Noise Sensitivity Characterization in the Context of the Environmental Design Space

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Abstract

Day-night-level (DNL) contours generated by the Aviation Environmental Design Tool (AEDT) are dependent on Noise-Power-Distance (NPD) curves, but these metrics have not been traced back to the vehicle-level design variables that influence them. Sensitivity analyses on the Environmental Design Space (EDS) show that variables related to airframe design have the greatest influence on approach noise, while design variables related to bypass ratio have the greatest influence on departure noise. These results are consistent for both NPD-curves and sound-exposure-level (SEL) contour areas, but not for the certification effective-perceived-noise-level (EPNL) metrics.

Nomenclature

AEDT	=	Aviation Environmental Design Tool
ANOPP	=	Aircraft Noise Prediction Program
ANOVA	=	Analysis of Variance
ASDL	=	Aerospace Systems Design Laboratory
CAEP	=	Committee on Aviation Environmental Protection
CBAP	=	Cutback and Approach
dB	=	Decibel
DNL	=	Day-Night-Level
DOE	=	Design of Experiments
EDS	=	Environmental Design Space
EPA	=	Environmental Protection Agency
EPNL	=	Effective Perceived Noise Level
FAA	=	Federal Aviation Administration
ICAO	=	International Civil Aviation Organization
LHC	=	Latin Hypercube
LTO	=	Landing-Takeoff Cycle
NCP	=	Noise Compatibility Plan
NEPA	=	National Environmental Policy Act
NPD	=	Noise-Power-Distance
NPSS	=	Numerical Propulsion System Simulation
SEL	=	Sound Exposure Level
SL	=	Sideline

I. Introduction

GIVEN the projected growth of commercial aviation activity at approximately 5% per year over the next 20-25 years, the international aviation community has grown increasingly interested in the environmental impacts associated with aircraft noise and emissions.[1] In response to these concerns, the International Civil Aviation Organization (ICAO) created the Committee on Aviation Environmental Protection (CAEP) to create certification standards and metrics for assessing these environmental impacts. This committee meets every three years to discuss these standards and provide feedback and suggestions to national aviation regulatory departments, such as the Federal Aviation Administration (FAA) in the United States, which in turn establish aviation policies and restrictions. Unfortunately, there often is a lack of communication between policymakers who create restrictions on aircraft and the engineers who design the engines and airframes, often due to the proprietary nature of commercial aircraft design. This disconnect was acknowledged by CAEP at their meeting in 2007 when they recognized the need for more comprehensive analyses that assess the tradeoffs among noise and emissions impacts and economic costs to better inform policymaking decisions.[2]

In response to this need, the FAA Office of Environment and Energy, in collaboration with Transport Canada and NASA, have been developing a comprehensive suite of software tools that will allow for thorough assessment of the environmental effects and impacts of aviation.[3] Included amongst this tool suite are the Environmental Design Space (EDS) and the Aviation Environmental Design Tool (AEDT). The latter is a fleet-level tool that produces estimates of noise, fuel burn, and emissions at global, regional, and local levels. The Environmental Design Space is a physics-based vehicle-level tool capable of estimating source noise, exhaust emissions, and performance for future aircraft designs under different technological, operational, policy and market scenarios. This tool is continuously being developed at the Aerospace Systems Design Laboratory (ASDL) at the Georgia Institute of Technology under the direction of Dr. Michelle Kirby[a]. The tool stitches together multiple NASA codes to design the engine cycle, size the engine, fly design and off-design missions, and calculate emissions and noise metrics. ASDL has also created a tester version of AEDT capable of generating individual vehicle noise-footprints. This AEDT Tester has been seamlessly integrated into the EDS framework, enabling automated noise-grid generation to be included for approach and departure of each aircraft in the database.

[a] Senior Research Engineer, Aerospace Systems Design Laboratory

Currently, EDS models have been categorized by seat-class, with models developed for 50pax (Regional Jet – RJ), 150pax (Single-Aisle – SA), 220pax (Small Twin-Aisle - STA), and 300pax (Large Twin-Aisle – LTA) aircrafts. The analyses discussed in this report were performed for all four vehicles. Observed trends were mostly consistent across the different vehicles, but slight deviations from these trends will be discussed.

II. Problem Definition

Aircraft noise is one of the most significant environmental impacts of aviation, and it is the most common source of complaints from communities, particularly those in close proximity to airports. Studies have shown that regular exposure to aviation noise can have both behavioral and physiological impacts, ranging from general annoyance and loss of sleep to hypertension and mental health effects.[4] As a result, noise metrics have been established in order to quantify this impact on the surrounding community. Noise metrics are typically presented in terms of A-weighted decibels (dBA) which reflects the logarithmically increasing human physiological perception of sound. The “A-weighted” term implies that the metrics are filtered to approximate the sensitivity of the human ear and help us to assess the relative loudness of various sounds as a function of both the sound level and the frequency, or “pitch.” The distinction of pitch is important, as human ears are better equipped to hear mid- and high-frequencies, and thus we find them more annoying. While there are multiple metrics for sound, they are typically categorized as either single-event or cumulative metrics.

The metrics generated by the Aircraft Noise Prediction Program (ANOPP), the noise assessment tool within EDS which is a legacy code produced and supported by NASA Langley Research Center, fall into the single-event category, as they represent the noise from a single aircraft’s landing and takeoff (LTO) cycle.[5] Primary metrics of interest include the sound exposure level (SEL) and the effective perceived noise level (EPNL). The latter is a tone-corrected perceived noise level that accounts for human perception of pure tones and other spectral irregularities, and is most commonly used for new aircraft certification standards. These EPNL metrics are typically taken at three locations that correspond to aircraft approach noise during landing, cutback noise during takeoff, and sideline noise. SEL is a measure of cumulative noise exposure for a single aircraft flyover normalized to one second.[6] SEL data is commonly presented in the form of Noise-Power-Distance (NPD) curves, as exemplified in Figure 1. Each monotonically increasing curve represents a distance at which SEL measurements are taken. These measurements are taken for different thrust power settings, and the curves plot the SEL measurement versus the thrust settings for each distance from the observer. SEL data can also be presented in terms of a grid about a runway, such as those generated by the AEDT-Tester.

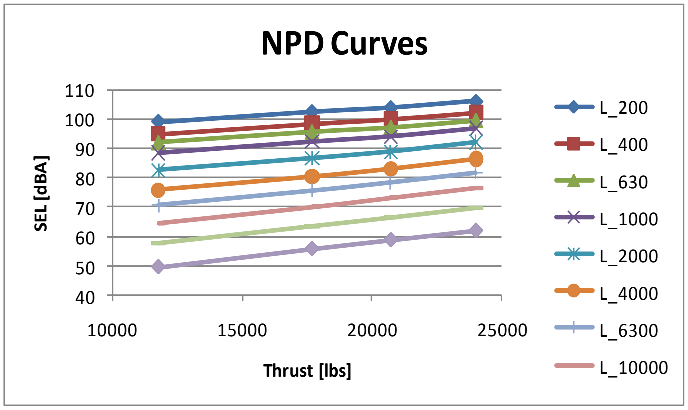

Figure 1. Sample Noise-Power-Distance Curves.

Cumulative noise metrics are more representative of long-term exposure to aircraft noise. The metric of interest in this case is the day-night-average level (DNL), which averages SEL data over the course of a 24-hour period and applies a 10 dB penalty for flights occurring at night. This penalty is applied because aircraft noise at night is often perceived as more intrusive due to the fact that nighttime ambient noise is less than daytime ambient noise. DNL grids and contours can be generated using AEDT, which incorporates the Integrated Noise Model (INM), a longstanding FAA legacy code for cumulative noise calculations around airports. INM, and hence AEDT, use airport schedules and NPD-curves for each aircraft within the schedule to calculate DNL contours. DNL contours are important because they can quantify the average community reaction and annoyance to local airport noise. According to the National Environmental Policy Act (NEPA), areas exposed to DNL levels of 65 dB or greater are entitled to federal aid in terms of elements of the Noise Compatibility Plan (NCP), such as sound insulation for homes.[7] The cost of sound-proofing these homes is passed on to the FAA, hence the interest in understanding the variables that impact these contours.

This study explores how the vehicle-level design variables of EDS flow into ANOPP and impact the resulting NPD curves, which in turn drive the sizes and shapes of the DNL contours. In addition to identifying the influential variables on the NPD curves, this study also examines the main drivers for the AEDT-Tester generated SEL contours. Because NPD curves are the language of communication between ANOPP and AEDT, it is expected that these SEL contours and NPD curves will be driven by similar design variables. Thus, tracking these SEL contour sensitivities will serve as a validation of the sensitivity analysis for the NPD curves.

III. Expected Key Contributions

Along with understanding of the key drivers of these noise contours, this analysis will also provide valuable information to aid ASDL's Generic Vehicle/Generic Fleet study. The goal of this ongoing study is to create a tool for rapid evaluation of the environmental impacts of technologies, procedural changes, and increased aviation activity. This physics-based screening tool will help policymakers to rapidly weigh their decisions with insight into the tradeoffs of costs and environmental impacts, thus providing the comprehensive analyses that were deemed necessary at the CAEP 2007 meeting.

In order to obtain accurate information, simulations must be performed for every type of aircraft in the fleet. Constructing individual models for each and every aircraft is both time and cost-prohibitive. If these aircraft could be binned into categories, however, and reduced to a handful of representative vehicles that can match aggregate fleet results for emissions and noise reasonably well, this would reduce the runtimes considerably, while still providing enough fidelity for a screening tool that policymakers can use to inform their decision making.

Previous work at ASDL has led to the development of generic vehicles using an average vehicle approach, which filters settings for vehicle design variables in order to reduce the error of aggregate results. This method is not unprecedented, as a similar approach was used by the Environmental Protection Agency (EPA) for conducting an analysis of annual automobile emissions data in the context of corporate average fuel economy regulations.[8] Previous ASDL work has shown that the average vehicle approach can match aggregate fleet data within a reasonable level of accuracy for the baseline reference fleet, a fleet with variations in operations, and a fleet with technology infusion. This work, however, only focused on aggregate fuel burn and emissions metrics.[9] Further work must be performed to tune these generic vehicles such that the fleet can match DNL contours as well as fuel

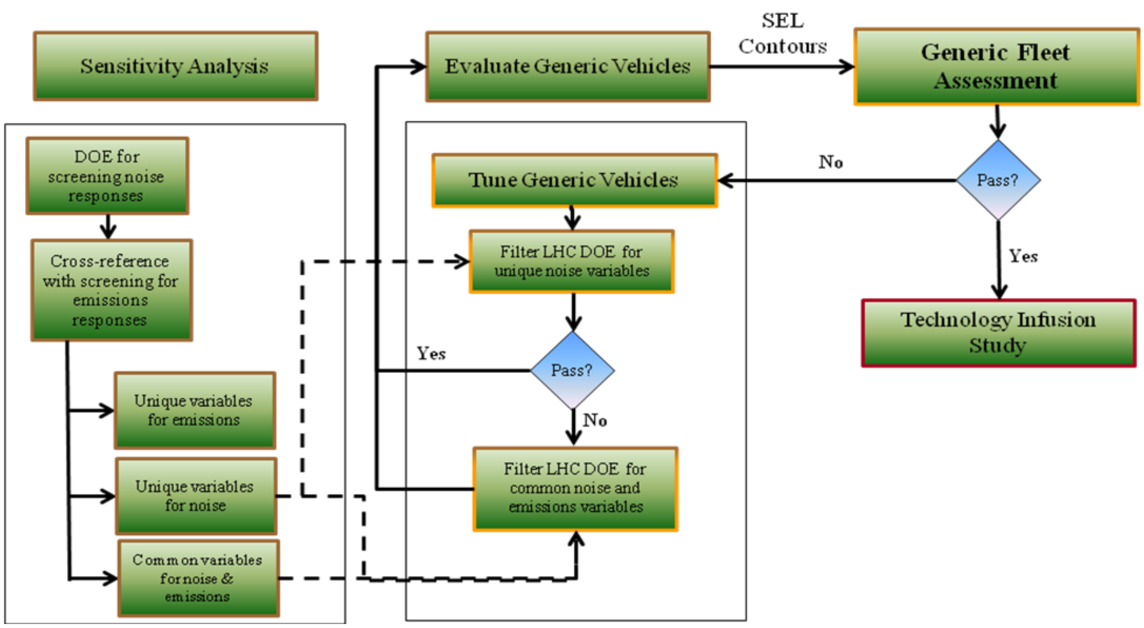

Figure 2. Roadmap for Generic Vehicle Development

burn and emissions.

In order to do this, the influential design variables for noise must be cross-referenced with the influential design variables for emissions and fuel burn. Changing design variables that are common to both noise and fuel burn/emissions responses would likely reduce the accuracy of the existing aggregate fuel burn/emissions calculations, and thus it is important to identify design variables unique to noise responses for tuning these generic vehicles. By performing this sensitivity analysis and cross-referencing the results with the significant design variables for fuel burn/emissions, these unique noise design variables can be identified, allowing the progression to the next step of the generic vehicle tuning process. A roadmap for the development of these generic vehicles can be seen in Figure 2. Sensitivity analysis represents a near-term task, generic-vehicle tuning represents a mid-term task, and technology infusion study represents a long-term task.

IV. Methodology

The diagram in Figure 3 demonstrates the general procedure for the ANOPP sensitivity analysis with respect to its function in EDS. The steps include identifying the EDS input variables that are mapped to ANOPP inputs within the EDS environment, building designs of experiments (DOE) on these design variables, and exploring their influence on the ANOPP outputs. These variable types include aerodynamic variables, engine design variables, airframe design variables, and additional miscellaneous variables. EDS creates separate input and output file streams for Cutback and Approach (CBAP) EPNL, Sideline (SL) EPNL, and NPD curves. While tracking the

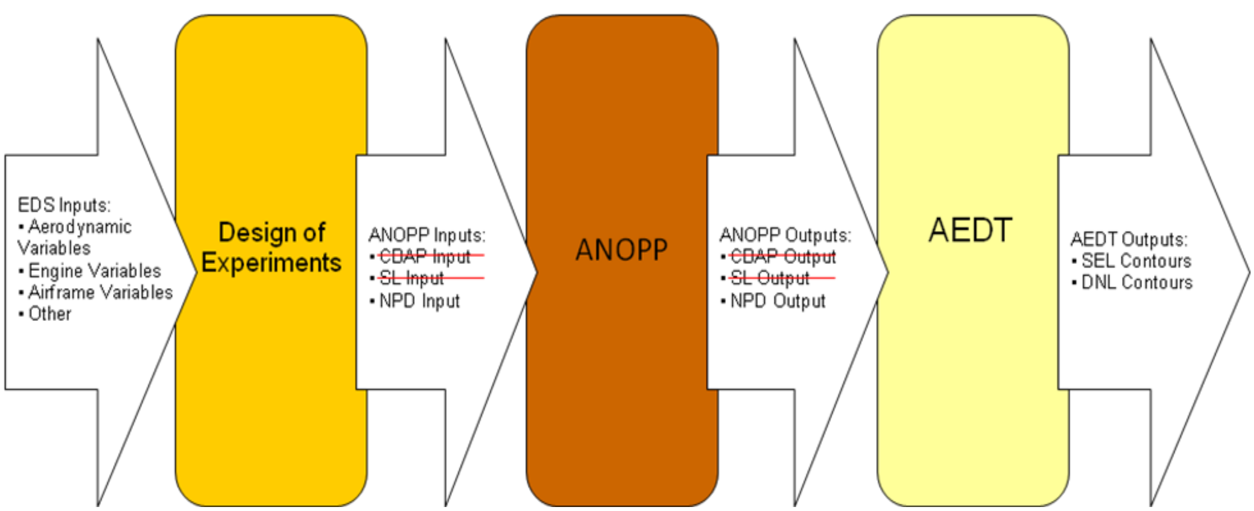

Figure 3. EDS-ANOPP-AEDT Sensitivity Assessment Process.

CBAP and SL data will provide valuable insight into the relationships between the design variables and noise, only the NPD outputs actually feed into AEDT, so only these sensitivities will impact the noise contours.

A. Identifying Design Variables and Responses

In order to identify the necessary design variables to include in this study, a thorough examination of the ANOPP input file structure proved necessary. EDS has over 200 possible input variables to choose from, but not all of these variables are actually mapped to ANOPP inputs. Since noise is primarily of interest during the LTO cycle, variables related to cruise conditions were obviously omitted. Additionally, miscellaneous variables such as passenger compartment lengths or the number of passengers in first class or coach were not included.

While airframe noise is considered a significant contributor to takeoff and landing noise, several of the aerodynamic and airframe related variables have redundant effects. For this reason, these variables were reduced to a slim few, including aspect ratio, sweeps on the wings and tails, thicknesses, flap ratios, and maximum lift coefficients at takeoff and landing.

The main contributors to LTO cycle noise are the engines, and thus the majority of the variables included in this study are engine-related variables. The ANOPP input files require the inclusion of an engine deck generated by the Numerical Propulsion System Simulation (NPSS), the thermodynamic-cycle design tool in EDS, and thus a majority of the cycle-design variables were included in the DOE. ANOPP also has inputs for applying chevron geometries to the core and fan nozzles of the engines, which directly influence the noise responses, and thus these variables were included as well.

In addition to these design variables, ANOPP has a series of suppression factor variables. These variables directly impact the noise contributions from various sources, such as the fan, landing gear, trailing edges of wings and tails, etc. These variables are not physics-based design variables, but rather correction variables for calibrating ANOPP. These variables were included in the DOE in order to grasp how influential they are on responses as compared to other design variables. It was expected that these variables would be more influential than the physics-based design variables. With the inclusion of these 29 suppression factors, the initial DOE included 92 variables overall (87 for the RJ because it has no low-pressure compressor).

As mentioned before, the responses of greatest interest were the NPD curves themselves. These curves, however, are not single point metrics, but rather a series of points that define approximately linear relationships between thrust and SEL for various observer distances. Rather than doing point-to-point comparisons, simple linear regressions were performed on each line, providing slopes and intercepts for each curve. These slopes and intercepts are the primary responses of interest, as they provide greater insight into the characteristics of the curves than a point-to-point comparison. EPNL data at the three certification points were also tracked as parallel responses. The sensitivities of these single-metric responses were expected to reflect similar trends as for the NPD curves, and thus were included as a sort of validation.

The final responses of interest were the SEL grids. In order to quantify the changes in these grids with respect to the design variables, it proved more useful to look at the size and shapes of the contours representing equal SEL values. Based on observations of a few test cases, it was determined that the most valuable information could be gained by evaluating the contours in 5 dB intervals between 55 dB and 90 dB. Below 55 dB, the noise exposure is not as significant, while above 90 dB the contours do not represent a single shape, but rather two individual islands. While the sensitivities of the contour areas were expected to provide the most insight, they do not capture the changes of the contour shapes, which are also important. In order to include these sensitivities, the maximum widths and lengths of the contours were also tracked. Example approach and departure SEL contours for the baseline vehicle are displayed below in Figure 4.

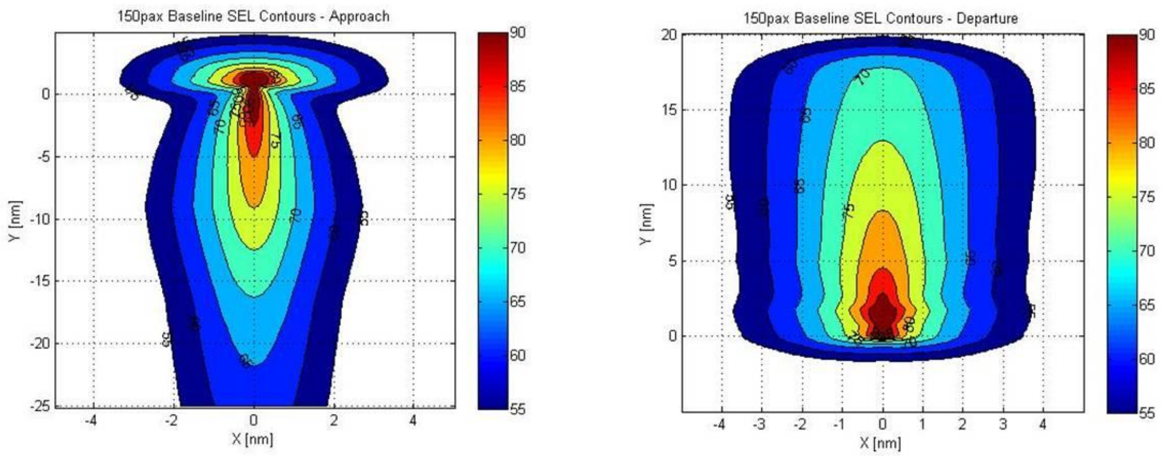

Figure 4. Sound Exposure Level Contours for 150pax Baseline Vehicle

B. Creation of Designs of Experiments and Preparation of Design Environment

The original approach was to construct a screening DOE for this initial exploration, but this resulted in the majority of the cases failing. Due to the number of codes that the variables must pass through (including ANOPP), the likelihood of failure of one of these codes at the edges of the EDS design space is very high. Additionally, the large number of variables included many interdependencies that led to failures, and thus it proved necessary to abandon the screening DOE approach for a space-filling DOE.

A Latin Hypercube (LHC) design was chosen in order to saturate the design space and generate more successful cases.[10] The failure rate, however, still proved to be fairly high, and thus some changes were made to the design environment. Since this analysis was strictly interested in the sensitivities of the variables, some of the failure checks were turned off in order to allow more successful cases. For example, a poorly designed engine might fail the required climb rate checks, and normally EDS would count this as a failed case and terminate the run. When this failure check is turned off, however, EDS continues the run all the way through ANOPP and provides the necessary response metrics. While this engine might not be a good design, it still provides a feasible response from the environment and thus can be included in the sensitivity analysis.

A small LHC design of 500 cases was performed first in order to explore the ranges of the design variables. By observing the successes and failures of the design space in a scatterplot matrix, the design variable ranges were tightened to improve the success rate. As the ranges were tightened, the rate of success for the cases increased, until a success rate of just over 70% was achieved. This was not an arbitrarily chosen success rate, but rather the point when additional improvements to design variable ranges and failure checks to create additional successes would cause previously successful cases to fail.

Once these variable ranges and failure checks were set, a larger LHC design of 5000 cases was run. This denser DOE resulted in a much larger number of successful cases, although the success rate of 70% proved to be fairly consistent. The responses from these successful cases were then prepared for analysis.

It should be noted that the SEL grids were not generated for this initial DOE, because these grids were time-consuming to generate. Since the first DOE was primarily meant to screen out non-influential variables, the SEL grid analyses were reserved for the reduced DOE that follows.

C. Sensitivity Analysis in modeFRONTIER®

The sensitivity analyses of the responses were performed in modeFRONTIER® due to the availability of several statistical tests as well as the fast calculation times. While many statistical tests were available, including Analysis of Variance (ANOVA), student t-tests, and half-normal probability plots, the latter was chosen for its visual clarity as well as its inclusion of both factor effects and interaction effects.

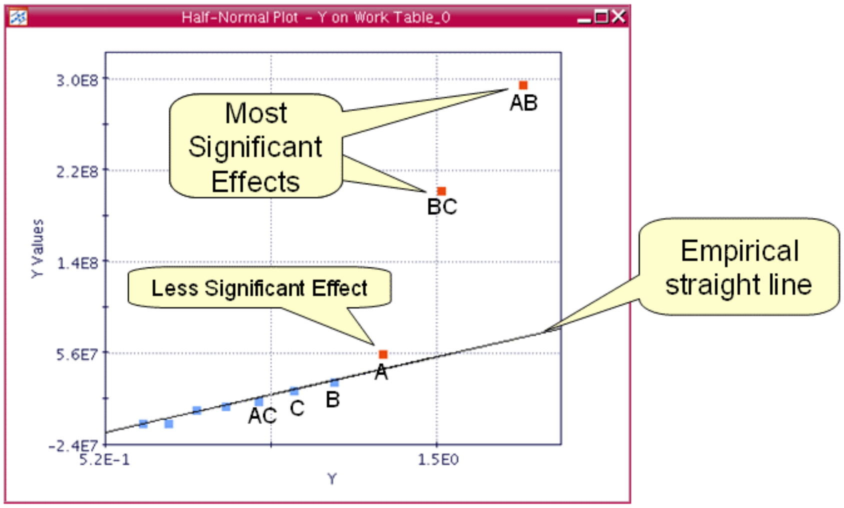

Figure 5. Sample Half-Normal Probability Plot

A half-normal probability plot is a graphical tool that uses ordered estimate effects based on least squares estimation to help assess which factors are important and which are unimportant.[11] The horizontal axis represents statistical medians from a half-normal probability distribution, while the vertical axis represents the ordered absolute value of the estimated effects for the main factors and interactions. For each factor, the distribution of errors from least-squared estimates is compared to a normal distribution. If the normal distribution is centered near zero, the factor is unimportant and will appear on an empirical straight line. If the normal distribution of errors is skewed and centered away from zero, the factor is important and will appear well off the empirical straight line, as is demonstrated in the sample half-normal probability plot in Figure 5. The plot is referred to as "half-normal" because the variables are ordered by the absolute value of the effect-size without consideration of whether the effect is positive or negative, thus representing the positive half of a normal distribution. The points are color-coded to distinguish whether the relationship is positive (i.e. direct relationship) or negative (i.e. inverse relationship).

D. Screening out Variables for new Design of Experiments

Once the half-normal probability plots for each response were generated, the results were cross-referenced against each other to determine which design variables consistently fell at the lower end of the effect-size spectrum for each response. These variables were then set to default values, and a new LHC DOE of 5000 cases was constructed on the reduced design space. Then the above procedure was repeated to produce new half-normal probability plots for NPD slopes and intercepts as well as for SEL contour lengths, widths, and areas. Qualitative tables defining the significant variables for approach and departure were then prepared to easily understand the relative influence of significant variables.

V. Results & Discussion

The methodology was carried out for all four vehicle models. Through the process of these analyses, dozens of plots and tables were created, but due to page limitations only a few representative examples will be included in the following sections. Discussions will revolve around general trends observed and possible explanations for these trends in the context of engine and airframe design.

A. Initial Design of Experiments Results

The initial design of experiments consisted of 92 design variables, 29 of which were ANOPP suppression factor terms. As was expected, these suppression factors tended to dominate the impacts for all of the response metrics. Unfortunately, these dominating impacts tended to cloud the impacts of the other physical design variables, reducing the meaning that could be derived from the resulting plots.

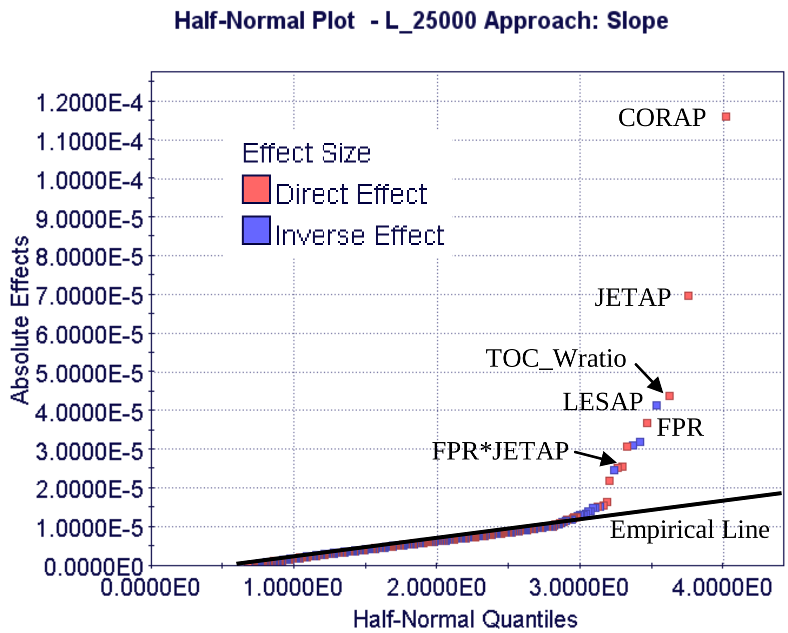

Figure 6. Half-Normal Probability Plot for Slope of L_25000 Approach NPD-curve.

An example of these resulting plots is presented in Figure 6. As can be seen from this figure, three of the top four influential variables for the slope of the 25,000-ft observer distance are ANOPP suppression factors, labeled on the plot as CORAP, JETAP, and LESAP. These variables represent suppression factors for the core, jet, and leading-edge slat noises, respectively. The designation AP indicates that these suppression factors are applied for approach conditions only. Similarly, the takeoff (TO) suppression factors dominated for the departure NPD-curve slopes and intercepts. Other variables labeled on the plot in Figure 6 include the mass flow ratio of the top-of-climb to the aerodynamic design point (TOC_Wratio) and the fan pressure ratio (FPR), as well as the interaction effect between FPR and JETAP. This was primarily included to demonstrate that these half-normal probability plots include both main factor as well as interaction effects.

Since the dominance of the suppression factors appears to mask the impact of the physical design variables, all 29 of these variables were removed for the subsequent reduced LHC DOEs. Additional variables that consistently placed at the bottom of the effect-size ranking for the 10,000-ft, 16,000-ft, and 25,000-ft observer distances were also removed from the subsequent reduced DOE.

B. Reduced Design of Experiments Results

With the removal of the insignificant variables as well as the suppression factors from the DOE, a much clearer picture of the sensitivities comes into view. These results will be discussed in three sections corresponding to the following response metrics: NPD-curve sensitivities, certification EPNL sensitivities, and SEL contour sensitivities.

1. NPD-curve Sensitivities

The first immediate observation was that the trends were very consistent across the three furthest observer distances (10000, 16000, and 25000-ft), which have the greatest influence on the 65-dBA contour of interest.

Table 1. List of Influential Variables on NPD-curves for SA-Vehicle.

Variable Name	Physical Description	Impact on Approach Curves	Impact on Departure Curves
FLAPR	Area ratio of flaps to total wing area	Flat	Flat
SW	Wing area	Flat	Flat
TOC_Wratio	Mass-flow ratio of the top-of-climb to the aerodynamic design point	Steep	Steep
FPR	Fan pressure ratio	Steep	Steep
Ext_Ratio	Extraction ratio at aero design point	Flat	Flat
PER1	Ratio of core-nozzle perimeter with chevrons to core nozzle with no-chevron	Flat	Flat
Rating	NPSS thrust rating fraction for uprating or derating of an engine after design	Steep	Steep
T4max	Maximum allowable temperature at combustor exit/turbine inlet	Reduced Slope	Reduced Intercept
LPCPR	Low-pressure compressor pressure ratio at aero design point	Flat	Flat
HPCPR	High-pressure compressor pressure ratio at aero design point	Flat	Flat

Legend
Dominant
Significant
Minimal
Insignificant

In the latter table, there are four types of impacts listed: Flat, Steep, Reduced Slope, and Reduced Intercept. All impacts are in reference to an increase in the value of the given variable. The term “Flat” implies that for an increase in the listed variable the intercepts of the curves increased while the slopes decreased, thus resulting in a flatter curve. The term "Steep" implies the exact opposite such that an increase in the listed variable led to a decrease in the intercept and an increase in the slope, thus resulting in a steeper curve. The term "Reduced Slope" implies that for an increase in the listed variable (in this case *T4max*) the slope is decreased with little impact on the intercept. Similar tables to that in Table 1 were created for the other three vehicles (LTA, STA, and RJ).

In general, the dominant variables for the NPD curves tended to be consistent across all of the vehicles. Fan pressure ratio (*FPR*) and mass-flow ratio of the top-of-climb to the aerodynamic design point (*TOC_Wratio*) tended to drive both approach and departure towards steeper NPD curves. Approach curves were also dominantly more flat due to increases in airframe variables such as flap ratio (*FLAPR*) and wing area (*SW*), which had little to no impact on departure curves. Departure curves were dominantly more flat due to increases in extraction ratio (*Ext_Ratio*) and core-nozzle chevron perimeter ratios (*PER1*). Extraction ratio is defined as the ratio of bypass duct discharge pressure to core stream discharge pressure, and thus is closely related to bypass ratio. Chevron perimeter ratios are defined as the ratio of the nozzle-perimeter with chevrons applied to the same nozzle without chevrons.

2. Certification EPNL Sensitivities

While certification EPNL metrics for cutback, approach, and sideline noise are not fed into AEDT, it is interesting to track their sensitivities in parallel to the NPD-curve sensitivities. The cutback and sideline EPNL metrics are generally associated with departure procedures, while the approach EPNL is obviously associated with approach procedures. A summary of the common and unique influential variables between NPDs and EPNLs for the SA-vehicle is presented below in Table 2. Similar tables were created for each vehicle.

Table 2. Comparison of Influential Design Variables for NPDs and EPNLs for SA-Vehicle.

Op-Mode	Common Influential Variables between NPDs and EPNLs	Influential Variables Unique to NPDs	Influential Variables Unique to EPNL
Approach	SW, FPR, FLAPR, TOC_Wratio	Ext_Ratio, PER1, Rating	Fan_Dutip, LPC_AR_Fact, Fan_Duct, Fan_Deff, Duct15_Dp, HPC_AR_Fact
Departure	Rating, FPR, PER1, LPCPR, Ext_Ratio, TOC_Wratio	HPCPR, T4max	SW, LPC_AR_Fact, Fan_Duct, Fan_NcDes, Fan_Dutip, HPC_AR_Fact

For approach in Table 2, the EPNL metrics are dominantly dependent on wing-area and fan pressure ratio, which is consistent with the approach NPD-curves. Flap ratio and mass-flow ratio at top-of-climb were also influential variables, but not nearly as significant as they were for the NPD-curves. For the other three vehicles, it was found that flap ratio had little impact at all, which was inconsistent with the NPD-curve trends. Cutback and sideline EPNL metrics were dependent on a larger range of variables than the departure NPD curves. Sideline noise proved to be dominantly dependent on fan pressure ratio, except for the RJ vehicle which was more dependent on extraction ratio. Cutback noise was dominated by engine rating, but also showed a dependence on fan design variables such as duct lengths behind the fan, tip speeds, and aspect ratios on fan blades. Most of these variables showed little to no influence on departure NPD curves. As can be seen in Table 2, several additional variables proved to have medium or dominant significance on EPNL calculations despite having little to no impact on the NPD-curves. These lists of unique EPNL impact variables were different for each vehicle.

As mentioned before, EPNL metrics are not used as inputs to AEDT/INM. These drastic discrepancies show that the calculation methods for certification EPNL and NPD-curves are very different and are driven by different influential variables. This suggests that using EPNL data to model DNL contours, as was attempted in Reference 12, may lead to erroneous responses due to the differences in the design-variable dependence of EPNL and NPD calculations.[12]

3. SEL Contour Sensitivities

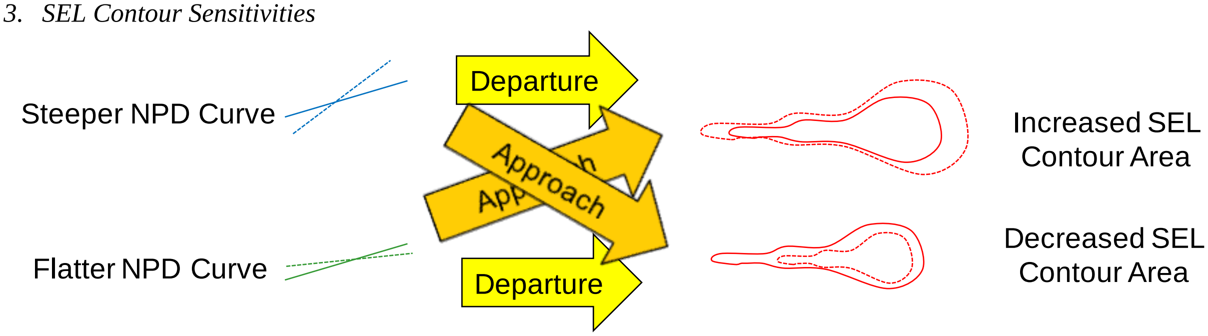

Figure 7. Relationship between NPD-Curve and SEL-Contour Area Trends

In order to calculate the design variable dependences of the SEL contours, the areas of the contours from 55-dB to 90-dB at 5-dB intervals were calculated for each successful case using MATLAB, with particular interest focused on the 65-dB contour. After analyzing half-normal probability plots for these area calculation responses, it became clear that they shared the same dependencies as the NPD-curves, which was to be expected. The general relationships between NPD-curves and SEL-contour areas are shown in Figure 7. Steeper departure NPD-curves lead to larger contour areas, whereas flatter NPD-curves lead to smaller contour areas. The opposite is true for approach, where steeper NPD-curves lead to smaller contour areas, whereas flatter NPD-curves lead to larger contour areas. This matches expectations because engines operate at highest engine ratings at departure but drop to near idle operating conditions at approach. Thus a steeper NPD curve for departure would correlate to louder noise at the typically high thrust values, whereas a steeper NPD curve for approach would correlate to quieter noise at the typically low thrust values.

Understanding the latter relationships allow us to consider physical explanations for the dominance of certain variables. The departure curves were more dependent on engine-sizing variables because the engines are operating at highest performance levels during takeoff. Increasing fan pressure ratio (*FPR*) leads to higher turbulence levels, increasing broadband fan noise. This variable also contributes to higher jet noise by driving the fan nozzle jet velocity higher. Therefore, an increase in *FPR* leads to steeper NPD-curves and increased contour areas. Mass-flow ratio of the top-of-climb to the aerodynamic design point (*TOC_Wratio*) is inversely proportional to bypass ratio. Higher bypass ratios drive fan noise up due to increased tip speeds and stronger shocks, but this is countered by a reduction in jet noise from better shielding of the higher-velocity core flow and improved mixing with the cooler fan-nozzle flow. Since jet noise tends to have a bigger impact than fan noise, the net effect of increased bypass ratio is typically lower overall noise.[13] Therefore, increases in *TOC_Wratio* drive smaller bypass ratios, leading to steeper NPD-curves and larger noise contours. Extraction ratio (*Ext_Ratio*) is directly proportional to bypass ratio, so increases in this variable drive larger bypass ratios, leading to flatter NPD-curves and smaller noise contours. Chevron geometries (*PER1*) are designed specifically to reduce noise, so it comes as no surprise that increasing *PER1* leads to flatter NPD-curves and smaller noise contours.

For approach, it was observed that flap ratios (*FLAPR*) and wing areas (*SW*) both contribute to flatter NPD-curves, which results in larger contour areas and thus louder approach noise. During approach the flaps and other high-lift devices are deployed in order to increase drag to slow down the aircraft. Aerodynamic noise is closely associated with drag creation mechanisms because of discrete frequencies that arise where air flow separates from the vehicle surface.[14] Similarly, increasing the wing area increases the areas of the deflected flaps, as flap ratio is defined with respect to the given wing area. Some of the influential variables for departure seem to display an influence on approach NPDs and contours as well. This is most likely explained by the use of thrust-reversers during runway landings. Evidence of this is suggested by the bulbous region for the approach contour example shown in Figure 4.

VI. Conclusions & Future Work

Understanding the physical design variables that influence DNL contours is of great importance to the international aviation community. Awareness of these factors will provide insight to both engineers and policymakers as they pave the way for the next generation of quieter aircraft, and in the near term these results will help in the development of screening tools for rapid decision making concerning technologies for reducing the environmental impacts of aviation.

A few important conclusions can be drawn from the sensitivity studies for this report:

1) Design variables for the airframe have the greatest impact on approach noise.
2) Design variables that drive the engine size/bypass ratio have the greatest impact on departure noise.
3) Engine-sizing variables can also contribute to approach noise due to thrust reversers.
4) Discrepancies between NPD-curve sensitivities and certification EPNL sensitivities suggest that EPNL data should not be used to model DNL contours for fleet level studies.

The true leverage that this work provides is an ability to move forward with the development of the generic vehicles, as outlined in the roadmap presented in Figure 2. With an increased understanding of the influential design variables on NPD-curves and noise contours, these variables can be cross-referenced with the influential design variables for aggregate fuel burn and emissions. Identifying which variables are unique to noise responses and which ones are common to both noise and fuel burn/emissions will allow for efficient tuning of the existing generic vehicle models to match DNL contours as well as fuel burn and emissions. These tuning efforts are expected to shine light on tradeoffs between noise and fuel burn/emissions. Additional difficulties may arise from trying to make these generic vehicle designs reflect a legitimate aircraft design within the given seat class, which can be monitored via constant comparisons of the generic vehicles to benchmark vehicles from the AEDT database.

Once these generic vehicles have been properly tuned, technology infusion studies can be performed. Eventually a screening tool for rapid evaluation of the environmental impacts of aviation technology can be developed to provide the members of CAEP and the policymakers they influence an understanding of the tradeoffs between noise, emissions, and economic costs.

Acknowledgments

Work for this paper supports FAA Award Number 09-C-NE-GIT, Amendment No. 001. The author would like to thank Joe Dipardo and other collaborators at the FAA for their guidance and feedback on this study.

The author would like to thank Dr. Michelle Kirby and Dr. Dimitri Mavris for their support over the past few years. He would also like to thank Christopher Perullo for his EDS tutorial, Scott Wilson for his EDS coding expertise, Graham Burdette for his help with the AEDT Tester, and Taewoo Nam for additional input.

Student Biography

Matthew J. LeVine is currently a PhD student at the Georgia Institute of Technology. He works as a graduate research assistant at the Aerospace Systems Design Laboratory (ASDL). He began his collegiate career at Emory University in 2004, where he majored in music with a focus on music composition. Mr. LeVine graduated Magna Cum Laude with a B.A. in Music from Emory in 2007 for completion of an undergraduate thesis in the form of an hour-long composition and performance. Mr. LeVine continued his undergraduate education at the Georgia Institute of Technology in the Fall of 2007 as part of the Dual-Degree Program between Emory and Georgia Tech. He graduated Summa Cum Laude with a B.S. in Aerospace Engineering from Georgia Tech, a degree which culminated in a first place finish for the AIAA Undergraduate Team Space Design Competition 2009-2010 for the Space Weather Experiment PlaTform (SWEPT), a satellite constellation design for characterizing the strength, size, and extent of the magnetotail at the second Lagrange point of the Earth-Sun system. Immediately following his graduation, Matthew began his graduate career at ASDL, continuing work that he began as a student assistant as an undergraduate. Mr. LeVine supports the development of the Environmental Design Space and Generic Fleet studies with a focus on characterizing and projecting aviation noise for future fleet mixes and technology scenarios.

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