Creating and Comparing Source Models of UAS in Various Flight Patterns UAS Noise

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ABSTRACT

UAS, more commonly referred to as drones, are becoming a popular means of recreation, delivery, and even travel. They also have strong implications in terms of military applications, in terms of search and rescue, scouting, and working together with other UAS or manned vehicles in carrying out missions. For both commercial and private enterprises, drone noise can pose a problem in either annoyance predictions or detection. While research has been done on the noise generated by drones, unfortunately this research is limited, and the models associated with its prediction are lacking. In conjunction with Sinclair College in Dayton, Ohio, Air Force Research Laboratory has performed multiple measurements of UAS in order to better characterize drones as a noise source. Using a fly-through array as well as a circular ground arc and recorded at varying drone heights, good angular coverage of the noise source was generated. This paper attempts to use these measurements to accurately characterize the noise source for both stationary and rotating drones, as well as two drone sources interacting with each other. Being able to predict directivity and levels generated will lead to better model predictions. These source model predictions will then likely feed into new standards and regulations for commercial flights, such as number of deliveries per day in a residential area, or flight paths recommended for limited noise exposure. They can also be used in predictions of where a drone is coming from or what type of drone it is e.g. hex-copter vs. quad-copter.

1.0 INTRODUCTION

In recent years, usage of UAS, or more commonly referred to as drones, have seen a spike in usage, both public and private enterprises. For government entities, drones can be an effective method of communication and in resupply, along with other usages. On the commercial front, many entities are seeking to implement UAS as a means of delivering goods [1-5] or in private transportation [6-10]. Unfortunately, with increased implementation comes increased demand for understanding drones as a noise source. For the military, understanding drones via detection or classification can provide an edge in war. For local communities, being able to accurately predict noise levels will allow for decreased noise exposure, as well as inform commercial entities' potential practices to implement to optimize delivery of goods or personnel.

Commercial entities have been looking into developing new drones which are both quieter and more efficient [11-17]. They would love to be able to fly as much as possible, and noise may become a deciding factor. For larger UAS, one starts to get into the realm of small personal helicopter, which will be heavily regulated. Baylor university and USAFA have teamed up to investigate propellor blade design [18-20]. Each research group has noted the intricacies and difficulties of improving and accurately measuring the noise source [21-23]. Existing models for drone noise are unfortunately lacking [24].

At AFRL, two initial studies recently investigated drone noise sources as they flew through a square array. They showed that drone noise is not vertically symmetric, and that downwash can have a major impact on ability to measure noise below the source [25]. The other study focused on using machine learning to predict what acoustic qualities best predicted drone characteristics. It was shown that roughness and loudness correlated well to drone size [26]. These were the first measurements carried out and have been encouraging.

This paper is a follow-up to the fly-through measurement. It seeks to build on the knowledge gained from the fly-through and apply it to measurements carried out at the Sinclair Community College indoor flight hall. This measurement focused more on horizontal measurements and measuring differences between stationary and rotating drones. In addition, a second set of measurements was carried out in the same location with the same setup to compare a single drone to multiple drones. One of the overarching goals of each measurement is to develop a larger database of drone data, as it is also lacking.

While sources have been developed using the most recent measurement data, they are limited to below the source. They are also currently limited to stationary and rotational flight patterns. Due to lack of symmetry and scalability, it is still recommended to gather more data on flight patterns and drone types to increase the database. Multi-drone scenarios increase problem difficulty. Nevertheless, the measurements provide a solid baseline from which further validation and modelling can be done. This will in turn lead to a better understanding of the noise source for all flight maneuvers and increase ability to detect and regulate drones.

2.0 MEASUREMENTS

2.1 Equipment

For all three measurements described within this paper similar equipment was deployed. There were two main system types used for data acquisition: NI PXI systems and Remote Acoustic Acquisition System (RAAS) devices. Each system sampled at 50 kHz and was GPS time-synced for consistent analysis. The NI system was operated using the ALARMS (AFRL LABView Acoustic Recording Measurement System) program developed at AFRL.

At each measurement location, a GRAS 46A0 pre-polarized pressure microphone was deployed. These microphones have nominal sensitivities well suited for drone measurements, as they have a low noise floor relative to the measurement conditions. Microphones were placed at grazing incidence, as required. All microphones were also calibrated on-site to ensure fidelity.

2.2 Fairgrounds Flythrough Measurement

The first measurement performed was at the Montgomery County Fairgrounds in October 2022. This measurement focused on a fly-through array and is described more in detail in Rasband et. al.'s NOISECON proceedings paper [25]. While more information can be found there, the measurement schematic shown in Figure 1 highlights the measurement itself. The fly-through array was composed of 19 microphones. Other microphones were placed in the vicinity using RAAS devices.

This measurement was much smaller in terms of number of drones and was the group's initial foray into drone measurements. In total, 3 drones flew through or over the array. Some major takeaways include noting the difficulty of telemetry data acquisition as well as on-board collision detection countering fly-through speed. Future fly-through measurements are planned, including using a larger array and more drones.

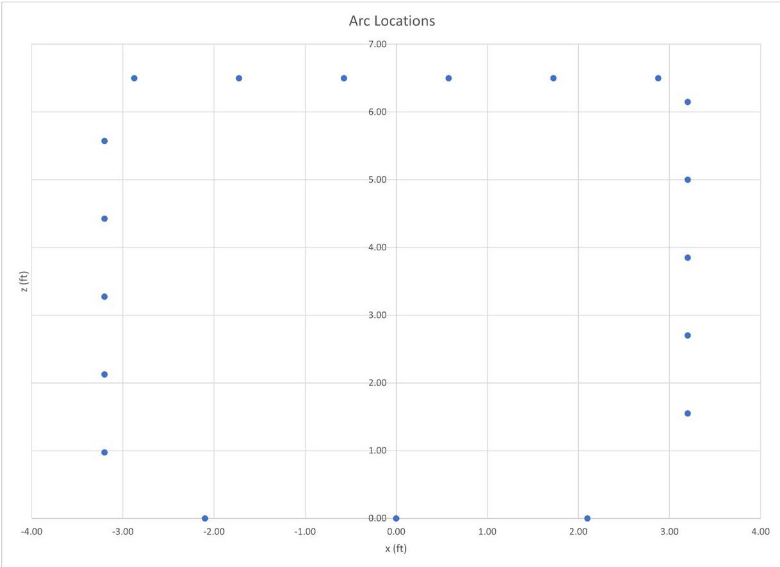

Figure 1: Schematic of sensor locations of the fly-through array. The drone would fly through the array at roughly one meter off the ground, or at locations above the array.

2.3 Sinclair Indoor Measurements

Two different measurements were carried out in the Spring of 2023 within Sinclair's indoor Flying Pavilion. The room is ideal for measurements, as it reduced potential wind-effects. The measurement setup for both measurements was the same, and the microphone placement schematic is shown in Figure 2. In addition to the shown microphone locations, sensors were placed in pseudo-random locations around the room using RAAS devices. The first set of measurements focused more on single UAS measurements, while the second set added multi-drone scenarios to the recording plan.

The primary array consisted of a circular arc array around a central location with a radius of 2 m with an angular resolution of 30°. GRAS 46AO microphones were lain on the floor at grazing incidence to the center of the array. Each microphone also was covered with a reticulated foam ball windscreen to potentially reduce effects of any downwash.

For these measurements, several drones were able to perform the following maneuvers:

- Hovering at a height of 1 m above the ground at a heading of 0°, 90°, 180°, and 270°.
- Hovering and continuously rotating clockwise or counterclockwise about the z-axis in the center of the array at 1 m above the ground.
- Repeating those four stationary measurements and one rotational measurement at 3 m and 5 m above the ground.
- Performing "hops," meaning they would quickly rise and drop a couple feet within the air.
- For some drones, performing the maneuvers listed above in tandem with another drone, however not centered in the array.

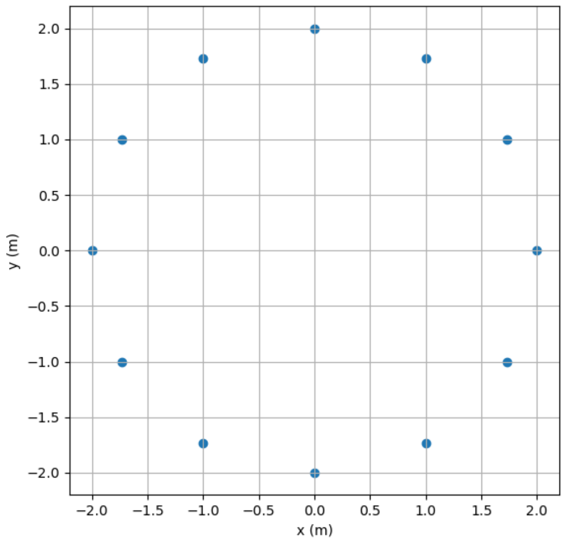

Figure 2: Site layout for main array at the indoor Sinclair measurements. The main array is a circular arc of radius = 2 m, with 30° angular resolution. The drone would hover or rotate at (0,0) at heights of 1 m, 3 m, or 5 m.

These measurements provide a rich dataset from which modeling and analysis can begin. Unfortunately, while drone movements are relatively precise, their exact locations were slightly variable. Particularly during continuous rotations, some UAS tended to deviate slightly from their central location as they rotated. This can lead to some errors and will be discussed.

3.0 ANALYSIS

3.1 Symmetry and Scalability

For most of the analyses in the paper, the plots are focused on the Parrot ANAFI USA. This is a medium sized quadcopter, and the analyses shown can be repeated for further drone types and scenarios. An image of this drone and the Parrot ANAFI AI can be seen in Figure 3.

Figure 3: Image of Parrot ANAFI USA (left). This is drone used for most of the shown analyses. On the right is the Parrot ANAFI AI. Images taken from https://www.parrot.com/en/drones/anafi

One of the first questions to ask for source modelling is where symmetry can be applied. Unfortunately, UAS are anything but symmetric, particularly in comparing the sides of the system to locations below or above it. Rasband et al. showed that for the fly-through measurement, spectra are quite different at locations around the drone [25]. These results are shown in Figure 4, taken directly from the proceedings paper. Downflow dominates low frequency noise for the microphone below the drone and seems to have ground effects prevalent in higher frequencies. Both the top and bottom of the array contain more energy at higher frequencies. There is some symmetry on the sides of the drone, but it is not such a simple system to be treated as a monopole.

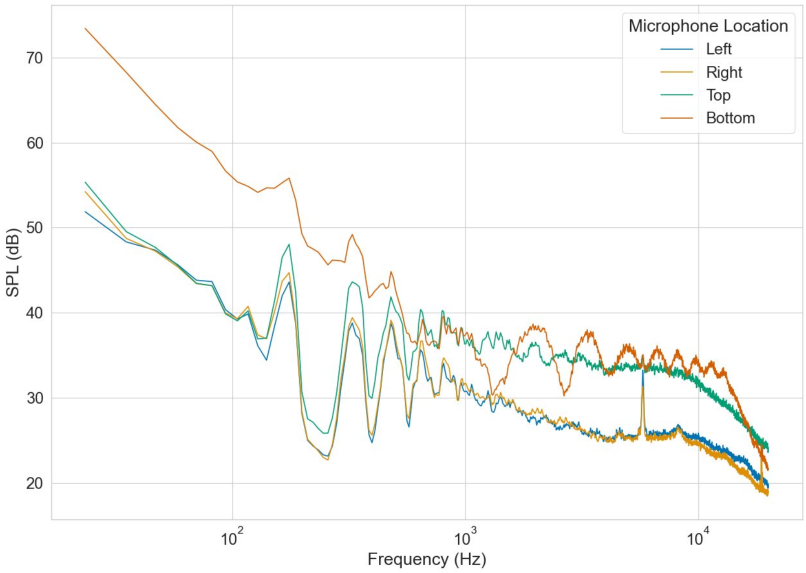

Figure 4: Narrowband spectra from microphones around the fly-through array from the Montgomery County Fairgrounds measurement for one quadcopter.

In order to better determine symmetry around the drone, one can look to the indoor measurements. Figure 5 shows the directivity pattern for the overall sound pressure level of the Parrot ANAFI USA drone. Directly in front of the drone the level tends to the highest, and there is not a majorly consistent pattern around the drone itself. There may be some variability due to inexact position in the center of the array. There is a roughly 5 dB spread from lowest angle to peak angle.

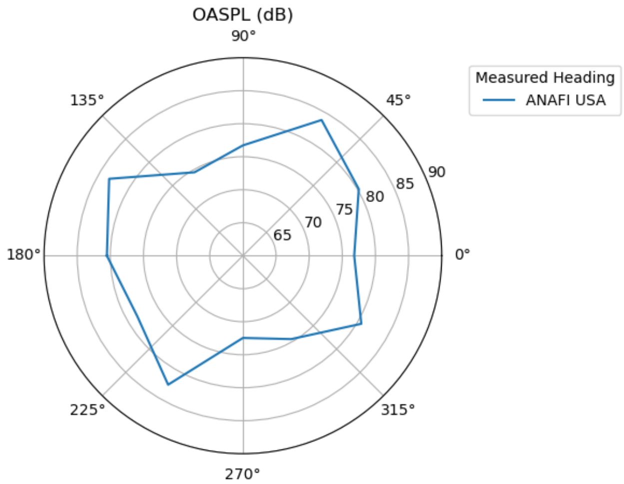

Figure 5: OASPL as a function of angle for the Parrot ANAFI USA drone. Measurement angles are relative to drone heading.

As with the fly-through measurement, spectra were calculated for each angle relative to the UAS heading and plotted in Figure 6. The levels for each direction are very similar, and to the naked eye are tough to discern. Consistent with the directivity plot, at 0° the levels are on average slightly higher than at other headings. It is not the authors' recommendation to use azimuthal symmetry in predictions where possible, although for a stationary measurement, particularly with more consistent drone telemetry information, this recommendation is subject to change.

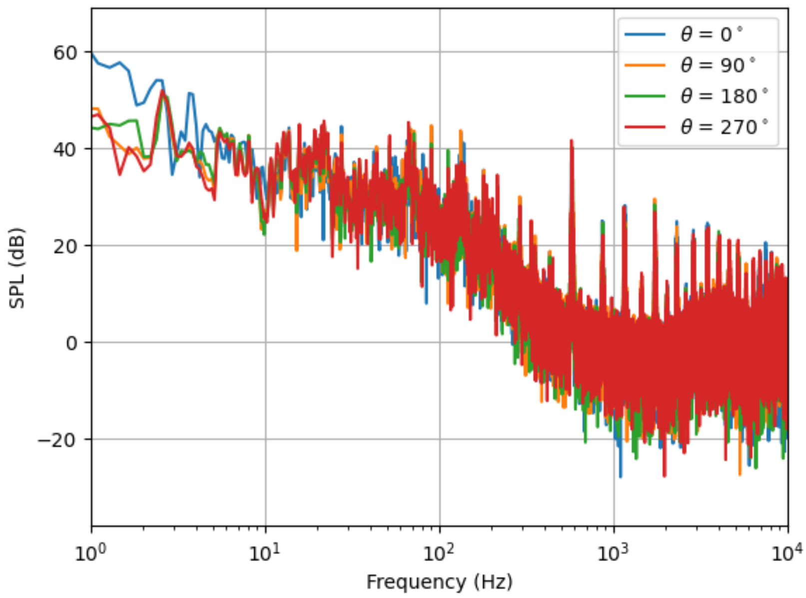

Figure 6: Spectra measured around the Parrot ANAFI USA drone at four angle relative to drone heading. Above 10 Hz, levels are relatively consistent.

For the measurement, each drone was placed at four cardinal headings, for each height. Due to sensor geometry, this should theoretically mean that the sensors are measuring the same configuration four times, albeit with a slightly different room geometry. By using these four measurements, one can determine measurement consistencies (or inconsistencies). Figure 7 shows these four measurements' overall sound pressure levels for the Parrot ANAFI USA. The red line (90° heading) has the largest difference in shape of the four, and this is likely due to deviation from the center location. The other three are similar in level and shape. It is worth noting that level deviations reach up to 5 dB at any angle, with worse angles having larger disparities. This result again highlights the importance of telemetry, as well as the difficulty in acquiring precise drone measurements. This will, however, not be as relevant at large measurement distances away from the source. Overall, it makes source creation less certain, and promotes further measurement.

While different in shape, both the ANAFI AI and ANAFI USA are designed by Parrot and are quadcopters. The USA weighs 500 g while the AI weighs 898 g. Figure 8 shows the directivity patterns for each drone around the array. They follow similar patterns but do not always share a consistent level disparity. Assuming required thrust scales with mass of the drone, one would assume thrust would be roughly 80% higher for the AI than the USA. Carrying that idea through to energy, that would not amount to large change in the acoustic level – roughly 5 dB. Due to drone design and blade pass frequency, sound pressure level scaling via weight seems flawed.

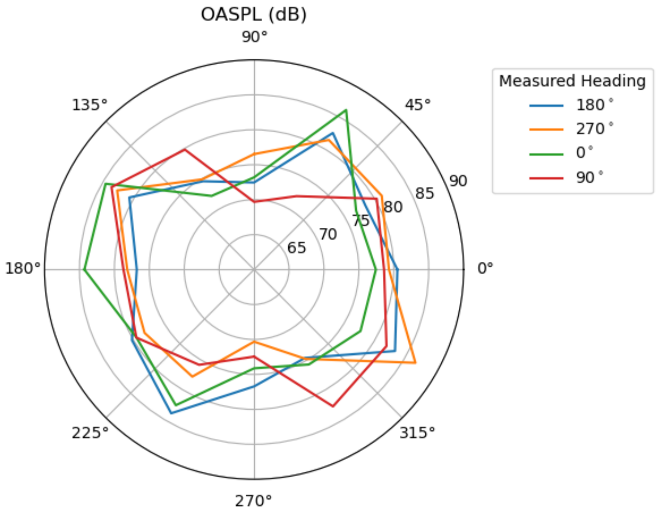

Figure 7: Directivity pattern measured at each drone heading relative to north. Each heading is then set with an effective directivity of 0° for comparison of measurement consistency.

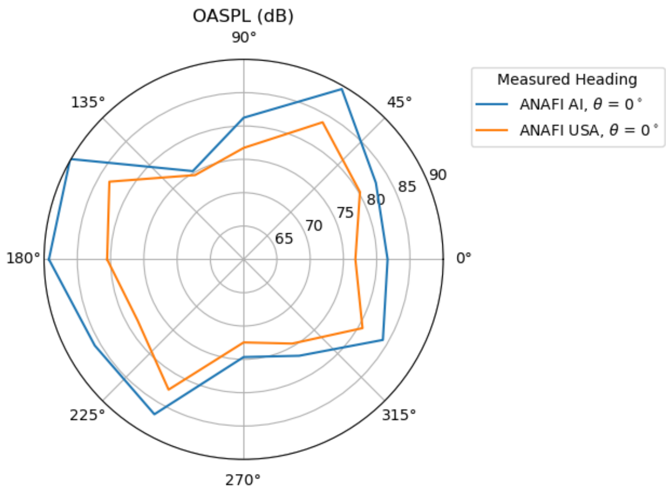

Figure 8: Directivity pattern comparisons of the Parrot ANAFI AI and Parrot ANAFI USA drones. The AI drone weighs roughly 898g while the USA weighs roughly 500g. Both are quadcopters.

Performing the same comparison for the AI and USA in spectral regime tells a better story. This is shown in Figure 9. The spectra created by the AI are on average higher level than the USA, but content itself is slightly different. This is likely due to blade pass frequency as well as drone geometry and shows, again, that scaling is not a great approach for accurate modeling of UAS. As a physical equation does not yet accurately characterize drone noise, developing a large database is valuable.

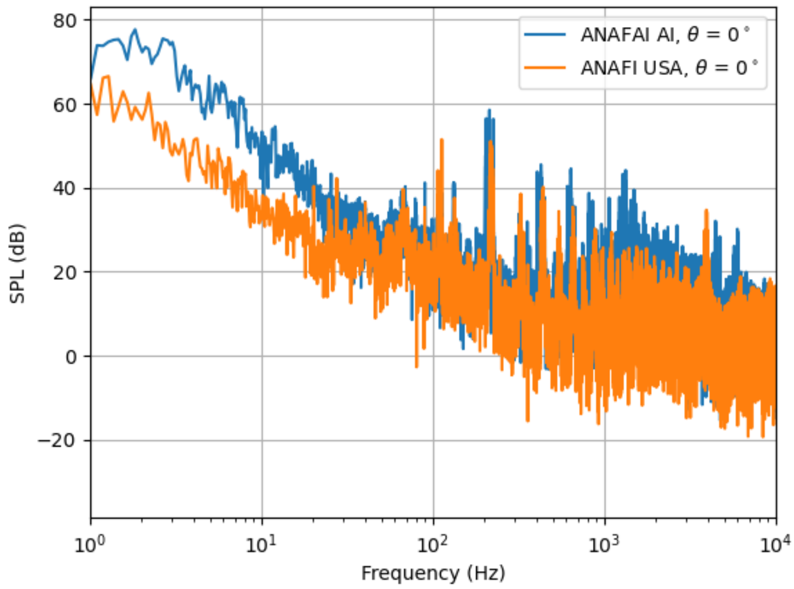

Figure 9: Narrowband spectra comparison of the Parrot ANAFI AI and Parrot ANAFI USA drones. The AI drone weighs roughly 898g while the USA weighs roughly 500g. Both are quadcopters.

3.2 Source Creation

Because drones lack symmetry and scalability, measured data can be used to create equivalent sources for UAS. For the measurements performed at Sinclair, only lower hemisphere predictions can be made, but this still covers a large majority of potential source-to-receiver angles in real-life scenarios. While a more complete source involves the full sphere, these half-sources will be invaluable in prediction and detection of various drones.

Sources are created via the following approach:

- Determine relevant levels and spectra at each measurement location.
- Scale these data to a distance of r = 1 m using a spherical spreading assumption.
- Interpolate levels around the hemisphere for desired source model.

For the levels measured at Sinclair, the data can be taken from Figure 10 on the left and scaled to fit the hemisphere shown on the right. There are some drawbacks to this approach. One of the major issues is in predicted values directly below the source. As seen from the outdoor measurement, levels below the drone are highly influenced by downflow. While much of this energy is removed by a-weighting, there remains more energy in the higher frequency bands. Interpolation of the measured points at Sinclair can miss out on this critical information.

A question to ask, and the authors are not currently suggesting a solution, is to whether effects of downwash should be included in an accurate characterization of the source. There are also issues with potential ground effects as all interpolated points were recorded on the ground. Further investigation and application of source models is required to provide a definitive answer for the best modelling techniques.

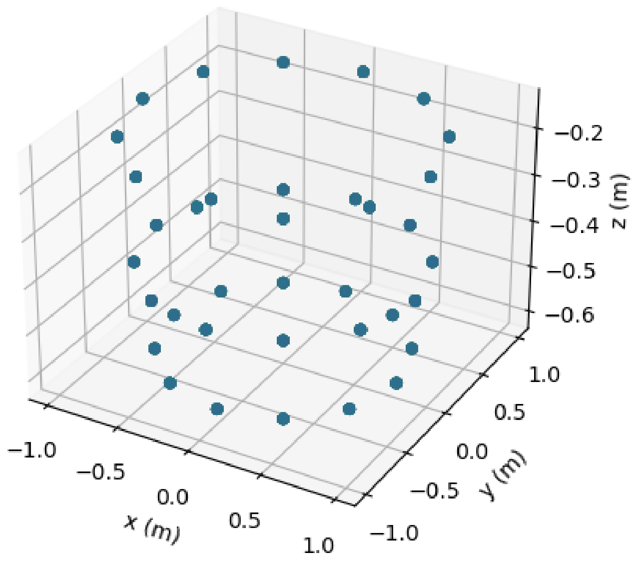

Figure 10: Scatter plot representing all measurement points recorded for each drone in the Sinclair indoor measurements scaled for source creation. By interpolating using the above points, hemispheres can be created to characterize the source.

For the Parrot ANAFI USA two source models are shown in Figure 11 and Figure 12. Figure 11 represents the A-weighted overall sound pressure level while Figure 12 shows the energy contained in the third-octave band centered at 200 Hz. It can be slightly difficult to discern what is shown in the source models, but they have high value. Each theta-phi combination can be propagated to any distance and should predict levels for whatever frequency band or overall level they represent. The a-weighted levels are much more symmetric than a no-weighting measurement, but again point to a potential limitation with predictions directly below the source. Further improved fly-through measurements will provide potential validation of the source models.

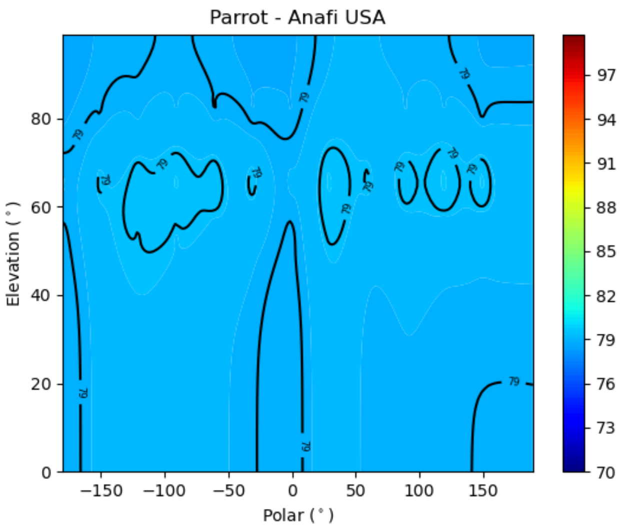

Figure 11: A-weighted SPL source model for the Parrot ANAFI USA drone. This color plot represents all angles below the drone.

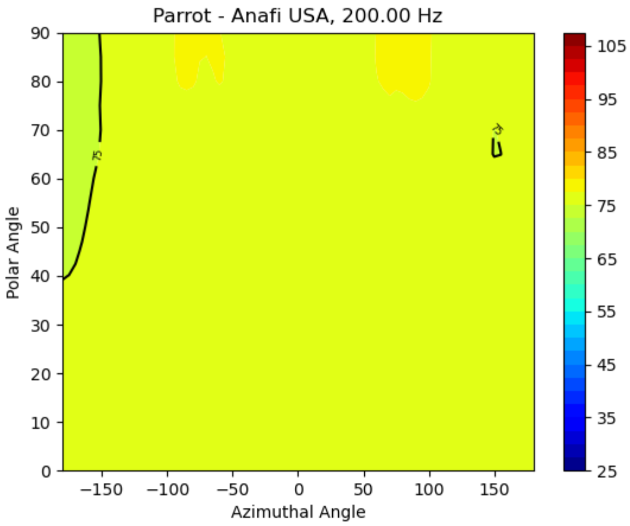

Figure 12: Like the A-weighted source plot, this plot highlights the one specific frequency band for the Parrot ANAFI USA drone. This highlights the source's ability to predict levels for any frequency band.

3.3 Rotation

In order to more accurately predict drone noise, one must also consider drone movement. The discussion in previous sections mainly focused on the UAS in a stationary hovering flight-pattern. Comparing rotational movement and static hovering gives insight into the importance of further developing source models to include predictions for drones performing maneuvers.

Just like the scalability comparisons, level and spectral comparisons can be made for a stationary drone and the same drone as it rotates. Figure 13 shows a directivity comparison of a stationary Parrot ANAFI USA and the same drone performing a clockwise rotation. As one might predict, the prediction over the course of the rotation shows more consistent, or less directive, levels around the source. On average, the levels are higher for the rotating drone than the stationary one.

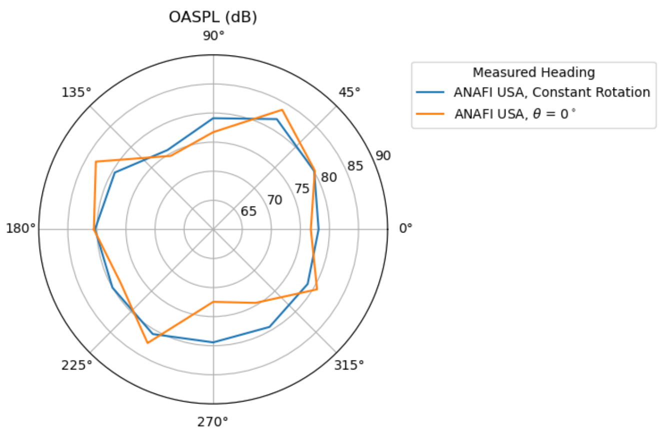

Figure 13: Directivity comparison of a stationary drone and the same drone continuously rotating about the z-axis in the center of the array.

The spectra in Figure 14 highlight some other differences between a stationary drone and a rotating one. The spectra for the rotating drone still contain peaks and valleys, but there is more energy around 100 Hz. With rotation, each rotor provides different levels or thrust, or in other words, have different blade pass frequencies. While this is not that novel of an observation, it points to the notion that a simple stationary measurement will not be able to accurately characterize the source alone.

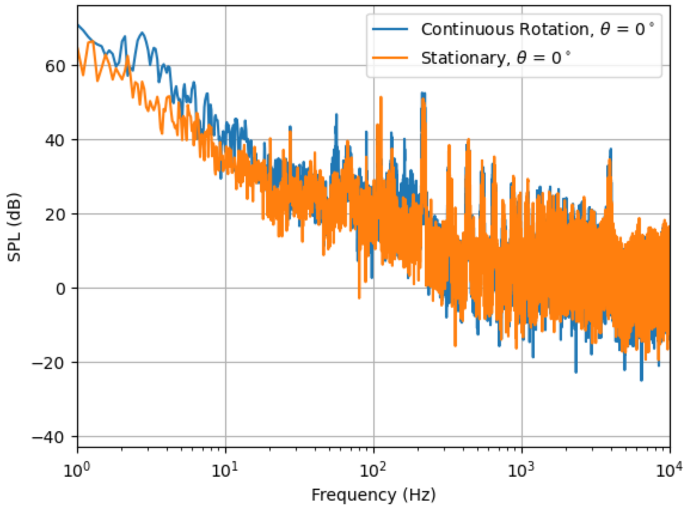

Figure 14: Narrowband spectra comparison of a stationary drone and the same drone continuously rotating about the z-axis in the center of the array.

As another attempt to compare data measured of a rotating drone and a stationary drone, one can use rough estimates of drone telemetry to derive angular data as if the drone were stationary. Doing this produces Figure 15. Consistent with the directivity patterns, the rotating drone overpredicts what the stationary drone would output. For conservative estimations, overpredicting is always good in terms of exposure, but it is less effective in detectability for receivers. However, overpredicting is better in avoiding detection, which can be quite valuable as well. The directivity pattern itself is also slightly different than what was measured.

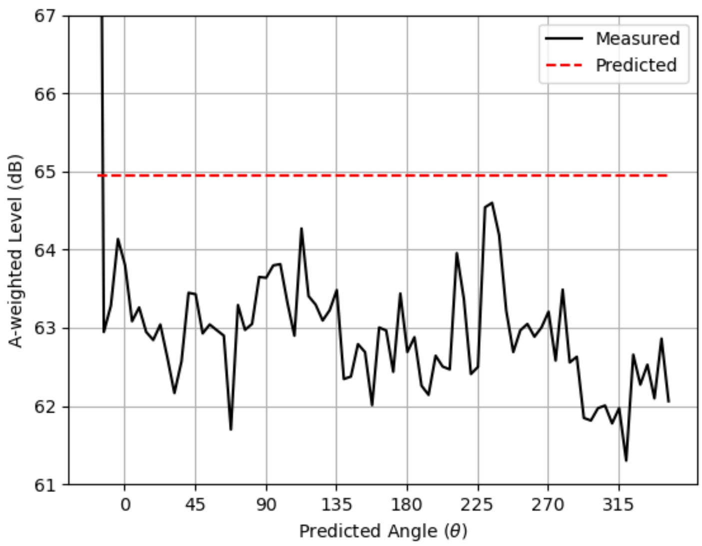

Figure 15: Using the continuously rotating drone, predictions are made of the levels at each angle of the array compared to a stationary drone. Predicted levels are 2-dB higher than measured levels.

3.4 Multi-UAS Scenarios

One of the more relevant scenarios that drones will fly in is as a fleet. Multi-drone scenarios increase the complexity of the problem, particularly if they are performing various flight maneuvers. In this measurement's case, two drones were flown roughly above either side of the circular array and performed various maneuvers. In Figure 16 the spectral comparison of two stationary drones versus one are shown. There is no level scaling, and several angles of the single drone are shown for easier comparison.

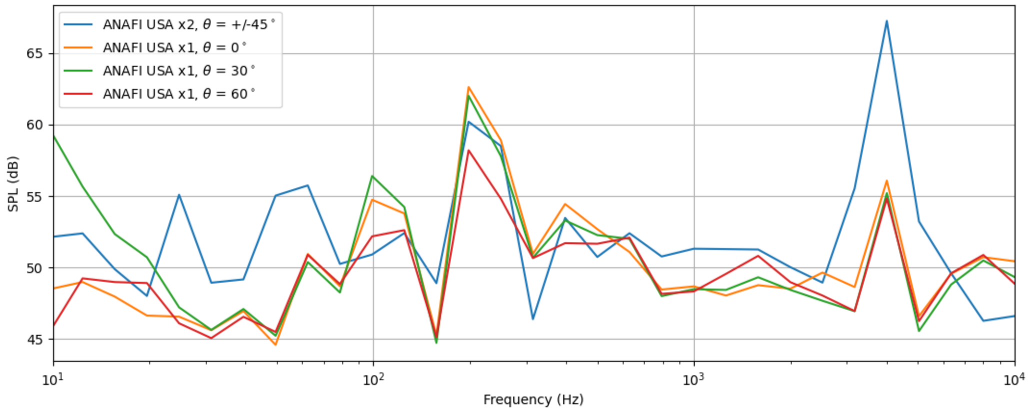

Figure 16: Spectral comparison of two drone sources versus one. For the single drone source, several angles are shown to give a rough comparison angle of the two-drone configuration.

The major disparity in the spectral content is at around 5 kHz. This is likely the dominant blade pass frequency. It is also interesting that there is more low frequency content (<100 Hz), likely highlighting the more complex nature of the airflow created from two sources. Above 500 Hz, the spectrum for the two-source configuration is also flatter, pointing to complex interactions. Looking at the overall sound pressure level, while accounting for distance with spherical spreading, the difference in level is around 4 dB. This is close to incoherent addition (3 dB), and does seem within the range of error, but is inconclusive. Using the source models provides the same estimation, as the sources are created via the measured data. Increasing the database of multi-drone configurations, performing various maneuvers, will also be valuable.

4.0 CONCLUSION

At the risk of repetition, drone noise is complex, and predictive models are limited. Sources created using the data gathered at Sinclair will provide a base from which further validation and measurements can be done. While source models are limited, they show some of the relevant problems of drone noise, namely lack of symmetry or scalability, and the effects of performing flight maneuvers. Adding multiple drones to the scenario increases prediction difficulty. Overall, there is still much to be done to improve predictive capabilities as well as ability to accurately detect UAS.

Different approaches can be used in detectability, such as using machine learning in conjunction with various acoustic qualities to predict drone types/maneuvers. For modeling however, continued measurement endeavors to increase drone source information databases are vital, particularly for drones performing various maneuvers. In addition, performing human perception studies can be used to further determine the most efficient way to improve understanding. Regardless of what is lacking, these source models still provide a firm foundation for predictions and validation. Using the same approaches taken here, further source creation can be performed, and later validated.

5.0 ACKNOWLEDGMENTS

The words written in this paper are the author's views, and do not necessarily reflect the views of the United States government. This document was cleared for public release on 24 August 2023 with a reference number RH-23-124673.

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