# A Process to Validate the Predictive Capability of the Environmental Design Space through Error Quantification and Uncertainty Propagation

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## 1 Abstract

This paper describes a methodology for the verification and validation of the Environmental Design Space analysis tool. The ability of EDS to represent existing systems and generate future vehicles for use in policy making requires a structured, repeatable approach for uncertainty analysis. Through a three-step process of benchmarking against existing engine/airframe combinations, identifying significant system drivers and creating a future vehicle trade space this assessment effort attempts to provide the outline for this approach, with a focus on identifying a method for validating the predictive capability of the tool.

## 2 Introduction

The Environmental Design Space (EDS) represents one of a suite of tools being developed by the FAA's Office of Environment and Energy in association with NASA for the express purpose of evaluating the impact of commercial aviation on the environment. A primary goal of the tool suite development is to be able to categorize the interdependencies related to emissions, noise and fuel consumption trades, allowing for the ability to conduct detailed policy evaluations.

EDS is a series of numerical simulation tools linked together to assess commercial aircraft engines and airframes from a thermodynamic, weight, and mission analysis perspective. The primary objective of EDS is to identify future vehicles to represent potential responses to varying environmental policy scenarios. The goal of this paper is not to provide the details of the EDS process but instead to provide an overview of some of the challenges inherent to, and

potential solutions for, the creation and validation of a complex system for evaluating policydriven vehicle generation.

The main thrust of the EDS assessment effort is to create a structured, repeatable, and verifiable process for benchmarking existing vehicles, and determining associated environmental trades for use within the framework of the tool suite. Central to this effort is the need to identify an approach for the verification of the system and the validation of its predictive capability by categorizing model fidelity through detailed error and uncertainty analysis.

The overarching assessment plan for the FAA tool suite is centered on the concepts of uncertainty categorization and quantification, propagation of model inputs and the effect of model limits and assumptions on the module results. In order to address these issues, a detailed, sequential method has been created which will allow for the calibration of existing systems, the determination of input and assumption sensitivities and the exploration of environmental trades along with the identification of potential vehicle designs within that exploration. This method, discussed in more detail below, includes the calibration process, the sensitivity analysis and the parametric exploration.

### **3** Calibration Process

The calibration process serves to benchmark the analysis tools as well as identify initial parameter inputs and their associated settings. This process also allows for an initial investigation into the accuracy that can be expected when attempting to recreate existing vehicles, as well as an approach to vehicle communization within specified passenger classes. The calibration process begins the progression of identifying and quantifying errors and uncertainties that exist within the EDS outputs and is illustrated in Figure 1.



FIGURE 1: EDS CALIBRATION PROCESS

### 3.1 Validation Data Identification and Calibration Vector Creation

The first step in the calibration procedure is a determination of which vehicles will be modeled by EDS. Given the necessary constraint that each vehicle is modeled using publicly available information there are two specific data requirements that must be available to EDS. These are a two-dimensional cross section of the engine and a payload range chart. This information is critical to EDS' capability to benchmark the existing system.

After identifying and categorizing the different type of input and output data, the calibration vector can be created. The calibration vector represents all of the significant inputs to

the analysis tools for which no known value exists. The central goal of the calibration process is to determine the combination of input settings for this vector that allow the EDS model to most closely resemble an existing vehicle system. To employ this calibration vector it is necessary to identify potential ranges over which the inputs will be allowed to vary.

The ranges of the vector are determined through of a combination of engineering judgment based on the level of technology of the system being modeled as well as specific recommendations and feedback provided through external review processes. Due to the significant uncertainty in identifying this vector the variable input ranges are often wide and can produce infeasible designs, which is why the application of a series of clearly defined design rules to any of the resulting systems remains an important part of the verification process. Once the calibration vector and ranges of interest are established the space exploration and resultant design selection becomes possible.

#### 3.2 Design Space Exploration Techniques and Processes

The goal of the design space exploration is to determine the combination of settings for the calibration vector that causes the resulting output to match the existing validation data. There are a number of different approaches that can be taken to this space exploration. Perhaps the most common, and simplest to implement, is a one-change-at-a-time approach where the calibration vector is set to an initial point which is guessed based on engineering judgment and experience. Then the settings of specific variables are modified to attempt to match the output data with the validation data. While easy to set up, this process has a number of drawbacks. First, it is time consuming as the engineer modifies an input and then waits for the analysis tool to execute, compares the output data and repeats the process. It is also very path-dependent, both in terms of the initially guessed starting point as well as the variables and settings the engineer decides to modify. When a calibrated point is finally arrived at, only a single-point solution is provided and nothing is learned about the calibration space as a whole.

An alternative approach which has been developed as part of the EDS assessment, the Comprehensive Space Exploration (CoSE), attempts to reduce or eliminate many of the drawbacks associated with traditional one-variable-at-a-time optimization while providing significantly more information about the space of interest. The CoSE allows the designer to populate a significant portion of the design space through many unique executions of the analysis tools. The most significant drawback to this approach, the increased number of executions of the analysis tool required for the complete space exploration, is mitigated through the use of an internal distributed computing environment. When this problem is overcome, the method offers a number of unique advantages. Perhaps most importantly, there is no path-dependence in this technique as the space is uniformly sampled. This results in a more complete understanding of the entire calibration space which in turn allows the designer to query multiple areas of interest while avoiding regions of infeasible design. When used iteratively, this process can provide multiple solutions to the calibration vector rather than single point designs, providing the freedom to base the selection on the implemented design rules.

The calibration process EDS employs centers around the application of a Monte Carlo exploration while making use of automated optimization through the use of a genetic algorithm and sequential response modeling. By applying these techniques simultaneously, information is gained about the whole design space while also allowing the identification of calibration vectors that match the validation data as closely as possible given the limitations of the analysis tools and design rules. After the initial space exploration, the resulting outputs are then compared to existing validation data to determine the combinations of vector settings that most closely resemble the systems of interest. This represents the Monte Carlo filtering step within the EDS calibration process identified in Figure 1. The filtering is in part a mathematical identification of the designs that minimize the error between an EDS produced system and that represented by public-domain data. Additionally, engineering judgment is applied to ensure any selected designs are technically feasible within the established design rules. This is an iterative process as regions of the design space where the best potential solutions exist are explored in more detail by modifying the ranges of the calibration vector and continuing the CoSE until an acceptable solution is identified.

### 3.3 Initial Calibration Error Analysis

The calibration process results in the identification of a vehicle which will serve as a comparison to the public domain benchmark and allow for the first quantification of error within the EDS architecture. Given the limited information available to EDS it is impossible to suggest that every input to the analysis tools exactly matches those of the engine and airframe manufacturers. Instead, it is the goal of EDS to identify a combination of settings that allows for the minimization of error with respect to the important outputs that have been identified.

As the process matures, the error will be probabilistic in nature to reflect the fact that the validation data itself is not a deterministic value but rather a most likely value with an associated band of uncertainty. Again, given the limitations of EDS, namely the inability to determine precisely the characteristics of existing vehicle systems, it becomes important to quantify and propagate this additional uncertainty within the model as illustrated in Figure 2. This part of the

assessment is ongoing as EDS continues to investigate methods to visualize and propagate error within the model.



FIGURE 2: NOTIONAL EXAMPLE OF PROBABILISTIC ERROR QUANTIFICATION

#### 3.4 Common Space Error Analysis

One goal of the EDS system is not to create vehicles that are direct variants of existing systems but rather to create generic vehicles within specified passenger classes. For example, within the designated 300 passenger class, the Boeing 777-200ER aircraft can be modeled with both GE90-94B and PW4090 engines. EDS begins by attempting to replicate both systems to provide an initial benchmark, but then it is necessary to "merge" engine characteristics to create a generic or "common" space entry which accurately reflects existing technology, while not biasing the results towards one family of designs

The creation of this common space, to be able to describe multiple frameworks simultaneously, requires a compromise between some of the specific design characteristics that are unique to each vehicle system. Any time a compromise is introduced into the model this reduces the ability of the analysis tools to accurately replicate the original validation data. Obviously the degree of accuracy lost depends on the particular compromises made and how different the vehicle systems are within a particular class. This communization procedures introduces a second error that EDS will categorize and propagate forward during the assessment process. Figure 3 shows the notional impact of this new error from a purely deterministic point of view.



FIGURE 3: NOTIONAL EXAMPLE OF COMMUNIZATION ERROR DURING VEHICLE CALIBRATION

# 4 Sensitivity Analysis

The sensitivity analysis begins the process of investigating how EDS can be used to represent future vehicle designs as well as understanding the limitations and compromises that result from the approach that has been employed. Through a main effects statistical analysis combined with a genetic algorithm selection tool the independent variables that have the greatest contribution to the key measures can be categorized and selected. The enumeration of input parameters effects on output metrics will become important when considering areas of EDS that may require increased fidelity as data propagates downstream. In addition, this analysis allows for the determination of the optimal settings of the less important contributors with the goal of reducing error introduced into the final parametric model. Figure 4 illustrates the steps involved in the sensitivity analysis which will be explained in detail.



FIGURE 4: FLOWCHART OF SENSITIVITY ANALYSIS

### 4.1 Sensitivity Vector and Space Exploration

The independent variables that make up the generic sensitivity vector are decided upon at the conclusion of the calibration process. Depending on the policy scenario and year of interest it may be necessary to add parameters to be able to capture additional effects within the trade space. One example of this would be for a NOx stringency study where the effect of a combustor swap out on NOx production must be characterized. In this case a specific independent variable that defines a percentage NOx reduction would be added to the sensitivity vector to simulate the effect of the proposed engine modification.

Once the sensitivity vector is finalized based on policy requirements, the ranges for the study must also be set. The key driver in determining these ranges will be the policy year under investigation. Obviously an evaluation of the parameters for a policy scenario 30 years from now

would require wider ranges than one for a policy scenario 10 years from now to reflect the possibility of improved technological capabilities. No one can say exactly what engine component efficiencies will be in 30 years, but the potential design space of the time period must be captured as closely as possible, again using engineering judgment with respect to current and historical design trends.

### 4.2 Analysis of Variance (ANOVA)

The first step in performing the ANOVA on the comprehensive space exploration was to determine and remove technically infeasible designs. The remaining cases could be considered to effectively capture the potential range of outputs for a given policy scenario and year.

The absolute contribution of each main effect and its percent relative contribution were determined as part of a Pareto analysis. As part of the sensitivity analysis, the impact of the sensitivity vector was evaluated and used to determine the key drivers on the output metrics. Based on the Pareto analysis, the effect of the independent variables from the sensitivity vector and their relative percent contribution to the three key measures of fuel burn, NOx production and cumulative noise was quantified. Using this information, it was then necessary to reduce the set of independent variables to a more manageable list to be used for the parametric space exploration and surrogate model creation.

### 4.3 Reduced Variable Set Selection

One objective of the sensitivity analysis is to document the independent variables that have the most significant impact on the outputs of interest. Once these variables are identified they will be used to establish the final parametric space from which designs will be selected and trends will be explored. For the case of the 300 passenger class there were approximately 75 independent variables. If one were to assume for a moment that only 30 variables were to be active in the parametric space, this would still require evaluating approximately  $8 \times 10^{20}$  combinations to determine the "best" combination of 30 independents. Even for such a very simplified problem this is not feasible. The evaluation of the best group of parameters does not rely on a single objective function but rather some weighted combination of all of the key output measures, further complicating matters.

This problem demands the ability to formalize an approach to selecting the best set of independent variables while quickly evaluating potential combinations for a multiple of variability levels and a variety of potential objective functions. For each metric of interest, the minimum variability to be captured by the reduced input set is identified and an optimization routine determines the fewest number of independents that can meet those requirements. This in turn raises the issue of what level of variability should the final set of parameters reflect. In order to address this concern it is necessary to determine the impact of reducing the set of active variables on the error associated with the important output metrics.

There is a direct relationship between the number of variables that are removed from the list of contributors and the amount of error introduced into the model. It is necessary to balance the difficulty of modeling the parametric space with an excessive number of variables, against the error that is introduced into the process for every input parameter that is fixed to some compromise value instead of being allowed to vary. This trade cannot be determined solely within the context of EDS but rather is influenced by the required fidelity of the inputs to the other modules within the tool suite.

# **5** Parametric Space Exploration

The parametric space exploration contains the end result of EDS, a common space application of potential vehicle trades, and will be used to propagate these designs forward. The parametric space allows for the investigation and validation of trends as well as the selection of Pareto-efficient design points. In addition, this third step in the EDS process represents the linkage from EDS to the other tools within the suite. As such, the quantification of error and uncertainty that has been tracked through the entire process must be totaled for propagation outside of EDS. Figure 5 illustrates the steps involved in the parametric space exploration.



FIGURE 5: FLOWCHART OF PARAMETRIC SPACE EXPLORATION

After completion of the sensitivity analysis, the reduced set of variables is then used to generate surrogate models of the EDS environment. These models are explored to verify trends and key measures, allowing for increased interaction with potential reviewers and consumers of EDS information. The surrogate models are also employed to create the trade space and select

Pareto-efficient vehicles which are then passed on to other modules within the overarching suite of tools.

#### 5.1 Parametric Space Uncertainty Analysis

In order to create the parametric space it is necessary to reduce the number of input variables used to describe the space. The techniques described in the sensitivity analysis process attempt to reduce the accumulation of error and uncertainty, but as with the communization process it is an unavoidable outcome. The error resulting from the reduced order model represents the last error introduced into the EDS process. A notional visualization of this error, from a deterministic perspective, is illustrated in Figure 6.



FIGURE 6: NOTIONAL EXAMPLE OF ERRORS WITHIN THE EDS PROCESS

At this point in the process it becomes necessary to relate the existing errors to each other and attempt to quantify a total uncertainty introduced over the course of the system development. Investigations are underway for determining techniques for relating multiple errors within a design space to each other and understanding how these errors will contribute to uncertainties associated with new vehicle systems generated within and across passenger classes. The goal of this uncertainty analysis is to formally quantify the probabilistic nature of the designs generated within the EDS module which will allow them to be propagated throughout the tool suite. Figure 7 shows a notional example of this concept with regards to identifying replacement vehicles for a given policy scenario and year.



FIGURE 7: NOTIONAL EXAMPLE OF ERROR PROPAGATION WITHIN EDS

# 6 Conclusions and Future Work

This paper has provided an overview of a detailed architecture for the verification and validation of a physics based tool in the public domain. This three-step process allows EDS to generate vehicles that will be used for environmental policy decision-making. The calibration process describes a method for providing an initial benchmark capability for identifying how effectively an existing vehicle can be represented within the confines of EDS. This first step defines an approach for quantifying the initial error of the system which is necessary to begin the process of validating the predictive capability of the system. The sensitivity analysis serves the dual purpose of recognizing the most important contributors to variance in the model as well as providing a first verification that the environment is behaving as expected. The parametric space

creation in turn relies on the results of the sensitivity analysis to identify the set of input parameters that will define the final trade space and allow for the investigation of key trends and outputs.

Throughout the EDS assessment architecture, the need for identifying and quantifying sources of error and uncertainty has been emphasized. An initial approach for cataloging and visualizing the error has been introduced at various phases with a focus towards how it can be aggregated to accurately describe the final vehicle trade space. Traditional verification and validation efforts have focused on comparing analysis tools to existing systems through direct experimental comparison. In the case of EDS, there is a need to identify a method to validate the predictive capabilities of the tool when it will be used for future policy making. This area represents the focus of future work within the EDS assessment efforts.

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