Project 053 Validation of Low Exposure Noise Modeling by Open-source Data Management and Visualization Systems Integrated with AEDT

Stanford University

Project Lead Investigator

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University Participants

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- PI(s): Prof. Juan J. Alonso
- FAA Award Number: 13-C-AJFE-SU-022
- Period of Performance: October 1, 2020 to September 30, 2021
- Task(s):
    1. Complete the Metroplex Overflight Noise Analysis (MONA) prototype, including Aviation Environmental Design Tool (AEDT) integration
    2. Validate and verify AEDT noise predictions in DNL 55–65 dB areas
    3. Develop data science formats and perform scientific computations for large-scale airspace analyses
    4. Investigate viable alternative approach routes into the San Francisco Bay Area metroplex

Project Funding Level

Year 2 of ASCENT Project 53 has been allocated FAA funds in the amount of $400,000. Cost sharing in excess of this amount has been identified from various sources. Mr. Thomas Rindfleisch is contributing all of his time, uncompensated, and Mr. Donald Jackson is also contributing part of his time, uncompensated, to the project. In addition, contractor costs for the development of the MONA project website, the cost of support for undergraduate students and summer interns, and some equipment purchases (including installation costs) are also being used to generate cost sharing for this project. During the first 18 months of this project, more than $850,000 of cost sharing had already been accounted for.

Investigation Team

The investigation team consists of the faculty, graduate and undergraduate students, and collaborators listed below with their respective areas of expertise/contribution:

1. Juan J. Alonso (PI, Stanford Aeronautics & Astronautics): Overall responsibility for the project and its technical and administrative elements
2. Nick Bowman (Graduate Student, Stanford Computer Science): MONA project cloud infrastructure, cloud-based execution of AEDT analyses, and Apache Kafka-based data collection (Jan. 1–Aug. 31, 2021)
3. Brynne Hurst (Graduate Student, Stanford Computer Science): Flight trajectory database analysis and synthesis (Jan. 1–Mar. 31, 2021)
4. Donald Jackson (Collaborator, Independent Consultant): Overall MONA project infrastructure (servers, databases, hardware/software monitoring), geographical information systems (GIS), web-based visualization deployment, and technical guidance (full period of performance)

5. Priscilla Lui (Co-term Student, Stanford Computer Science): Real-time sound-level monitor (SLM) software, metrics, and raspberry Pi connectivity (Jan. 1–Jun. 30, 2021)
6. Vikas Munukutla (Graduate Student, Stanford Computer Science): Automation of AEDT analyses via generation/query of input/output databases on the cloud (Oct. 1–Dec. 31, 2020)
7. Chetanya Rastogi (Graduate Student, Stanford Computer Science): Overall database infrastructure improvements and noise monitoring/filtering software (Oct. 1–Dec. 31, 2020)
8. Thomas Rindfleisch (Collaborator, Stanford University Emeritus): Noise monitoring and filtering, aircraft trajectory collection/processing, and visualization (full period of performance)
9. Aditeya Shukla (Undergraduate Student, Stanford Aeronautics & Astronautics): Artificial intelligence (AI)/machine learning (ML) classification of aircraft trajectories and real-time SLM software (full period of performance)

Project Overview

The Metroplex Overflight Noise Analysis project (MONA) was initiated to provide real-time and objective data, analyses, and reports to key stakeholders and policy makers to mitigate the noise impacts of the deployment of new NextGen procedures. This system (a) collects and archives air traffic data using a network of antennae and receivers, (b) analyzes noise impacts using a variety of metrics, (c) visualizes resulting large-scale datasets, and (d) uses a network of sound-level monitors to enhance the quality of noise predictions. The goal of this ASCENT project is to improve upon the noise predictions of MONA through tighter integration with AEDT. In particular, our work is focused on the following three tasks: (1) integrate and automate AEDT's noise analysis capabilities, (2) validate and verify (V&V) AEDT's noise predictions in DNL 55–65 dB areas, and (3) propose software engineering/architectural choices for future AEDT development to enhance usability in multiple workflows, including API formulation, visualization interfaces, resilient data acquisition and storage, and cloud computing.

The expected benefits of this project mirror the tasks mentioned above, including (a) the ability to automate complex noise analyses in metroplexes so that they are available in near-real time after the preceding 24-hr period, (b) a better understanding of the accuracy of AEDT's current noise models in low-noise (DNL 55–65 dB) areas and the reasons for discrepancies (if any) in existing predictions, and (c) recommendations for software developers on flexible architectures and APIs for AEDT to make the tool more versatile and generally applicable. AEDT predictions are built around the policy context of an average annual day. All of the V&V results produced and shared by the MONA team will be focused on a cumulative daily basis for which flight track data are directly collected.

Background and Previous Accomplishments

The MONA project started approximately three years ago with the main objective of providing real-time and objective data, analyses, and reports to key stakeholders and policy makers to help in mitigating noise impacts from the deployment of new NextGen procedures. Since then, we have developed and deployed a system that (a) collects, archives, and makes available air traffic data using a series of networked antennae and receivers 24/7, (b) analyzes noise impacts using a variety of metrics (based on both a MONA-developed noise prediction tool and the noise prediction tools within AEDT), (c) visualizes resulting large-scale datasets in a simple, user-friendly fashion using both a bespoke website and Uber's kepler.gl and deck.gl large-scale data visualization toolboxes, and (d) has deployed a small network of low-cost, Stanford-owned sound-level monitors scattered across the Bay Area and has included data from noise monitors deployed by San Francisco International Airport (SFO) to cross-calibrate measurements by MONA and SFO monitors, collect noise measurements over a broader geographic region, and enhance noise predictions so they describe exactly the actual noise levels experienced.

The longer-term objectives of the MONA project are to (a) ensure the validation and verification of all noise predictions provided by AEDT or other tools for areas near the airport and areas further away from the airport, (b) achieve full automation of complex noise analyses in regions around airports in the United States, including AEDT-based noise predictions, (c) make all results web-accessible for in-depth interpretations of historical and proposed changes, (d) eventually study potential alternative traffic patterns in complex airspace to mitigate aviation environmental impacts, and (e) export the proven and validated MONA technology to other airport regions via open-source software/hardware.

At the present time (December 2021), the MONA software has achieved a number of significant objectives that well position the team to achieve the work described in this grant proposal. First, MONA has deployed a small network of ADS-B/MLAT antennae, and the necessary software has been completed to merge data streams from all of these antennae including de-duplication of sightings, identification of aircraft equipment and routes flown, physical interpolation of data missing from joint observations, and archiving (in appropriate database formats) of information collected for successive analysis. Second, MONA has achieved a level of integration with FAA's AEDT software that enables fully automatic processing of noise exposure

at arbitrary receptor locations for arrival routes into the San Francisco Bay Area airports. Third, MONA has incorporated measurements from networked sound-level monitors into the system via the Apache Kafka system and has developed and validated approaches for non-aircraft-noise filtering (of raw noise data) based on digital filtering, aircraft position information, and automated identification of background noise levels that have been validated and verified.

Finally, over the past year, we have continued our efforts to interface the above-described MONA software modules with the kepler.gl open-source visualization framework, developed by Uber, to be able to visualize and animate aircraft positions and paths, noise predictions, various routes and procedures, etc., in order to better communicate the results of our work (see Figure 1). A preliminary version of the MONA website, which provides access to and visualization of the same information for a less experienced user and leverages the deck.gl library, has also been created (see Figure 2). Furthermore, our capabilities now allow us to compare traffic and noise patterns for multiple days (see Figure 3).

Figure 1. MONA visualization (using kepler.gl and deck.gl) of traffic patterns in the San Francisco Bay Area, including a 24-hr view of aircraft traffic patterns. Trajectories are colored by altitude, with purple/magenta indicating low altitudes and blue indicating high altitudes.

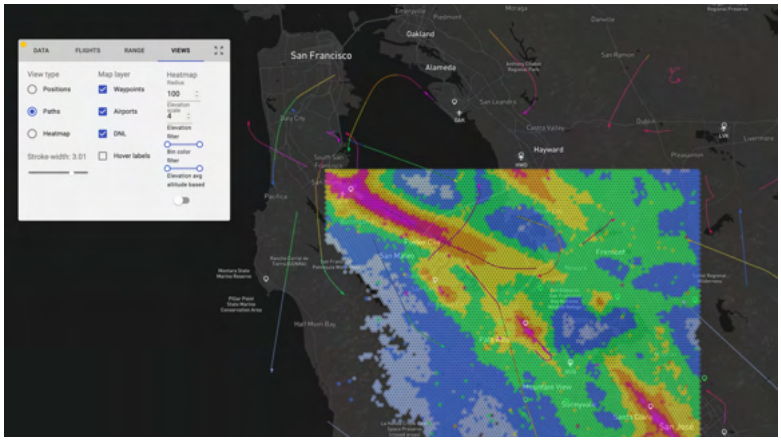

Figure 2. Current MONA web-access prototype for real-time aircraft location and 24-hr DNL contours.

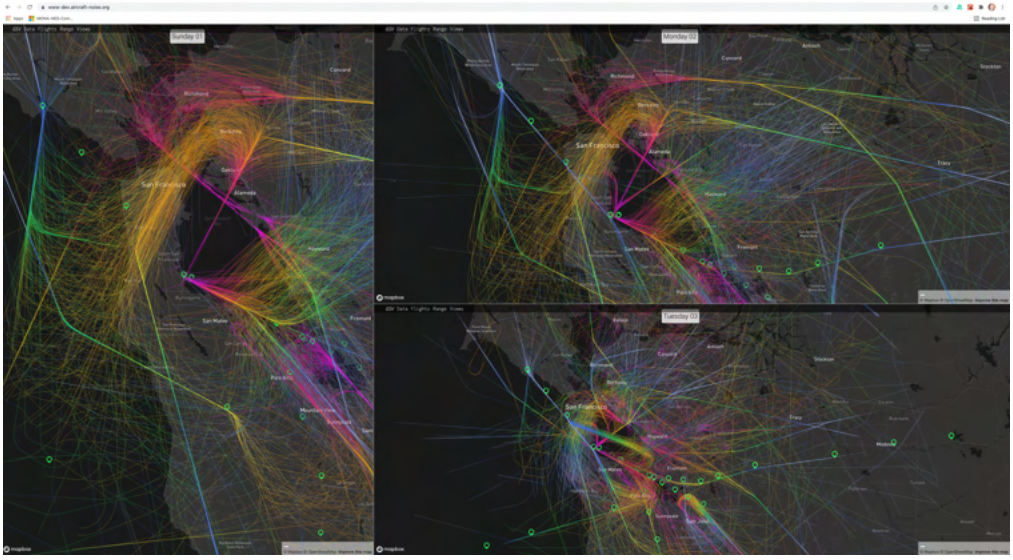

Figure 3. Comparative analysis of San Francisco Bay Area traffic patterns on different days obtained fr visualization system.

Task 1 – Complete the MONA Prototype, Including AEDT Integration
Task 3 – Develop Data Science Formats and Perform Scientific Computing for Large-scale Airspace Analyses

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Given that the vision of MONA is to make 24/7 aircraft noise information available through a simple visualization interface, predictions of aircraft noise are a fundamental component of the overall effort. We have begun to validate noise predictions with data collected from strategically located, Stanford-owned and SFO-owned, sound-level monitors (SLMs) whose raw sound level data has been appropriately filtered to eliminate non-aircraft noise sources. This section focuses on the development and completion of the first MONA prototype, including hardware, software, and data formats (corresponding to Tasks 1 and 3 of this Annual Report), with a description of our progress on integrating AEDT as seamlessly and tightly as possible.

The automation of the entire workflow has required the implementation and automation of a number of key steps, including:

1. Starting from a set of MONA-acquired and preprocessed flight paths and associated aircraft equipment for the previous 24-hr period, the necessary AEDT inputs are generated in an SQL study database that can be later consumed by AEDT. The input database must contain the actual location and three-dimensional geometry of the aircraft flight profile as a function of time, the specific aircraft equipment, and other auxiliary parameters needed for the analysis.
2. The setup of a noise analysis in AEDT, including all of the necessary metric descriptions, receptor locations, annualizations, and additional input data, must be automatically generated and included in the input study database as permitted by AEDT v3.
3. Automated execution of arbitrary analyses can then be pursued to allow AEDT to be run through a batch process without user intervention. For this batch process, we have developed and improved a cloud-based solution that automatically fires up a cloud instance, sets up the necessary communication structures, runs the AEDT study, and returns the study results to the computer executing the study.
4. A module for extracting the computed metrics and their spatial distributions for arbitrary metric computations has also been developed. Interactions with the output of AEDT analyses occur directly through the SQL output study database, which contains and stores all of the necessary information.

During the period covered by this report, we have continued to build upon the progress made during the first year of the grant to deploy a fully operational prototype that has been used to (see Task 2 progress) carry out preliminary comparisons between SLM experimental data and AEDT predictions for arrival routes into SFO. Our automation methodology is based on our own cloud-based AEDT execution environment (which we have named **`raedt`** for *remote* AEDT) that works on Google Cloud Project instances of arbitrary size (number of processors, memory, etc.). The reader is referred to the Project 53, 2020 Annual Report for additional details regarding **`raedt`**. The remainder of this section gives a detailed description of the current state of the MONA system and our efforts over the period of performance to complete our proposed tasks.

Overview

As a consequence of community complaints regarding changes in air-traffic patterns over the San Francisco Bay Area metroplex during the past five years, it has become increasingly clear to the PIs that there is a dearth of high-quality aircraft noise data (from measurements and/or predictions), particularly for areas away from the airport boundary that have not traditionally been the main focus of noise complaints. In addition, through a number of community interactions, we have also become aware of the difficulties involved in relating potential flight route changes to noise impacts on the ground. This lack of actionable data and methods for effectively communicating with broad and often nontechnical communities led us to develop the MONA system. The MONA project set out to achieve the following objectives:

- To measure and analyze ground noise data generated by aircraft overflights in complex metroplex situations,
- To create, curate, and archive experimental datasets that can serve as an openly available database for verifying and validating improved noise prediction methods,
- To fully automate noise analyses based on the AEDT without the need for user intervention, and
- To share key analysis results with broad communities of stakeholders through compelling and interactive visualizations.

Once ASCENT 53 started, the main goals of MONA were set up as research tasks to be accomplished, two of which are described in this section of our annual report. Our hope is that experimental and computational studies conducted using the MONA system can inform decisions involving aircraft noise, aircraft routes, and potential impacts of the FAA's NextGen procedure changes on overflown communities at varying distances from the airport. We also hope that the open-source nature of the design, software, and hardware of the MONA system can be easily replicated in many metroplexes around the world at relatively low cost, to provide a source of high-quality data to inform conversations and future steps.

A secondary goal of the MONA project is to share, through analyses and visualizations, key results with broad communities of stakeholders who generally lack access to this kind of data. In this section of the annual report, we describe the MONA system architecture, its design, and its current set of capabilities.

Data Measurement and Collection

To quantify and analyze the noise impact of aircraft overflights, we need to know both the trajectories of aircraft flights and the resulting ground noise. To that end, we collect the following types of data:

- Aircraft flight profiles (via ADS-B) and speed over ground
- Sound levels,
- Flight and aircraft metadata,
- Air traffic routes and procedures, and
- Wind and weather conditions.

To date, MONA ground stations have been deployed primarily at the houses of interested and motivated members of the public, with costs borne by those volunteers, including the PIs. In the following subsections, we describe the key elements of the MONA ground station and measurement and collection system.

Sensor Controller

Measurements of sound levels and reception of ADS-B transmissions require a distributed network of sensors mounted outdoors throughout the geographic region of interest and the means to access/retrieve these data. For the MONA project,

we have implemented a series of sensor controllers, incorporating a single-board computer (SBC) and a global positioning system (GPS) receiver (to provide highly accurate time pulses and three-dimensional (3D) location data), with both network connectivity and power via Power over Ethernet (PoE). These components are integrated within a waterproof/weatherproof enclosure to support long-term outdoor deployments. The sensor controller runs a network time protocol (NTP) daemon, configured to utilize the pulse per second (PPS) output of the integrated GPS receiver, to provide a Stratum-1 time base and to minimize time differences between our distributed sensor network. We have developed software to collect each sensor output and transmit/publish the output in real time to a centralized aggregator hosted in a data center via the internet. A single sensor controller is capable of simultaneously supporting both ADS-B reception and sound-level monitoring. Because of the long-term field deployment of the sensors, autonomous operation and secure remote access are essential. Remote access is accomplished by using reverse-SSH tunnels established by the sensor controller to another server, and whenever possible, maintenance of the sensor host is performed via Ansible configuration management scripts through these SSH tunnels.

Figure 4 shows our standard MONA ground station installation and a view of the sensor controller components inside a weatherproof enclosure.

Figure 4. Sensor controller rooftop deployment with ADS-B and a SLM (left). Sensor controller components (right).

ADS-B Receiver

The primary ADS-B receivers in the MONA network are based on the PiAware/`dump1090-fa` software from FlightAware, with a standard RTL-SDR dongle (inside the sensor controller enclosure in the right panel of Figure 4), connected to an ADS-B antenna affixed to the same enclosure. Every second, the JSON output of `dump1090-fa` is captured by a software daemon, and the ADS-B messages within are minimally processed and then transmitted/published to our centralized aggregator, implemented as an Apache Kafka cluster. The collector daemon also publishes receiver metadata (including GPS location and sensor controller status) to the same aggregator. For sites that prefer the commercial, fully integrated Radarcape ADS-B product, we developed a variant of the collector daemon to capture and transmit messages and metadata from this receiver.

Sound-Level Monitor (SLM)

We used SLMs (Convergence Instruments [CI]) connected via USB to the sensor controller to measure noise levels. Another software daemon captures the SLM outputs and transmits/publishes the outputs in real time to a centralized server, again using Apache Kafka. Recent models of the CI SLM optionally support a USB-audio feature, providing access to the sampled audio waveform, which we selectively save/transmit in order to capture both noise metrics and audio recordings of aircraft overflights. The SLM collector daemon publishes SLM metadata (including SLM configuration, GPS location, and sensor controller status) to the central server.

Flight and Aircraft Metadata
Aircraft ADS-B positions alone do not provide a complete description of the flight. Important/valuable missing metadata include:

- Airport(s) of arrival and departure,
- Assigned runways,
- Air traffic control (ATC)-assigned routes and procedures, and
- Airframe, engine, and ownership.

Arrival and departure airport information can often be obtained via external API access or can be inferred by comparing the first or last known ADS-B position with airport/runway locations. ATC-assigned procedures, routes, and runways can be inferred by comparing the aircraft's trajectory to the locations (and sequence) of waypoints and runways. An area of ongoing development is the integration/incorporation of the FAA System-Wide Information Management (SWIM) data feeds, in order to fuse this rich source of metadata with ADS-B aircraft positions. SWIM messages are ingested into Kafka topics, providing reliable reception of these real-time data feeds. Airframe, engine, and ownership information are obtained by joining the aircraft's ICAO24 unique identifier (included in the ADS-B message) with aircraft registration datasets, including the FAA Aircraft Registry (for U.S. aircraft) and OpenSky's Aircraft Metadata Database (for others).

Air Traffic Routes and Procedures
The FAA Coded Instrument Flight Procedures (CIFP) is one definitive source for air traffic route and procedure information, which we download, parse, and archive monthly. The CIFP provides airport, runway, and waypoint locations that can be used for geospatial processing and queries. Flight procedures are converted to a directed-graph representation and are then processed using both standard and custom graph algorithms.

Wind and Weather
ADS-B messages usually provide the aircraft's ground speed, but not its airspeed, which is an important factor for predicting noise. We obtain wind speed and direction measurements from the National Oceanic and Atmospheric Administration (NOAA) High-Resolution Rapid Refresh (HRRR) dataset, and in conjunction with the ADS-B-provided ground speed and heading information, we estimate the net airspeed, which is used to define the specific aircraft trajectory for noise prediction.

Data Collection, Archival Storage, Access, and Management
Real-time ADS-B messages, SLM measurements, and SWIM data feeds are received and stored by a distributed-event streaming platform implemented using Apache Kafka. These streams are processed and subsequently ingested into a Postgres database, augmented with both PostGIS (supporting geospatial queries) and TimescaleDB (supporting very large time-series tables). ADS-B messages from multiple receivers are de-duplicated and segmented into flights, and relevant metadata are added. Trajectories are included in each flight record/row, encoded as PostGIS 4D LineStrings, which enables arbitrary spatiotemporal queries supporting statistical analyses on vast numbers of flights over arbitrary time periods. In our work, we often need to know the point, distance, and/or time of closest approach (PCA, DCA, and TCA, respectively) of an aircraft trajectory with respect to a location of interest (LOI) such as the position of an SLM. PostGIS queries can dynamically compute, filter, and return these values for any stored flight trajectory and LOI combination. Visualization of a full day of flights, including each aircraft position over the entire San Francisco Bay Area, requires low-latency access to thousands of flight records, which contain millions of positions. Thus, the ability to rapidly sequence/step/animate through a range of dates is important tool to understand flight traffic changes over time. Local access to these data is key for reasonable performance, and an optimized binary representation of a trajectory is included in the database to minimize visualization processing delays. MONA applications and services can use/access real-time data streams and/or historic data in the database as needed.

Data Processing and Analysis
The raw data acquired by the MONA system must be processed before it can be used as input to our analyses and to compute statistics of the collected information. This section describes some of the data analyses we have automated in MONA. Once aircraft trajectories and measured noise have been captured, stored, and made available for future use, we process, analyze, quantify, compare, categorize, and summarize the noise impacts.

Attribution of Sound Levels to Aircraft Overflights

The sound-level measurements obtained both from MONA SLMs and other providers (such as SFO's sound monitoring stations) include sampled aggregate sound power levels generated from every source, but only the noise resulting from aircraft overflights is relevant to our research. A number of techniques for attributing sound peaks to aircraft are described in the literature. Particularly relevant examples include threshold-and-duration methods, directional and/or arrayed microphones, and spectral identification/categorization. Based on our experience, we have identified an effective methodology, which we have termed "Determined Aircraft Position/Location for Aircraft Noise Extraction." (DA-PLANE). This algorithm involves computing the time and distance of an aircraft's closest approach to the SLM location (from ADS-B trajectory data), which gives the estimated time of arrival of the aircraft sound peak maximum at the SLM. Then, we use time-series filtering and analysis to locate peaks above the time-varying background in the sound profile that may have been caused by aircraft overflights. These peaks are time-matched with the closest approach data to isolate and identify sound peaks resulting from specific aircraft. The net profile amplitudes of isolated peaks above the background are then analyzed to extract desired noise metrics for each identified overflight event. Other implementations of this technique include those of Harding and Ferrier and Giladi (see references). In the MONA system, the maximum $LAeq_{1s}$ value and SEL metric are extracted and stored in the database, with relations to both the flight (aircraft) and SLM (measurement) location.

Metric Computation

With aircraft trajectories encoded as geospatial datatypes and measured noise metrics attributed to specific aircraft flights and precise locations, we compute standard noise metrics such as the number above noise level, DNL/CNEL, time above noise level, and background level. Non-noise metrics such as overflight counts per day (within a distance or range) are also computed.

Geographic Aggregation of Metrics

It is desirable to analyze both aircraft overflight counts and noise metrics over aggregated geographic areas to estimate annoyance, health, and other impacts on affected populations. These aggregation processes can be performed for either civic regions or grids, which are described below and illustrated in Figure 5.

- Civic regions: City, county, and U.S. congressional district boundaries are published in common GIS formats, which we use in conjunction with PostGIS and client-side GIS software libraries to aggregate and report metrics by civic region.
- Grids: Aggregation over a regular grid is a powerful technique for representing metrics with uniform granularity over a geographic area. We use the H3 hexagonal hierarchical geospatial indexing system in a variety of resolutions (sizes) as a standard, regular, geometric grid defined for the entire Earth. H3 hexagon grids are fused with other geographic data sources; for example, we have computed population count estimates for H3 hexagons by apportioning U.S. Census block population data by the block boundary's percentage containment within the hexagon. The resulting population count of each hexagon enables weighting of metrics aggregated per hexagon by the number of people impacted.

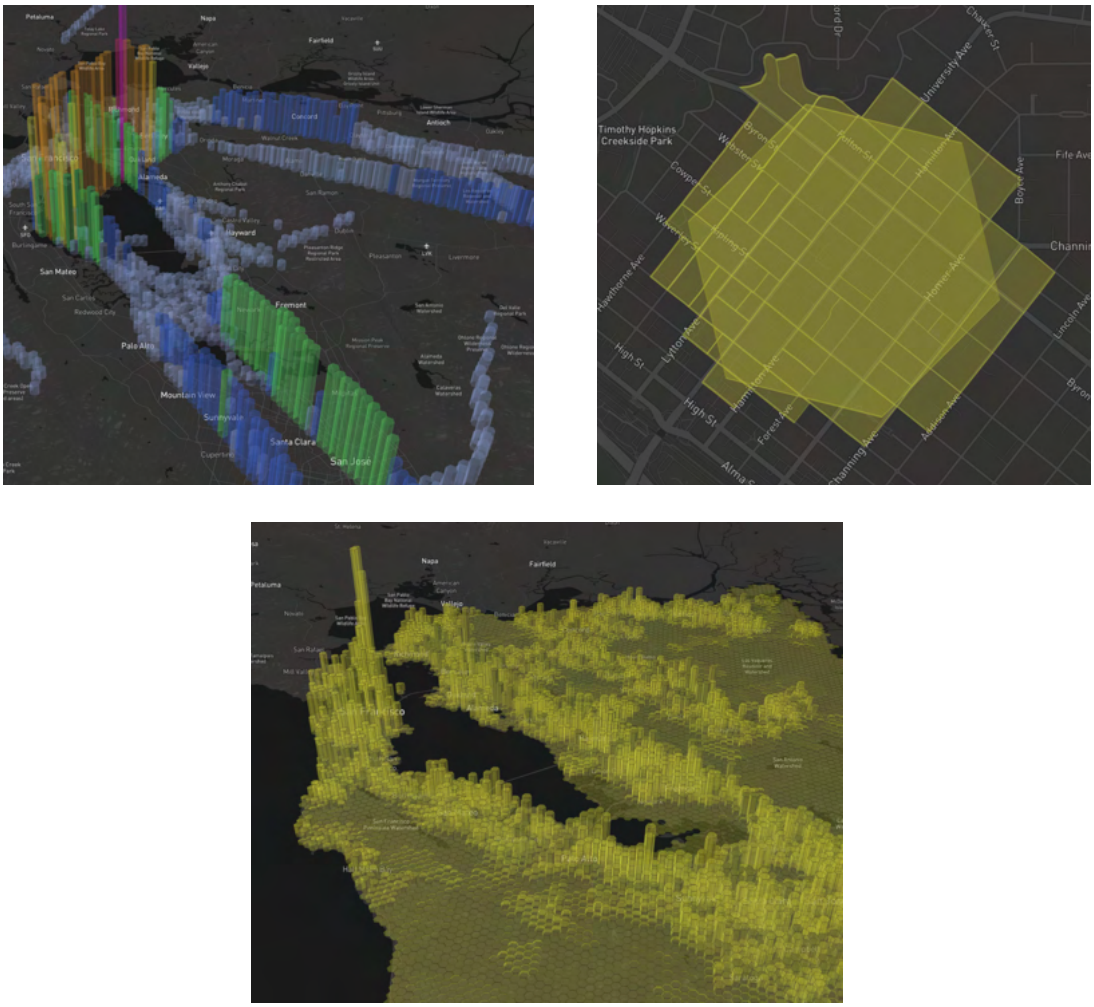

Figure 5. Full-day overflight count by hexagon (top left), apportioning the census-block population to a hexagon (top right), and population per hexagon in the San Francisco Bay Area (bottom).

Aircraft Noise Prediction It is infeasible to deploy SLMs with sufficient number and geographic density to obtain measured noise throughout an entire set of geographically connected airports (cost and logistics being two significant constraints). However, it is feasible to capture all flight traffic via ADS-B by deploying a relatively small number of receivers over the metroplex. Ideally, we could use the collected trajectory data to predict the noise generated by each and every aircraft on a fine-grained receptor grid to estimate noise metrics across the entire region of interest.

The FAA's AEDT is the required software application for assessing U.S. regulatory actions related to aircraft noise and emissions. Our (aspirational) goal is to run AEDT predictions for every aircraft flight across the San Francisco Bay Area each day and aggregate the resulting predicted noise metrics to provide quantified noise impacts across the entire metroplex as a function of location and time.

To this end, we are working to:

- Automate AEDT study creation, execution, and metric result extraction,
- Accurately model AEDT flight trajectories using ADS-B data, and
- Evaluate and compare AEDT's noise predictions to measured noise levels, in a manner similar to that of Giladi and Menachi.

More detailed descriptions of these individual tasks are provided below.

AEDT automation
Current AEDT implementation and workflows are primarily focused on desktop personal computer use via a graphical user interface. This usage model does not support the automated processing of thousands of flights per day over many years. To implement an automation capability, we leveraged AEDT's use of and reliance on a Microsoft SQL Server database. Using AEDT's database schema documentation in conjunction with a database table "diff" tool we developed, we gained an understanding of how to create and populate the tables necessary to describe a complete AEDT study. We then developed a software library to facilitate scripted study creation over a network connection to the SQL Server database used by AEDT. AEDT provides a command-line utility, `RunStudy.exe`, to initiate the execution of a specified study that we can invoke over the network. The computed metrics of an AEDT study are written into the SQL Server database, which allows us to access and extract these results over the network.

We created a virtual machine (VM) disk image including AEDT and all pre-installed supporting packages, which can be instantiated and run at any scale, on a commercial cloud provider. We then developed a study-executor application that takes a study description as input, orchestrates and connects to an AEDT VM, creates an AEDT study using the trajectory of the flight's database ID (provided in the study description) including altitude and speed controls to match the observed trajectory, executes the study, and extracts/stores the metric results in our database. Next, we developed a study-creation application that generates any number of study descriptions (based on SQL queries specifying any desired database column criteria) and submits each resulting study description onto a job queue. Finally, the study executor was enhanced to query the job queue for a study description to process. As a result, we can run any number of AEDT studies in parallel, limited only by the number of AEDT VMs and study executors we create. Both the job and extracted metric queues are implemented using the Apache Kafka cluster.

AEDT trajectory modeling from ADS-B data
AEDT is typically used to model flights from a number of specified ground track positions (without altitude). AEDT combines the specified ground track with flight performance models from the Aircraft Noise and Performance (ANP) Database and EUROCONTROL's Base of Aircraft Data (BADA) to simulate the aircraft's trajectory for its predictions. This computed, simulated trajectory may differ from the trajectory reported by ADS-B. The AEDT provides additional functionality to add altitude and airspeed control codes to the ground track (Section 3.9.1 "Track Control Flights" in the AEDT3d Technical Manual), which we utilize to more closely model the reported trajectory.

We use the following ADS-B trajectory processing steps:

- Smoothing and filtering to remove anomalies that AEDT would reject (e.g., increases in altitude during a descent),
- Line segment simplification (see Douglas, Peucker, Ramer 1973), and
- Estimation of the aircraft's airspeed, using the ADS-B-provided ground speed and heading in combination with wind speed and direction data obtained from NOAA.

Comparison of AEDT noise prediction to measured noise
Our AEDT studies specify the LAMAX and SEL noise metrics, per flight at each receptor (SLM) location. These metric values are stored in our database, with relations to the flight and location, just as we do with the measured noise peaks attributed to aircraft (described previously). With both predicted and measured noise, comparisons are made across various cohorts of flights, which can be specified by filtering, grouping, analyzing, and reporting for any available set of metadata fields (e.g., aircraft model and route). At present, we are actively using this system to predict and compare thousands of flights each day over several years (see Task 2 progress). We plan to publish the results of these comparisons once we have carefully reviewed and validated an amount of data that we deem to be statistically significant. This step is likely to take place during the summer of 2022.

Visualization
Flight traffic information and noise metric contours are visualized using a web-based application that provides 3D geospatial views, based on the `deck.gl` library (see Figure 6). Historic flight-track visualizations obtain archived flight trajectories from the database, and real-time flight visualizations obtain streaming trajectories from Kafka. Real-time access to both SLM and ADS-B data has provided unanticipated benefits: we recently developed another web application that displays SLM metrics overlaid with aircraft TCAs (see Figure 7). Viewing this real-time visualization while simultaneously hearing passing aircraft is a powerful tool to generate ideas and form hypotheses about how and when overflights may result in community concerns.

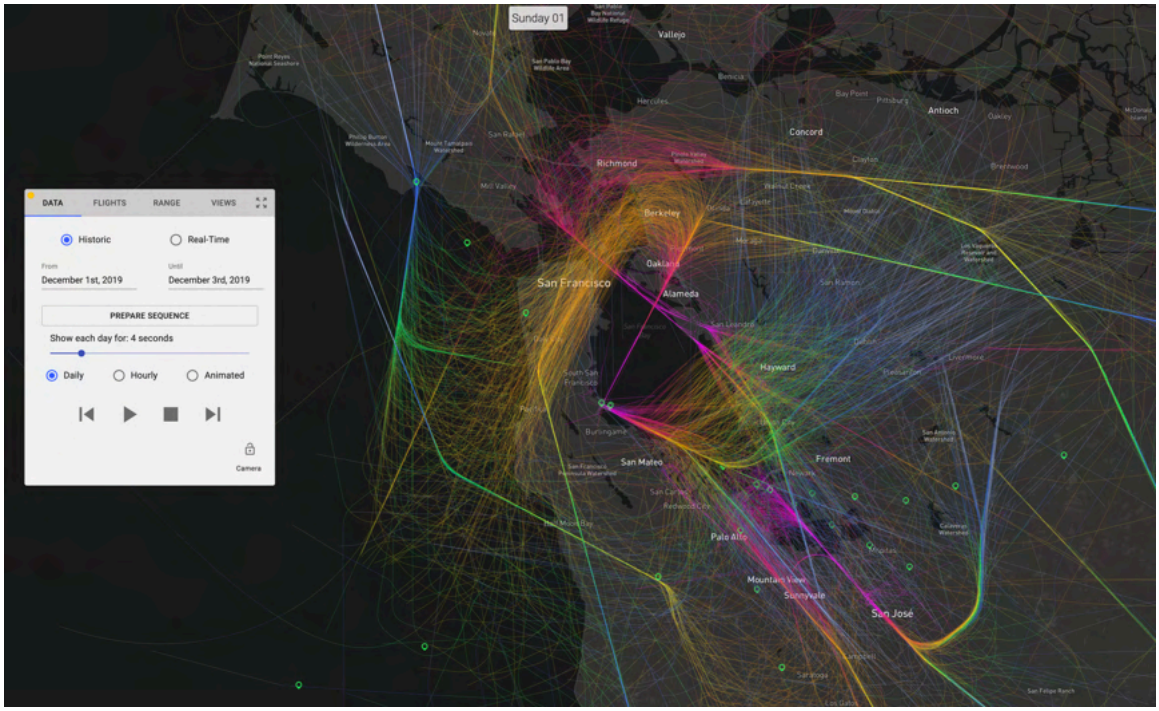

Figure 6. Visual representation of historic traffic patterns over the San Francisco Bay Area metroplex.

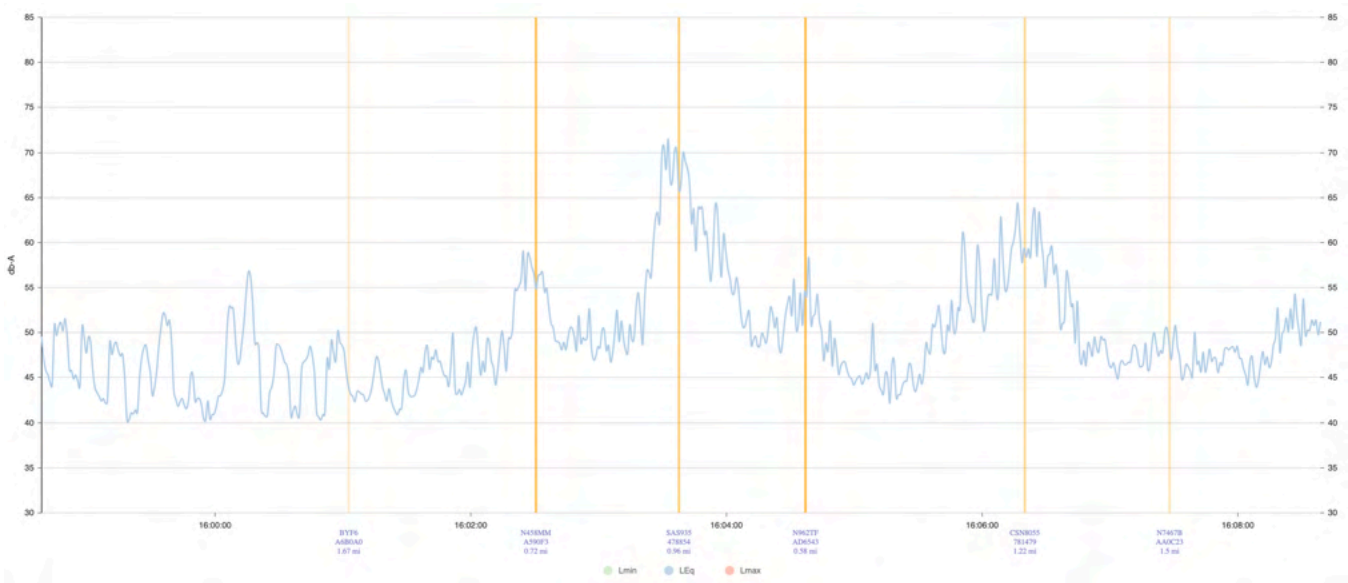

Figure 7. Real-time visualization of sound profiles with aircraft peaks and times-of-closest-approach indicated/overlaid.

Task 2. Validation and Verification of AEDT Noise Predictions in DNL 55–65 dB Areas

Stanford University

The noise prediction modules of AEDT, based on noise power distance (NPD) relationships and certification data, were primarily developed and calibrated for areas of objectionable noise close to airports (> DNL 65 dB), at a constant velocity (160 knots), and for a particular aircraft high-lift system and landing gear configuration. Despite efforts such as those in ASCENT Project 53 (which re-evaluated NPD curves using ANOPP analyses and the ability to change the aircraft configuration during arrival/departure procedures) there is evidence that the accuracy of AEDT's predictions in areas of lower noise (between DNL 55 and 65 dB) may warrant review and improvement. For these reasons, in this task, we have undertaken a preliminary evaluation of the accuracy of AEDT's predictions when measured against sound level readings from a small network of SLMs that the MONA project has acquired, tested, and cited. These efforts *must be viewed as preliminary and do not provide final conclusions*. To issue a final set of conclusions, the ASCENT 53 team is increasing the number of flights in our datasets from 4,000 to nearly 100,000. In addition, we will compare predictions for a larger set of SLM locations beyond the two presented in this annual report. Once available, our final recommendations will include our best efforts to control for individual factors (aircraft weight, weather/airspeed, performance model accuracy, aircraft state, atmospheric column variability, and accuracy of NPD curves for different aircraft models) affecting the discrepancies between measurements and predictions. This step will require significantly more data than we currently have collected and generated and a rigorous apportioning of the variability in prediction errors to the various factors identified. This work is ongoing and is expected to be completed during the summer of 2022.

Currently (December 2021), we are in the process of incorporating additional SLM sources (generously contributed by SFO) across areas with different noise levels for both arrival and departure routes, in order to lend statistical credibility to any results that are eventually published in a peer-reviewed forum.

Research Approach

To accomplish the objectives of this task, we pursued the following steps:

1. We are performing data acquisition and archiving for noise measurements at 3–4 locations under arrival routes into SFO. We have completed the acquisition of raw noise data (Leq samples at 1-second intervals) over a period of approximately three years. All of these data have been curated to provide meaningful comparisons with AEDT predictions.
2. As a pre-processing step to the verification and validation () portion of this work, we developed a series of non-aircraft noise removal algorithms (described in a previous section) that combine filtering techniques, automatic identification of multiple aircraft peaks, automatic detection of background and peak noise levels, and real-time information regarding the position, velocity, and heading of aircraft to maintain high levels of accuracy.
3. We are conducting a validation process based on experimental observations in the DNL 55–65 dB areas of the Bay Area metroplex. This step is the primary component of Task 3, for which we present preliminary results below.

All of the data used for validation purposes will be processed at both the aggregate level and the level of individual flight predictions so that data-driven methods can be pursued in the future to improve the noise and performance data used in AEDT (or data produced in ASCENT Project 43). For example, if all of the recorded overflights of a particular aircraft type, which have variability in aircraft weight, atmospheric conditions, high-lift system configuration, etc., have a corresponding time history for the recorded sound pressure level at an observer location, a learning algorithm could be devised to correct the AEDT predictions as a function of altitude, airspeed, and distance to the observer. Such a data-driven methodology may lead to improved predictions in AEDT.

Raw SLM data for multiple locations are currently being captured and stored in an Apache Kafka centralized database with associated timestamps, that can be retrieved by running respective SQL queries. These data come from calibrated networked Convergence Instruments equipment that we have installed at various locations around the San Francisco Bay Area (as described earlier in this report) and that we have tested with co-located sound measurement equipment loaned by SFO, which agree with our equipment to within 0.1–0.2 dB.

The result of our raw noise data processing algorithm is a filtered signal that is guaranteed to correspond to a conservative estimate of the actual aircraft noise, as the possibility exists that some aircraft noise events (such as sensitive flights) are recorded but not identified in our simultaneously collected flight database. This process can also be run for any subset of the day (a subset of the recorded data) to prepare actual recordings of flight events at multiple locations for comparisons with AEDT predictions. For example, flight recordings obtained during the early hours of the day (1am –4 am) tend to have very low levels of background noise and, therefore, are prime candidates for comparisons with AEDT predictions.

Using filtered noise data for two SLM locations, we have been able to arrive at a number of preliminary conclusions, which are provided at the end of this section. It is important to note that these preliminary conclusions are based on the data we have acquired thus far; however, we are in the process of conducting a significantly larger number of simulations and collecting additional sources of data that will allow us to clarify the main causes of any measurement–prediction discrepancies in the near future. Until these additional data are examined, processed, and analyzed, it would be premature to strongly state the reasons for the discrepancies observed thus far. To provide current evidence of our preliminary conclusions (restricted to arrival routes into SFO and observations at two SLM locations), we present a number of statistically significant comparisons based on approximately 3,700 flights.

The two SLM locations in our plots are: (see Figure 8):

- SIDBY: This SLM is located near the SIDBY waypoint of the SERFR route, but is also overflown by aircraft following the BDEGA and PIRAT routes. This SLM is located in an approximately DNL 55 dB area and is approximately 15 miles (along the standard flight path) from touchdown at runways 28L/R of SFO.
- SFO-12: This SLM is located directly under the final approach to runways 28 L/R of SFO and approximately 6 miles from touchdown. The SLM is located in an area of approximately DNL 62.5 dB and thus has a considerably higher noise level than the SIDBY SLM. Aircraft approaching SFO along the SERFR, PIRAT, BDEGA, and DYAMD routes either directly overfly or fly nearby (1/2 miles north, in the case of DYAMD approaches) this SLM.

Figure 8. Locations of two SLMs (SFO-12 and SIDBY) used in this study.

Among the various SLMs for which we have data, these two are particularly interesting because, even though they are both under arrival tracks, they correspond to two very different noise-level areas. SFO-12 is, presumably, in an area for which the

noise predictions of AEDT are relatively accurate (near the airport), whereas SIDBY is significantly farther from the airport and in an area that was not specifically targeted during the development of the noise prediction algorithms in AEDT. The use of these two locations will allow us to test the hypothesis that AEDT is more accurate in its predictions for SFO-12 than for SIDBY.

The following figures are meant to provide statistically significant information. Conclusions are preliminary because as we have yet to understand the reasons for the observed discrepancies. These reasons must be understood before final conclusions are drawn from this study. For the results presented below, we believe that the dataset contains a sufficient number of flights for the variabilities to average out: the entire dataset contains approximately 3,679 flights from the 4-week period spanning July 19, 2021 to August 18, 2021. The dataset includes all types of aircraft, but predominantly E75L, B73X (B737-800, B737-900), and A320/A321. We have removed all general aviation flights from this dataset and have ensured that no flights are included whose line-of-sight elevation at the point of closest approach (PCA) to a SLM is less than 40 degrees (so that aircraft not in the proximity of the SLM are disregarded).

SIDBY SLM Results

Figure 9 presents a histogram of all 3,679 flights considered in this study. The data have been binned in 0.5-dB intervals and represent the difference (for each individual flight) between the AEDT LAmax prediction and SLM measurement (after background noise has been removed). The dataset includes aircraft/flights that can be modeled only with BADA3 and aircraft/flights that can be modeled with BADA4. In this dataset, the mean shows an underprediction of 2.2 dB by AEDT when compared with the SLM measurements. Surprisingly, the variability in the differences between measurements and predictions is rather broad: the standard deviation in the histogram is approximately 4.7 dB. This observation clearly implies that the variability in input variables not considered in AEDT (aircraft weight, headwind, aircraft state, atmospheric conditions, etc.) leads to significant variability in the observations.

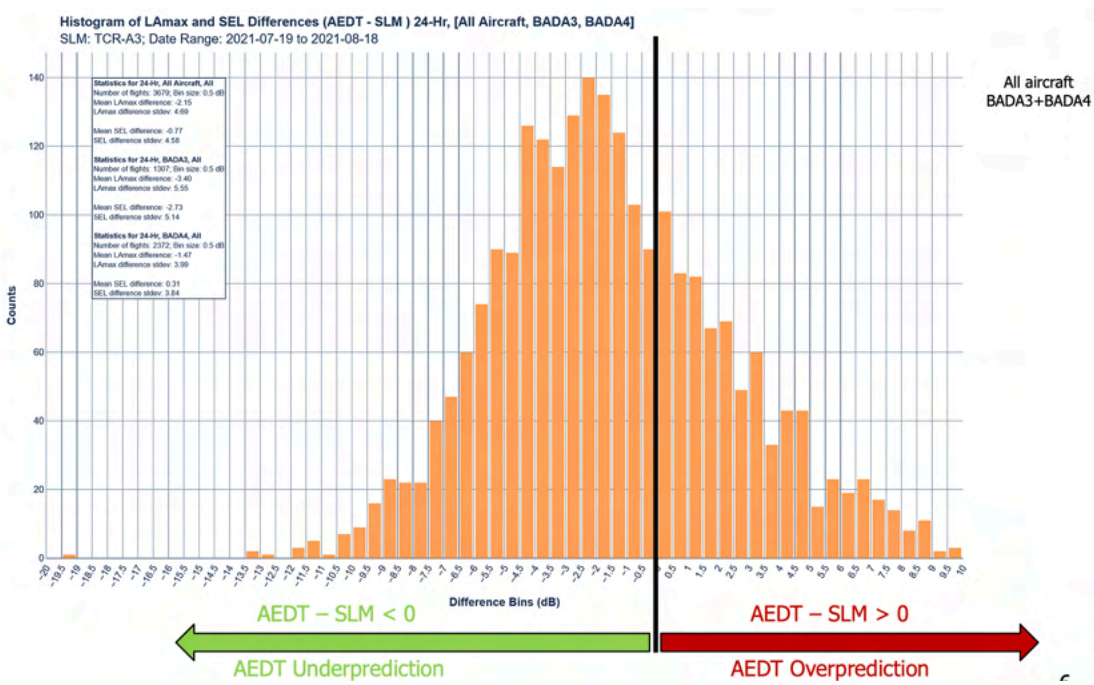

Figure 9. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SIDBY SLM. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

Figure 10 shows the same dataset but includes only E75L-type aircraft, which are modeled by AEDT using BADA4, representing a total of 905 flights during the period under consideration. Similar trends in standard deviation (4.2 dB) are observed, but the mean difference between the prediction and measurement is significantly smaller, with an overprediction of only 0.3 dB, which can be considered quite accurate in comparison with results for other aircraft types that we have

observed. As shown in Figure 11, the same trend is not observed for B73X aircraft, including B737, B738, and B739, which are largely modeled using BADA4.The large value of the standard deviation is still significant, implying that the over/underprediction of AEDT for individual flights can typically be as high as +0.75 db and -6.3 db. Such differences indicate that the current prediction error variability is significantly higher than desired, and additional improvements in the modeling strategy might be required if the standard deviation of the differences needs to be reduced. Such improvements may include some or all of the following: better assessments of aircraft weight, more detailed airspeed measurements (or inferences based on flight path data), a better understanding of the aircraft state, and improved NPD curves. The relative importance of each of these factors is currently under investigation, but at this point, we do not have sufficient information to conclusively state anything beyond what has been written.

Figure 11 shows the same data as Figure 10 for B737, B738, and B739 aircraft, for which we observed 815 flights in the dataset, with the vast majority (808 flights) being simulated using BADA4. As briefly mentioned above, the predictive quality of AEDT is worse in this case than for the E75L aircraft, with a mean difference (underprediction) of 2.9 dB and a large standard deviation of 3.4 dB. The difference in the mean between the E75L and B73X aircraft types is sizable, and further investigation is warranted to determine why the mean values of the prediction errors differ by more than 3 dB. Although not presented here, a similar trend was observed for A32X-type aircraft (data are available upon request and were presented at the ASCENT Annual Meeting in October 2021).

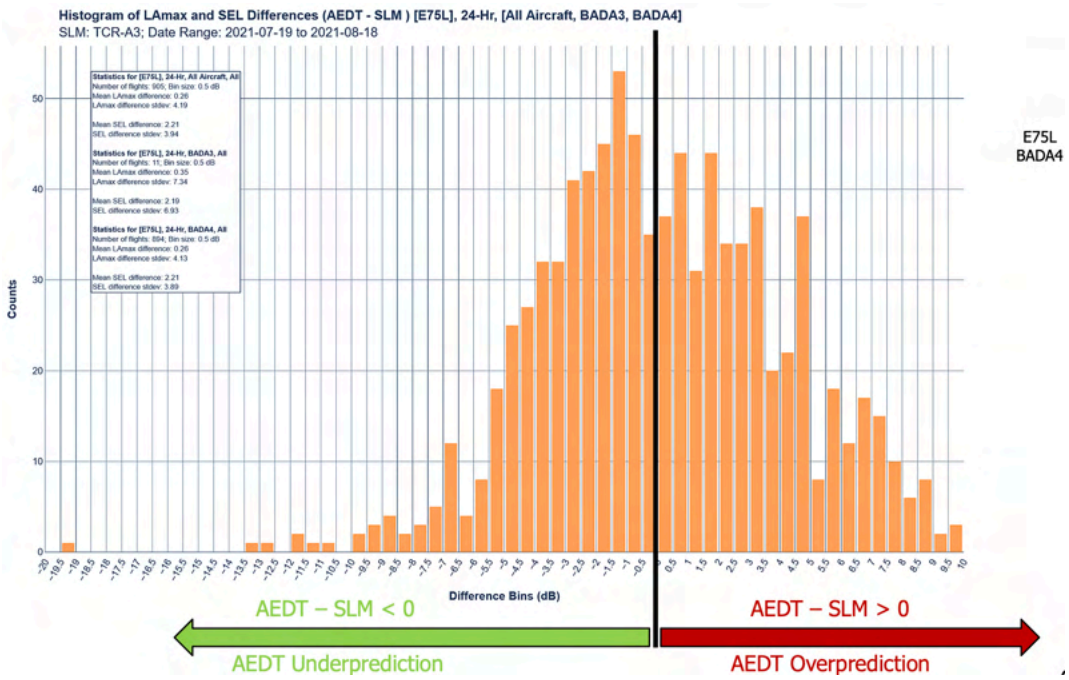

Figure 10. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SIDBY SLM for E75L aircraft. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

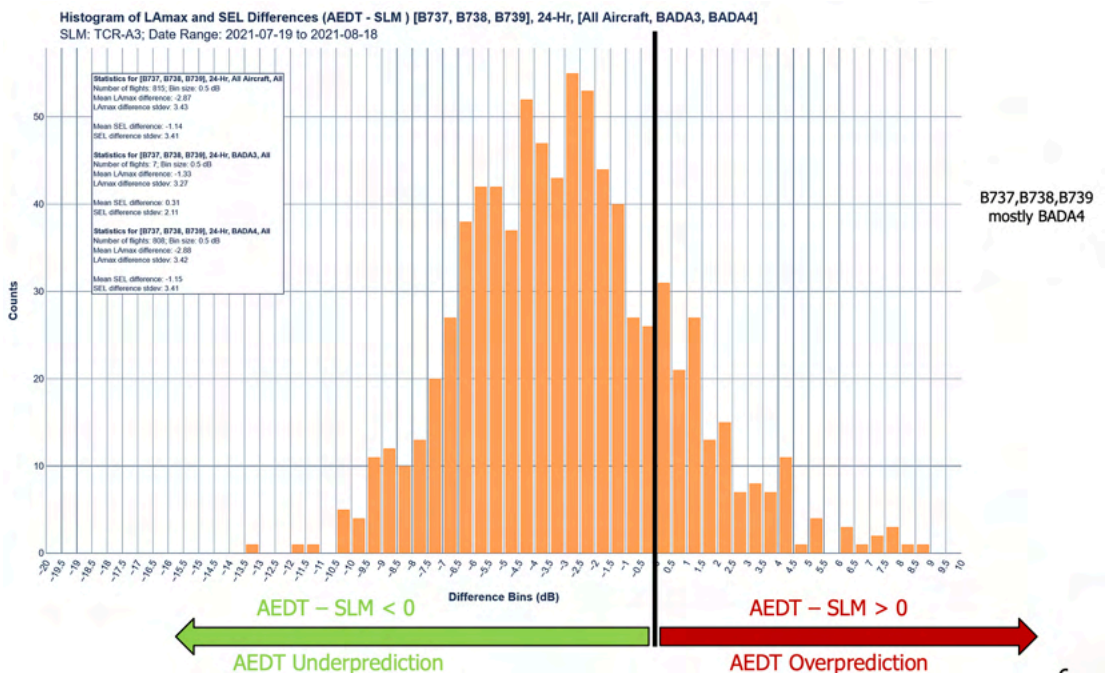

Figure 11. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SIDBY SLM for B737, B738, and B739 aircraft. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

SFO-12 SLM Results

Figures 12–14 show similar results for the predictions and measurements at the SFO-12 SLM, in contrast to the results for the SIDBY SLM. It should be noted that because SFO-12 is located alongside the runways for all approaches to SFO, including DYAMD, in addition to SERFR, BDEGA, and PIRAT, there are more aircraft in the cohort (6,228 vs. 3,679 at SIDBY). Given that this SLM is in an area of higher noise (~ DNL 65 dB) and assuming that AEDT is "tuned" to be more accurate at higher noise levels, we would expect the mean error in the AEDT predictions to be smaller. However, the data we have collected thus far do not support this observation. The aggregate plot in Figure 12 shows an overall mean LAmax difference of -3.1 dB, an underprediction for nearly all flights in the neighborhood of this SLM location. However, the standard deviation of the error at this location is lower than that at SIDBY (3 dB vs. 4.7 dB). This smaller standard deviation can likely be attributed to the significantly higher concentration of flight trajectories during the final approach to SFO and the reduced level of uncertainty about the aircraft state close to the touchdown location. At this location, AEDT noise models can over/underpredict aircraft noise by up to 0.6 dB and -6.3 dB on average.

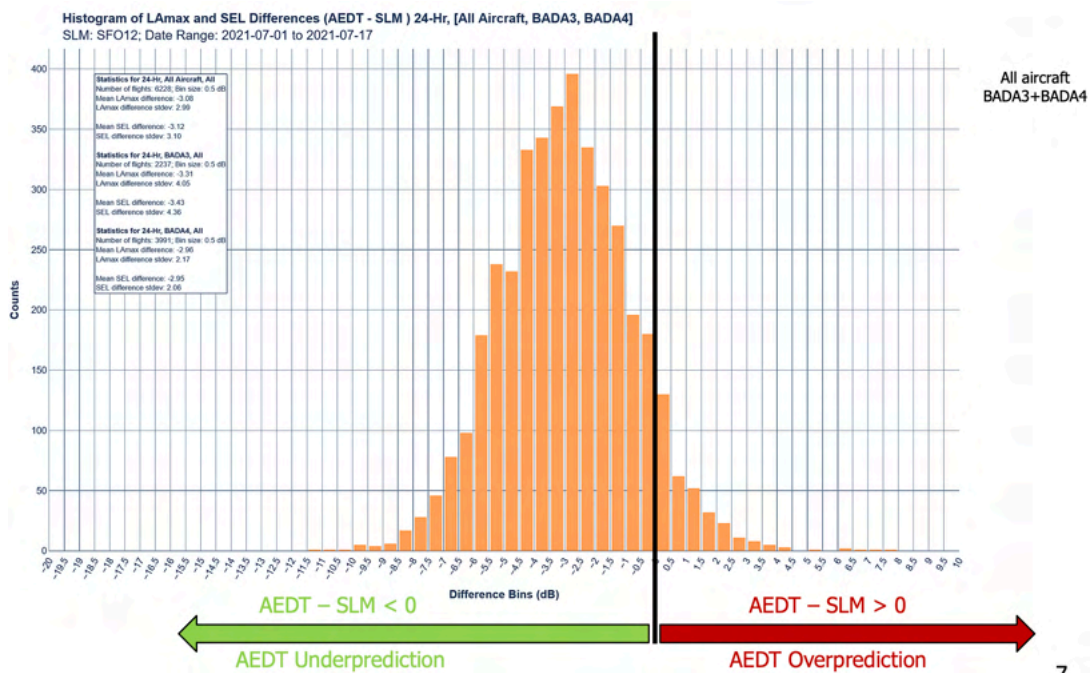

Figure 12. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SFO-12 SLM. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

Figure 13 shows the same dataset errors for the E75L cohort. Just as for the SIDBY SLM, the AEDT predictions for the SFO-12 SLM improve for the E75L cohort (-2.4 dB) compared with other aircraft types. In fact, similar to Figure 11, Figure 14 shows that the predictions at SFO-12 for B73X aircraft have a mean underestimation of -3.7 dB, which was not expected, given that the mean underestimation at SIDBY was only -2.9 dB. Thus, the expected trends do not seem to be materializing. We note that the SFO-12 data include DYAMD flights, but it is not clear why this inclusion should skew the results.

At the moment, one can only argue that all of these data have been collected at only two arrival locations and for approximately 4,000–6,000 flights, and thus, the conclusions cannot yet be generalized. As our work proceeds, we expect to extend these comparisons to additional SLM locations, including some under departure flight tracks.

Finally, Figure 15 shows the estimated and measured 24-hr DNL metric for each of the 30 days in our sample dataset. As can be observed, the underestimation of AEDT predictions in the DNL metric can be as good as 1 dB and as bad as 2.6 dB with an average value of approximately 2 db.

Overall, the preliminary conclusions of our early comparisons between AEDT predictions and SLM measurements can be summarized as follows, with the caveat that these conclusions are preliminary and will be strengthened once additional predictions and measurements, which we are currently pursuing, become available:

- Preliminary investigations point to a potential underestimation of noise predictions for individual-event sound levels on arrival operations by ~2–3 dB (mean values) regardless of the DNL area. More data are needed to refine this conclusion.
- BADA4 aircraft modeling results in a significant improvement in noise predictions over BADA3 aircraft of ~0.5–2 dB depending on the DNL area. This improvement is likely related to the better aircraft performance model available in BADA4 (for some aircraft types only), leading to a better estimation of the engine noise component. Further comparisons across multiple aircraft classes (with BADA3 vs. BADA4) are planned to strengthen this observation.
- Variability in the difference between measurement and prediction is *very significant*, with a standard deviation of ~3–5 dB. We believe that this is important area that warrants further investigation to ascertain the main causes of such large variability. We intend to understand this variability by attempting to control for variables such as aircraft

weight and aircraft state, as we continue to increase the size of our datasets to hundreds of thousands of flights. The larger cohorts will allow us to subdivide the traffic along more parameter values and thus better understand the impact of input unknowns and their ranking in order of importance.

- In the dataset that we have processed, we observed significant bias for different aircraft models (especially when the performance of some aircraft models can only be represented using BADA3). The observed trends appear to be consistent regardless of the DNL area (low or high).
- The expectation of improved AEDT accuracy in noise estimates for higher DNL noise areas does not appear to be borne by the data for the two arrival locations examined. As our study progresses, we intend to examine this preliminary conclusion for a number of other locations and with significantly more data to ascertain whether our observations change.
- AEDT predictions for aggregate noise metrics (not individual flights) still show significant differences (e.g., DNL 1–2.6 dB for different 24-hr periods), which are only slightly better than the predictions for individual flights. We are continuing our work to determine whether this assertion holds for additional SLM locations under both arrival and departure routes.

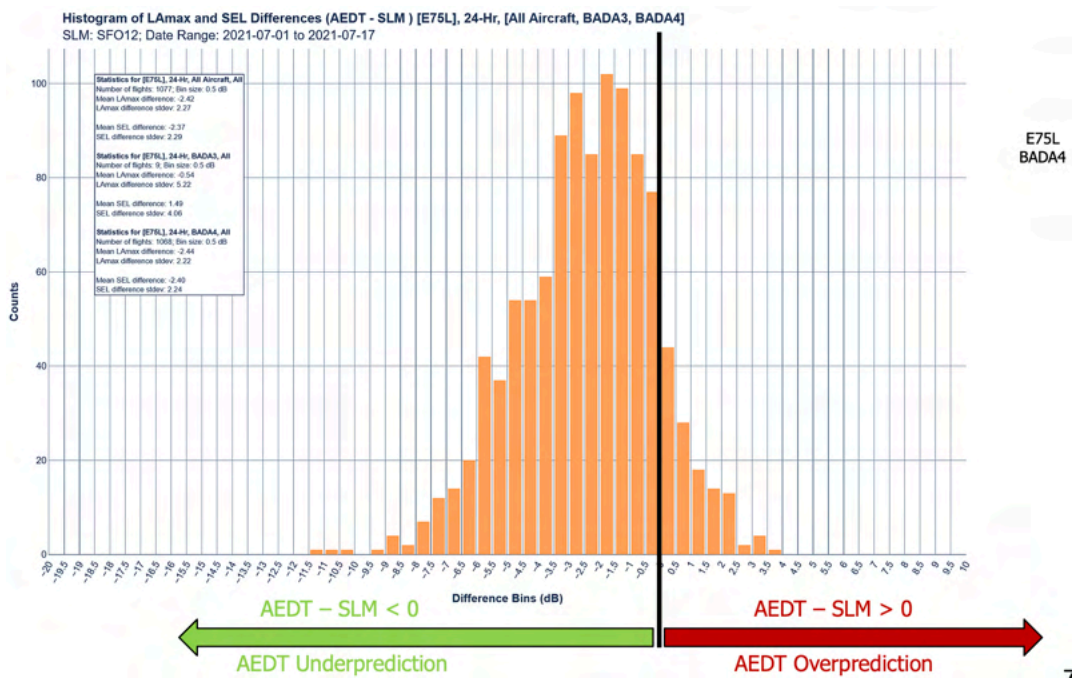

Figure 13. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SFO-12 SLM for E75L aircraft. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

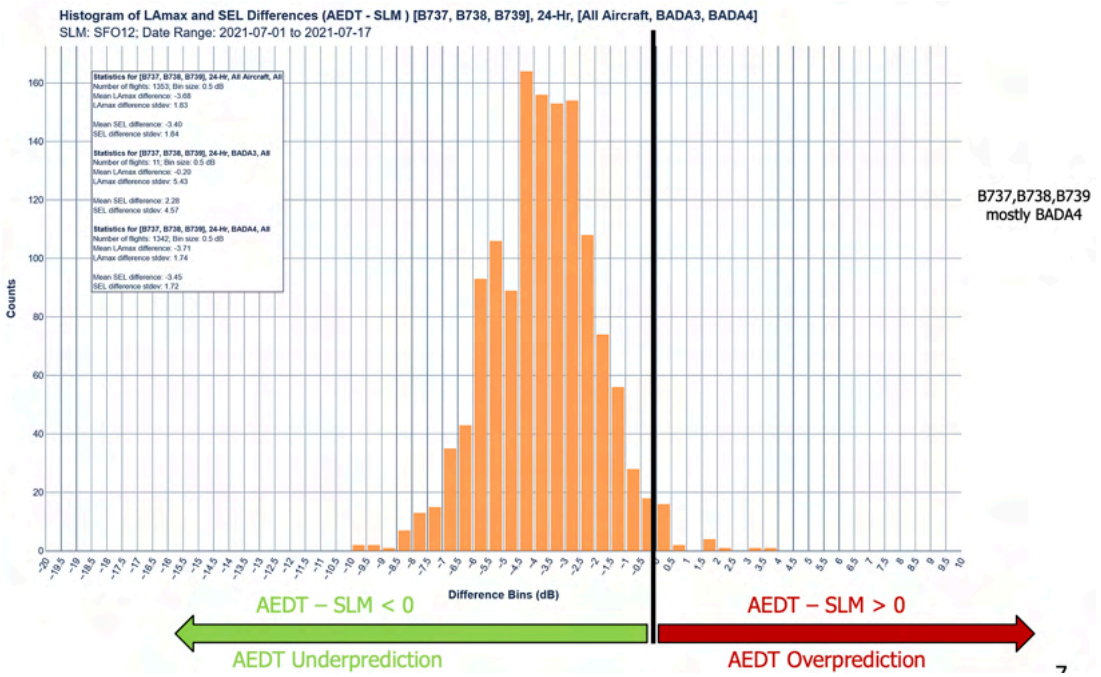

Figure 14. Histogram of the LAmax difference between AEDT predictions and SLM measurements at the SFO-12 SLM for B737, B738, and B739 aircraft. Positive values indicate overprediction by AEDT, whereas negative values indicate underprediction by AEDT.

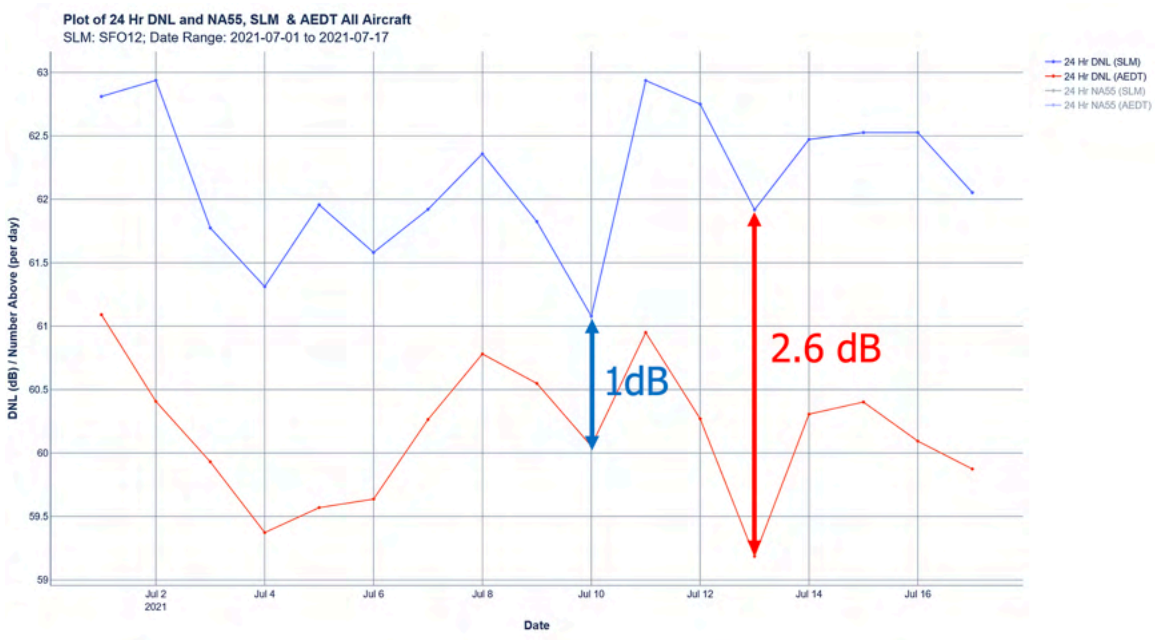

Figure 15. AEDT predictions (red) and SFO-12 SLM measurements (blue) of 24-hr DNL levels. Minimum (1 dB) and maximum differences between measurements and predictions are highlighted for July 10 and July 13, 2021.

Task 4. Investigate Viable Alternative Approach Routes into the San Francisco Bay Area Metroplex

Stanford University

This task is still in its beginning stages and will continue to develop over the coming months. In this task, in collaboration with FAA staff and other technical experts, we plan to continue the process of proposing and analyzing alternative procedure designs for the SERFR arrival route into SFO and for approaches that currently tie into SERFR. The longer-term intent of this task is to propose procedure designs for two alternative arrival routes and to assess the potential of those routes to reduce noise, while maintaining airspace efficiency and safety. This task can be viewed as a first step toward proposing routes and flight procedures that may lead to noise benefits for a variety of stakeholders.

In particular, we have been investigating the possibility of splitting the SERFR arrival route and the approaches that merge into SERFR at significant distances away from the airport into a number of sub-routes that will then merge into the existing SERFR route in a *herringbone pattern* so that the distances flown are kept essentially constant while the number of overflights (measured with a metric similar to the number above LAmax noise level, i.e., the number of overflights above a specified maximum noise exposure level) for different portions of the existing SERFR route can be substantially decreased, by a factor of two or three, depending on the distance from the runway.

There are no additional substantial results to report at this time.

Major Accomplishments

- Created a completely new infrastructure for ASCENT 53/MONA that can scale to the types of data collection and analysis expected for a complex metroplex such as that of the Bay Area
- Developed a working version of the non-aircraft noise filtering process to compare sound recordings with AEDT predictions
- Created a cloud-based automated approach to conduct AEDT studies to enable automation in the Bay Area metroplex
- Demonstrated full automation of the AEDT analysis pipeline and of noise prediction/measurement comparisons for arbitrarily large datasets
- Demonstrated the use of modern databases, data formats, and data acquisition methodologies (based on Apache Kafka) in the context of airspace and noise analysis
- Collected necessary data to generate a database of almost 4,000–6,000 individual flights which was used in our preliminary AEDT verification and validation study
- Drew preliminary conclusions from comparisons between AEDT predictions and SLM measurements at two locations (SIDBY and SFO-12) under arrival routes to SFO

Publications

Jackson, D. C., Rindfleisch, T. C., & Alonso, J. J. (2021). A system for measurement and analysis of aircraft noise impacts. Engineering Proceedings, *13*, 6. https://doi.org/10.3390/engproc2021013006

Outreach Efforts

Over the past few months, we have developed a closer relationship with SFO and the technical leads at EnviroSuite, which deploys, monitors, and makes available noise data for approximately 40 locations around the Bay Area. These outreach efforts have resulted in the sharing of noise data at a large number of locations including historical datasets and a commitment to continue sharing datasets as they are acquired in the future.

Awards

None

Student Involvement

A number of undergraduate and graduate students have been part of our team during this past year, as described at the beginning of this document. Several of these students have graduated during the current period of performance, but we

have managed to enlist new students to continue our work. Their contributions are acknowledged here, as the project would not be as far along without them.

Plans for Next Period

We intend to complete all three tasks in our Statement of Work as planned. In addition to the completion of all milestones, we expect to release appropriate parts of the ASCENT 53/MONA project and demonstrate various capabilities through participation in aircraft noise-related meetings and conferences, as permitted by the COVID-19 situation.

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