restrictions on commercial sUAS operations[15], there is little room for multiple levels (also see the "horizontal-maneuvers" TCAS work for UTM[16]). Thus, our setup is essentially two-dimensional. We ran two series of experiments: in one all UAVs flew at h=50m, in the other all flew at 75m.



(a) (b) (c)

Figure 1: (a) A typical UAS flight path[5], (b) Bay Area population density[17] & (c) Norrköping population density[18].

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 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 (i.e. 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 (Figure 1b & 1c). In each of the regions, we simulated 12 hours of traffic. For a statistically significant sample that indicates UAS traffic in near future, we used N = 5000. Below we explain how the results for other N are obtained.

B. Noise Calculation and Metrics Definition

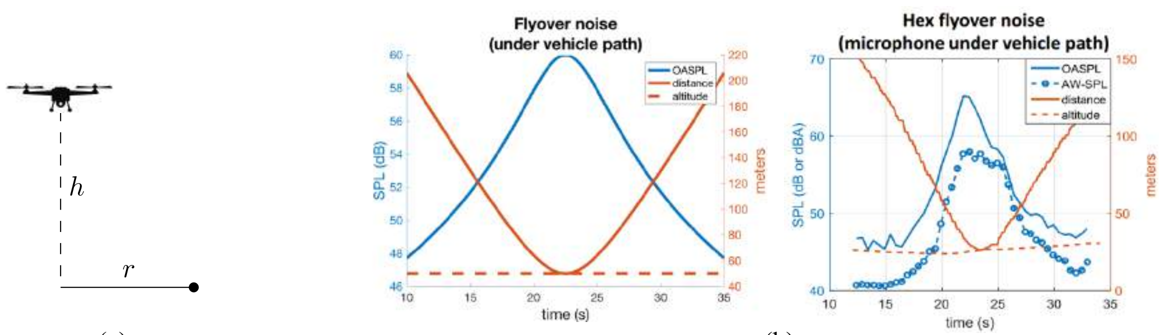
Many factors influence sUAS sound level - vehicle weight and payload, speed, wind direction, etc. For calculating long-term average noise levels (our focus), we assume that any drone produces the same reference noise of L_h = 60dB at the point directly under (i.e., at distance h from) the drone. This captures the noise directly below some of the loudest drones for commercial operations available today. The square of the sound pressure at the point is –

$$p_h^2 = p_0^2 \cdot 10^{L_h/10} \qquad (1)$$

where p_0 = 20μPa is the reference sound pressure[19] (any arbitrary value of p_0 could alternatively be chosen without influencing the results as p_0 cancels out from equation (4)). Similarly, sound propagation depends on source directionality, atmospheric effects, ground effects, and other factors. A good first approximation of sound propagation is the spherical spreading (6 dB drop in sound level per doubling of distance from the source):

$$I(r) \sim \frac{1}{h^2+r^2} \quad \text{or} \quad p^2(r) = \frac{p_h^2 h^2}{h^2+r^2} \qquad (2)$$

Here $I(r)$ is the sound intensity and $p(r)$ is the sound pressure at distance r from the point directly under the drone (Figure 2a). 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. 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] (Figure 2b).



(a) (b)

Figure 2: (a) Location of point where intensity/sound pressure is measured, (b) Left: Flyover noise for a point under UAV path in our model. Right: Experimental measurement from the presentation of [4] (courtesy of NASA)

We computed the following four metrics:

- L_{eq}: *long-term average noise level*. At every cell l of the domain, we take the average of the intensity during the simulated day and convert it to dB[20].

$$L_{eq}(l) = 10 \log_{10} \frac{1}{T_s} \sum_{i=1}^{N} \int_0^{t_i} \frac{p_i^2(l,\ t)}{p_0^2} dt \qquad (3)$$

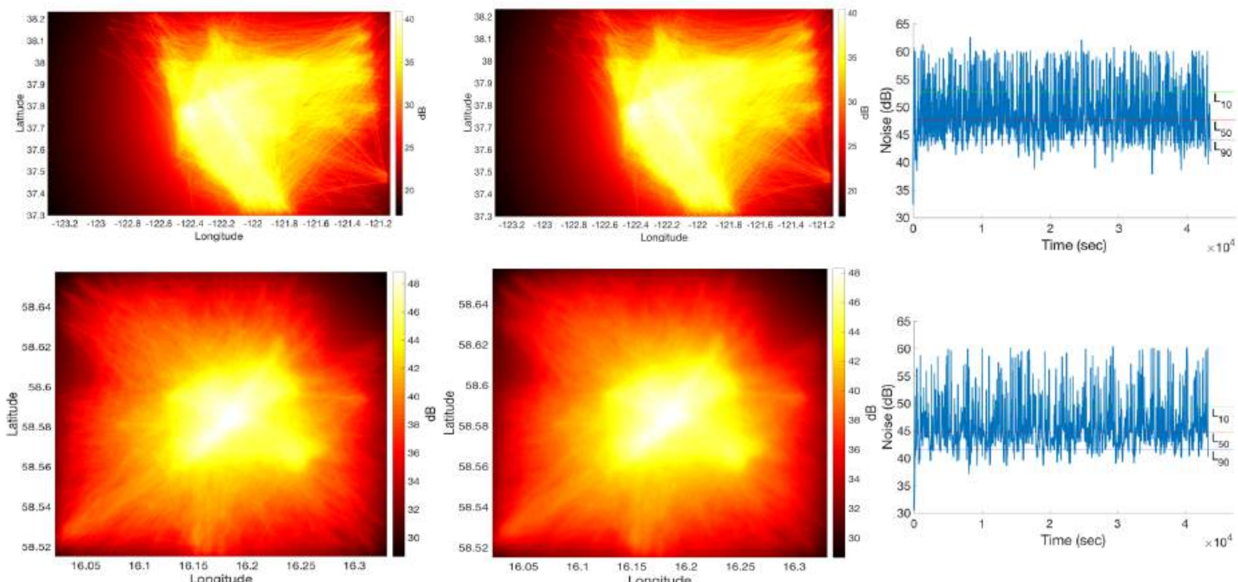
  where t_i is the drone flight duration, $p_i(l, t)$ is the sound pressure at l from the drone i at time t and T_s is the total duration of the entire simulation.

- 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 cell l, and build the graph $L_l(t)$ of how the noise at the cell changes with the time. Then, for a horizontal line running at some noise level L, we look at the total time $T(L)$ when $L_l(t) > L$. The function $T(L)$ is non-increasing: if $L = 0$, *T(L)* = 100% of time while 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} > 55dB – it can be directly obtained from the L_{eq} map. Every cell *l* where $L_{eq}(l)$ > 55dB, contributes one cell area to A_{55}.
- P_{55}: *population affected by noise above 55dB*. Similar to A_{55} but the area is weighted by the population density. Every cell *l* where $L_{eq}(l)$ > 55dB, contributes the population at *l* to P_{55}.

3. RESULTS AND DISCUSSION

The main output from our simulations is the noise footprint. Our default simulation parameters were L_h = 60dB and N = 5000. Figure 3a shows L_{eq} maps or the noise footprint for *h* = 50m and 75m. All areas have slightly reduced noise levels as expected because the drones fly higher by 25m. Hence, the rest of our results are presented for h = 50m, as more conservative measures of expected noise level impact.



(a) (b)

Figure 3: Top Row: Bay Area. Bottom Row: Norrköping. a) The noise footprint. Left: *h*=50m. Right: *h*=75m. b) Noise as a function of time at a particular location in the white region. The horizontal lines show L_{10}, L_{50} and L_{90}.

The other metrics are computed from the L_{eq} footprint. Results for other values of the reference UAV noise L_h and the traffic intensity N can be obtained from the L_{eq} maps for the default values without re-running the simulations. Assume that L_h is changed to some new value $L_h' = L_h + \Delta L$ (ΔL can be positive or negative). This simply changes the L_{eq} value at each cell by the difference ΔL. By equations (1) and (2), at any cell l the ratio $p_l'^2/p_0^2$ changes from $10^{L_h/10}$ to $10^{L_h'/10} = 10^{\Delta L/10} \cdot 10^{L_h/10}$ i.e. the integrand (and hence, the integral) in (3) is multiplied by $10^{\Delta L/10}$. Therefore, L_{eq} changes by ΔL. Consequently, we uniformly change L_{eq} by ΔL and re-compute other metrics. Similarly, if *N* is changed to *N'*, the average noise L_{eq} changes by $10\log_{10} N'/N$. Again, we change L_{eq} accordingly to re-compute the other metrics without redoing the simulations.

Figure 3b shows daily graphs of the noise over certain locations with L_n noise levels for n = 10, 50, 90 indicated for our default parameters. The graphs for other reference noise L_h' are just shifted by $L_h' - L_h$. Consequently, the L_n's are also uniformly shifted up. This behavior is depicted in Figure 4, left. Also, when *N* = 5000 changes to *N'*, the noise is multiplied by $10\log_{10} N'/N$ – Figure 4, right. L_{10} stays below 55dB, while L_h stays below 70dB with N=5000 and while N is below 10,000 for L_h=60dB. This shows that for expected sUAS traffic in near future, noise levels alone may not be a nuisance. Innovative designs that reduce the source noise of future drones for civilian applications, would contribute to ensuring this further, even at higher traffic densities.

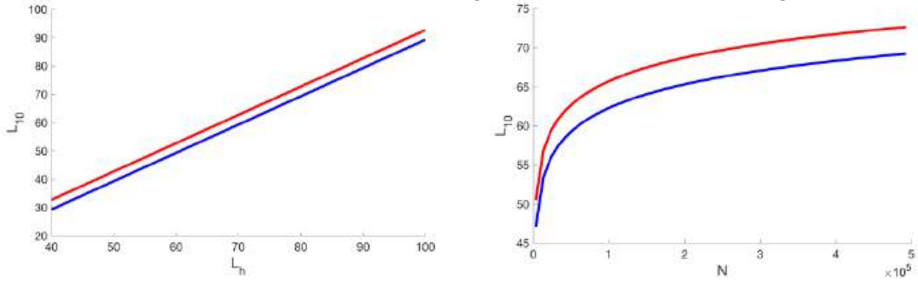


Figure 4: Left: L_{10} as a function of reference noise L_h ($N = 5000$). Right: L_{10} as a logarithmic function of traffic density N. ($L_h = 60$dB). Red: Bay Area. Blue: Norrköping.

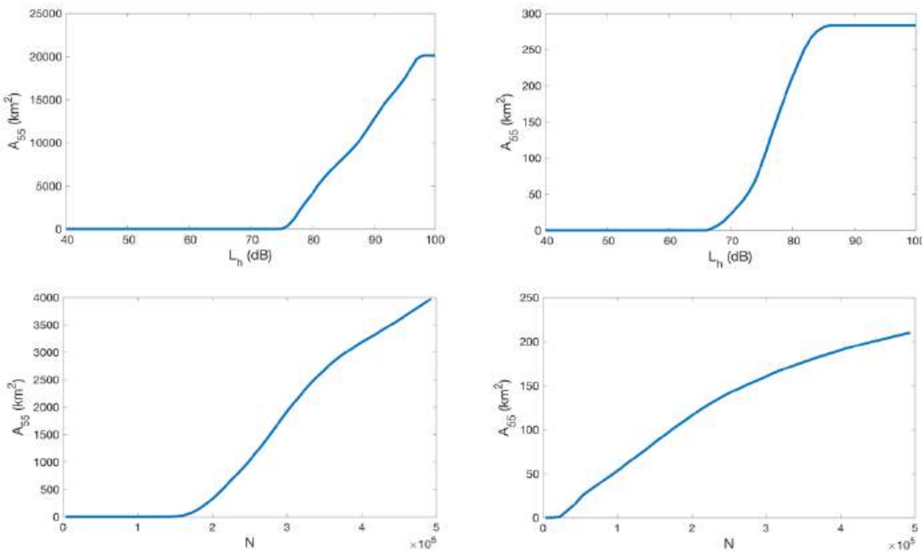


Figure 5: Top row: A_{55} as a function of reference noise L_h. Bottom row: A_{55} as a function of the traffic density N. Left: Bay Area. Right: Norrköping

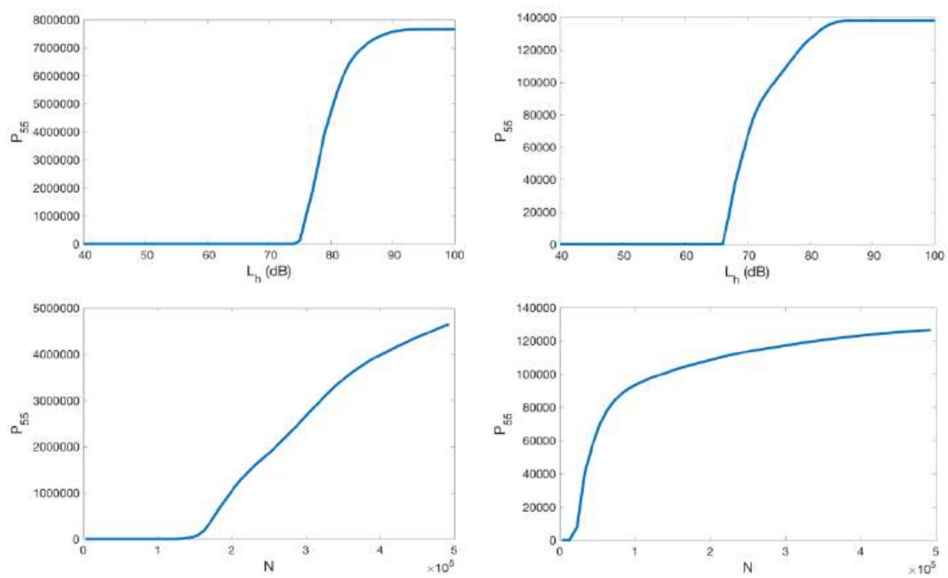


Figure 6: Top row: P_{55} as a function of reference noise L_h. Bottom row: P_{55} as a function of the traffic density N. Left: Bay Area. Right: Norrköping

Figure 5, left shows A_{55} as the function of reference noise L_h. This dependence cannot be given by any closed-form formula. To compute the metric, for every L_h', the noise maps (Fig. 3) are shifted by $L_h'–L_h$ (at every cell), and the affected area is recalculated. Similarly, the dependence of A_{55} on N is also obtained - Figure 5, right. Figure 6 shows the P_{55} metric calculated similar to A_{55}. For near future sUAS traffic, any considerable area or population is affected only at extremely high source noise levels. At the expected source noise, this happens at over 100,000 flights per day in the Bay Area and over 20,000-30,000 flights per day over Norrköping. This reiterates that noise levels alone may not be a nuisance for future sUAS traffic.

5. CONCLUSIONS AND FUTURE WORK

We estimated noise footprint and associated noise pollution metrics for UAV operations in low-altitude urban airspace. We do not provide estimations of annoyance from the noise. This depends on the spectral variation of the frequency content of the noise (observed and perceived). Because we are not aware of any research following Schultz[21] for UAS to measure such psycho-acoustic effects, we can only speculate that the dose–response curves for sUAS traffic will lie even higher than for the airplanes (i.e., 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 itself extends the vast research on airspace capacity in ATM[22-27]. In [28], capacity was studied in terms of the UAS's de-confliction capabilities. It was observed that the transfer from conflict-free to unsafe regime exhibits threshold properties akin to phase transition. This is not the case entirely with the noise. When the traffic density and/or the reference noise level changes, our noise pollution metrics change smoothly. Only the area and affected population metrics shows some hint of a phase transition. This sharp contrast between safety and noise as the capacity-limiting factors is worth considering when deciding the specifics of the UTM.

Other models – e.g., taking obstacle(geo-fences) avoidance into account, merit future investigations. It would also be interesting to estimate other metrics, such as the population affected by frequent noisy flyovers. One might consider UAVs using different flight levels, as studied for conventional manned aviation[26]. We did not consider L_{DEN} (nor any other time-of-day combinations like L_{DN}). The reason is twofold: first, we assume that drones operate during the day and second, we are interested in understanding the basic picture. The necessary standard adjustments for the evening and night flights may be done straight forwardly. Last but not least, delineating the dose-response curves for UAVs noise pollution is of ultimate importance for assessing the societal impact of future sUAS traffic.

ACKNOWLEDGEMENTS

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 NASA Langley Research 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. We thank Dr. Tobias Andersson Granberg from Linköping University for his help with reviewing the concepts utilized in this paper. The work of LS and VP is part of UTMOK and UTM50 projects supported by the Swedish Transport Administration (Trafikverket) via the Swedish Air Navigation Service provider LFV (Luftfartsverket).

REFERENCES

1. A. Barr and G. Bensinger, “Google Is Testing Delivery Drone System,” *Wall Street Journal*, Aug, 2014.
2. P. Kopaderkar, “Safely enabling UAS operations in low-altitude airspace,” *Digital Avionics Systems Conference (DASC), 2016* IEEE/AIAA 35th, 2016, plenary talk.
3. N. Intaratep, W. N. Alexander, W. J. Devenport, and A. Dropkin, “Experimental study of quadcopter acoustics and performance at static thrust conditions,” *22nd AIAA/CEAS Aeroacoustics*, 2016, p. 2873.
4. R. Cabell, F. Grosveld, and R. McSwain, “Measured noise from small unmanned aerial vehicles,” *INTER-NOISE and NOISE-CON Cong. and Conf. Proceedings*, vol. 252, no. 2. INCE, 2016, pp. 345–354.
5. V. Bulusu, R. Sengupta, and Z. Liu, “Unmanned aviation: To be free or not to be free? a complexity based approach,” *7th International Conference on Research in Air Transportation*, 2016.
6. L. S. Finegold, M. S. Finegold, J. Maling, and C. George, “An overview of us noise policy,” *Noise Control Engineering Journal*, vol. 51, no. 3, pp. 131–142, 2003.
7. Federal Aviation Administration, “Airport noise compatibility planning,” 14 CFR Part 150, 2016.
8. E. R. Boeker, E. Dinges, B. He, G. Fleming, C. J. Roof, P. J. Gerbi, A. S. Rapoza, and J. Hemann, “Integrated noise model (INM) version 7.0 technical manual,” Federal Aviation Administration, Tech. Rep.,2008.
9. J. Koopmann, M. Ahearn, E. Boeker, A. Hansen, S. Hwang et al., “Aviation environmental design tool (aedt): Technical manual, version 2a,” Federal Aviation Administration, Tech. Rep., 2012.
10. K. Herreman, “Proposed measurement method for uav sound levels,” *INTER-NOISE and NOISE-CON Cong. and Conf. Proceedings*, vol. 252, no. 2. Institute of Noise Control Engineering, 2016, pp. 615–622.
11. P. Kopardekar, “Unmanned aerial system traffic management system,” Talks at Google, 2016.
12. SESAR, “European drones outlook study,” 2016.
13. M. Arntzen, R. Aalmoes, F. Bussink, E. Sunil, and J. Hoekstra, “Noise computation for future urban air traffic systems,” *44th Inter-Noise Congress: Implementing Noise Control Technology*, San Francisco, USA, 2015.
14. United States Environmental Protection Agency and Office of Noise Abatement and Control, Information on levels of environmental noise requisite to protect public health and welfare with an adequate margin of safety. Supt. of Docs., US Govt. Print. Off., 1974, vol. 74, no. 4.
15. “Federal Aviation Administration - Unmanned Aircraft Systems,” https://www.faa.gov/uas/, 2016.
16. R. E. Tompa, B. Wulfe, M. P. Owen, and M. J. Kochenderfer, “Collision avoidance for unmanned aircraft using coordination tables,” *Digital Avionics Systems Conference (DASC*), 2016 IEEE/AIAA 35th, 2016, pp. 1–9.
17. “ArcGIS USA Population Density,” https://www.arcgis.com/home/index.html, 2016.
18. “Swedish University of Agricultural Sciences,” http://www.slu.se/en/, 2016.
19. R. Roeser, M. Valente, and H. Hosford-Dunn, Audiology: Diagnosis, ser. Thieme Publishers Series. Thieme, 2007. [Online]. Available:https://books.google.se/books?id=Hj6v1Nt044C
20. G. Licitra, Noise Mapping in the EU: Models and Procedures. Taylor & Francis, 2012. [Online]. Available: https://books.google.se/books?id=RavqdF3HqsC
21. T. J. Schultz, “Synthesis of social surveys on noise annoyance,” *J. Acoust. Soc. Am.*, no. 64, p. 377-405, 1978.
22. A. Majumdar, W. Ochieng, and J. Polak, “Estimation of European airspace capacity from a model of controller workload,” *Journal of Navigation*, vol. 55, no. 03, pp. 381–403, 2002.
23. A. Majumdar, W. Y. Ochieng, J. Bentham, and M. Richards, “En-route sector capacity estimation methodologies: An international survey,” *Journal of ATM*, vol. 11, no. 6, pp. 375–387, 2005.
24. A. Klein, L. Cook, B. Wood, and D. Simenauer, “Airspace capacity estimation using flows and weather-impacted traffic index,” in 2008 *Integrated Communications, Navigation and Surveillance Conf.* IEEE, 2008
25. J. Krozel, J. Mitchell, V. Polishchuk, and J. Prete, “Airspace capacity estimation with convective weather constraints,” *AIAA Guidance, Navigation, and Control Conference*, 2007.
26. E. Sunil, J. Hoekstra, J. Ellerbroek, F. Bussink, A. Vidosavljevic, D. Delahaye, and R. Aalmoes, “The influence of traffic structure on airspace capacity,” *7th International Conference on Research in Air Transportation*, 2016.
27. E. Sunil, J. Ellerbroek, J. Hoekstra, A. Vidosavljevic, M. Arntzen, F. Bussink, and D. Nieuwenhuisen, “Analysis of airspace structure and capacity for decentralized separation using fast-time simulations,” *Journal of GCD*, 2016.
28. V. Bulusu and V. Polishchuk, “Capacity estimation for low altitude airspace,” AIAA Aviation ATIO, 2017, to appear. [Online].Available: http://weber.itn.liu.se/~valpo40/pages/nr.pdf