# Project 054 AEDT Evaluation and Development Support

## Georgia Institute of Technology

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## University Participants

**Georgia Institute of Technology**

- P.I.s: Dr. Dimitri Mavris, Dr. Michelle Kirby
- FAA Award Number: 13-C-AJFE-GIT-098, 114, and 122
- Period of Performance: September 24, 2021 to September 20, 2023
- Tasks:
    1. Improved Departure Modeling
    2. Arrival Profile Modeling
    3. Full Flight Modeling
    4. System Testing and Evaluation of the FAA's Aviation Environmental Design Tool (AEDT)

## Project Funding Level

Georgia Institute of Technology has received $900,000 in funding for this project. In terms of cost-share details, Georgia Tech has agreed to a total of $900,000 in matching funds. This total includes salaries for the project director, research engineers, and graduate research assistants, as well as computing, financial, and administrative support, including meeting arrangements. Georgia Tech has also agreed to provide tuition remission for the students, paid for by state funds.

## Investigation Team

**Prof. Dimitri Mavris**, P.I., Georgia Institute of Technology, all Tasks
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**Jirat Bhanpato**, Graduate Student, Georgia Institute of Technology, Task 1 & 3
**Howard Peng**, Graduate Student, Georgia Institute of Technology, Task 1 & 2
**Keletso Mmalane**, Graduate Student, Georgia Institute of Technology, Task 2
**Anushka Moharir**, Graduate Student, Georgia Institute of Technology, Task 2
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**Santusht Sairam**, Graduate Student, Georgia Institute of Technology, Task 4

## Project Overview

This project provides data and methods to continue to improve modeling of aircraft weight, take-off thrust, and departure and arrival procedures within the FAA's AEDT, as well as the AEDT's full flight modeling capabilities. Some of the modeling assumptions in AEDT are considered to be overly conservative and could be improved by using industry and airport flight operation data. Funding for this project will continue to support the implementation of these methods and data in AEDT4. To facilitate these efforts, the Georgia Tech team will utilize real-world flight data and noise monitoring data to improve departure, full flight, and arrival modeling.

## Task 1 - Improved Departure Modeling

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### Objective

Prior research in ASCENT Project 45 provided recommendations for noise abatement departure procedures (NADPs) to be modeled in future versions of AEDT. Comparisons were made between NADP profiles within the NADP library to determine the differences between each profile. As a result, two profiles were found to best represent the variability among each type of NADP. This task aims to investigate the similarities between the recommended NADPs and real-world departure operations for multiple airlines and airports.

From October 2021 to September 2022, the focus of the project was to specifically investigate the effects of specific profiles and weather conditions on the differences between NADP results and real-world data. This work helped narrow down specific parameters in the process of generating noise and performance results that could lead to significant differences between AEDT calculations and corresponding real-world results.

### Research Approach

**Methodology**

This project previously generated NADPs that could be implemented in AEDT as recommendations for minimizing the effects of noise during the take-off portion of a commercial flight. These recommendations were derived from two datasets, designated the OpenSky and Threaded Track datasets, which together cover a large number of airports and aircraft. However, while the datasets are extensive, they do not capture all variables, such as thrust data for each flight. In addition, the Threaded Track dataset, which captures many of the flights, lacks information below an altitude of 1,000 ft, representing a significant lack in data. This gap in data leads to questions about how much variability is not being captured by the data and whether that variability significantly influences the accuracy of the models generated for recommendations.

To bridge this gap, another dataset, designated Flight Operations Quality Assurance (FOQA) data, was brought for comparison with the current data. FOQA represents data on flights from KATL (Atlanta International Airport), complete with thrust data and data below 1,000 ft. In addition, we applied weather data from the Automated Surface Observing System to determine whether there are any correlations between weather and flights that could cause differences between the flight profiles and flight data.

To assess for correlations, a set of Python scripts was used to run cases and compare both performance and noise data. To provide a baseline, Boeing 737-800 and 737-900 flights from KATL were used for comparison, as these flights were included in all datasets and provide a good representation of a generic commercial aircraft. The data to be compared were separated into three categories, as shown in Table 1. In particular, the team sought to assess sound exposure level (SEL) noise contours and performance data and to identify differences resulting from weather or profile differences.

**Table 1.** Categories of comparison. FPP stands for Fixed-Point Profile

| DEFAULT | PROCEDURAL+WEATHER | FPP+WEATHER |
|---|---|---|
| The current profile, as in the Aviation Environmental Design Tool, using as many defaults as possible | The current profile, but with default, averaged weather substituted for actual weather corresponding to the flight data | The data from FOQA, instead of noise abatement departure procedures (NADPs) |
| • Using NADP 2-11 and STANDARD profiles<br>• Weight set to "Alternate Weight," with the load factor more indicative of real-world flights<br>• Reduced thrust 15% (RT15)<br>• Default, averaged weather conditions across all airports | • Using NADP 2-11 and STANDARD profiles<br>• Weight set to "Alternate Weight," with the load factor more indicative of real-world flights<br>• RT15<br>• Weather corresponding to real-world data | • Using FPP defined from FOQA data, including real-world thrust, altitude, weight, and ground speed<br>• Weather corresponding to real-world data |

Cases were then run, and flights in each of the categories were compared with each other via pairwise comparisons.

Afterwards, we closely examined the noise contours resulting from the cases. The percentage differences for the metrics of area, length, and width were calculated using the following equation:

$$\Delta\% = \frac{Case - Default}{Default}$$

**Results and Discussion**

Default vs. Procedural

We first compared the NADP profile itself and the NADP profile with corrected weather data. Figure 1 shows each of the performance metrics compared with the cumulative ground distance and displays how the flights are distributed in this comparison.

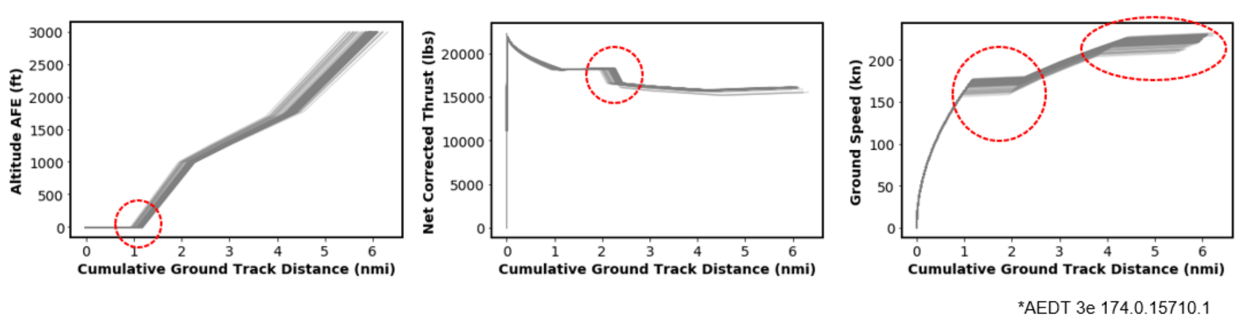



**Figure 1.** Plots with cumulative track distance. AFE: Above Field Elevation, nmi: nautical mile.

The differences in the metrics represent variation in the flight results solely due to differences in weather conditions. Key points in the flights are also highlighted here. The left panel shows differences in the lift-off point resulting from weather conditions. The middle panel shows the difference in the thrust cutback point, and the right panel shows the difference in ground speed. In Figure 2, the comparison between the AEDT-calculated lift-off and the actual lift-off shows that, in general, the NADP profiles underpredict where lift-off is occurring when weather conditions are utilized. Figure 2 also compares the weights calculated by AEDT, which were used for both the default and procedural cases, compared with the third FOQA weight, demonstrating that the errors in the weights are randomly distributed.

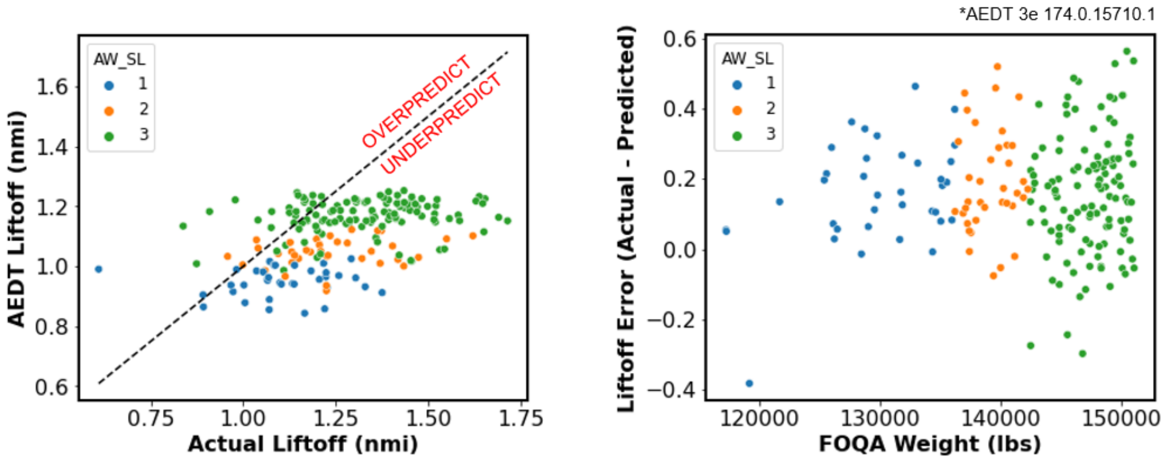



**Figure 2.** Comparison of Aviation Environmental Design Tool (AEDT) results and actual results. nmi: nautical mile; FOQA: Flight Operational Quality Assurance.

<u>Procedural vs. Fixed-Point Profiles</u>

For this comparison, the take-off distance is an important metric to assess. Figure 3 shows the difference between the take-off distance for the NADP and FOQA, with the same weather data used in both cases.

| Case | TEMPERATURE (F) | DEW_P (F) | REL_HUM | WND_SPD (KTS) | Liftoff Error (nmi) |
|---|---|---|---|---|---|
| Short TO | 46.40 | 42.80 | 87.194154 | 1.39 | -0.30 |
| Long TO | 46.40 | 42.80 | 87.194154 | 0.00 | +0.56 |

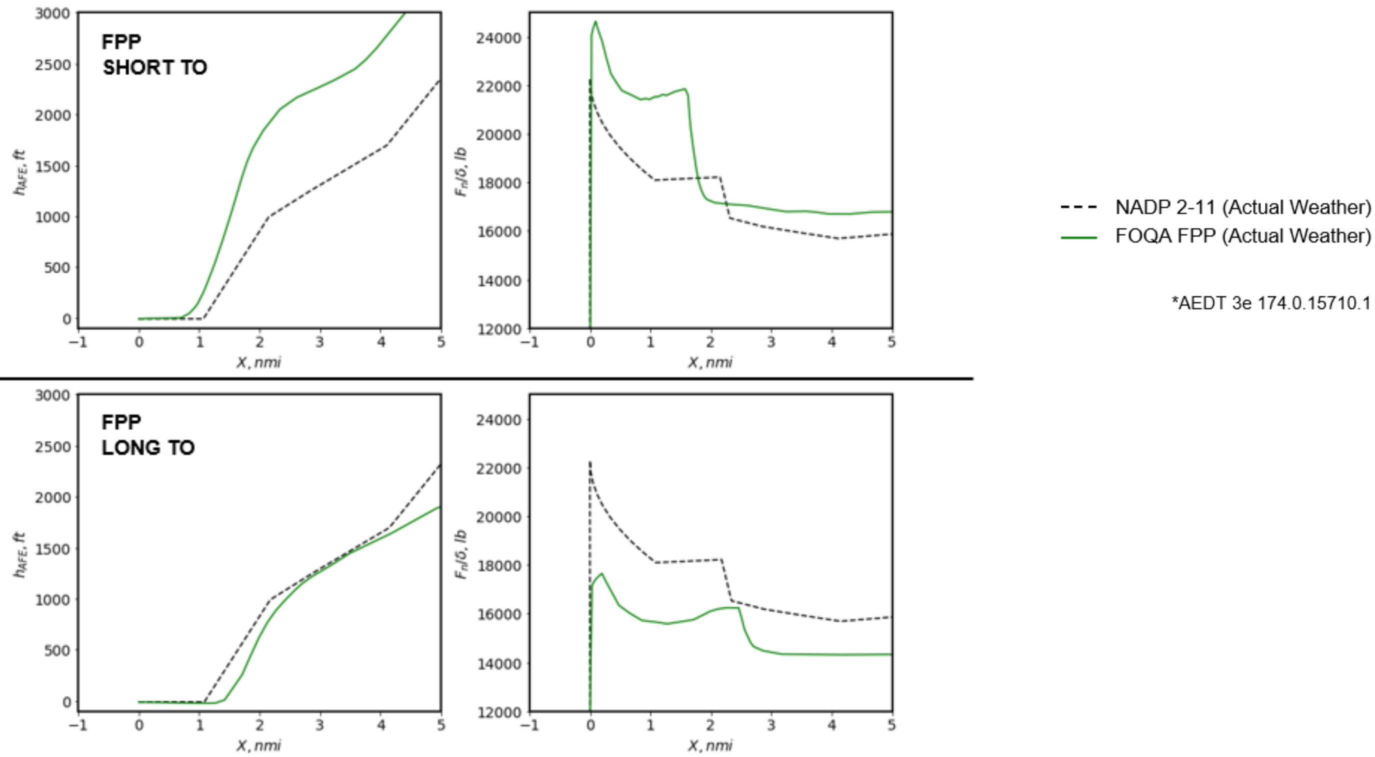



**Figure 3.** Effects of take-off (TO) distance. NADP: noise abatement departure procedure; nmi: nautical mile; FOQA: Flight Operational Quality Assurance; FPP: Fixed-Point Profile.

From these results, it is clear that there are significant differences between the two datasets below 1,000 ft. As shown in both the plots and the table, the NADP has the issue of underpredicting short take-off flights and overpredicting long take-off flights. The plots present the error in altitude and thrust due solely to differences in take-off. Although the plots visually show quite a bit of error, further work is needed to determine whether the magnitude of the error is sufficiently significant to warrant the creation of additional NADP profiles.

Effects on Noise

The most important parameters in this project are the noise metrics, and the results indicate a significant effect on noise. Figure 4 presents comparisons of the produced noise contours for different weather conditions modeled using the NADP 2-11 profile with alternate weights and reduced thrust 15. The heatmap displays the SEL difference (dB) between the NADP 2-11 profile modeled using the default AEDT average airport temperature and actual weather conditions.

| Case | TEMPERATURE (F) | DEW_P (F) | REL_HUM | WND_SPD (KTS) |
|---|---|---|---|---|
| Default | 63.93 | 52.46 | 66.35 | 6.94 |
| Low Temperature | 32.00 | 23.00 | 69.06 | 5.79 |
| High Temperature | 93.20 | 64.40 | 38.76 | 6.13 |

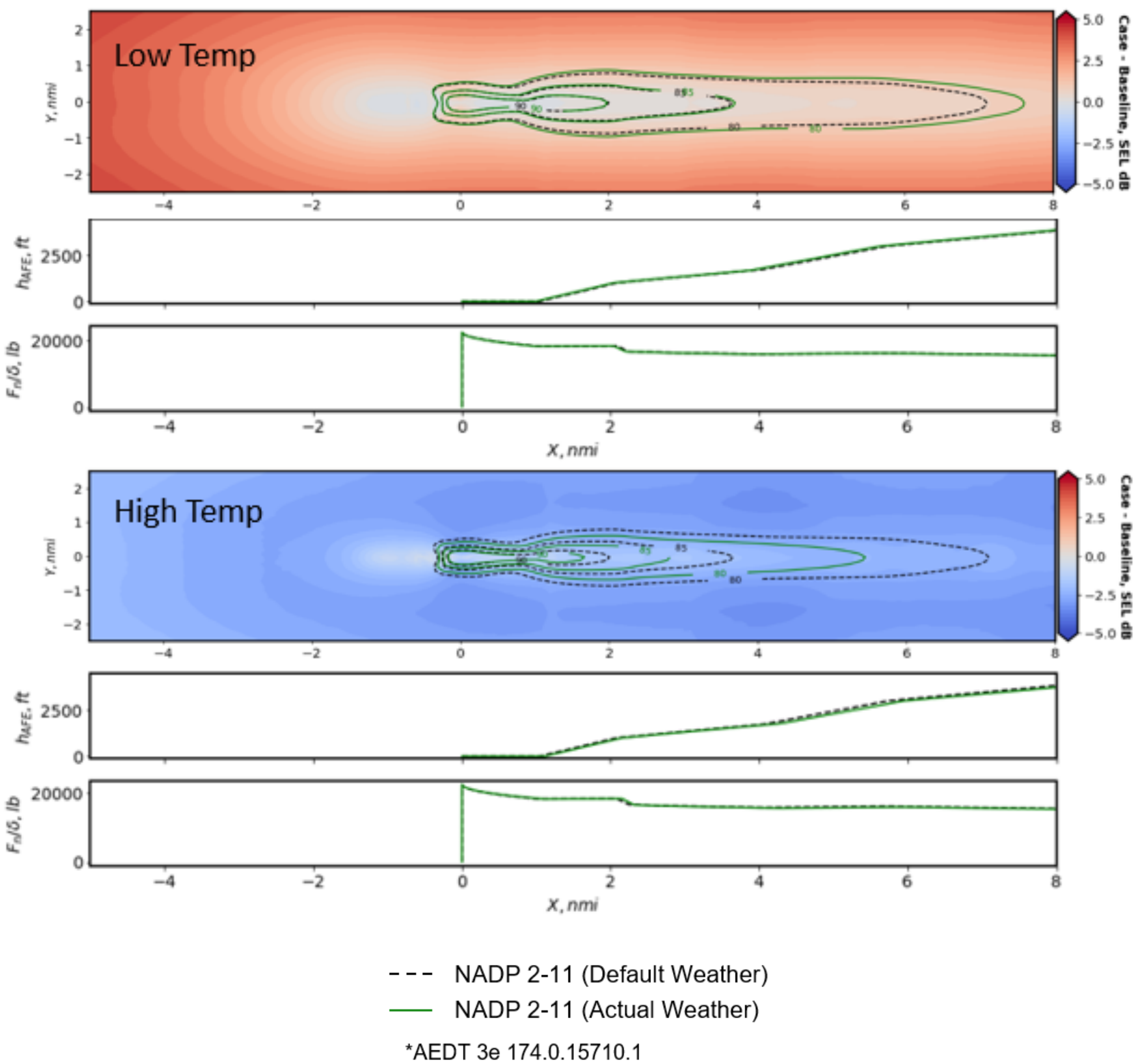
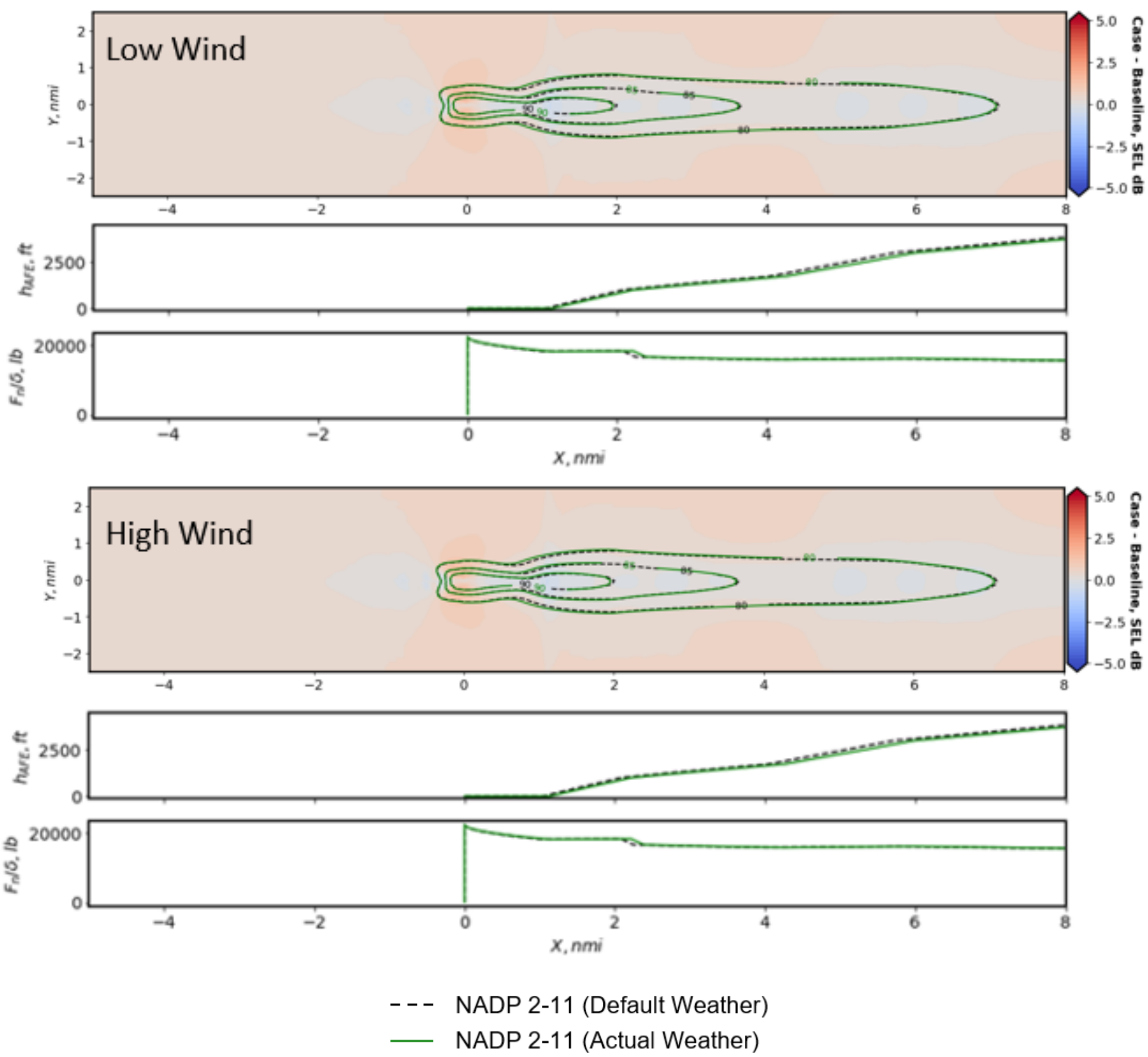



**Figure 4.** Noise effects due to temperature. AEDT: Aviation Environmental Design Tool; NADP: noise abatement departure procedure; SEL: sound exposure level.

When weather conditions are varied for the high-temperature case, the contour areas diminish in size. This effect may be attributed to the combined effects of temperature and humidity differences between the default weather and the actual weather used in modeling. This effect is presumably due to the atmospheric absorption and acoustic impedance adjustment, which are highly dependent on these weather parameters. Further investigation is needed before any conclusive remarks can be made.

In Figure 5, the effect of headwind on the noise contours is shown. That data indicate that the noise is not significantly affected by the headwind, as the noise contours do not visibly change for low-wind vs. high-wind conditions.

| Case | TEMPERATURE (F) | DEW_P (F) | REL_HUM | WND_SPD (KTS) |
|---|---|---|---|---|
| Default | 63.93 | 52.46 | 66.35 | 6.94 |
| Low Wind | 66.20 | 64.40 | 93.93 | 0.00 |
| High Wind | 60.80 | 51.80 | 72.22 | 12.99 |




*AEDT 3e 174.0.15710.1

**Figure 5.** Noise effects due to wind. AEDT: Aviation Environmental Design Tool; NADP: noise abatement departure procedure; SEL: sound exposure level.

Another factor to consider is take-off performance, notably the thrust and lift of each flight and their effects on the noise contour. It was found that differences in thrust and lift-off significantly affect the noise contours, but there are also several additional factors, such as temperature, that have a lesser effect. In general, as the take-off distance increases, the width of the noise contour decreases and the contour length increases.

Although there are differences, it appears as though the noise contours are still constrained to a limited area around the airport for the given airport and runway. In both cases, the 90-dB contour remains isolated inside the airport and does not extend outside the airport. However, there are substantial changes for some of the 80- and 85-dB contours. It may be useful to further examine these contours in future work.

The SEL curves and contours are reasonable and indicate that the process and results for determining the SEL are suitable. Work will be continued along these lines in order to better compare the differences currently observed between real-world flights and NADP results. In particular, we plan to examine day–night average sound level contours, using AEDT to generate airport-level contours by aggregating flights from each of the three aforementioned categories and comparing them with each other and SEL results. This work will provide further details about these differences and their sources.

## Milestone(s)

- None

## Major Accomplishments

- Acquired relevant weather and real-flight data for comparing NADP profile results to actual flights
- Created experiment cases based on NADP profiles, real-world weather, and actual flight data and generated noise results through AEDT
- Analyzed SEL contours to determine factors for noise and performance differences between NADP profiles and real-world flights

## Publications

None

## Outreach Efforts

Biweekly calls
Bi-annual ASCENT meetings

## Awards

None

## Student Involvement

- Jirat Bhanpato and Howard Peng (Graduate Research Assistants, Georgia Institute of Technology) participated in this research.

## Plans for Next Period

- Perform airport-level analyses to compare differences in performance and noise due to weather and profile differences.
- Investigate any resulting significant differences.

# Task 2 - Arrival Profile Modeling

Georgia Institute of Technology

## Objective

The AEDT currently models arrival profiles using specified fixed-point trajectories or manufacturer-provided procedures. In Task 2, we compare data from real-world flights to the AEDT models to make recommendations on how to improve AEDT models to better capture real-world operations.

The objective of Task 2 is to identify and develop recommendations for AEDT that will allow it to better capture aircraft behavior during arrival. The specific focuses of this task are to (a) accurately capture the arrival of aircraft at airports based on real-world data and (b) enhance the ability of AEDT to model aircraft approaches and classify them as one of several arrival profiles suggested by analyses of real-life data. The goals for this period were to perform clustering based on the optimal clustering algorithm and to verify the sensitivity of the clusters by executing arrival profile modeling in AEDT. At the end of this project, recommendations will be made regarding which AEDT arrival profiles should be integrated into the system and what information those profiles should include.

## Research Approach

### Methodology

In the previous year, it was determined that clustering would be the best method for accomplishing the goals of this task, as this approach reduces the number of individual arrival flights to be analyzed. A range of potential algorithms that could be used to perform clustering were identified, as shown in Table 2, each with a different mathematical approach and formulation.

**Table 2.** Exploring clustering algorithms.

| Method | Details | Advantages | Disadvantages |
|---|---|---|---|
| **K-Means** | Distance-based | Fastest algorithm; tighter clusters compared with hierarchical methods | Requires knowledge of the number of clusters |
| **K-Medoid** | Distance-based | More robust to noise compared with K-Means | Assumes spherical data; requires knowledge of the number of clusters |
| **Agglomerative** | Hierarchical | Orders objects | Requires knowledge of the number of clusters |
| **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)** | Reachability- and density-based | No need to pre-specify the number of clusters | Does not handle different densities well |
| **Mean Shift** | Centroid-based | No need to pre-specify the number of clusters | Cannot control the number of clusters |
| **OPTICS (Ordering points to identify the clustering structure )** | Reachability- and density-based | Handles different densities better then DBSCAN; no need to pre-specify the number of clusters | Slower than DBSCAN |
| **BIRCH (Balanced iterative reducing and clustering using hierarchies)** | Hierarchical | Faster than other hierarchal algorithms | Slower than K-Means; requires knowledge of the number of clusters |

After identifying the best clustering method, trends in cluster allocation were studied. The distribution of cluster points aided in recognizing how the data can be generalized for AEDT recommendations. Eight metrics were explored for this purpose: (1) level-off height, (2) level-off length, (3) level-off distance to airport, (4) total flight distance, (5) level-off delta V, (6) longitude, (7) latitude, and (8) airport altitude. The clusters had similar behavior across these metrics and led to a reduced number of points for AEDT generalization. As shown in Figure 6, the largest level-off heights (ft, Above Ground Level (AGL)) occurred in 3 of the 20 clusters (clusters 7, 12, and 19). Clusters 0–3 and 15–17 were similar to each other, with similar trends for the level-off height, length, and distance to the airport. In Figure 7, the level-off delta V was rounded to the nearest multiple of 10 knots. Here, more differences were observed between clusters 0–2 and 15–16.

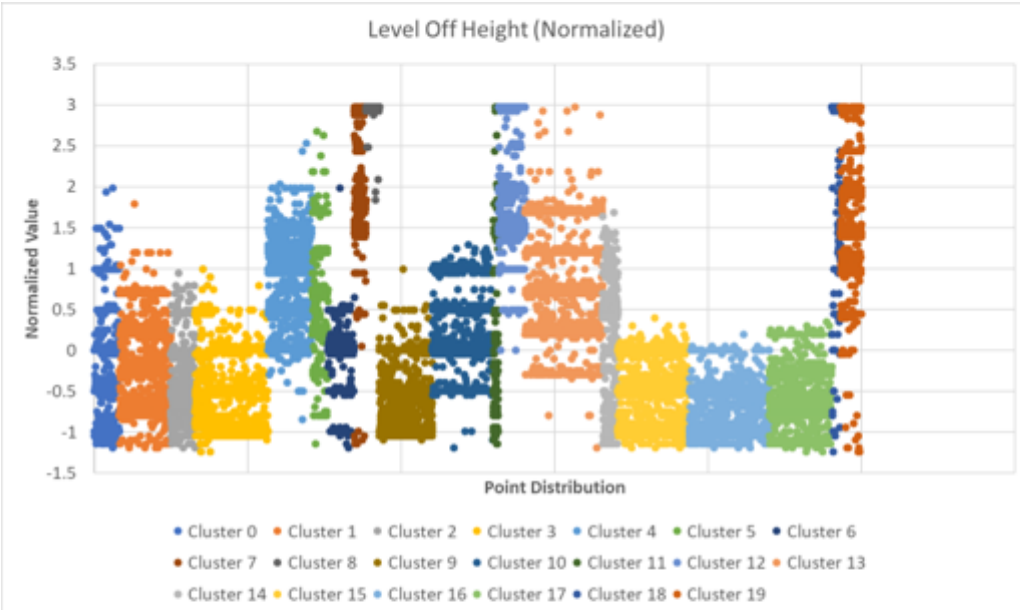



**Figure 6.** Point distribution of clusters for level-off height.

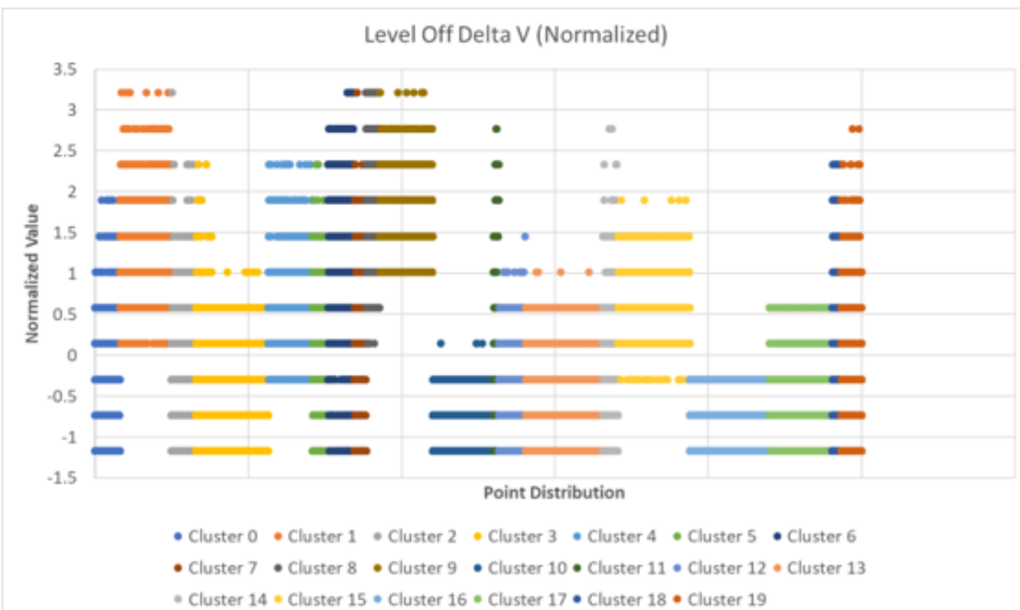



**Figure 7.** Point distribution of clusters for level-off delta V.

Visualizations were created to assess how the clustering is affected by geography. The goal of the visualization was to plot all clusters on a map to visually determine whether there were clear groupings of airport arrival patterns within clusters. Tableau was used to construct the map-based visualization. To verify the sensitivity of the clusters, arrival modeling was performed with AEDT, comparing the centroid of each cluster to the default STANDARD profile. The nature of all clusters was determined by comparing the environmental metrics obtained from the results of arrival modeling. The modeling gave the range of level-off parameters, i.e., the minimum and maximum of each level-off parameter.

**Table 3.** Procedural definition of random flights from cluster 2 arrival operation for the Boeing 737-800 at KATL.

| Step | Flap ID | Step Type | Altitude (ft) | Calibrated Airspeed (knots) | Distance (ft) | Glide Slope |
|---|---|---|---|---|---|---|
| 1 | A_00 | Descend | 8,400 | 249 | | 3 |
| 2 | A_00 | Level | 5,400 | 250 | 21,500 | |
| 3 | A_01 | Level | 5,400 | 246 | 3,671 | |
| 4 | A_05 | Level | 5,400 | 243 | 5,209 | |
| 5 | A_15 | Descend | 5,400 | 240 | | 3 |
| 6-9 | Same as Default | Same as Default | Same as Default | Same as Default | Same as Default | Same as Default |

**Results and Discussion**

K-Means and BIRCH were identified as the best clustering methods based on three quantitative scoring metrics that indicate the quality of the identified clusters: the silhouette score, Davies–Boudlin index, and Calinski–Harabasz index. The clustering score comparisons are shown in Figure 8. After the clustering methods were selected, they were implemented on a test dataset consisting of all level-offs from the three busiest airports in the full dataset to determine the primary features that significantly affect level-off parameters.

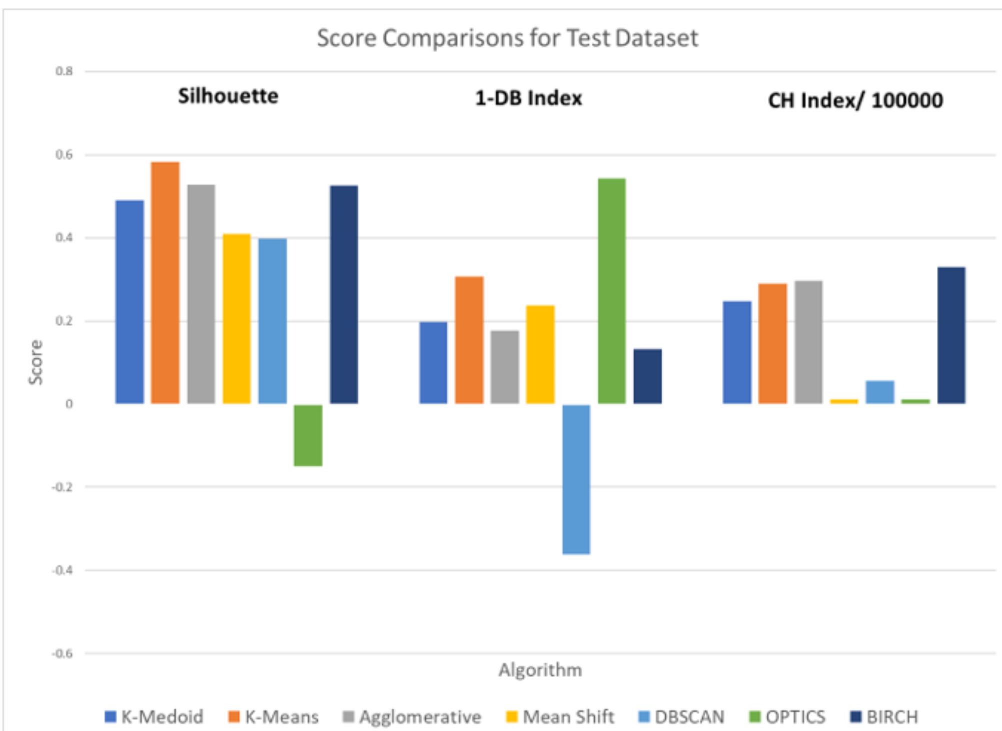



**Figure 8.** Score comparisons for a test dataset. CH: Calinski–Harabasz; DB: Davies–Boudlin; DBSCAN: Density-Based Spatial Clustering of Applications with Noise; OPTICS: Ordering points to identify the clustering structure; BIRCH: Balanced iterative reducing and clustering using hierarchies.

The cluster distribution was plotted against the chosen metrics for three types of datasets: test, small, and large. It was observed that the cluster distributions were similar for the test and large datasets, with a poor correlation between the metrics for small and large datasets. Figure 9 shows the cluster distribution for the BIRCH algorithm across 10 clusters for a complete dataset. The y-axis consists of the percentage for each cluster, and the x-axis gives the cluster label (0–9). The plot shows that BIRCH has one prominent cluster in which a significant number of points are distributed. Figure 10 shows the cluster distribution for the K-Means algorithm (10 clusters) applied to a complete dataset. The axis definitions are the same as those in Figure 9. The plot shows that the K-Means distribution is spread more evenly than the BIRCH distribution.

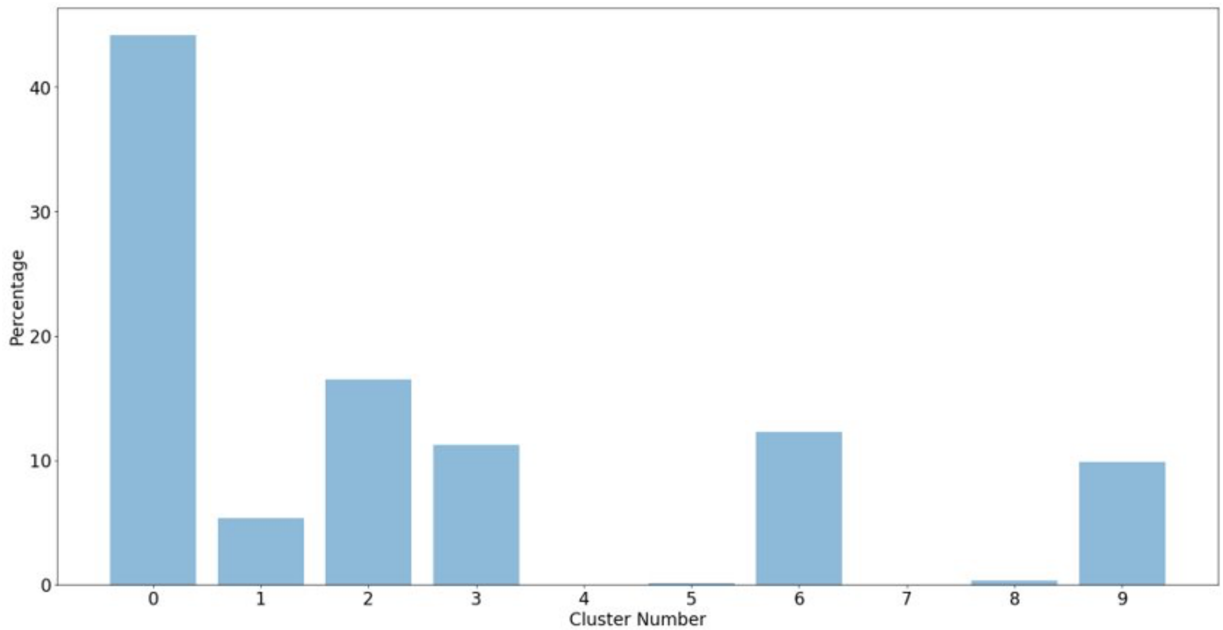



**Figure 9.** Cluster distribution for the BIRCH algorithm.

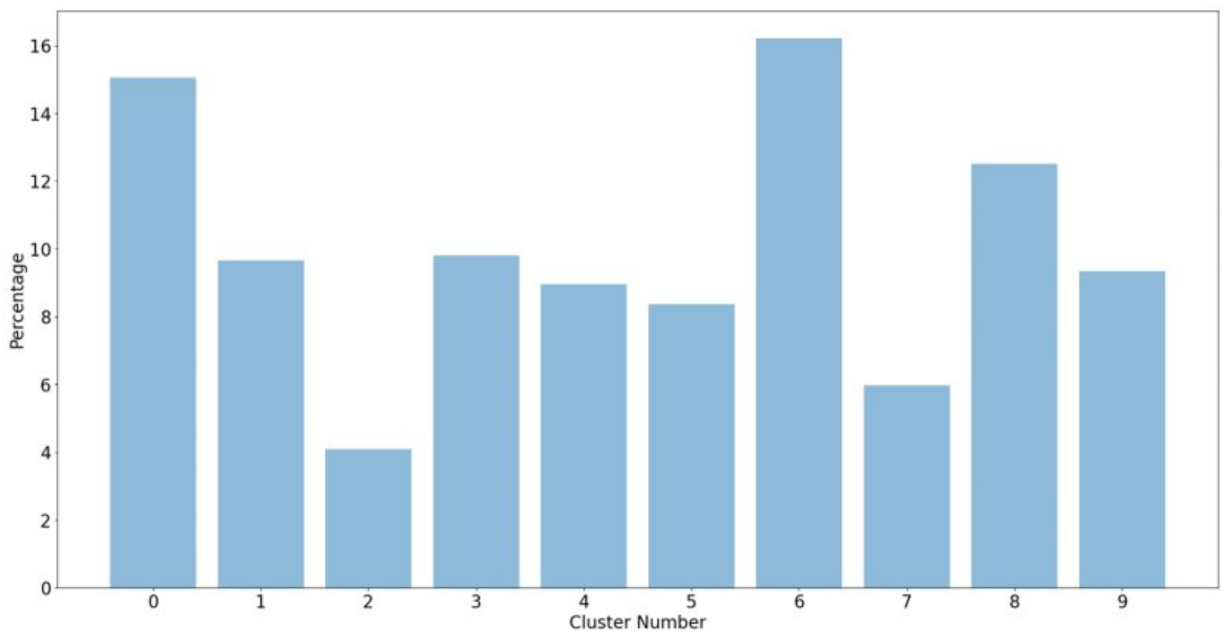



**Figure 10.** Cluster distribution for the K-Means algorithm.

Tableau was selected as the platform to produce data visualizations as a dashboard. The dashboard includes the locations of airports on a U.S. map, displaying cluster distributions, airport diagrams, scatter plots of level-off length vs. height, histograms for level-off fields vs. flight counts at each airport, the distribution of flights across clusters, centroids for each cluster, etc. As shown in Figure 11, data for a specific airport are filtered, and the histograms contain detailed flight counts for different metrics, which are useful for analyzing the flights arriving at an airport.

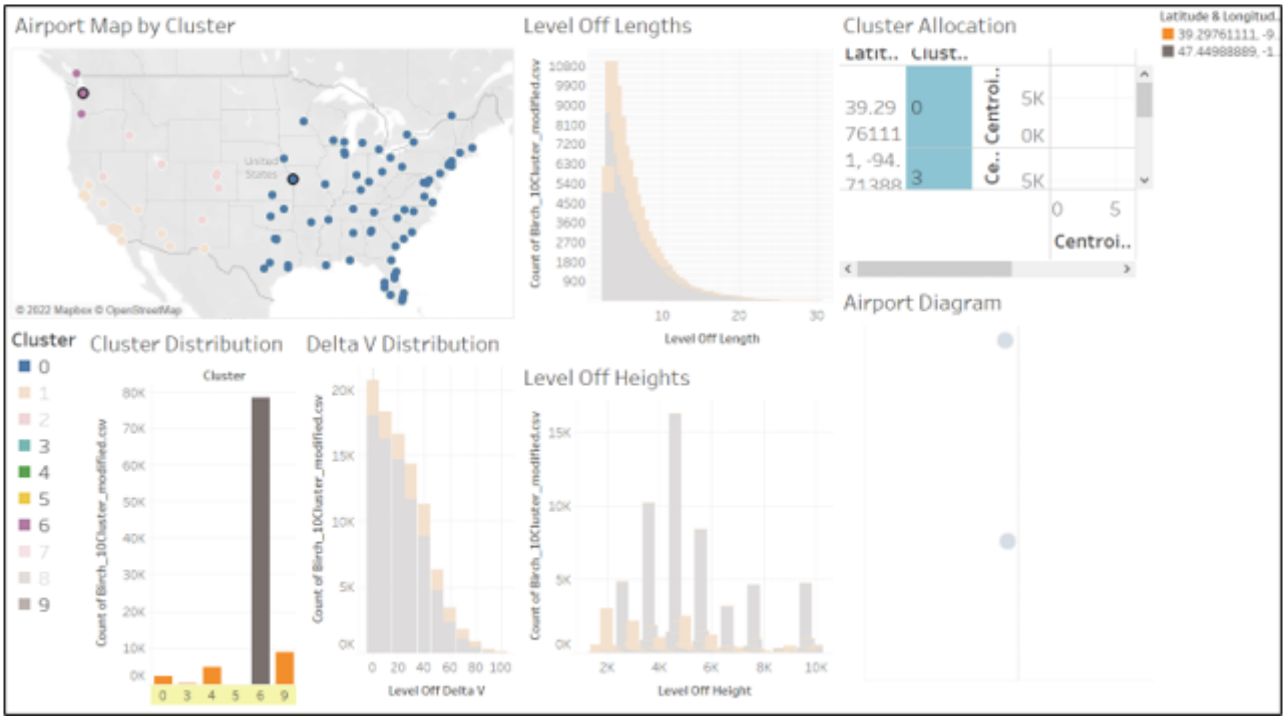



**Figure 11.** Tableau comparing KSEA (Seattle-Tacoma International Airport) and KMCI (Kansas City International Airport). BIRCH: Balanced iterative reducing and clustering using hierarchies

A study was designed in AEDT to understand and quantify the sensitivity of performance, noise, and emission metrics to the level-off definitions yielded by the clustering results. The default STANDARD arrival was compared with Random Flight 1 and Random Flight 2 arrivals at KATL. It was observed that Cluster 2 had a larger area for the 65-, 70-, and 75-dB contours, which was likely due to the shorter level-off lengths of Random Flight 1 and Random Flight 2.

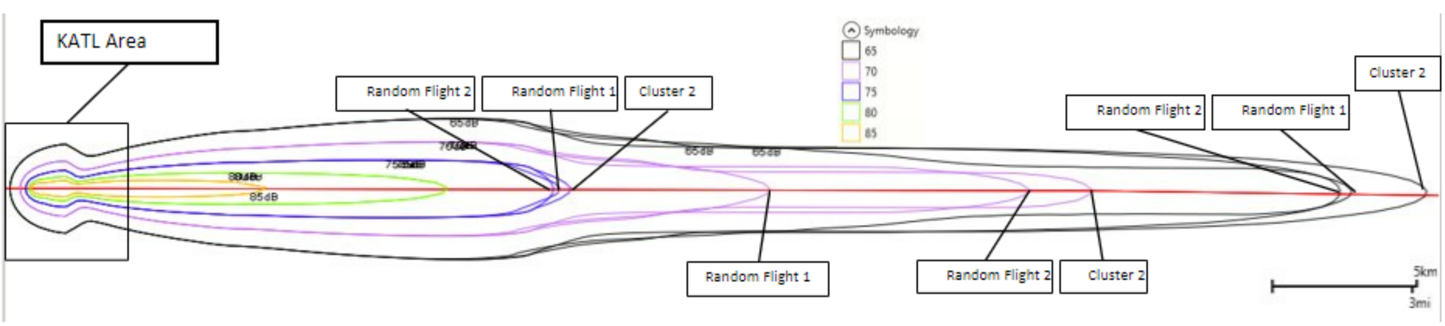



**Figure 12**. Example of cluster centroid vs. randomly clustered flights.

The clustering shown here indicates reasonable allocations for the level-off data. The sensitivities also produce results that are aligned with expectations. Thus, the next steps are to assess the sensitivities in detail, confirm the results and parameters that differentiate the clusters, and start moving the task closer to making recommendations for arrival profile implementation. In the next year, the efforts of ASCENT 43 will be merged with Task 2 of ASCENT 54. With this merge, the modeling of Noise-Power-Distance data (NPDs) for multiple speeds and configurations will also be considered within this task.

## Milestones
None

## Major Accomplishments
- Identified K-Means and BIRCH as the best clustering methods based on three quantitative scoring metrics
- Analyzed cluster distribution by plotting against set metrics and identified K-Means as having a uniform spread of distribution
- Created visualizations in Tableau to compare cluster parameters and geographical distribution parameters
- Determined the sensitivity of the clusters by performing arrival modeling on AEDT while maintaining the cluster centroid as the default

## Publications
None

## Outreach Efforts
Biweekly calls
Bi-annual ASCENT meetings

## Awards
None

## Student Involvement
- Keletso Mmalane and Anushka Moharir (Graduate Research Assistants, Georgia Institute of Technology) participated in this research.

## Plans for Next Period
- Continue to analyze variability in environmental metrics from profiles in all clusters.
- Use percentiles of each level-off parameter for modeling instead of five randomly selected values.
- Include the modeling of speed- and configuration-dependent Noise Power Distance data (from ASCENT 43).

# Task 3 - Full Flight Modeling
Georgia Institute of Technology

## Objective
This task aims to improve the usability of the full flight modeling within AEDT without employing the often complicated and time-consuming process of using the sensor path functionality that is the current standard for AEDT. In the previous year, Task 3 attempted to verify the notion that the use of threaded track data as an input to AEDT full flight modeling could be validated by comparison to actual/historical flight data provided via FOQA datasets. Ideally, proper comparisons would validate the use of thread track data as a source for determining typical routing between city pairs and substantiate the associated fuel consumption models using either Base of Aircraft Data (BADA) 3 and/or BADA4 datasets. A successful validation would provide an alternative to the more laborious and time-consuming use of sensor path data.

The results of the work completed during the last year have led to a proposed re-definition of the approach that may be most appropriate for AEDT to support simplified, yet statistically valid modeling of the National Airspace System flight frequency and cumulative fuel burn/emission analysis. This approach utilized a more rudimentary method, such as the great-circle distance (GCD) + % additive correctly integrated with seasonal wind/temperature history. This analysis was enabled by the supplementary tool set PaceLab Mission Suite (PLMS). PLMS has integrated seasonal wind data that are not currently available in the AEDT system via Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2).

In addition, based on the results of the work completed in the past years, the Georgia Tech team recommends that a new AEDT functionality be developed to allow for the input of statistical wind histories (MERRA-2 datasets are too granular for large-scale studies). As an alternative, it is proposed that AEDT be modified to allow for fixed input wind/temperature models. According to a discussion with the Volpe development team, it may be possible to accomplish this effort by using the existing software structure. The creation of a "nominal" wind/temperature dataset as a default may provide a solution.

While each of these recommendations would need further investigation and vetting, the overall approach would allow for the use of GCD + % system modeling in a rapid and efficient manner to provide statistically valid modeling of National Airspace System route densities and cumulative emission analyses.

The report material is subdivided into the following areas with corresponding methodology, results, and discussion sections:

- Great Circle Route Planning
- Seasonal Average Wind Model

## Research Approach

**Investigation 1. Alternative Methodology: Great Circle Route Planning**

**Methodology**

An alternative approach has been taken to demonstrate that a simplified route based on seasonal wind averages can provide a statistically valid prediction for time and fuel. This alternative approach was chosen because AEDT's weather data modeling hinder AEDT's time and fuel predictions when using a single notional route vs. actual flight histories. We used the PLMS tool to compare actual FOQA flight histories. The PLMS tool is a commercial tool for route and aircraft economic analysis and produces metrics such as payload capacity, maximum range, trip time, and fuel burn by flight segment. Because the aircraft performance modeling of the PLMS tool is derived from the Original Equipment Manufacturer (OEM) dataset and the wind data are based on the Boeing commercial model, the PLMS is a suitable tool for comparing real FOQA flights. As a proof of concept, we performed a sensitivity analysis between the FOQA flights and the range of GCD + % variance using the PLMS tool.

**Results and Discussion**

In the first step, we determined how well the predicted trip distance matches the FOQA flight histories within the cluster obtained in Investigation 2 by adding some variance to the GCD in the PLMS tool. Histograms were generated for city pairs and used to find the closest trip distance obtained using the PLMS tool with respect to the actual flight histories. We added 25 nautical miles to the analysis with the PLMS tool, considering the influence of vectoring by air traffic controllers near departure or arrival airports.

**Error! Reference source not found.**The histogram bin width was set to 5 nautical miles, and the results of a sensitivity analysis of trip distances for KATL-KSEA-KATL are shown in the histogram in Figure 13. The red vertical dotted line represents the median trip distance of FOQA flights within the cluster. The blue and purple vertical dotted lines show the GCD + 3% and 5% variance, respectively, as the trip distance predicted by the PLMS tool. The histogram is not a perfect bell shape, especially for KSEA-KATL, because the FOQA data do not include all flights for a given city pair over a selected time period. However, considering the limitations of the FOQA data, it is still possible to compare the trip distance representing the actual FOQA flights. As shown in Figure 13, for the histogram of KATL-KSEA-KATL, the GCD + 3% gives the trip distance closest to the median trip distance of the FOQA flights within the cluster. Moreover, the median trip distance of the FOQA flights for KSEA-KATL is larger than the median trip distance of the FOQA flights for KATL-KSEA due to wind conditions during the flight.

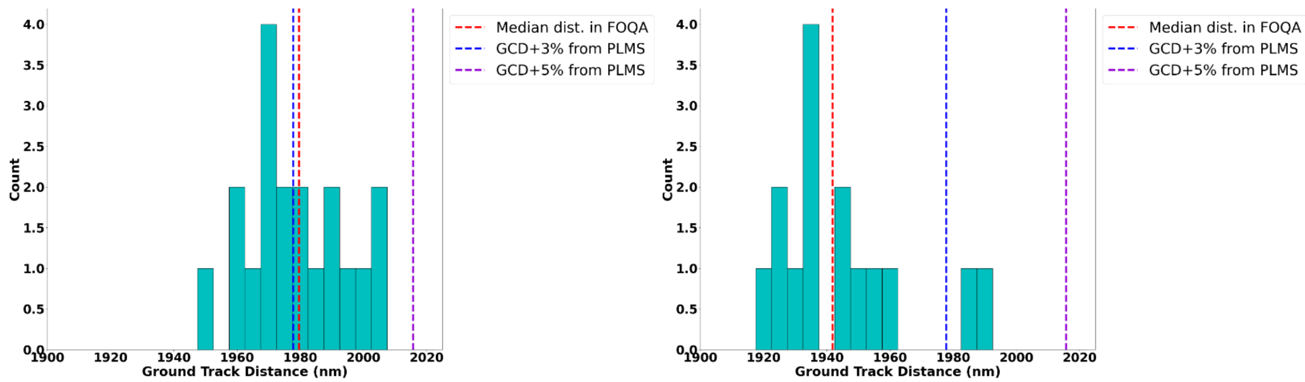



**Figure 13.** Histogram from a sensitivity analysis of trip distance for KATL-KSEA (left) and KSEA-KATL (right). nm: nautical mile; PLMS: PaceLab Mission Suite.

The histograms in Figure 14 display the average wind distribution for FOQA flights within the cluster. The red vertical dotted line is the median of the average wind of the FOQA flights. The blue dotted line is the wind condition with 50% reliability obtained by the PLMS tool. There is no significant difference between the red and blue dotted lines. The average wind condition is always positive for KATL-KSEA, whereas the average wind condition for KSEA-KATL is always negative except for one case. The headwind conditions during the flight for KATL-KSEA lead to a greater trip distance.

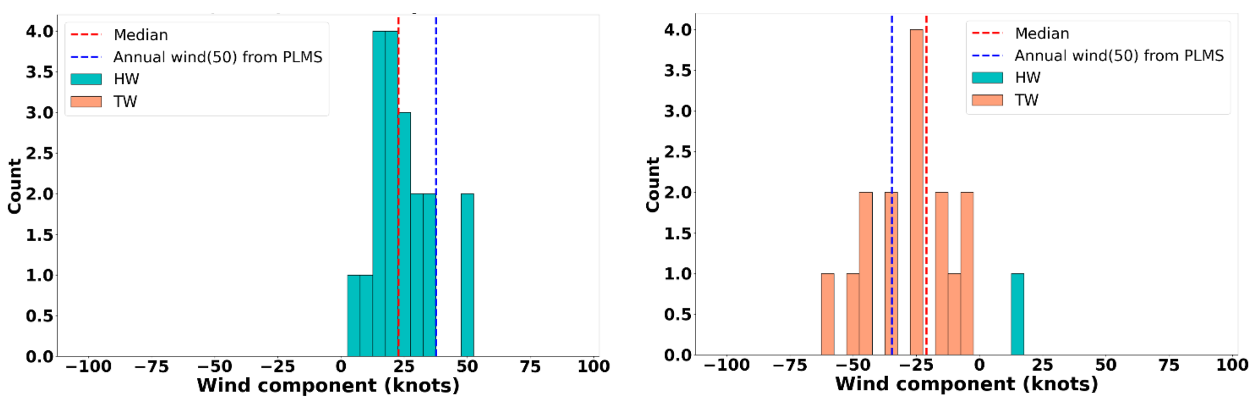



**Figure 14.** Histogram for sensitivity analysis of average wind conditions for KATL-KSEA (left) and KSEA-KATL (right). HW: headwind; PLMS: PLMS: PaceLab Mission Suite; TW: tailwind; FOQA: Flight Operational Quality Assurance.

**Error! Reference source not found.**The results of a sensitivity analysis for the trip distance between FOQA flights and the PLMS product are given in Table 4. The GCD + 3% variance shows the smallest error compared with the median trip distance of the FOQA flights for all identified city pairs. KATL-KSEA and KSLC(Salt Lake City International Airport)-KLAS(Las Vegas International Airport) have the most significant error of 1.9% for the comparison between the median trip distance of the FOQA flights and the GCD + 3% variance obtained by the PLMS tool.

**Table 4.** Sensitivity analysis of the trip distance between FOQA flights and the PaceLab Mission Suite tool.

| City pair | Avg. Ground Track Distance (nm) within the cluster (FOQA) | Trip distance (nm) from Pace Lab | | | % Error | | |
|---|---|---|---|---|---|---|---|
| | Median | GCD + 0% | GCD + 3% | GCD + 5% | GCD + 0% | GCD + 3% | GCD + 5% |
| ATL - LAS | 1562.7 | 1517.8 | 1588.3 | 1618.1 | -2.9 | 1.6 | 3.5 |
| LAS - ATL | 1567.3 | 1517.8 | 1588.3 | 1618.1 | -3.2 | 1.3 | 3.2 |
| ATL - MSP | 838.0 | 787.7 | 836.3 | 852.0 | -6.0 | -0.2 | 1.7 |
| MSP - ATL | 838.5 | 787.7 | 836.3 | 852.0 | -6.1 | -0.3 | 1.6 |
| ATL - SEA | 1979.6 | 1895.9 | 1977.8 | 2015.7 | -4.2 | -0.1 | 1.8 |
| SEA - ATL | 1941.8 | 1895.9 | 1977.8 | 2015.7 | -2.4 | 1.9 | 3.8 |
| ATL - SLC | 1450.3 | 1381.4 | 1447.9 | 1475.5 | -4.8 | -0.2 | 1.7 |
| SLC - ATL | 1444.4 | 1381.4 | 1447.9 | 1475.5 | -4.4 | 0.2 | 2.2 |
| ATL – LGA | 711.1 | 661.6 | 706.4 | 719.7 | -7.0 | -0.7 | 1.2 |
| LGA - ATL | 695.6 | 661.6 | 706.4 | 719.7 | -4.9 | 1.6 | 3.5 |
| LAS - SLC | 352.7 | 319.4 | 354.0 | 360.3 | -9.4 | 0.4 | 2.2 |
| SLC - LAS | 351.5 | 319.4 | 354.0 | 360.3 | -9.1 | 0.7 | 2.5 |
| | 347.4 | 319.4 | 354.0 | 360.3 | -8.1 | 1.9 | 3.7 |

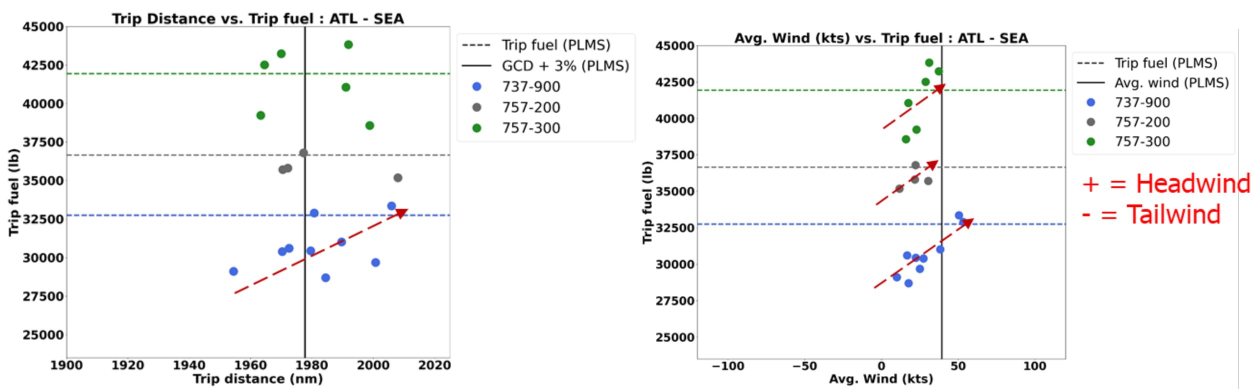



**Figure 15.** Comparison of the total fuel burn between FOQA flights and results obtained via the PLMS tool for KATL-KSEA. GCD: great-circle distance; PLMS: PaceLab Mission Suite.

In the previous step, the GCD + 3% variance obtained via the PLMS tool gave the closest representation of the actual FOQA flights. Therefore, the cumulative total fuel burn and wind based on the GCD + 3% variance from the PLMS tool were predicted and compared with values for actual FOQA flights. The PLMS analysis results based on GCD + 3% variance consistently correlate with actual FOQA fuel burn data and wind predictions. As shown in Figure 15, the total fuel burn data for FOQA flights are consistently scattered around an estimate of the trip fuel for each aircraft obtained via the PLMS tool, with an influence from aircraft performance and structural limits.

**Investigation 2. Alternative Methodology: Seasonal Wind Model**

**Methodology**

A direct comparison of AEDT's time and fuel predictions based on notional single routes vs. actual flight histories is hampered by AEDT's weather data modeling. A simplified route based on seasonal wind averages could enable an alternative approach to provide statistically valid predictions for time and fuel. This task aims to develop a weather model representing seasonal averages compatible with AEDT.

AEDT can use high-fidelity, airport annual average, and International Standard Atmosphere (ISA) weather data for performance modeling used for noise and emission modeling. MERRA-2 is one of the high-fidelity weather data sources that

AEDT can use. MERRA-2 covers the world and has a grid resolution of 0.5 degrees in latitude and 0.625 degrees in longitude. MERRA-2 data files are provided in netCDF-4 format. AEDT takes weather information from the MERRA-2 instantaneous weather data according to a specified location and time. From MERRA-2, seven variables are retrieved, including temperature, geopotential height, specific humidity, eastward wind, northward wind, surface pressure, and sea-level pressure.

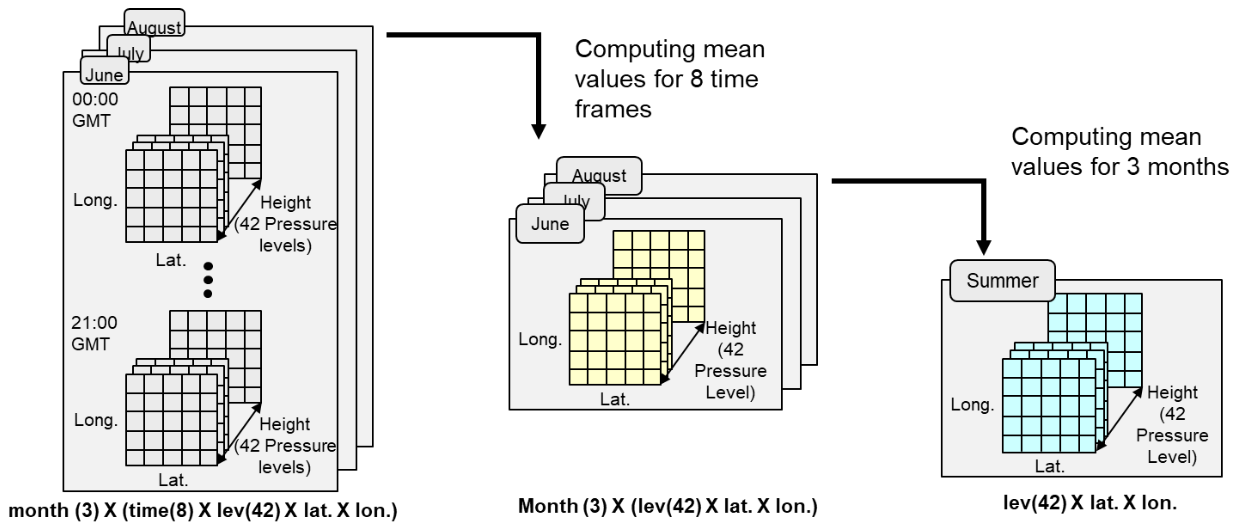



**Figure 16.** Procedure for data fusion (e.g., summer).

AEDT uses “inst3_3d_asm_Np” weather files for three-dimensional weather data and “inst1_2d_asm_Nx” weather files for surface (two-dimensional) weather data. However, “instU_3d_asm_Np” and “instU_2d_asm_Nx” are used to develop seasonal weather models because of the convenience and computational cost of averaging the variables through Python code. “instU_2d_asm_Nx” and “instU_3d_asm_Np” give instantaneous two- and three-dimensional monthly diurnal means in MERRA-2, respectively. “instU_3d_asm_Np” contains variables that define the dimensions of longitude, latitude, and time at 42 pressure levels. The data in “instU_3d_asm_Np” are collected every 3 hr, starting from 00:00 UTC. (i.e., 00:00, 03:00, ..., 21:00 UTC).

The procedure for developing a seasonal model is shown in Figure 16. Data from 2016 to 2020 were downloaded and divided according to the corresponding seasons as follows:

- Winter: December, January, and February
- Spring: March, April, and May
- Summer: June, July, and August
- Fall: September, October, and November

For example, let us suppose that we are creating a summer seasonal weather model. As mentioned above, each variable in the data has dimensions of time (8) x pressure level (42) x latitude x longitude. In the first step, average values are computed over the eight time frames in each data collection to create dimensions of pressure level (42) x latitude x longitude. The next step calculates the average values for the summer months of June, July, and August. All steps are implemented via Python code and use the “NC$WXEditorWPF.exe” application to ensure that the generated file format is correct. Lastly, a fuel consumption study is performed in AEDT using the FOQA trajectory input to compare the total fuel burn based on different weather data sources.

**Results and Discussion**

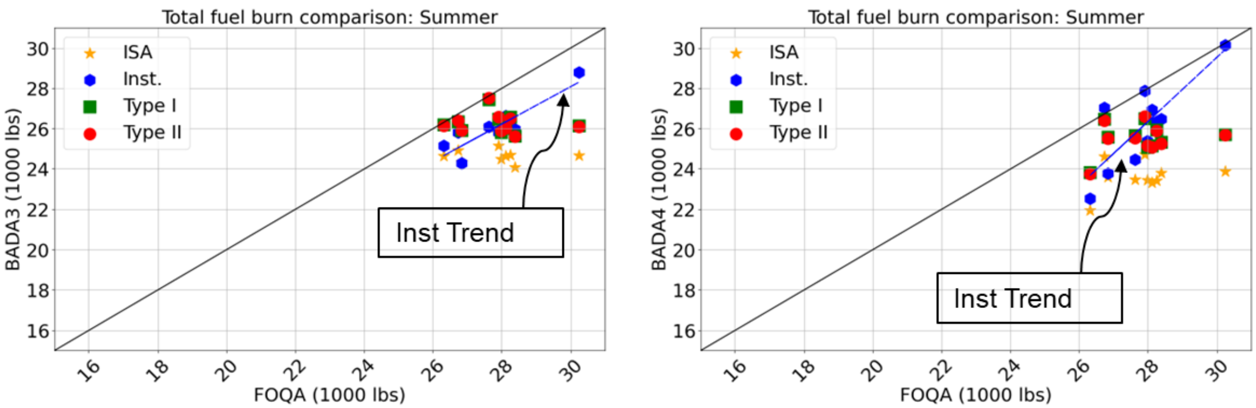



**Figure 17.** Total fuel burn comparison for KATL-KSEA. BADA: Base of Aircraft Data; ISA: International Standard Atmosphere; FOQA: Flight Operational Quality Assurance.

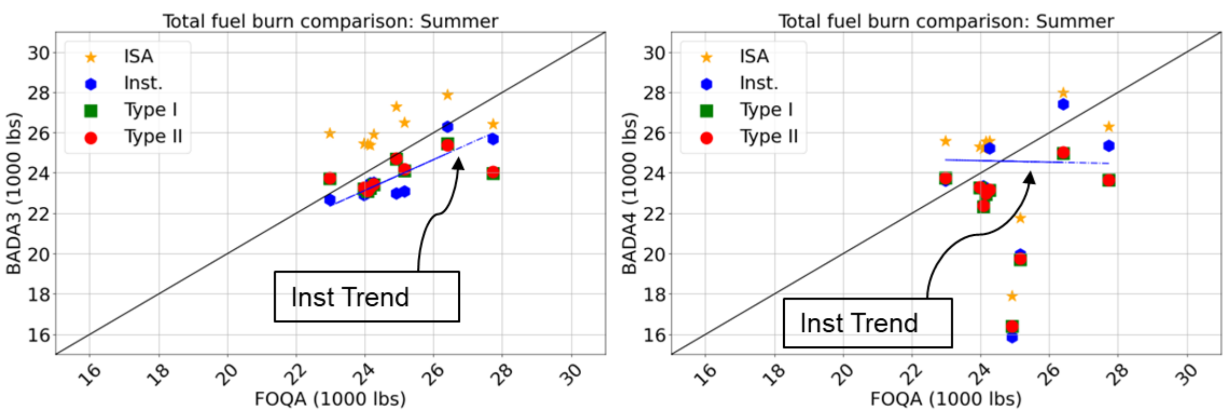



**Figure 18.** Total fuel burn comparison for KSEA-KATL. BADA: Base of Aircraft Data; ISA: International Standard Atmosphere, FOQA: Flight Operational Quality Assurance.

The cumulative fuel burn was compared using AEDT modeling with different weather data types. Figures 17 and 18 compare the fuel burn for KATL-KSEA and KSEA-KATL, respectively. In each figure, the left plot is the fuel burn computed by BADA3 modeling, and the right plot shows the fuel burn obtained by BADA4 modeling. The B739 airframe type was used in these comparisons. Note that only the en-route phase of the flight (FL100, >10,000 ft) is considered.

The four different weather data types compared in each figure are as follows:

1. ISA (yellow)
2. MERRA-2 instantaneous weather data (blue)
3. Type I seasonal weather data, considering the time frame, time (8) x pressure level (42) x latitude x longitude (green)
4. Type II seasonal weather data, disregarding the time frame, pressure level (42) x latitude x longitude (red)

In Figures 17 and 18, each point represents the total fuel burn for one flight. The location of each point along the x- and y-axes denotes the cumulative fuel burn for the flight in FOQA data and the AEDT model based on different weather data, respectively. The figures also show a solid black line for which the values along the horizontal and vertical axes are equal; if a data point falls on this line, the total fuel burn predicted by AEDT matches the total fuel burn reported by FOQA data.

According to Figures 17 and 18, the total fuel burn predicted using the instantaneous MERRA-2 weather data that matches the date of the FOQA flight is generally most similar to the total fuel burn obtained from FOQA data. This finding is consistent with the basic expectation that the instantaneous MERRA-2 weather data most closely track the actual values recorded in the FOQA data. The blue trend line generated from the blue dots (predicted from MERRA-2 instantaneous data) shows a slope similar to that of the solid black line, where the total fuel burn between FOQA and AEDT modeling is equal, especially for BADA3 modeling. The gap between the two lines arises because the fuel required from FOQA data may vary substantially depending on factors such as engine degradation and the status of engine maintenance.

In addition, the ISA dataset underpredicts the fuel required for westbound flights (KATL-KSEA) because it does not consider actual headwinds (i.e., higher value of equivalent static air miles). Moreover, the ISA dataset overpredicts the fuel required for eastbound flights (KSEA-KATL) because it does not take advantage of the tailwind (smaller value of equivalent static air miles). Moreover, when ISA weather data or seasonal weather models are applied, the fuel burn prediction based on BADA3 modeling is closer to the total fuel burn obtained from FOQA data than the fuel burn prediction based on BADA4 modeling.

We note that minor differences in fuel burn prediction arise when two types of seasonal weather models are used (types I and II), as shown by the green and red dots in Figures 17 and 18. Therefore, only type II models are recommended for the seasonal average weather because of the convenience in data processing.

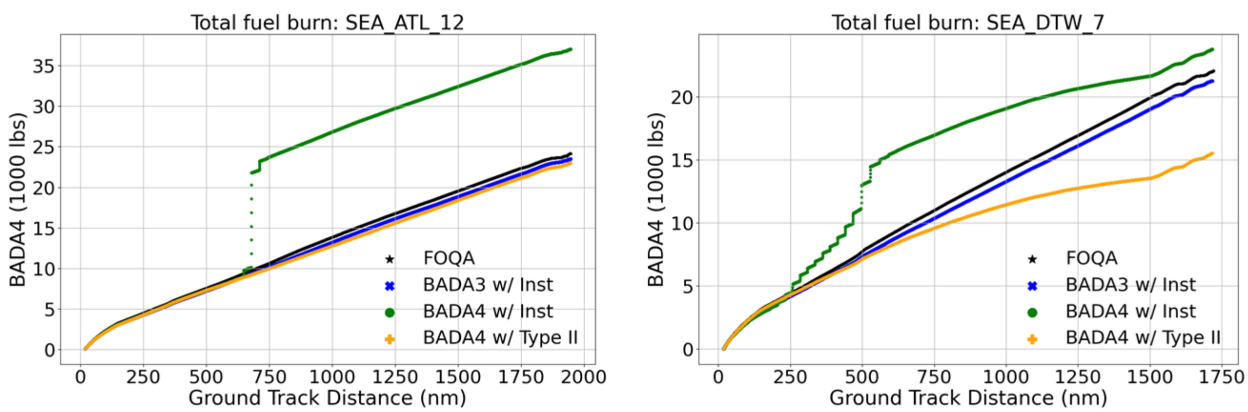



**Figure 19.** Total fuel burn comparison between FOQA and Aviation Environmental Design Tool modeling. BADA: Base of Aircraft Data; FOQA: Flight Operational Quality Assurance.

The total fuel burn was compared between FOQA and AEDT modeling using different weather data sources. The legend in Figure 19 is as follows.

- FOQA: Black
- BADA3 modeling with MERRA-2 instantaneous weather data: Blue
- BADA4 modeling with MERRA-2 instantaneous weather data: Green
- BADA3 modeling with type II seasonal weather data: Yellow

Numerous cases/conditions produced fuel flow discontinuities (high fuel flow over a short time period) in the AEDT output, resulting in a step function additive to the integrated fuel burn when the BADA4 model is used with MERRA-2 instantaneous weather data. This behavior was not observed when BADA3 was used with MERRA-2 instantaneous weather data. Moreover, discontinuity segments did not appear in the total fuel burn calculation for BADA4 modeling with type II seasonal weather data. Further investigation into these BADA4 discontinuities will be implemented.

## Milestones

None

## Major Accomplishments

- Conducted sensitivity analysis between FOQA flights and a range of GCD + % variance using a supplementary/independent route analysis tool: PLMS
  - PLMS route fuel burn analysis integrates historical seasonal wind data and applies reliability factors.
- Based on the success of the PLMS analysis, developed a weather model (i.e., wind) representing seasonal averages compatible with AEDT
  - This modeling was derived from publicly available MERRA-2 datasets.
- Generated two supplemental reports:
  - ASCENT Project 054: AEDT Evaluation and Development Support
  - ASCENT Project 054: Supplementary AEDT Functionality Analysis

## Publications

None

## Outreach Efforts

Biweekly calls
Bi-annual ASCENT meetings

## Awards

None

## Student Involvement

- Hyungu Choi and Jirat Bhanpato (Graduate Research Assistants, Georgia Institute of Technology) participated in this research.

## Plans for Next Period

- Continue investigating causes of BADA4 discontinuities in the BADA4 fuel burn calculation.
- Further investigate GCD + % system modeling.
- Develop alternative aircraft routing history data sources (System Wide Information Management, OpenSky, FlightAware Research Hub) to replace consistent sourcing of FOQA data from airlines, which is problematic.

# Task 4 - System Testing and Evaluation of AEDT

Georgia Institute of Technology

## Objective

To provide the best possible environmental impact modeling capabilities in AEDT, the FAA Office of Environment and Energy continues to develop AEDT by improving existing modeling methods and data and adding new functionalities. The FAA Office of Environment and Energy seeks an independent effort in system testing to evaluate the accuracy, functionality, and capabilities of AEDT and to support future model development. The objective of this task is to provide the FAA with high-quality systematic testing and evaluation of the capabilities of AEDT 3 and its future releases and to identify gaps in the tools' functionality and areas for further development.

## Research Approach

Within this task area, the Georgia Tech research team has been coordinating with the FAA and Volpe National Transportation Systems Center on upcoming AEDT features and testing and evaluating newly incorporated capabilities. For each AEDT release, depending on the update type, key features and functionalities are identified for capability demonstration to ensure that the implemented features are working properly. We are then either provided with or define for ourselves the scope and test cases for the system testing and evaluation effort. These cases are typically defined based on the key changes to the AEDT version from the previous releases. Due to the dynamic nature of the AEDT development process, we remain flexible in the choice of the testing and evaluation approach and the scope of our work. The best available methods and data are used to ensure accuracy in the functionalities of newly released AEDT versions. When required, uncertainty quantification analysis is conducted to understand the sensitivities of output responses to variation in input variables and to quantify the major contributors to output uncertainties.

In the following subsections, the various features and functionalities that were tested from October 2021 to September 2022 are described. In addition, various bugs were identified, reported, and re-tested to support the AEDT development process.

**AERMOD Performance Updates**

AEDT's American Meteorological Society/Environmental Protection Agency regulatory model (AERMOD) module performs modeling of pollutant dispersion within short distances of industrial sources, and its integration into the software enables higher-fidelity emission analyses. This task aimed to discern the extent to which AERMOD taxes computer memory in its calculations and to identify specific computational bottlenecks in these processes.

Testing was conducted through the creation of a large-scale study featuring over 1.5 million arrival and departure operations split across Auxiliary Power Units (APUs) and Ground Support Equipment (GSEs). AERMOD's involvement in emission calculations was monitored using software designed to track memory usage at important computational junctures and compared with results from both prior tests and varying study settings.

Results demonstrated a 15% improvement in overall AERMOD efficiency relative to prior AEDT releases, but these outcomes were localized only to cases involving emission dispersion calculations (rather than inventory tabulations).

**Touch-and-Go/Circuit Profile Development**

This task focused on the development of touch-and-go and circuit profiles for two new aircraft in AEDT 3e, namely the 7879 and 747-400RN, using the existing approach and departure procedures as the baseline. This development was performed for both Aircraft Noise & Performance database (ANP) fixed-wing civil aircraft with defined procedural profiles, and the developed profiles were provided to the AEDT development team for integration into the FLEET database.

Profiles were created using programming scripts to copy appropriate steps from the relevant departure or arrival profile. All created profiles were tested for accuracy by modeling noise metric results over a noise grid.

**Ability to Import Flight Operations from CSV Files**

This feature adds the ability to import aircraft operations and tracks from CSV input files into an existing AEDT study via both the graphical user interface (GUI) and command line tool. Incorporation of this option into AEDT streamlines the process of setting up large studies by eliminating the need to directly interface with the underlying Structured Query Language (SQL) database containing operations and their properties.

We performed testing by attempting to import a series of both properly and improperly formatted aircraft and helicopter operation CSV files. Results indicated proper feature functionality, with both GUI and command line interfaces importing correct operations and rejecting improperly formatted files.

**View/Edit Individual Tracks**

This feature focused on testing the new track visualization updates in AEDT 3e, which allowed the user to generate the full airport layout, only the ground elements, or only selected tracks with ground elements and interact with each of these layers in the airport designer. Additionally, the user can now change the maximum number of tracks that can be displayed at one time in the AEDT settings menu.

A large study containing tens of thousands of tracks was used for testing purposes. Most of the visualization tests (e.g., generating all layout options, testing track selection availability, testing the maximum number of tracks) were successful, with the exception of a few small display issues in the AEDT user interface that were identified as bugs. Furthermore, due to machine limitations, the maximum track number setting was changed from 25,000 to 100 when the visualization was performed in the GUI. The correct warning and error messages were displayed when the user tried to visualize more tracks than the actual maximum setting.

**Updated Start-of-Takeoff-Roll Noise Directivity**

Updates to the International Civil Aviation Organization (ICAO) methodology for noise directivity calculations necessitated a corresponding change to AEDT's noise maps for all affected aircraft. These modifications were examined by comparing the take-off noise contours of all airplanes in the FLEET database between a prior and current AEDT version. A full cross-examination of all AEDT aircraft demonstrated a consistent shift in noise directivity in the current release, in line with ICAO specifications. The typical extent of ICAO's alterations is apparent in Figure 20, which presents modeling results of aircraft departure from the KATL airport.

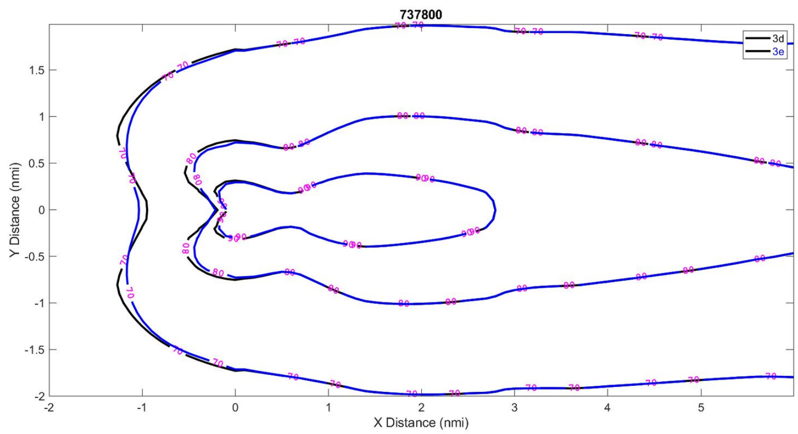



**Figure 20.** Previous and current 737-800 noise contours. nmi: nautical mile.

## Milestones

None

## Major Accomplishments

- Conducted several detailed investigations and testing efforts for system testing of new AEDT features
- Completed the first draft of a comprehensive Uncertainty Quantification report, currently being reviewed by the FAA

## Publications

None

## Outreach Efforts

- Bi-weekly calls
- Attendance at bi-annual ASCENT meetings
- Attendance at the American Institute of Aeronautics and Astronautics Aviation Conference and OpenSky Symposium to present conference papers

## Awards

None

## Student Involvement

Bogdan Dorca and Santusht Sairam (graduate research assistants, Georgia Institute of Technology) participated in this research.

## Plans for Next Period

- Continue system testing efforts to support ongoing AEDT development.
- Revise the Uncertainty Quantification report draft based on FAA feedback and finalize the draft for publication.