Project 036 Parametric Uncertainty Assessment for the Aviation Environmental Design Tool (AEDT)

Georgia Institute of Technology

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- FAA Award Number: 13-C-AJFE-GIT, Amendment 019, 29, 30, 40, and 49
- Period of Performance: September 1, 2018 to August 31, 2019
- Task(s): Parametric Uncertainty Quantification for BADA4

Project Funding Level

The current funding for this project is based on amendments 30, 40, and 49 for a total of $300,000 from May 31, 2019 to May 30, 2020. The Georgia Institute of Technology has agreed to a total of $300,000 in matching funds.

Investigation Team

- Prof. Dimitri Mavris (PI) oversees the entire project.
- Dr. Yongchang Li (Co-PI, project lead) leads the research team in performing capability demonstrations and tests and in validating various functionalities of different AEDT versions.
- Dr. Michelle Kirby (Co-PI) oversees the entire project and supports all of the research activities.
- Dr. Dongwook Lim (research staff) conducts capability demonstrations, verifications, and validations of new AEDT features and functionalities.
- Zhenyu Gao (graduate student) conducts parametric uncertainty quantification analyses for the BADA4 model, created the AEDT study, and performed a sensitivity analysis for this study.
- Yee Chan Jin (graduate student) developed a BADA4 calculator in the form of a spreadsheet using BADA4 equations to quantify aircraft performance.
- Ameya Behere (graduate student) supports the system testing of AEDT features.
- Dr. Holger Pfaender (research staff) provides consultation and support.

Project Overview

The FAA's Office of Environment and Energy (AEE) has developed a comprehensive suite of software tools that allow for a thorough assessment of the environmental effects of aviation, particularly for assessments of interdependencies among aviation-related noise, emissions, performance, and cost. As the heart of this tool suite, the high-fidelity AEDT is a software system that models aircraft performance in space and time to estimate fuel consumption, emissions, noise, and air quality impacts. This software has been developed by the FAA AEE for public release as the next-generation FAA environmental consequence tool. AEDT enables evaluations of interdependencies among aircraft-related fuel consumption, emissions, and noise. AEDT 2 was released in four phases. The first version, AEDT 2a, was released in March 2012 (US FAA, AEDT 2a UQ Report, 2014; US FAA, AEDT 2a SP2 UQ Supplemental Report, 2014) and the second version, AEDT 2b, was released in May 2015 (US FAA, AEDT 2b UQ Report, 2016). The third and fourth versions, AEDT 2c and AEDT 2d, respectively, were released in September 2016 and September 2017. A new version, AEDT 3b, was released in September 2019, with major updates, including the inclusion of the BADA4 performance model for fuel consumption, emissions, and noise and the implementation of reduced thrust and alternative weight profiles for departure operations.

The uncertainty quantification applied in this project comprehensively assesses the accuracy, functionality, and capabilities of AEDT during the development process. The major purposes of this effort are as follows:

- Contribute to the external understanding of AEDT
- Demonstrate and evaluate AEDT's capability and fidelity (ability to represent reality)
- Help AEDT users to understand the sensitivities of output responses to variations in input parameters/assumptions
- Identify gaps in functionality
- Identify high-priority areas for further research and development

The uncertainty quantification consists of verification and validation, capability demonstrations, and parametric uncertainty/sensitivity analysis.

Task 1- Parametric Uncertainty Quantification for BADA4

Georgia Institute of Technology

Objective(s)

The implementation of BADA4 in the new series of AEDT 3 created additional needs for model verification and validation, as well as uncertainty analysis. For aircraft trajectory simulation and performance modeling within air traffic management, the BADA4 model is an important update of its precedent version, BADA Family 3. The BADA4 model consists of more complex performance models with significantly more performance parameters. By identifying and quantifying how the key AEDT outputs respond to variations in BADA4 performance parameters, we can better identify the primary contributors to AEDT output uncertainties under BADA4 for future tool development and enhancement and can inform users regarding the expected variation in AEDT outputs.

Research Approach

To perform a system-level parametric uncertainty analysis on BADA4 parameters and to gain insights for future AEDT improvements, a four-step uncertainty quantification process has been applied, including uncertainty characterization, sensitivity analysis, uncertainty propagation, and global sensitivity analysis (Lim et al., 2018). As the first step, uncertainty characterization identifies and mathematically represents the uncertainty sources that may impact key AEDT outputs. Second, the sensitivity analysis quantifies the influence of each uncertainty source on the outputs of interest by varying each input parameter within a reasonable range. The third step, uncertainty propagation, is applied to propagate uncertainties across all uncertainty sources through a system model to obtain nondeterministic distributions of the outputs. Finally, the global sensitivity analysis quantifies the contribution of variance in each output. Table 1 lists the key methods used in the four-step uncertainty quantification process, and the following subsections provide details on the current progress of the BADA4 parametric uncertainty quantification.

Uncertainty Characterization

Uncertain BADA4 parameters

Uncertainty characterization is the first step in performing uncertainty quantification for a complex model. The uncertainty characterization step in this work includes three components: (1) a list of BADA4 input parameters that may have a significant impact on key AEDT outputs, such as fuel burn, emission, and noise metrics; (2) a mapping and understanding of how the BADA4 parameters are applied to calculate key performance metrics, leading to a tool for rapid BADA4 analysis; and (3) a list of uncertain physical factors in real-world operations, such as uncertainties in weather, weight, or takeoff profile, that may influence the outputs of interest and their uncertainty ranges.

BADA4 coefficients are stored in different tables of the FLEET database, and a summary of the BADA4 parameters is provided in section 7.2 of the BADA4 user manual (Eurocontrol Experimental Centre). In this study, we focus on aircraft with turbofan engines, with a total of eight BADA4 parameter categories. Detailed information of the eight BADA4 parameter categories and subcategories is given in Table 2.

Table 1. Four steps of the uncertainty quantification process and key methods.

Step	Methods
Step 1 Uncertainty Characterization	**Mapping** of key Aviation Environmental Design Tool (AEDT) inputs to key environmental metrics based on literature reviews and expert knowledge Analysis of AEDT Fleet DB to **quantify the variability** in AEDT input parameters **Correlation analysis** of AEDT input parameters
Step 2 Sensitivity Analysis	**One-factor-at-a-time (OFAT) design of experiments**, in which each input parameter is varied one at a time while the other parameters are held constant at baseline values
Step 3 Uncertainty Propagation	**Screening test** to reduce the number of variables for surrogate models; screening test with 5,000 cases using the Latin hypercube sampling technique; use of an ANOVA test and a regression model to yield a Pareto plot **Surrogate modeling** using an artificial neural network **Monte Carlo simulation** **Copulas theory** to capture correlations between input parameters
Step 4 Global Sensitivity Analysis	Assessment of the impact of input parameters on the outputs **Total sensitivity index** to measure the relative impact of each input parameter

Table 2. Summary of BADA4 parameter categories.

Category	Subcategory
Aerodynamic Forces and Configuration Model (AFCM)	Clean drag model coefficients (D)
	Nonclean drag model coefficients (D_NC)
	Other performance parameters
Propulsive Forces Model (PFM)	Other performance parameters
Turbofan Model (TFM)	Turbofan idle rating thrust coefficients (TI)
	Turbofan idle rating fuel coefficients (FI)
	Turbofan non-idle rating thrust coefficients (A)
	Turbofan non-idle rating fuel coefficients (F)
	Turbofan flat-rated area throttle coefficients (Bn)
	Turbofan temperature-rated area throttle coefficients (Cn)
Kinematic Limitations Model (KLM)	Other performance parameters
Geometric Limitations Model (GLM)	Other performance parameters
Buffet Limitations Model (BLM)	Maximum lift clean configuration buffet coefficients (BF)
	Maximum lift nonclean configuration buffet coefficients (CL_MAX)
	Other performance parameters
Dynamic Limitations Model (DLM)	Other performance parameters
Airline Procedure Model (ARPM)	Other performance parameters

Each aircraft with turbofan engines has BADA4 coefficients from all eight categories. The exact number of BADA4 coefficients in each category depends on the aircraft model and is typically within the range of 200–300. In addition to BADA4 coefficients, in this uncertainty quantification work, aircraft noise and performance (ANP) and airport weather parameters were also studied, as these parameters have a strong impact on AEDT outputs produced by the BADA4 model. The BADA4 uncertainty quantification task deals with a much larger number of parameters than the uncertainty quantification task conducted for BADA3. Taking the Boeing 737-700 as an example, the total number of parameters changed from 16 to 193 between the BADA3 and BADA4 models. With an increased number of input parameters, the expected computational cost and complexity for the entire uncertainty quantification process also grow.

Uncertain physical parameters

In the last step of the uncertainty characterization process, the physical parameters in real-world operations are identified and quantified. The two major sources of such uncertainties are airport weather parameters and departure profiles. Among airport weather parameters, six key parameters are used in AEDT performance calculations: temperature, sea-level pressure, station pressure, dew point, relative humidity, and wind speed. These weather parameters can change significantly over a one-year period and can even vary significantly from morning to evening, depending on the airport location. In addition, the reduced thrust and alternative weight departure profiles developed under ASCENT project 45 reflect actual operation-level uncertainties during departure. In the characterization of physical uncertainty sources, both components are included and quantified. Taking Atlanta International Airport (KATL) as an example, a list of uncertain physical parameters and their uncertainty ranges are given in Table 3.

Table 3. Uncertain physical parameters at Atlanta International Airport (KATL).

Item	Baseline Value	Upper Bound	Lower Bound
Temperature @ KATL	62	94	25
Sea-level Pressure @ KATL	1018.02	1032	1004
Station Pressure @ KATL	980.61	993	968
Dew Point @ KATL	50.86	74	9
Relative Humidity @ KATL	67.65	100	20
Wind Speed @ KATL	7.03	24	0
Alternative Weight	Baseline Weight	Alternative Weight	
Takeoff Thrust	100%	Three Reduced Thrust Levels: -5%, -10%, -15%	

The upper and lower bounds of the six weather parameters at KATL, as shown in Table 3, were developed based on historical data. In this process, a histogram of data for each parameter over the past 40 years was created, with the upper and lower bounds given as the upper and lower boundaries of the 95% confidence interval, respectively. The alternative weight and takeoff thrust uncertainties are represented by the previously defined alternative weight and reduced thrust profiles.

Sensitivity analysis procedure

Because the uncertainty quantification process for AEDT and BADA4 involves manipulating the input parameters and running a number of cases with the updated parameter values, an automated, replicable process is needed for effectively conducting the analysis. Such an automated process was initially developed to perform a one-factor-at-a-time (OFAT) computer experiment. The OFAT design of experiment (DoE) is a type of computer experiment in which only one input parameter is varied at a time, while the remaining input parameters are maintained at their baseline values. By implementing the OFAT DoE, one can assess how each individual input influences the outputs. More specifically, the results of an OFAT experiment can provide insight into how variations in inputs impact the variations in outputs with respect to direction and magnitude. In this study, an automated process was developed to facilitate the computer experiment, as shown in Figure 1. In this automated process, a Python script was created to integrate different tools, including the SQL server management studio, AEDT, and batch report, and to automatically process each case sequentially.

The process depicted in Figure 1 can be applied for an OFAT DoE study for both BADA4 coefficients and physical parameters. This process consists of three main steps:

1. Create a table storing the input parameters of interest, their variation ranges, and the location of the parameters in the STUDY database. The parameter location is normally denoted by the name of the table in the STUDY database and row/column identifiers, which can uniquely identify the parameter. Quantification of the variation range for each parameter is a crucial step in uncertainty quantification analysis, which typically uses two methods for different analysis steps. In the sensitivity analysis step, lower and upper bounds with a uniform percentage variation (e.g., ±10%, based on engineering judgment or subject-matter-expert [SME] opinions) are given for each parameter. If the objective is to study the propagation of uncertainty through a system model to precisely quantify the variation in outputs due to variations in inputs, the variation range and probability distribution of each parameter must be determined through a data analysis process.
2. Run the Python script to automatically process all of the cases and to generate performance, emissions, and noise reports for each case.
    1. The Python script reads the information regarding the first parameter from the table created in Step 1 and uses the information to generate SQL queries for manipulating the parameter value in the STUDY database.
    2. The Python script executes the SQL queries and edits the parameter value in the STUDY database.
    3. The Python script calls AEDT to run the case with the updated parameter value.
    4. The Python script calls the AEDT report run tool to generate the performance, emission, and noise reports.

5. The Python script calls the SQL script to reset the parameter to the baseline value.
6. Steps 2.1–2.5 are then repeated for the next parameter.

3. After all of the cases have been run, implement a developed MATALAB script to postprocess all of the sensitivity analysis results.

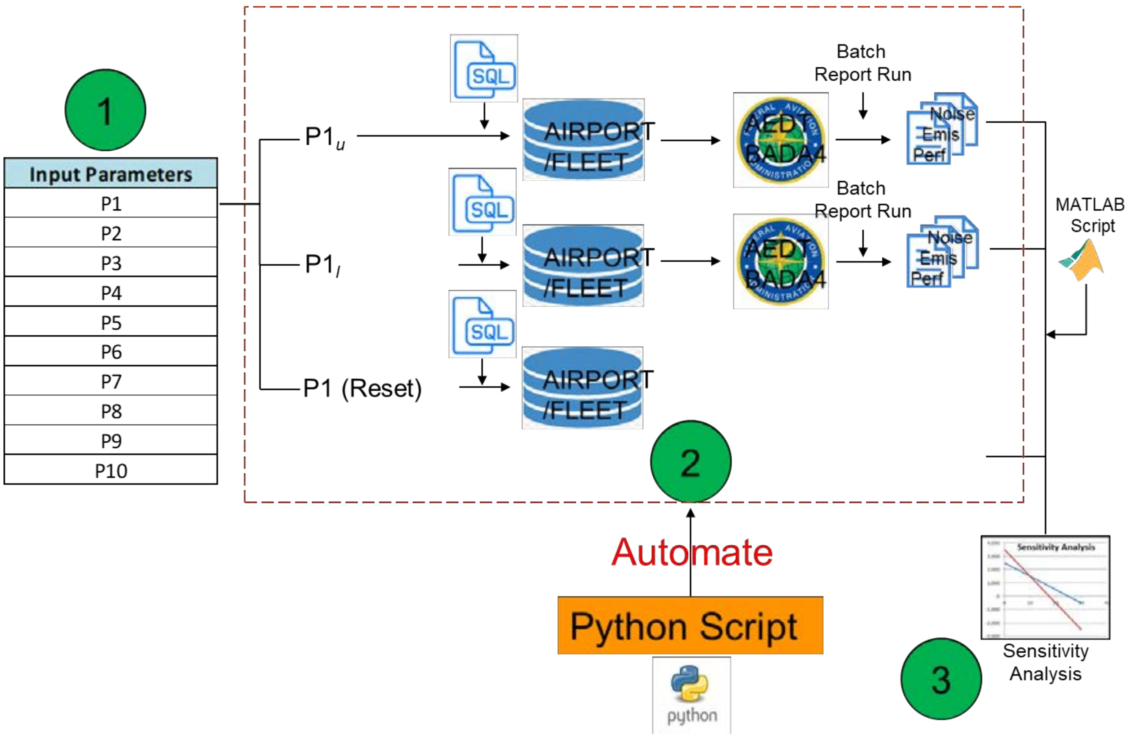

Figure 1. Automated one-factor-at-a-time (OFAT) experiment process.

Sensitivity analysis results for physical parameters

The automated process described above can conduct a complete computer experiment by repeating the analysis for each case according to the DoE table. Using this process, we conducted an OFAT DoE study for the parameters defined in Table 3. To conduct a sensitivity analysis on the outputs, an AEDT study must be designed using these parameters. Table 4 shows the basic information regarding the AEDT study created for sensitivity analysis. This study includes two aircraft with both departure and arrival operations, operating at runway 08 of KATL. For the outputs, both full-flight performance metrics and departure/arrival-level metrics were analyzed to provide more insight.

Table 4. Information provided for sensitivity analysis.

Aircraft	Airbus A320-200 and Boeing 737-800
Airport	Atlanta International Airport (KATL), runway 08
Operations	Arrival and departure
Number of Outputs (21)	Fuel burn (6): overall + fuel burn at five segments
	NOx emission (6): overall + NOx emission at five segments
	Noise (9): contour area, length, and width at 70, 75, and 80 dB for arrival and at 75, 80, and 85 dB for departure
Parameter Range	Airport weather and operation uncertainties
Number of Cases	Departure: 8 parameters, 16 cases; Arrival: 6 parameters, 12 cases
Experiment Type	One-factor-at-a-time (OFAT) design of experiment (DoE)

The results of the case runs were processed and analyzed by a MATLAB script. For each case, the analysis script first obtains the performance output values directly from the performance reports, and the noise output values are obtained by plotting the noise contours and calculating the contour characteristics. Subsequently, the output values for each case are compared to output values for the baseline case, based on percentage changes in the outputs. Because there are four aircraft and operation combinations, four result tables were generated.

The sensitivity analysis results are summarized in Table 5 - Table 8. Due to space limitations, only the full-flight fuel burn and NOx emission results are shown in the tables, with the omission of segment-level results. Each table presents results for a specific aircraft and operation combination. Some general observations are made based on the sensitivity analysis results:

1. Among weather parameters, temperature, sea-level pressure, and wind speed have observable impacts on all outputs, including fuel burn, NOx emission, and noise, for both departure and arrival operations.
2. Relative humidity does not influence fuel burn, but does impact NOx emission and noise.
3. Dew point and station pressure do not impact any of the outputs of interest.
4. Alternative weight and reduced thrust profiles influence the outputs in departure, with significant influences on the noise contours, particularly at higher noise levels.

Table 5. Sensitivity analysis results: B737-800 arrival.

Case No.	Parameter Name	Bounds	Fuel Burn	NOx Emission	70 dB: Area	70 dB: Length	70 dB: Width	75 dB: Area	75 dB: Length	75 dB: Width	80 dB: Area	80 dB: Length	80 dB: Width
1	TEMPERATURE (F)	94	-0.6%	-25.1%	-35.6%	-16.0%	-22.6%	-28.7%	-8.0%	-25.0%	-34.0%	-18.2%	-19.0%
2		25	0.9%	11.9%	-6.5%	-4.2%	-1.3%	-7.8%	-3.2%	-6.6%	-14.5%	-6.8%	-8.1%
3	SLP_PR (mb)	1032	0.7%	1.6%	1.1%	0.5%	0.5%	0.9%	0.6%	0.6%	1.5%	0.8%	0.8%
4		1004	-0.7%	-1.6%	-1.2%	-0.5%	-0.5%	-0.9%	-0.6%	-0.6%	-1.5%	-0.7%	-0.8%
5	ST_PR (mb)	993	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6		968	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	DEW_P (F)	74	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8		9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	REL_HUM (%)	100	0.0%	-6.5%	-2.1%	-0.7%	-1.6%	-1.2%	-0.4%	-1.4%	0.1%	0.0%	0.2%
10		20	0.0%	10.3%	-27.2%	-12.9%	-16.6%	-23.4%	-7.0%	-20.4%	-32.3%	-17.2%	-18.2%
11	WND_SPD (Knots)	24	10.7%	15.5%	7.7%	2.2%	7.7%	10.9%	3.9%	9.6%	19.7%	9.2%	9.9%
12		0	-3.7%	-5.3%	-2.9%	-0.7%	-2.7%	-4.1%	-1.3%	-3.9%	-6.4%	-3.2%	-3.3%

Table 6. Sensitivity analysis results: A320-200 arrival.

Case No.	Parameter Name	Bounds	Fuel Burn	NOx Emission	70 dB: Area	70 dB: Length	70 dB: Width	75 dB: Area	75 dB: Length	75 dB: Width	80 dB: Area	80 dB: Length	80 dB: Width
1	TEMPERATURE (F)	94	-0.7%	-19.3%	-32.1%	-16.2%	-17.2%	-28.3%	-13.0%	-19.3%	-28.7%	-12.2%	-17.1%
2		25	0.8%	12.1%	-2.9%	-1.7%	0.1%	-7.7%	-3.1%	-4.2%	-13.3%	-4.1%	-8.3%
3	SLP_PR (mb)	1032	0.7%	1.3%	1.5%	0.5%	0.7%	1.5%	0.8%	0.8%	1.5%	0.7%	0.9%
4		1004	-0.7%	-1.3%	-1.5%	-0.5%	-0.7%	-1.5%	-0.7%	-0.9%	-1.5%	-0.6%	-0.9%
5	ST_PR (mb)	993	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6		968	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	DEW_P (F)	74	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8		9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	REL_HUM (%)	100	0.0%	-6.8%	-0.6%	-0.2%	-0.4%	0.4%	0.2%	0.0%	1.9%	0.7%	1.2%
10		20	0.0%	10.7%	-25.5%	-13.0%	-12.8%	-25.2%	-10.9%	-16.6%	-30.8%	-13.0%	-18.7%
11	WND_SPD (Knots)	24	8.9%	15.8%	7.0%	1.7%	5.7%	10.2%	4.4%	7.5%	13.7%	4.3%	8.7%
12		0	-3.1%	-5.4%	-2.7%	-0.8%	-2.2%	-3.7%	-1.2%	-2.8%	-5.2%	-1.7%	-3.3%

Table 7. Sensitivity analysis results: B737-800 departure.

Case No.	Parameter Name	Bounds	Fuel Burn	NOx Emission	75 dB: Area	75 dB: Length	75 dB: Width	80 dB: Area	80 dB: Length	80 dB: Width	85 dB: Area	85 dB: Length	85 dB: Width
1	TEMPERATURE (F)	94	6.3%	-21.2%	-17.2%	12.6%	-15.5%	-43.8%	-23.1%	-19.7%	-46.5%	-27.1%	-25.2%
2		25	-3.5%	10.3%	20.4%	-2.2%	25.0%	24.1%	5.1%	11.2%	7.9%	2.5%	5.9%
3	SLP_PR (mb)	1032	-0.2%	0.6%	-1.7%	-1.6%	0.0%	-1.6%	-1.5%	0.0%	-1.6%	-1.4%	0.0%
4		1004	0.2%	-0.6%	1.8%	1.6%	0.0%	1.6%	1.6%	-0.1%	1.6%	1.5%	-0.1%
5	ST_PR (mb)	993	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6		968	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	DEW_P (F)	74	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8		9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	REL_HUM (%)	100	0.0%	-5.5%	3.5%	0.2%	2.1%	1.7%	0.8%	0.6%	-1.0%	-0.5%	-0.3%
10		20	0.0%	8.7%	-9.5%	-2.1%	-5.8%	-19.7%	-10.4%	-7.6%	-25.5%	-16.1%	-10.3%
11	WND_SPD (Knots)	24	-1.2%	-1.5%	-4.0%	-5.6%	2.0%	-3.2%	-5.0%	2.2%	-3.5%	-5.9%	2.5%
12		0	0.5%	0.6%	1.7%	2.4%	-0.8%	1.4%	2.1%	-0.9%	1.5%	2.5%	-1.0%
13	ALT WEIGHT	-	1.7%	2.3%	2.6%	2.6%	-0.6%	2.5%	2.7%	-0.7%	2.3%	2.6%	-0.8%
14	REDUCED THRUST	-5%	0.0%	0.0%	-1.7%	0.3%	-3.4%	-2.0%	0.6%	-7.7%	-4.2%	1.4%	-9.6%
15	REDUCED THRUST	-10%	1.6%	2.2%	-5.2%	10.5%	-13.4%	-19.7%	-5.1%	-15.3%	-23.1%	-7.1%	-18.5%
16	REDUCED THRUST	-15%	1.7%	2.2%	-6.1%	11.2%	-14.0%	-21.0%	-4.1%	-19.7%	-25.2%	-4.7%	-25.4%

Table 8. Sensitivity analysis results: A320-200 departure.

Case No.	Parameter Name	Bounds	Fuel Burn	NOx Emission	75 dB: Area	75 dB: Length	75 dB: Width	80 dB: Area	80 dB: Length	80 dB: Width	85 dB: Area	85 dB: Length	85 dB: Width
1	TEMPERATURE (F)	94	7.0%	-16.4%	-35.8%	-18.6%	-9.1%	-39.6%	-25.6%	-13.1%	-32.0%	-26.3%	-16.3%
2		25	-3.3%	-3.6%	15.0%	8.3%	6.3%	-5.1%	-4.3%	1.5%	-14.9%	-12.0%	-3.3%
3	SLP_PR (mb)	1032	-0.3%	0.1%	-1.6%	-1.3%	-0.4%	-1.8%	-1.4%	-0.4%	-2.1%	-1.7%	-0.3%
4		1004	0.3%	-0.1%	1.6%	1.4%	0.4%	1.8%	1.4%	0.3%	2.1%	1.8%	0.3%
5	ST_PR (mb)	993	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6		968	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	DEW_P (F)	74	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8		9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	REL_HUM (%)	100	0.0%	-5.5%	2.5%	1.5%	1.1%	1.1%	0.5%	0.5%	1.6%	1.3%	0.5%
10		20	0.0%	8.6%	-19.3%	-11.1%	-7.2%	-25.6%	-15.6%	-10.1%	-28.2%	-20.7%	-13.6%
11	WND_SPD (Knots)	24	-1.1%	-1.6%	-3.9%	-5.4%	1.7%	-4.6%	-6.8%	2.2%	-4.5%	-6.5%	2.8%
12		0	0.4%	0.7%	1.6%	2.4%	-0.7%	1.9%	2.8%	-0.9%	1.9%	2.5%	-1.1%
13	ALT WEIGHT	-	1.6%	2.2%	2.4%	2.6%	-0.6%	2.2%	2.7%	-0.7%	1.9%	3.0%	-0.7%
14	REDUCED THRUST	-5%	-0.1%	-0.1%	-0.9%	0.9%	-5.4%	-1.3%	1.7%	-6.0%	-1.8%	3.4%	-6.4%
15	REDUCED THRUST	-10%	2.2%	-2.2%	-14.8%	-2.8%	-10.7%	-14.4%	-2.2%	-11.6%	-14.6%	-6.2%	-12.5%
16	REDUCED THRUST	-15%	2.3%	-2.0%	-15.7%	-1.5%	-16.2%	-15.7%	0.2%	-17.8%	-16.7%	-2.1%	-19.2%

Overall, it was observed that uncertainties in temperature, relative humidity, and wind speed can cause variations in the estimated outputs. Therefore, to accurately model the performance and noise metrics for departure and arrival, it is important to take such uncertainty sources into account. To illustrate the influences of weather parameters and other physical factors, we plotted noise contours at all noise levels for all cases, as shown in Figure 2, for each aircraft and operation combination. In each plot, the purple, green, and yellow lines represent the lowest, middle, and highest noise contour levels, respectively. It can be seen that for a given noise level, the noise contour can vary significantly from case to case, resulting in differences of up to 50% in contour area, length, and width compared with the baseline weather and operation values.

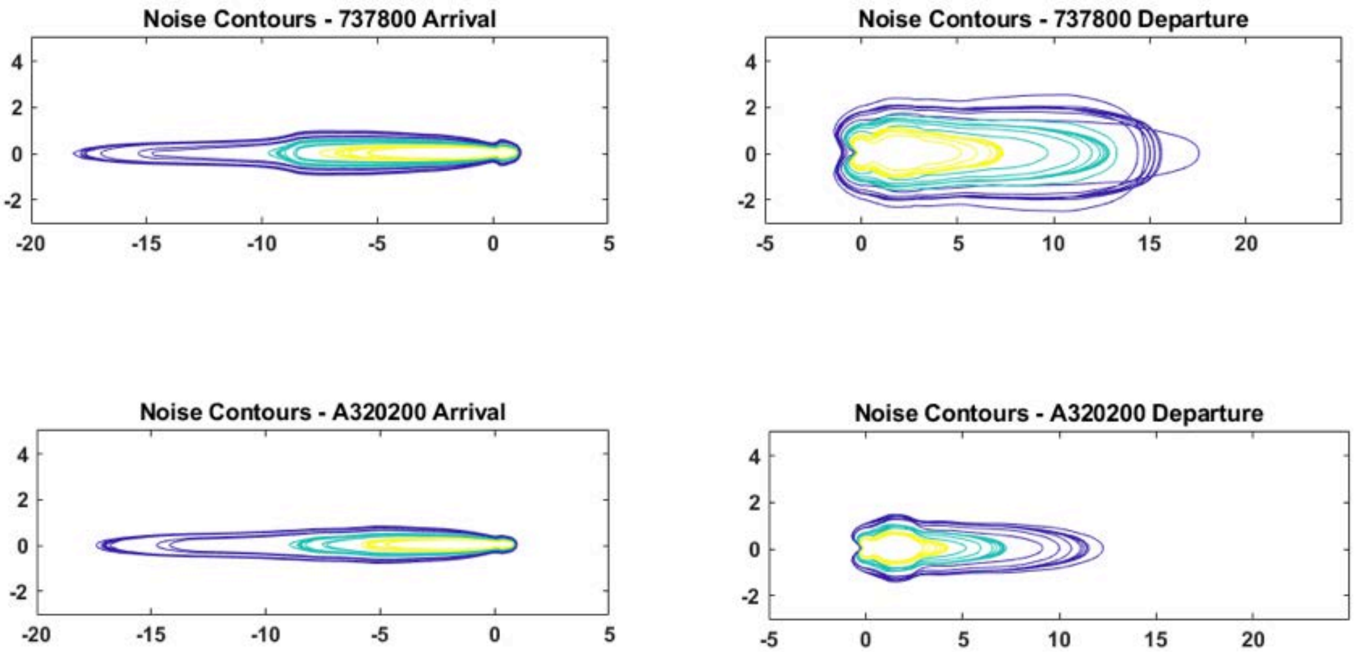

Figure 2. Noise contour variations under weather and operation uncertainties.

In addition, it was observed that different weather parameters influence the noise contours in various ways. Taking the 75-dB departure noise contours for aircraft B737-800 as an example, the noise contour changes caused by temperature, sea-level pressure, relative humidity, and wind speed are shown in Figure 3. In each plot, the red, black, and blue lines represent the noise contour for the upper bound, baseline value, and lower bound of the parameter studied.

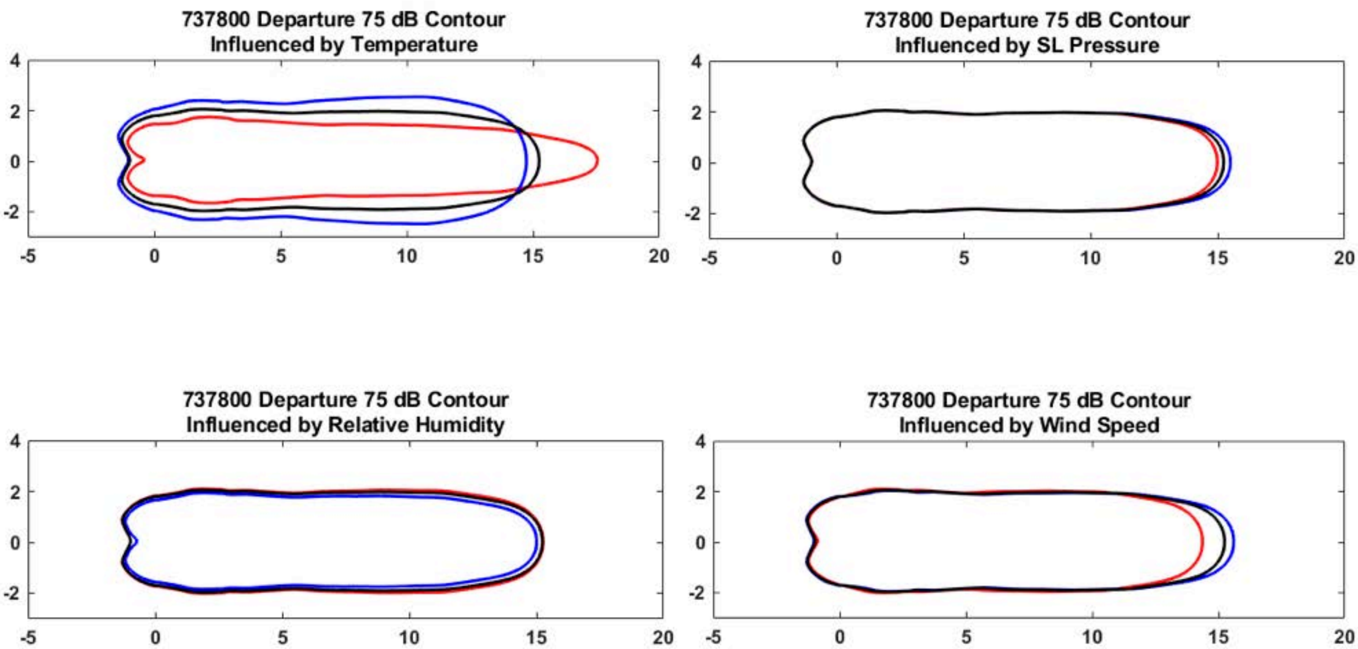

Figure 3. Noise contour changes for B737-800 departure at 75 dB.

The panel in the upper left of Figure 3 shows that under high-temperature conditions, the contour area decreased (17.2% smaller than at the baseline temperature), and the contour shape changed significantly. Compared to the baseline case, the contour length under high-temperature conditions increased by 12.6%, and the contour width decreased by 15.5%. In contrast, for the low-temperature case, the contour variation shows the opposite trend. The contour shape has a lower aspect ratio, and the contour length and width change by -2.2% and +25.0%, respectively. Moreover, when the relative humidity varied, the contour area, length, and width changed in the same direction. That is, all three contour metrics increased at higher relative humidity and decreased at lower relative humidity. Although the influences of sea-level pressure and wind speed are not as significant as those for temperature and relative humidity, these factors also exhibit a pattern. They primarily influence the contour area due to a change in contour length, with little to no impact on contour width.

Uncertainty propagation

After the uncertainty characterization and sensitivity analysis, uncertainty propagation analysis is performed. In uncertainty propagation, the uncertainty is mapped from uncertain inputs to the output through a system model. Subsequently, a statistical analysis of the nondeterministic output results can be conducted for further decision-making. A typical uncertainty propagation process is illustrated in Figure 4.

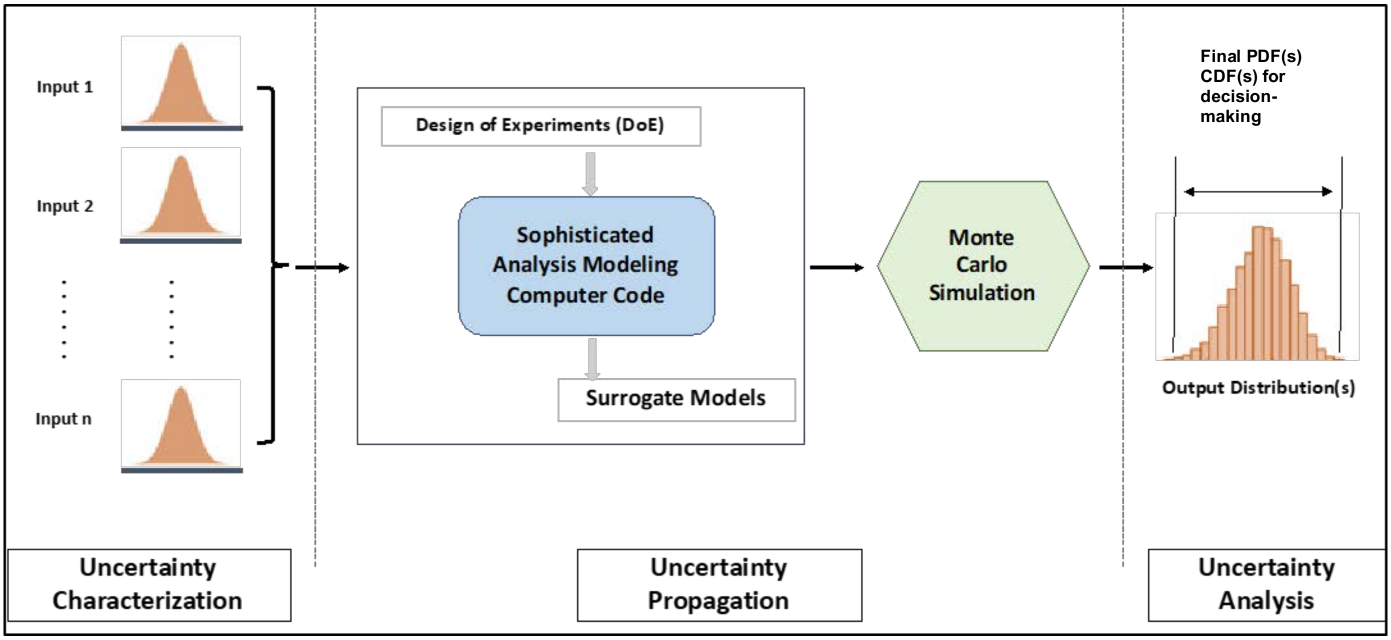

Figure 4. Uncertainty propagation analysis process.

The uncertainty propagation analysis shown in Figure 4 is implemented through three primary steps. Before the uncertainty propagation can be conducted, the uncertainty of each parameter must be represented mathematically. This representation is typically obtained through data analysis, computer experiments, and SME opinions, with the objective of assigning a probability distribution to represent the uncertainty of each input parameter. Unlike the OFAT sensitivity analysis, in which the uncertainty bounds for all parameters are set to $\pm 10\%$, the goal of this step is to ensure that the uncertainty representation of each parameter reflects their real-world behavior as much as possible. In the second step of uncertainty propagation analysis, the uncertainties of the input parameters are propagated to the outputs through the AEDT and BADA4 models. Because these models are complex and the processes are computationally expensive, further experimental design and surrogate modeling can be used to facilitate this process. Monte Carlo simulations provide an effective means for conducting uncertainty propagation in this case because these simulations can handle a large number of probabilistic inputs, various distribution types, and highly nonlinear models. Finally, an uncertainty analysis is conducted based on the uncertainty propagation results, which are expected to reflect the uncertainty in the output of interest. This uncertainty propagation step, together with the global sensitivity analysis described in the next section, are expected to be conducted in the next stage of the project.

Global sensitivity analysis

Global sensitivity analysis is another future avenue of this work. In contrast to the OFAT sensitivity analysis, a sensitivity analysis is considered to be global if all input parameters are simultaneously varied over their entire uncertainty ranges. This approach is used to decompose the total uncertainty of each output and attribute it to different input parameters. This step provides insight into how strongly each input parameter affects and contributes to the total uncertainty of an output. The key metrics used in this step include the total sensitivity index, which measures the relative impact of each input parameter.

Milestone(s)

Milestone	Due Date	Estimated Date of Completion	Actual Completion Date	Status	Comments (Problems & Brief Resolution Plan)
A36 Kickoff Meeting	5/3/2016	5/3/2016	5/3/2016	Completed	
Quarterly Report (Aug)	7/31/2016	7/31/2016	7/31/2016	Completed	
ASCENT Meeting	9/27-28/2016	9/27-28/2016	9/27-28/2016	Completed	
Quarterly Report (Nov)	10/31/2016	10/31/2016	10/31/2016	Completed	
Annual Report	1/18/2017	1/18/2017	1/13/2017	Completed	
Quarterly Report (Jan)	1/31/2017	1/31/2017	1/27/2017	Completed	
Quarterly Report (Mar)	3/31/2017	3/31/2017	3/31/2017	Completed	
ASCENT Meeting	4/18/2017	4/18/2017	4/18/2017	Completed	
Quarterly Report (Jun)	6/30/2017	6/30/2017	6/30/2017	Completed	
ASCENT Meeting	9/26/2017	9/26/2017	9/26/2017	Completed	
Quarterly Report (Oct)	10/30/2017	10/30/2017	10/30/2017	Completed	
Annual Report	11/30/2017	11/30/2017	11/30/2017	Completed	
Quarterly Report (Jan)	1/31/2018	1/31/2018	1/31/2018	Completed	
Quarterly Report (Mar)	3/31/2018	3/31/2018	3/31/2018	Completed	
ASCENT Meeting	4/3-4/2018	4/3-4/2018	4/3-4/2018	Completed	
Quarterly Report (Jun)	6/30/2018	6/30/2018	6/30/2018	Completed	
ASCENT Meeting	10/9-10/2018	10/9-10/2018	10/9-10/2018	Completed	
Quarterly Report (Oct)	10/30/2018	10/30/2018	10/30/2018	Completed	
Annual Report	11/30/2018	11/30/2018	11/30/2018	Completed	
Quarterly Report (Jan)	1/31/2019	1/31/2019	1/31/2019	Completed	
ASCENT Meeting	4/18-19/2019	4/18-19/2019	4/18-19/2019	Completed	
Quarterly Report (Apr)	4/30/2019	4/30/2019	4/30/2019	Completed	
Quarterly Report (Jul)	7/31/2019	7/31/2019	7/31/2019	Completed	
ASCENT Meeting	10/22-23/2019	10/22-23/2019	10/22-23/2019	Completed	
Quarterly Report (Oct)	10/31/2019	10/31/2019	10/31/2019	Completed	
Annual Report	11/30/2019	11/30/2019	11/30/2019	In Progress	

Major Accomplishments

As of December 2018, all new AEDT Sprint releases, including Sprints 112-129, have been tested. Eighteen AEDT Sprints have been tested, focusing on new features and added capabilities. Some of the new features/capabilities were minor updates to the GUI, bug fixes, or data updates. Major updates included track control, NO_2 emissions dispersion modeling, and a user-defined profile editor. To understand the background of new AEDT features, all relevant documents were reviewed, including software requirement documents, database design documents, AEDT Sprint release notes, updated technical manuals, user manuals, and research papers/reports. Basic tests of all new AEDT versions were completed to confirm their functionality, and issues were reported to the FAA and the development team via biweekly ASCENT project teleconferences and weekly AEDT development-lead calls. Identified issues and follow-up actions taken by the developers were documented and shared through the Team Foundation Server (TFS) online system. The TFS also allows for reporting of any potential areas of improvements in AEDT algorithms and user friendliness.

Finally, a sensitivity analysis was conducted to investigate how variations in input parameters impact the variations in output parameters in the AEDT BADA4 model. Physical parameters, including weather parameters, takeoff weight, and thrust, were identified as input parameters for the sensitivity analysis. An automated process was developed to automatically call AEDT to run each case with updated parameter values and to generate performance, emissions, and noise reports. The sensitivity results provide insights into how the input parameters impact the AEDT outputs with the BADA4 model in terms of magnitude and direction.

Publications

Written reports

ASCENT quarterly reports (Jan. 2019; Apr. 2019; Jul. 2019, Oct. 2019)
ASCENT annual report (Nov. 2018)

Peer-reviewed journal publications

Gao, Z., Behere, A., Li, Y., Lim, D., Kirby, M., & Mavris, D.M. Quantitative assessment of the new departure profiles with improved weight and thrust modeling. To be submitted to Journal of Aircraft.

Outreach Efforts

N/A

Awards

None.

Student Involvement

Zhenyu Gao is a third-year PhD student who started in fall 2016. Mr. Gao has conducted a literature review on uncertainty quantification methods and has performed tests of newly released AEDT features. Mr. Gao is being trained on related tools such as INM, AEDT Tester, AEDT 2e, and AEDT 3b.

Ameya Behere is a third-year PhD student who started in fall 2016. Mr. Behere has conducted a literature review on uncertainty quantification methods and has performed tests of newly released AEDT features. Mr. Behere is being trained on related tools such as INM, AEDT Tester, AEDT 2e, and AEDT 3b.

Yee Chan Jin is a second-year Master student who started in fall 2018. Mr. Jin has conducted a literature review on uncertainty quantification methods and has performed tests of newly released AEDT features. Mr. Jin is being trained on related tools such as INM, AEDT Tester, AEDT 2e, and AEDT 3b. Mr. Jin graduated in Dec. 2019 and is currently employed by Southwest Airlines.

Plans for Next Period

This project officially ended on August 31, 2019; however, some of the tasks performed by GT will be continued under the new ASCENT project 54. GT will perform the system testing, validation, and verification tasks for the new versions of AEDT 3c and beyond to identify any issues that should be addressed by the development team. The detailed tasks will be discussed with FAA project managers.

References

Eurocontrol Experimental Centre. (Mar. 2016) User manual for the base of aircraft data (bada) family 4.
Lim, D., Li, Y., LeVine, M.J., Kirby, M., & Mavris, D.M. (2018). Parametric uncertainty quantification of aviation environmental design tool. 2018 Multidisciplinary Analysis and Optimization Conference, AIAA AVIATION Forum, (AIAA 2018-3101)
US FAA, AEDT 2a UQ Report, 2014
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US FAA, AEDT 2b UQ Report, 2016