System Level Assessment of Uncertainty in Aviation Environmental Policy Impact Analysis

by

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Abstract

This thesis demonstrates the assessment of uncertainty of a simulation model at the system level, which takes into account the interaction between the modules that comprise the system. Results from this system level assessment process aid policy-makers by identifying the key drivers of uncertainty in model outputs, among the input factors of the various modules that comprise the system. This knowledge can help direct resource allocation for research to reduce the uncertainty in policy outputs. The assessment results can also identify input factors that, when treated as deterministic variables, will not significantly affect the output variability.

The system level assessment process is demonstrated on a model that estimates the air quality impacts of aviation. The model comprises two modules: the Aviation Environmental Design Tool (AEDT), which simulates aircraft operations to estimate performance and emissions inventories, and the Aviation environmental Portfolio Management Tool (APMT)-Impacts Air Quality module, which estimates the health and welfare impacts associated with aviation emissions. Global sensitivity analysis is employed to quantify the contribution of uncertainty in each input factor to the variability of system outputs, which here are adult mortality rates and total health cost. The assessment results show that none of the input factors of AEDT contribute significantly to the variability of system outputs. Therefore, if uncertainty reduction in the estimation of adult mortality and total health cost is desired, future research efforts should be directed towards gaining more knowledge on the input factors of the APMT-Impacts Air Quality module.

This thesis also demonstrates the application of system level assessment in policy impact analysis, where policy impact is defined as the incremental change between baseline and policy outputs. In such an analysis, it is important to ensure that the uncertainty in policy impacts only accounts for the uncertainty corresponding to the difference between baseline and policy scenarios. Some input factors have a common source of uncertainty between scenarios, in which case the same representation of uncertainty must be used. Other input factors, on the other hand, are assumed to have independent variability between the different scenarios, and therefore need to have independent representation of uncertainty. This thesis demonstrates uncertainty assessment of a technology infusion policy analysis.

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Chapter 1

Introduction

The use of numerical simulations to support policy- and decision-making analysis has become increasingly widespread. Such analyses include many uncertainties, such as those due to a lack of knowledge as well as those due to the natural randomness of the system. These uncertainties impose further challenges on the policy process. Proper characterization and analysis of uncertainty associated with numerical simulations are thus imperative. This thesis discusses the assessment of uncertainty in models that evaluate the air quality impact of aviation to support policy analysis. In particular, a *system level assessment* is performed, where the assessment of uncertainty is done in an integrated manner on a system model that comprises two modules.

This chapter begins by presenting the motivation for uncertainty assessment in Section 1.1, followed by the motivation for the more specific system level assessment in Section 1.2. A brief overview of uncertainty assessment in policy impact analysis is presented in Section 1.3. Section 1.4 describes the terminologies that will be used throughout this thesis. The specific objectives of this research are then stated in Section 1.5, followed by a section presenting the organization of the remainder of this thesis.

1.1 Motivation for Uncertainty Assessment

It is a widely adopted practice to use results from numerical simulations—which enables numerical evaluation of a system when the physical systems are too complex to allow analytical evaluations [59]—to support policy analyses. Deterministic analyses are commonly performed in policy analysis setting, where the model is assumed to be completely known

[98]. However, the inherent presence of uncertainty in input factors, model parameters, and the model itself, coupled with the inclusion of subjective choices and assumptions, deem deterministic analyses insufficient in policy- or decision-making processes. In order to make policy decisions to the best of our knowledge, the inherent uncertainty needs to be carefully characterized and incorporated in the model development and analysis processes [104]. A complete uncertainty assessment process includes both uncertainty and sensitivity analyses. This process represents, characterizes, and analyzes the uncertainty of a model [1]. In the context of policy- and decision-making process, performing uncertainty assessment helps investigate whether an informed decision can be made based on the current state of knowledge on input data and parametric uncertainties. When knowledge improvement is required to enhance our confidence in the analysis results, the assessment process will help directing resource allocation [98]. The discussion in this thesis is only limited to the assessment of uncertainty of input factors, and excludes other sources of uncertainty, e.g., model uncertainty.

Uncertainty analysis is defined as the process to determine the uncertainty in model output based on the uncertainty in input factors [41]. By performing this analysis on a numerical simulation model, the model outputs are now represented by some probability distributions instead of a single evaluation value [108]. Care must be taken when characterizing uncertainties in input factors, as the desired outcome of the uncertainty analysis should be wide enough to include all possible assumptions but narrow enough to be useful in making policy decisions [60]. In addition to performing uncertainty analysis, a sensitivity analysis can be performed on the system to gain insights into the impacts of uncertainty in input factors on the variability of model output. For example, global sensitivity analysis can provide the importance ranking of input factors based on their significance, by means of the apportionment of the output uncertainty to contributions from different sources of uncertainties in model factors [90]. The results from such an analysis can guide channeling research efforts to reduce model output uncertainty, as stated by the Intergovernmental Panel on Climate Change (IPCC) in their 1990 report [46]. A general review of various sampling-based uncertainty and sensitivity analysis methodologies can be found in [41]. Chapter 2 will provide a survey of methods to perform uncertainty quantification and sensitivity analysis, with emphasis given to global sensitivity analysis methods, which are employed in this thesis. Among the available global sensitivity analysis methods (see

[39, 49, 87, 88] for an overview of the available methods), this thesis will explore the use of a variance-based method [44, 96, 89, 90], which will be demonstrated in Chapters 3 and 4.

Although there are no specific techniques to perform uncertainty assessment on a certain problem, several possible approaches are presented in [25, 72]. The step-by-step guideline to uncertainty assessment for general complex models intended to support policy- and decision-making processes is discussed in detail in [1]. For complex models, the uncertainty assessment process can also support model development, e.g., by identifying gaps in functionality and assumptions, in addition to supporting policy- and decision-making analysis [103]. Uncertainty assessment processes have been applied to various fields. For example, the uncertainty assessment of the Water Isolation Pilot project [39], hydrologic model [71], economics [66], and hysteretic model in mechanics [65]. In the context of aviation environmental impact analysis, the different representations of uncertainty in climate modeling are discussed in [48, 77], and the comparison of various uncertainty assessment and sensitivity analysis techniques (local and global sensitivity analyses, deterministic and variance based methods) can be found in [52].

1.2 Motivation for System Level Assessment

Real-world problems are typically complex, spanning a wide range of disciplines. Simulation models representing such problems thus often comprise a number of sub-modules. For example, in the aviation environmental impact analysis tools-suite developed by the U.S. Federal Aviation Administration's Office of Environment and Energy (FAA-AEE), aircraft performance, aircraft emissions, and environmental impacts are modeled in separate modules [78]. The modules interact with each other, forming a *system*. According to the definition proposed in the NASA Systems Engineering Handbook, a system is a *"a construct or collection of different elements that together produce results not obtainable by elements alone"* [76]. Performing an uncertainty assessment on such a tools-suite needs to be done in an integrated manner; that is, by considering the relation among the different modules, and how they interplay. This assessment will henceforth be called the *system level assessment* in this thesis.

Discussions of the propagation of uncertainty and sensitivity analysis performed at the system level are available in several literature sources. For example, the uncertainty propagation between modules in the context of multidisciplinary system design and optimization is presented in [32, 33, 34]. A demonstration of the use of system-level uncertainty propagation to support model validation process can be found in [22]. A software toolkit developed to facilitate uncertainty quantification in large computational engineering models is described in [109]. In [94], local sensitivity analysis is performed on internally coupled systems, by computing the local sensitivity derivative of the output to inputs of the system. A global sensitivity analysis approach called Multi-Disciplinary Multi-Output Global Sensitivity Analysis with Reducible Interval Uncertainty (MIMOSA) is developed to compute the sensitivity of system and subsystem outputs to input uncertainties; however, the analysis is limited to only include uncertainties in input factors that can be represented by interval uncertainties [61].

In this thesis, the system level assessment is demonstrated by performing a variance-based global sensitivity analysis on a system, to investigate the impact of the uncertainty of one model input not only on its immediate module output, but also on the system output, by taking the interaction between modules into account. Depending on the importance of a particular module, an input factor that is deemed significant within the module may have little contribution to the overall system output. Channeling research effort to reduce uncertainty associated with that particular input factor may therefore be unnecessary. By doing system level assessment in addition to module level assessments, we can therefore further narrow down the list of input factors that require further research for knowledge improvement. The background, procedure, and demonstration of system level assessment will be presented and discussed in more detail in Chapter 3.

1.3 Uncertainty Assessment in Policy Analysis

Regulatory agencies analyze and compare a number of policy scenarios prior to enforcing a new policy or regulation. This comparison is often done deterministically, for example by means of cost-benefit analysis (CBA), cost-effectiveness analysis (CEA), and distributional analysis. CBA aims to maximize the net social benefit of regulation, computed by subtracting costs from benefits associated with a certain policy or regulation. This method requires a consistent unit, typically monetary, to enable direct cost and benefit comparison [83, 57]. In CEA, different policies with similar expected benefits are compared, and the policy scenario with least cost is selected [57]. Distributional analyses aims to identify the different stakeholders who benefit or bear the costs of the proposed regulations [23]. See, [67], for example, for a demonstration of CEA and CBA approaches to assess the tradeoffs between environmental benefits and economic costs in NO_x stringency analysis context.

Incorporating uncertainties into any policy-science interface always remains a challenge in policy analysis processes, which often leads to the exclusion of uncertainty in the analysis [104]. For example, environmental impact assessment is often excluded in the aviation-related policy-making process due to the growing uncertainty in estimating environmental impacts [67]. However, the importance of providing uncertainty estimates of policy outputs has been widely recognized in the recent years. For example, the "ten commandments for good policy analysis" enumerated in [72] include the explicit characterization of uncertainty, as well as systematic uncertainty and sensitivity analyses for a thorough policy analysis process. Also, in preparing for the Third Assessment Report of the IPCC, the researchers were encouraged to quantify uncertainty as much as possible to support their analyses [74].

Some earlier studies that incorporate uncertainty in policy analysis represent the policy outputs as an interval without assigned probabilities [16]. However, further studies have provided probabilistic estimates of key results [55, 92, 97]. Assigning probabilities to input factors in highly uncertain systems, for example global climate change, is a challenge as the process often involves subjective judgment that is prone to cognitive biases [73]. Some studies, however, have provided evidence that these biases can be reduced by means of formal quantitative approaches in incorporating uncertainty [72, 101]. There is a wide body of literature that discusses uncertainty assessment to support policy decisions in the context of global climate change. Works to include uncertainty assessment in cost-benefit analysis to study the marginal damage costs of Carbon Dioxide emissions are presented in [99, 100]. A comparison of the climate projection, which is estimated by taking uncertainty in both economic and climate components into account, corresponding to two different policy scenarios is demonstrated in [106].

In this thesis, focus is given to study the effect of uncertainties in input factors on *policy impacts*, instead of just policy outputs. To compute the policy impacts, a common baseline scenario must be selected, to which policy outputs are compared. Uncertainty assessment is then carried out on the incremental changes between the policy and baseline scenarios [38, 67, 86]. The background, procedure, and demonstration of a policy impact analysis will be discussed in Chapter 4.

1.4 Terminology

This section presents the definition of terms used in this thesis, to avoid potential confusions due to the interchangeable use of some terms in the literature, e.g., *input*, *variable*, *factor*, and *parameter* [13, 35, 91]. *Models* are developed to represent the real-world facility or process, to enable studies on the system. A model typically represents the system in terms of logical and quantitative relationships [59], often expressed in mathematical operations, and characterized by a set of quantities which are called *parameters*. A *factor* is defined as the external input to a model that does not characterize the model, i.e., not a parameter. Specifically in the context of sensitivity and uncertainty analysis, the term *input factor* is used to describe the uncertainty associated to the module input [98]. The outcomes or results of interest from the model is referred to as *output*. Further details on this terminology and definition can be found in [1].

1.5 Thesis Objectives

The key objective of this research is to perform *system level assessment* on systems of modules assessing the environmental impact of aviation. More specifically, the objectives of this research are,

1. Demonstrate the use of Monte Carlo Simulation and Global Sensitivity Analysis methods for the uncertainty assessment of complex systems with multiple modules.

2. Demonstrate how sensitivity analysis can be applied to policy impact analysis to identify the key drivers of uncertainty in impacts of introducing new policy scenarios with respect to the baseline scenario.

3. Show how a system level uncertainty assessment can support decision for a technology infusion policy in the context of environmental impact of aviation.

1.6 Thesis Organization

Chapter 2 provides the background for the aviation environmental impact analysis framework on which the system level assessment will be demonstrated, i.e., the Aviation environmental Portfolio Management Tool (APMT), as well as the uncertainty and sensitivity analysis methodologies in practice—particularly the global sensitivity analysis. The demonstration of system level assessment procedure on a real-world problem that assesses the aviation impact on air quality is presented in Chapter 3. Chapter 4 discusses the application of uncertainty assessment in the context of policy impact analysis. This thesis ends with summary and general conclusions of this work and is consolidated with some proposed future work, in Chapter 5.

Chapter 2

Background

The first section of this chapter provides an overview of the aviation environmental tools-suite and its components, on which the system level uncertainty assessment will be demonstrated. More detailed description is given for the two modules that are used in this research, namely the Aviation Environmental Design Tool (AEDT) and APMT-Impacts Air Quality module. Section 2.2 discusses the available methods for uncertainty and sensitivity analysis, focusing mainly on the Sobol' variance decomposition method, which is used in this thesis.

2.1 The FAA Environmental Tools-Suite

The U.S. Federal Aviation Administration's Office of Environment and Energy (FAA-AEE), in collaboration with NASA and Transport Canada, is developing a comprehensive suite of software tools to thoroughly assess the environmental impacts of aviation activity through the Partnership for AiR Transportation Noise and Emissions Reduction (PARTNER) Center [67, 78]. This development aims to enable the characterization and quantification of the interdependencies among aviation-related noise and emissions, health, welfare, and economic impacts, under different policy, technology, operational, and market scenarios. This tools-suite, which is illustrated in Figure 2-1, consists of the Environmental Design Space (EDS), the Aviation Environmental Design Tool (AEDT), and the Aviation environmental Portfolio Management Tool (APMT).

EDS generates fleet based on the new technology that is modeled through a vehicle-level trade space, which becomes input to AEDT to simulate aircraft operations and performance. APMT has two key functions: to simulate the demand and supply in aviation

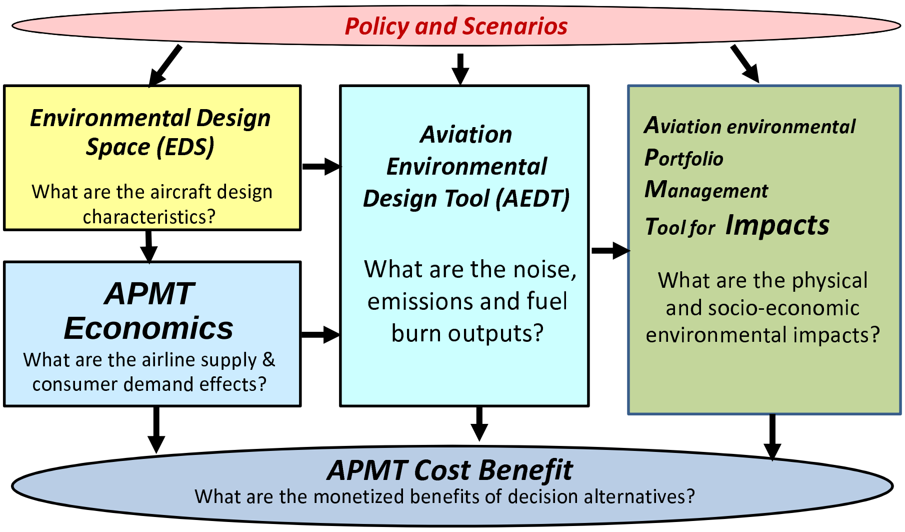


Figure 2-1: The FAA-NASA-Transport Canada Aviation Environmental Tool Suite.

industry, which is performed in the Economics module; and to quantify the environmental impacts, which are estimated in the Impacts block. APMT-Impacts is further subdivided into three modules: Climate, Air Quality, and Noise modules. The environmental impacts modeled within each module are described briefly in Table 2.1. The computed economic cost outputs and monetized environmental impact estimates allow policymakers to perform comprehensive cost-benefit and cost-effectiveness analyses. The two modules used in this thesis—AEDT and APMT-Impacts Air Quality module—are discussed briefly in the following. The reader can refer to [52, 67, 68] for further details on APMT-Climate modeling development, [7, 70, 86] for APMT-Impacts Air Quality module, [38, 53] for APMT-Impacts Noise module, and [36, 37] for APMT-Economics.

2.1.1 Aviation Environmental Design Tool (AEDT)

AEDT is an integrated system with the capability of analyzing aviation-related noise, emissions, and fuel burn on both local and global scales [78]. These analyses are performed by three main modules within AEDT, namely the Aircraft Performance Module (APM), Aircraft Emissions Module (AEM), and Aircraft Acoustic Module (AAM). To support the uncertainty assessment of the model, Volpe Transportation Center developed an *assessment application layer* that provides a wrapper around the computational module with the capability of running Monte Carlo simulations with randomized inputs. The assess-

Impact type	Effects modeled	Primary Metrics	
		Physical	Monetary
Noise	Population exposure to noise, number of people highly annoyed Housing value depreciation, rental loss	Number of people	Net present value
Air Quality	Primary particulate matter (PM), Secondary PM by NO_x and SO_x	Incidences of mortality and morbidity	Net present value
Climate	CO_2 Non-CO_2: NO_x-O_3, Cirrus, Sulfates Soot, H_2O, Contrails, NO_x-CH_4, NO_x-O_3 long	Globally-averaged surface temperature change	Net present value

Table 2.1: Overview of environmental impacts modeled in APMT [67].

ment application layer allows the user to set the distributional type (uniform, triangular) and parameters (minimum, peak, and maximum values) for each input factor. Users can pick from the following selectable options as the output format: segment level, flight level, airport inventory level, and global inventory level.

2.1.2 APMT-Impacts Air Quality module

Figure 2-2 illustrates the health impact pathway modeled in the APMT-Impacts Air Quality (AQ) module [7, 86]. The module quantifies the total health cost, which is the monetization of the seven health endpoints modeled in APMT-Impacts AQ module: (1) adult premature mortality, (2) infant premature mortality, (3) chronic bronchitis, (4) hospital admissions (respiratory), (5) hospital admissions (cardiovascular), (6) emergency room visits for asthma, and (7) minor restricted activity days.

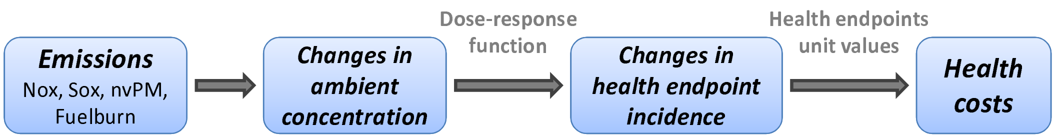


Figure 2-2: Health impact pathway for APMT-Impacts Air Quality module.

Aircraft emissions contain components of primary $PM_{2.5}$, which is considered as one of the predominant air pollutants causing health damages. $PM_{2.5}$ is defined by the EPA as fine particles of 2.5 micrometers or less, including solid, liquid, and heterogeneous (mixed solid and liquid) particles [102]. Changes in concentration of pollutants are computed from aircraft emissions using the Community Multiscale Air Quality (CMAQ) modeling system, which is a 3D grid-based Air Quality model [8, 9]. CMAQ is a complex model that simulates the chemical reactions and transport mechanisms of the atmosphere with a 36 km by 36 km Lambert Conformal grid resolution over the U.S. Population exposure. The dimension of the grid in the model is 148 $\times$ 112 cells. The expensive and long computational time of CMAQ, i.e., three days to simulate twelve months of data on an hourly basis, call for the use of reduced order models to enable policymaking applications as well as uncertainty and sensitivity analyses. Two reduced order models have been developed, namely the Intake Fraction model [86] and Response Surface Model (RSM) [7, 70]. In this thesis, RSM v2 (speciated) is used, which is described in detail in [7].

The RSM was built based on 27 high-fidelity CMAQ runs, where the 27 sample points were selected via a low-discrepancy Monte Carlo sampling procedure. The four independent parameters in the RSM linear regression model are multipliers for fuel burn, fuel sulfur content (FSC), inventory non-volatile PM (nvPM) Emissions Index, and inventory NO_x Emissions Index. *Multipliers* are defined as the ratio of emissions for the given scenario to the baseline aviation scenario emissions. The scenario used in the EPAct study (from [82]) with nvPM correction is used as the baseline. At each grid cell, the five components of PM concentration—organic particulate matter, ammonium (NH_4), PM Nitrates, PM Sulfates, and Elemental Carbon (EC)—are computed using RSM models separately. The general linear regression model for each grid cell and each PM component is shown in Equation 2.1,

$$[\cdot] = \beta_1 \cdot \text{FB multiplier} + \beta_2 \cdot \text{SO}_x \text{ multiplier} + \beta_3 \cdot \text{NO}_x \text{ multiplier} + \beta_4 \cdot \text{nvPM multiplier}, \quad (2.1)$$

where β_1 to β_4 are the regression coefficients that are derived based on the 27 CMAQ sample runs, and $[\cdot]$ denotes any components of the PM concentration mentioned above. The multipliers corresponding to each airport are first computed from the emissions inputs, and then assigned to the grid cell containing that particular airport. The current version of RSM accounts only for 314 U.S. airports, covering 95% of the national commercial aviation activity [82]. A spatial interpolation is then performed to obtain multipliers associated with grid cells with no airports, see [70] for details.

Changes in population exposure are obtained by multiplying the changes in the pollutant concentration corresponding to each grid cell with the affected population. Having obtained this metric, we can then compute the changes in health endpoints by means of concentration response functions (CRFs). The derivation of CRFs, which are also referred to as dose response functions, is based on epidemiological studies. The monetary valuations are then computed, depending on the given population's willingness to pay (WTP) and value of a statistical life (VSL), which are assigned by policymakers [86]. This computation is summarized in Equation 2.2.

$$\Delta\text{health cost} = \Delta\text{emissions} \times \frac{\Delta\text{ambient concentration}}{\Delta\text{emissions}} \times \frac{\text{health incidence}}{\Delta\text{ambient concentration}} \times \frac{\text{cost}}{\text{health incidence}} \tag{2.2}$$

2.2 Uncertainty and Sensitivity Analysis

This section presents a brief overview of the uncertainty quantification and sensitivity analysis methodologies used in this thesis.

2.2.1 Uncertainty quantification methods

Uncertainty quantification (UQ) methods propagate uncertainty from model inputs to outputs [75, 110]. There are two types of uncertainty. Uncertainty that is caused by natural randomness is classified as *aleatory* or irreducible uncertainty, whereas *epistemic* or reducible uncertainty refers to uncertainty that is due to a lack of knowledge [3, 45, 75]. Understanding this fundamental difference between the two types of uncertainty is important in interpreting the sensitivity analysis results. In many situations, however, the exact model formulation and distributional parameters, e.g., the nominal values of input factors or model parameters, are not known precisely and therefore subject to epistemic uncertainty. Consequently, those input factors and model parameters are subject to both epistemic and aleatory uncertainties [42]. For example, atmospheric temperature has an inherent natural randomness; and therefore its uncertainty is classified as aleatory. Nonetheless, an advancement in temperature measurement technology can help better define its uncertainty range. As such, atmospheric temperature uncertainty has an epistemic uncertainty layer on top of the aleatory one. In this thesis, all uncertainties that can potentially be reduced are treated as epistemic uncertainties.

Different UQ methods are employed for the different types of uncertainty. A probabilistic framework is the most commonly adopted mathematical representation for aleatory uncertainty. Non-probabilistic means of uncertainty quantification are often used for epistemic uncertainties [40], including evidence theory [79], possibility theory [19], fuzzy set theory [15], and imprecise probability theory [58]. An overview of available epistemic uncertainty quantification techniques is provided in [6].

The most common uncertainty quantification methods are Monte Carlo simulation and sampling-based methods. Monte Carlo simulations generates an ensemble of random realizations by running the model deterministically for different sets of random inputs. The statistical information of model outputs, e.g., mean and variance, are then extracted from this ensemble. Some non-sampling methods include perturbation methods [54, 63, 64], moment equations [112], operator based methods including Neumann series [93, 111] and the weighted integral method [20, 21], and polynomial chaos expansion [28, 75, 110]. Monte Carlo simulation is the favored method for high-dimensional and complex problems, as its convergence is only dependent on the number of realizations and not the dimension of problem [26]. Moreover, Monte Carlo simulation is non-intrusive, thus it is still applicable in the absence of governing equations. However, an expensive computational burden can be incurred if a certain level of accuracy is required, due to the need for a large number of realizations.

2.2.2 Sensitivity Analysis Methodologies

The main objective of performing sensitivity analysis is to investigate how uncertainty in input factors and model parameters affect the variability of model outputs [44]. Sensitivity analysis is particularly useful in studying systems, especially complex ones, as it helps to understand the behavior of the models, i.e., how they interplay in the system, and to check the coherence between a model and the physical system that it represents [89]. Sensitivity analysis methodologies can be classified into two main categories, *Global Sensitivity Analysis* (GSA) and *Local Sensitivity Analysis* (LSA). In LSA, the sensitivity of outputs to inputs is assessed only around a particular point of interest in the input space. GSA, on the other hand, takes the variations of input factors and model parameters over the entire input space into account. These sensitivity analysis methodologies are further elaborated in the following two subsections.

2.2.3 Local Sensitivity Analysis

Essentially, the main objective of LSA is to investigate the effect of changing the nominal values of an input factor on the model output. LSA typically involves the computation of the Jacobian of the model output with respect to input, and is sometimes normalized with respect to the means or standard deviations of the input or output. In practical settings where analytical gradients are not available, finite differencing is typically used to compute the gradient, where the factors are *perturbed* one at a time and the change in model output is observed. Other commonly used methods for estimating gradients include adjoint methods [10, 29], nominal range sensitivity method (threshold analysis) [27], automatic differentiation [31], and complex step differentiation [69]. Though LSA methods are mostly deterministic, that is, they do not have the capability to investigate the probabilistic uncertainty and interaction between factors, a local sensitivity analysis can still provide insight into how the model behaves under perturbations of one of its input factors.

2.2.4 Global Sensitivity Analysis

Unlike LSA, GSA is not limited to only a selected point in the design space. It also takes into account the interplay between factors. An overview of GSA methodologies is given below, followed by a more detailed discussion on variance-based methods, especially the current state-of-the-art Sobol' method. The practical implementation of Sobol' method via Monte Carlo is then described.

GSA Methods: an Overview

A review of some GSA methods, including the Monte Carlo based regression-correlation measures, the Fourier amplitude sensitivity analysis (FAST), and various differential analyses is provided in [39]. Some other GSA methods include efficient parameter screening—using data adaptive modeling [107], Iterated Fractional Factorial Design (IFFD) [2], and first order reliability analysis (FORM) [14]. A comparison of various GSA methods can also be found in [49, 87, 88].

Prior to the selection of the GSA method to be used, it is important to consider the output of interest and the concept of *importance* pertaining to the problem at hand. Some of the possible sensitivity analysis settings, namely factor prioritization, factor fixing, variance cutting, and factor mapping, are discussed in [90]. For this work, the focus is only on the first two settings. The goal of the *factor prioritization* setting is to rank input factors based on their importance, defined more specifically as their contribution to the output variability. This setting can help establish research priorities, and potentially provide a better understanding of the factors and thus reduce the uncertainty ranges associated with them. The *factor fixing* setting aims to identify factors that, when fixed in the model, will not affect the output variance. This setting can lead to model simplification and thus reduction in computational costs.

Variance Based Methods for GSA

Variance is commonly used as a measure of uncertainty, though it is just one of the many possible options [90]. With the presence of uncertainty, it is imperative to look at and compare the variance, in addition to the mean, when comparing different model outputs in making policy decisions. In many policy analysis settings, it is often more important and insightful to compare the *probability* of obtaining some values or ranges of model outputs, or the probability of risk, instead of comparing the expected output values from the different policy scenarios.

Developing sensitivity measures that rely on the variance decomposition methods is a very active research area. Variance-based methods were first used for sensitivity analysis in the early 1970s in the field of chemistry [17]. The first recognized method is FAST, which uses a search curve through the parameter space to evaluate the multi-dimensional integral instead of the Monte Carlo simulation [18]. The limitation of the first generation of FAST is that it only computes the main effect, i.e., the first order term [89, 90]. This limitation is overcome in the Sobol' method, which is similar to FAST as it also expresses the total variance of model output as a sum of terms of increasing dimensionality, but is able to compute the higher interaction terms [89]. Moreover, the Sobol' method can also compute total effect sensitivity index with the same computational cost as computing the main effect.

Sobol' Variance Decomposition Method

A Russian mathematician, I.M. Sobol', first developed a method for computing global sensitivity indices in early 1990s [95]. The method is classified as a variance decomposition method as it calculates the fractional contribution of the input factors to the variance of the model prediction [44, 96], from which the *main effect* and *total effect* sensitivity indices are computed. While the former only includes the first order effect, the latter measures the total contribution of a given input factor, including all the possible interaction terms between the input factors in the system [44]. The main effect sensitivity index is particularly relevant to the *factor prioritization* setting, as it allows the ranking of factors based on the expected variance reduction gained if the uncertainty associated with an input factor can be eliminated. In the *factor fixing* setting, on the other hand, total effect sensitivity index is more useful, as a low total effect sensitivity index indicates that the factor can be treated deterministically without any significant impact on the output variance.

The variance apportionment of Sobol' method is illustrated for a simple model with only two factors in Figure 2-3. For this simple example, the main effect of factor 1 will be the ratio of fractional contribution driven only by factor 1 to the total variance, whereas the total effect will be the main effect plus the ratio of the variance contributed by the interaction component (between factors 1 and 2) to the total variance. The derivation for the computation of both sensitivity indices and their Monte Carlo implementation will be briefly described below, following the work presented in [44, 90].

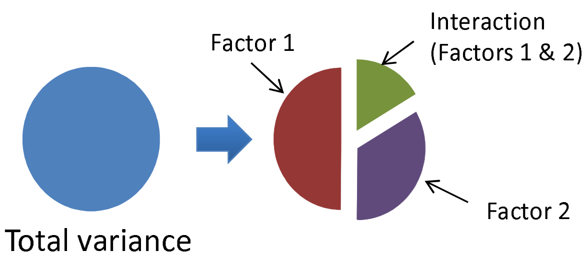


Figure 2-3: Apportionment of output variance [1].

The apportionment of variance makes use of the partial or conditional variance of the model output, which quantifies the variance reduction in the model output upon fixing a set of input factors. For a model output Y and an arbitrary input factor x_i, the unconditional variance can be decomposed to main effect, $\text{var}\left(\mathbb{E}\left[Y|\, x_i\right]\right)$, and residual, $\mathbb{E}\left[\text{var}\left(Y|\, x_i\right)\right]$,

$$\text{var}\left(Y\right) = \mathbb{E}\left[\text{var}\left(Y|\, x_i\right)\right] + \text{var}\left(\mathbb{E}\left[Y|\, x_i\right]\right). \tag{2.3}$$

The main effect sensitivity index can thus be expressed as

$$S_i = \frac{\mathrm{var}\left(\mathbb{E}\left[Y|\, x_i\right]\right)}{\mathrm{var}\left(Y\right)}, \tag{2.4}$$

and the residual, which can be interpreted as the expected remaining variance that would be left if x_i can be fixed, is given as follows,

$$\mathbb{E}\left[\mathrm{var}\left(Y|\, x_i\right)\right] = \mathrm{var}\left(Y\right) - S_i \cdot \mathrm{var}\left(Y\right). \tag{2.5}$$

Similarly, the output variance can also be decomposed in terms of main effect and residual, but conditioned with respect to all factors but x_i (x_{i^c}) as shown below,

$$\mathrm{var}\left(Y\right) = \mathbb{E}\left[\mathrm{var}\left(Y|\, x_{i^c}\right)\right] + \mathrm{var}\left(\mathbb{E}\left[Y|\, x_{i^c}\right]\right). \tag{2.6}$$

The ratio of the residual in the above variance decomposition to the total variance quantifies the total effect sensitivity index (τ_i),

$$\begin{aligned} \tau_i &= \frac{\mathbb{E}\left[\mathrm{var}\left(Y|\, x_{i^c}\right)\right]}{\mathrm{var}\left(Y\right)} \\ &= 1 - \frac{\mathrm{var}\left(\mathbb{E}\left[Y|\, x_{i^c}\right]\right)}{\mathrm{var}\left(Y\right)}, \end{aligned} \tag{2.7}$$

i.e., the portion of output variance that would be left if only x_i is allowed to vary.

The basis for computing the conditional variance, and therefore the Sobol' sensitivity indices, is the ANOVA[1] High-Dimensional Model Representation (ANOVA-HDMR) of the model function $f(\mathbf{x})$ that is assumed to be integrable [96]. In the derivation presented below, the function $f(\mathbf{x})$ is defined in an n-dimensional unit cube, i.e., $0 \le x_i \le 1, i = 1, \ldots, n$. This representation is expressed in Equation 2.8, where $\mathbf{x}$ is the vector of input variables, i denotes the variable index and n denotes the total number of variables that are within the system:

$$\begin{aligned} f(x) &= f_0 + \sum_{s=1}^{n} \sum_{i_1,\ldots<i_s}^{n} f_{i_1\cdots i_s}\left(x_{i_1}, \ldots, x_{i_s}\right) \\ &= f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{i<j} f_{ij}\left(x_i, x_j\right) + \ldots + f_{12\ldots n}\left(x_1, x_2, \ldots, x_n\right), \end{aligned} \tag{2.8}$$

[1]Analysis of Variance

where f_0 is a constant (the function mean), $f_i(x_i)$ is the term that is only dependent on x_i, $f_{ij}(x_i, x_j)$ is the function that is dependent on x_i and x_j, and so forth.

The uniqueness of the ANOVA-HDMR decomposition is enforced when the integral of every summand over any of its independent variables is zero,

$$\int_0^1 f_{i_1 \ldots i_s}(x_{i_1}, \ldots, x_{i_s})\, dx_k = 0 \text{ for } k = i_1, \ldots, i_s, \quad s = 1, \ldots, n, \tag{2.9}$$

which in turn guarantees the orthogonality for any two different summands,

$$\int f_{i_1 \ldots i_s}(x_{i_1}, \ldots, x_{i_s}) \cdot f_{k_1 \ldots k_t}(x_{j_1}, \ldots, x_{j_t})\, d\mathbf{x} = 0. \tag{2.10}$$

Using this orthogonality property, each component can be derived analytically; for details see, for example, [44, 96].

As previously mentioned, the function—and thus all the components—is assumed square integrable. We can then express the total variance, $\mathrm{var}(Y)$, as:

$$D = \int f(\mathbf{x})^2\, dx - f_0^2, \tag{2.11}$$

and the partial or conditional variance, $\mathrm{var}\left(\mathbb{E}\left[Y \mid x_{i_1 \ldots i_s}\right]\right)$, as:

$$D_{i_1 \ldots i_s} = \int f_{i_1 \ldots i_s}(x_{i_1}, \ldots, x_{i_s})^2\, dx_{i_1}, \ldots, x_{i_s}. \tag{2.12}$$

The fractional contribution of a set of input factors to the output variability can then be written as in the following,

$$S_{i_1 \ldots i_s} = \frac{D_{i_1 \ldots i_s}}{D}, \tag{2.13}$$

which is the basis in computing the main (S_i) and total effect sensitivity indices (τ_i), as shown in Equations 2.14 and 2.15, respectively.

$$S_i = \frac{D_i}{D}, \tag{2.14}$$

$$\tau_i = 1 - S_{i^c} = 1 - \frac{D_{i_c}}{D}. \tag{2.15}$$

Monte Carlo Implementation of Sobol' GSA Method

For complex functions $f(\mathbf{x})$ where the ANOVA-HDMR decomposition components are almost impossible to attain analytically, the indices are estimated by evaluating the multidimensional integral via Monte Carlo methods [44]. For a given sample size N, the constant term can be estimated as follows,

$$\hat{f}_0 = \frac{1}{N}\sum_{m=1}^{N} f(\mathbf{x}^m), \tag{2.16}$$

which is also the function mean. $\mathbf{x}^m$ is the m-th sample point in the n-dimensional hypercube, i.e., the input space. The *hat* is used to distinguish the estimate from the actual value. The estimate of output variance can also be computed via Monte Carlo,

$$\hat{D} = \frac{1}{N}\sum_{m=1}^{N} f(\mathbf{x}^m)^2 - \hat{f}_0^2. \tag{2.17}$$

For the estimation of the conditional variance D_i, the multidimensional integral is solved by computing the expected value of products of two terms: one with the samples in $\mathbf{x}^m$, and one with all factors resampled except x_i,

$$\hat{D}_i = \frac{1}{N}\sum_{m=1}^{N} f\left([x_1^m, \ldots, x_i^m, \ldots, x_n^m]^T\right) f\left([\tilde{x}_1^m, \ldots, x_i^m, \ldots, \tilde{x}_n^m]^T\right) - \hat{f}_0^2, \quad i = 1, \ldots, n, \tag{2.18}$$

where the notation $\tilde{x}_j^m$ is used for a new sample of x_j for the m-th Monte Carlo realization. With the estimates of total and partial variance, the main effect sensitivity index estimate, $\hat{S}_i$, is computed following Equation 2.14.

The estimate of the variance due to all factors except x_i, i.e., when only one factor is resampled (denoted as $\hat{D}_{i^c}$) is estimated following the similar procedure,

$$\hat{D}_{i^c} = \frac{1}{N}\sum_{m=1}^{N} f\left([x_1^m, \ldots, x_i^m, \ldots, x_n^m]^T\right) f\left([x_1^m, \ldots, \tilde{x}_i^m, \ldots, x_n^m]^T\right) - \hat{f}_0^2, \quad i = 1, \ldots, n. \tag{2.19}$$

Finally, the total effect sensitivity index is estimated by applying Equation 2.15, upon computing $\hat{S}_{i^c} = \hat{D}_{i^c}/\hat{D}$. The computation of variances (Equations 2.17 to 2.19) may suffer a loss of accuracy when the mean value $f_0(\mathbf{x})$ is large. A new *mean-subtracted* model function, $f(\mathbf{x}) - c_0$, where $c_0 \approx f_0(\mathbf{x})$, is used instead [95, 96].

The computation of error estimates corresponding to the Monte Carlo estimation of main effect sensitivity indices is provided below, following the derivation presented in [44]. The probable error corresponding to the estimated partial variance, $\delta\hat{D}_i$, is computed as follows,

$$\delta\hat{D}_i = \frac{\mathrm{CI}}{\sqrt{N}}\sqrt{F_i - I_i^2}, \tag{2.20}$$

where CI is the confidence interval. Some commonly used values for CI are 0.6745, 1.6449, and 1.9600 for 50%, 90%, and 95% confidence intervals, respectively. F_i and I_i are as defined in Equations 2.21 and 2.22.

$$F_i = \frac{1}{N}\sum_{m=1}^{N}\left[f\left([x_1^m,\ldots,x_i^m,\ldots,x_n^m]^T\right) f\left([\tilde{x}_1^m,\ldots,x_i^m,\ldots,\tilde{x}_n^m]^T\right)\right]^2 \tag{2.21}$$

$$I_i = \frac{1}{N}\sum_{m=1}^{N} f\left([x_1^m,\ldots,x_i^m,\ldots,x_n^m]^T\right) f\left([\tilde{x}_1^m,\ldots,x_i^m,\ldots,\tilde{x}_n^m]^T\right) \tag{2.22}$$

Similarly, the probable error on the total variance, corresponding to the same level of confidence, is computed as:

$$\delta\hat{D} = \frac{\mathrm{CI}}{\sqrt{N}}\sqrt{\hat{D}}. \tag{2.23}$$

The error estimate on the main effect sensitivity index, $\delta\hat{S}_i$, is then approximated as shown below,

$$\delta\hat{S}_i \approx \frac{\delta\hat{D}_i}{\hat{D}} + \hat{S}_i\frac{\delta\hat{D}}{\hat{D}}. \tag{2.24}$$

The population of S_i therefore falls within the range of $\hat{S}_i \pm \delta\hat{S}_i$ with the level of confidence that is associated with the value of confidence interval used in Equations 2.20 and 2.23. By following the same procedure, but replacing $\hat{S}_i$ with $\hat{S_{i_c}}$ and $\hat{D}_i$ with $\hat{D_{i_c}}$, the error estimate for the total effect sensitivity index can be computed.

To compute both total and main effect sensitivity indices for n factors, a total of $(n+2)$ Monte Carlo simulations are required. Each input factor that is considered in this analysis requires two sets of samples, with N samples within each set. Thus, for the factor x_i, we have x_i^m and $\tilde{x}_i^m$, for $m = 1, \ldots, N$. As with other Monte Carlo simulation-based methods, convergence of the Monte Carlo simulations is an important question that needs to be addressed. The convergence criteria, which are problem-dependent, will be illustrated and discussed in the demonstration of GSA in the context of aviation environmental impact analysis, which will be presented in Chapter 3.

Chapter 3

System Level Assessment on APMT

As stated in Section 1.5, the first objective of this thesis is *to demonstrate the use of Monte Carlo simulations and Global Sensitivity Analysis methods for the uncertainty assessment of complex systems with multiple modules*. This chapter describes the background and procedure to perform *system level assessment* (SLA), followed by the demonstration on a real-world problem in the context of aviation environmental impact analysis. The illustrative problem involves a system comprising the aviation performance and emissions modules within AEDT and APMT-Impacts Air Quality module.

3.1 System Level Assessment Background

For a system that comprises more than one module, for example the FAA-AEE aviation environmental tools-suite, a thorough assessment process should include both *module level* and *system level assessments*. In module level assessment, each individual module is assessed independently, involving only immediate inputs into and outputs from the module of interest, as illustrated in Figure 3-1. In SLA, on the other hand, the assessment is done on multiple modules in an integrated manner, taking into account the interaction between modules. The main purposes of SLA within APMT can be summarized as follows:

1. Assessing the impact of the uncertainty of input factors to the system output, instead of only to their immediate module outputs, in an integrated manner. The results from

this assessment process can support the policy- and decision-making processes, by providing policymakers with a more focused research direction, when the uncertainty reduction in system outputs is concerned.

2. Identifying any inconsistency of assumptions across the different modules by analyzing and comparing results from both module level and system level assessments

3. Identifying gaps in functionality and limitations of each module to contribute to the model development process

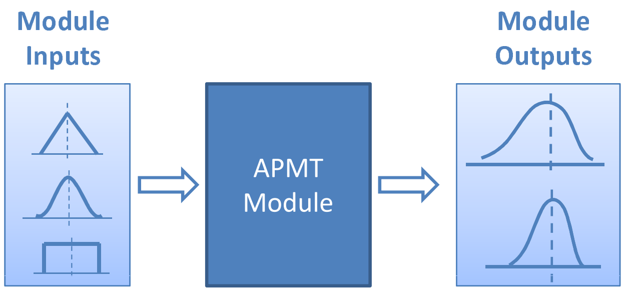


Figure 3-1: Module level assessment within APMT.

The module level assessments within APMT have been performed by the respective model developers for AEDT [78], APMT-Impacts Climate module [1, 52, 67], APMT-Impacts Air Quality (AQ) module [7], and APMT-Impacts Noise module [38]. The first SLA effort within APMT aims to assess AEDT and APMT-Impacts modules in an integrated manner. As discussed in Chapter 2 of this thesis, there are three modules within APMT-Impacts, i.e., Air Quality, Climate, and Noise. This thesis only focuses on performing system level assessment on a system comprising AEDT and APMT-Impacts Air Quality module.

3.2 SLA Terms and Definitions

The input factors to the system, system outputs, and intermediate variables for a simple system with two modules are shown in Figure 3-2. Inputs to the system include all module level inputs, except those that become intermediate variables at system level, which will be elaborated further next. For analysis processes where Sobol' Global Sensitivity Analysis method is needed, the number of inputs that are treated as random variables, i.e., *input factors* according to the definition stated in Section 1.4, determines the required number of Monte Carlo simulations, and therefore the computational cost of the analysis. When the limited computational resources only allow a handful of input factors to be included in such an analysis, priority is given to those that are deemed significant from the corresponding module level assessment results. *Intermediate variables* include module level outputs that are passed as inputs to other modules. The module where the intermediate variables are outputs will be referred to as the *source module*, whereas the module where the intermediate variables are passed to will be called the *receptor module*. *System outputs* are outputs of the system, which can be outputs of any modules within the system, of which the uncertainty and sensitivity will be assessed. Although Figure 3-2 only shows two modules in the system, it is not unusual that the system comprises more than two modules, potentially with some feedback loops. Feedback loop exists when a module passes its outputs to any of the predecessor modules. The presence of feedback loops in the system increase the analysis complexity, and therefore special care must be taken in handling them. This issue is, however, outside the scope of this thesis.

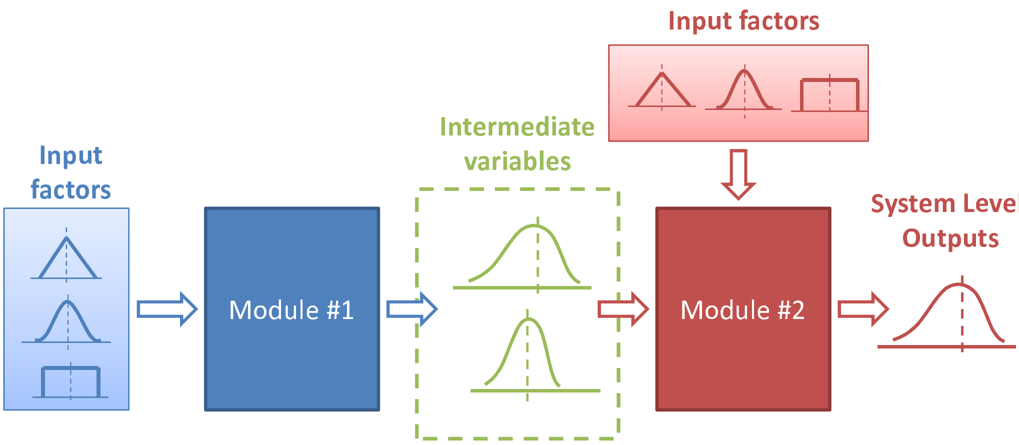


Figure 3-2: Coupling between modules in the system level assessment procedure.

One major source of complexity in system level assessment, as compared to the module level assessment, is the coupling or interaction between modules. *Data handoff mechanism*, which models the coupling between modules, thus plays an important role in the SLA procedure. The data handoff mechanism must facilitate the transfer of data between the different modules, and often includes data format conversion. It is common to have the different modules being developed in different institutions, e.g., universities or research centers, using different programming languages or platforms. Having different data format across the different modules is therefore not unusual. For example, Volpe Transportation Center develops modules using C# programming environment, whereas MIT does most of the code development for APMT-Impacts modules in MATLAB. In this case, data format conversion is an important part of the data handoff mechanism.

3.3 SLA General Procedure

Prior to any assessment processes, it is important to set up the key questions that need to be addressed by the assessment process. For example, do we only need to know the probability distribution of outputs, given the assumed variability of inputs? Do we need to get insights into which input factor, from which module, on which we need to focus our research to reduce the variability in output? Do we need to know the impact of changing the distributional type and parameters of a certain input factor to the system level output? Here, uncertainty analysis is sufficient for the first case, where the uncertainty in input factors is propagated through to the different modules via Monte Carlo simulations, whereas Global Sensitivity Analysis (GSA) is required to answer the second question. Additional distributional analyses are necessary to answer the last question. The step-by-step guideline to perform SLA on a system is presented below, which will be made clearer with the demonstration of the sample problem.

1. Define the system structure

   The main backbone of the system structure is the modules that comprise the system, which must be clearly defined at the beginning of the SLA process. Next, the uncertainty characterization of each input factor, e.g., probability density function (PDF), needs to be determined. Depending on which output uncertainty needs to be assessed in the SLA process, we can determine the system outputs of interest. Knowledge of the system and how the modules interact will help identify the intermediate variables that need to be passed between modules; the corresponding source and receptor modules can also be determined.

2. Assess the need of having a surrogate model

Surrogate modeling is an important consideration in the SLA procedure when it is prohibitive to carry out the complete analysis on the full model. A decision on whether a surrogate model is required is made based on the required computational efforts and the available computing resources. A very brief discussion on surrogate modeling methodologies is given in the next section. The derivation of a surrogate model is largely dependent on the problem at hand. Verification of the quality of the derived surrogate model in representing the full model must be carried out prior to its use in the analysis.

3. Determine the appropriate data handoff mechanism to connect the source and receptor modules for each intermediate variable
   The data handoff mechanism may require some code modifications or additional functions when the modules are not integrated yet. In doing so, some data format conversions may be required.

4. Perform the analyses
   Some analyses require additional post-processing modules. For example, an additional module to estimate sensitivity indices is required to perform GSA on the system.

3.4 Surrogate modeling

The large number of trials, typically in thousands, required in Monte Carlo simulations often makes uncertainty analysis too expensive to perform. Performing GSA on top of uncertainty analysis further exacerbates this computational burden, owing to the relation between the number of required Monte Carlo simulations and the number of input factors in performing GSA. As mentioned in Section 2.2.4, a total of $(n+2)$ Monte Carlo simulations are needed for GSA purposes, where n is the number of input factors to be assessed. The escalating requirements in computing power, computational time, and memory space call for the use of surrogate model, which is a simpler and less expensive model on which the required analyses can be performed with much less computational expenses.

Surrogate modeling methodologies can be classified into three main categories, namely data-fit, reduced-order, and hierarchical models [24]. The construction of data-fit surrogate models involves interpolation or regression of data generated by solving the large-scale system at a set of sample points, which are often generated using a design of experiment

[105]. An overview of many methods that belong to this category can be found in [81]. Most reduced-order models rely on the projection of the large-scale model onto a basis that spans a space of lower dimension. Readers can refer to [4] for an overview of available model reduction methods. The third category of surrogate modeling method involves the construction of hierarchical models, also referred to as multifidelity, variable-fidelity, or variable-complexity models [62, 84, 85].

3.5 SLA on a System Comprising AEDT and APMT-Impacts Air Quality module

The two modules within APMT that comprise the system for this SLA process are AEDT and APMT-Impacts Air Quality (AQ) module. The key objective of this assessment process is to quantify the contributions of input factors of the system to the variability of some selected system outputs. This information will facilitate the policymakers to channel research resources in efforts to reduce the uncertainty in system outputs, which in this case are the quantification of the impacts of aviation activity on air quality. In order to achieve this objective, GSA is performed to estimate the main and total effect sensitivity indices of outputs with respect to input factors. A convergence analysis is carried out as part of the GSA procedure, to study the relation between the number of Monte Carlo trials and the sensitivity index estimates. The important considerations that need to be taken into account to determine the required number of Monte Carlo trials, for general cases and then specific for this SLA process, will also be discussed.

3.5.1 System Structure

Figure 3-3 illustrates the coupling between AEDT and APMT-Impacts AQ module. The input factors to the system are tabulated in Table 3.1; the distributional type and parameters corresponding to these input factors are provided in Appendix A. The uncertainty in Response Surface Model (RSM) linear regression parameter, which is assessed in the module level assessment of APMT-Impacts AQ module, is not included in this SLA process, since results from the former assessment show that the sensitivity indices of all APMT-Impacts AQ module outputs to this input factor are less than 0.01, which are deemed insignificant. The system level outputs are the two main outputs of APMT-Impacts Air Quality module,

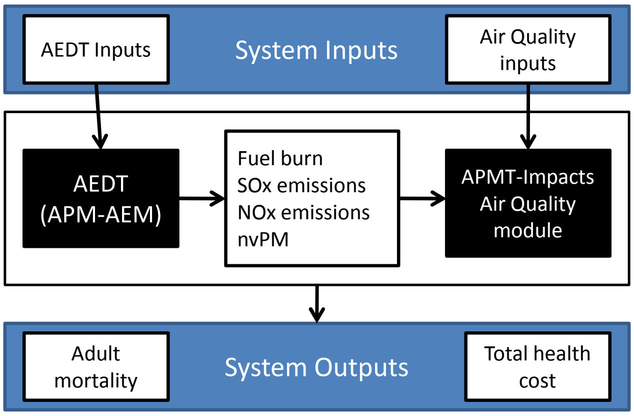


Figure 3-3: The structure of system level assessment involving AEM and APMT-Impacts Air Quality module.

namely adult mortality and the total health cost.

The intermediate variables in the system are fuel burn, Sulfur Oxide (SO_x) emissions, Nitrogen Oxide (NO_x) emissions, and non-volatile particulate matter (nvPM). As shown in Figure 3-3, the source module for all four intermediate variables is AEDT, and the receptor module is APMT-Impacts AQ module. Note that the emissions values admitted in APMT-Impacts AQ module are only those corresponding to the Landing and Takeoff Operation (LTO) procedure. SO_x emissions output should already capture fuel sulfur content (FSC) variability; however, until this analysis is completed this capability has not been incorporated into the numerical model that runs AEDT. At the system level setting, APMT-Impacts AQ module obtains random samples for the emissions species directly from AEDT, which is different from the module level assessment procedure, as depicted in Figure 3-4. For the module level assessment, APMT-Impacts AQ module obtains the nominal values for the emissions from an emissions inventory corresponding to the specific scenario in question. The random samples are then obtained by multiplying the inventory values by some random numbers whose nominal values are set to one. These *multipliers* are drawn depending on the distributional type and parameters assumed for the corresponding input factors.

Module	Input description
AEDT	**Atmospheric factors**
	Airport weather: • Temperature, pressure, headwind, relative humidity
	Aircraft performance factors
	Aircraft maximum stopping distance Aircraft thrust static Flaps Coefficients: • Coeff. B, Coeff. CD, Coeff. R Jet Thrust Coefficients: • Coeff. E, Coeff. F, Coeff. Ga, Coeff. Gb, Coeff. H Propeller Thrust Coefficients: • Efficiency, power Terminal fuel coefficients: • Coeff. 1, Coeff. 2, Coeff. 3, Coeff. 4 Profile weight BADA Mach Drag Coefficient BADA Fuel Coefficients: • Coeff. 1, Coeff. 2, Coeff. 3, Coeff. 4, Coeff. Cr NPD Curve: • L2001, L4001, L6301, L10001, L20001 • L40001, L63001, L100001, L160001, L250001
	Emissions indices
	Engine Carbon Monoxide (CO) Emissions Indices: • Takeoff, Climb out, Approach, Idle Engine Hydrocarbon (HC) Emissions Indices: • Takeoff, Climb out, Approach, Idle Engine Nitrogen Oxides (NO_x) Emissions Indices: • Takeoff, Climb out, Approach, Idle Engine Smoke Numbers (SN): • Takeoff, Climb out, Approach, Idle
APMT-Impacts Air Quality module	Concentration Response Function (CRF) adult mortality Value of a Statistical Life (VSL)

Table 3.1: List of inputs to the system (AEDT and APMT-Impacts Air Quality module).

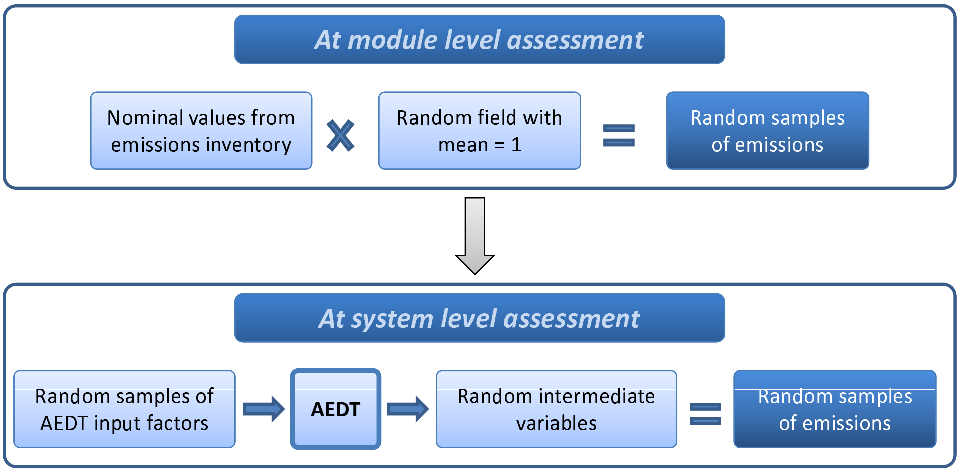


Figure 3-4: Obtaining random samples for input factors for module level and system level assessments.

3.5.2 Surrogate Modeling

For this SLA process, surrogate models are required for both AEDT and APMT-Impacts AQ module. The same Response Surface Model (RSM) that was used in the module level assessment of APMT-Impacts AQ module (see Section 2.1.2) is employed. The reader is referred to [7] for the verification of the RSM version used for APMT-Impacts AQ module, i.e., the comparison between the RSM results and results from the high-fidelity CMAQ model. In order to use this RSM, the emissions outputs from AEDT need to be in airport-by-airport format. As mentioned in Chapter 2, APMT-Impacts AQ module can admit 314 major US airports, inclusive of some military, regional, and international airports. The computational time required to run the aircraft performance and emissions modules pertaining to these airports on the assessment application layer can be prohibitive. For example, running 1000 trials for only JFK airport takes approximately three hours. Thus, completing Monte Carlo simulations required for GSA purposes, which depends on the number of input factors, for 314 airports may take approximately 3 years to complete on a single computer, assuming 1000 trials are sufficient. The use of a surrogate model is therefore appropriate to enable the many Monte Carlo simulations required for GSA. In particular, a hierarchical surrogate model is selected, where the full aircraft performance and emissions modules are run for only a few representative airports, instead of the entire 314 airports.

The surrogate model is derived by employing an aggregation (clustering) algorithm, which is applied to the 314 admissible airports. Further details on this algorithm can be found in [62]. The algorithm forms groups of *similar* airports, and from each airport group, a representative airport is then selected. The ensemble of these representative airports then form the surrogate model, on which AEDT will be run. The *similarity* between airports is determined by means of the average LTO fuel burn for each airport, which is computed by dividing the total departure and arrival fuel burn by the total number of flights flying to and from that particular airport. For this analysis, airports that have average LTO fuel burn within $\pm 15\%$ of each other are considered similar, and thus aggregated into the same group. This aggregation procedure produces 19 airport groups representing a total of 248 airports—thus there are a total of 19 representative airports. This number is less than 314, owing to the omission of groups that only have one airport. These groups are omitted due to the limited computational time available to run AEDT. The selection of the representative from each group is done by selecting an airport with *medium* size—in terms of number of flights—relative to other members of the same group. The list of representative airports and the number of airports within each group are tabulated in Table 3.2; the list of members of each group is provided in Appendix B.

Group no.	No. of airports	Airport code	Representative airport name
1	14	MAF	Midland International Airport (TX)
2	36	ICT	Wichita Mid-Continent Airport (KS)
3	13	MDT	Harrisburg International Airport (PA)
4	14	FAT	Fresno Air Terminal (CA)
5	4	LEX	Blue Grass Airport (KY)
6	9	LGA	La Guardia Airport (NY)
7	22	ORL	Orlando Executive Airport (FL)
8	21	CRW	Charleston Yeager Airport (WV)
9	20	PQE	Northern Maine Regional Airport (ME)
10	5	DTE	Destin-FT Walton Beach Airport (FL)
11	17	MHT	Manchester Airport (NH)
12	15	BLV	Midamerica Airport (IL)
13	16	ALB	Albany International Airport (NY)
14	17	OMA	Eppley Field (NE)
15	8	MEM	Memphis Airport (TN)
16	8	AOO	Altoona-Blair County Airport (PA)
17	5	LZU	Gwinnett County Airport (GA)
18	2	BOS	Boston Logan International Airport (MA)
19	2	JFK	John F. Kennedy International Airport (NY)

Table 3.2: List of airport groups and representatives.

In order to run APMT-Impacts AQ module, the emissions values associated with airports other than the representative airports need to be obtained. For this analysis, the emissions values for airports within a certain airport group are estimated based on the emissions values of the representative airport for that particular group. Specifically, within each group, the emissions values of the representative airport is multiplied by a ratio of the total number of flights departing from and arriving at a certain airport to the total number of flights of the representative airport to estimate the emissions values of that particular airport. This procedure will be referred to as the *scaling procedure* in the subsequent discussion. An illustration of this procedure is given in Figure 3-5. Having obtained the emissions values corresponding to each airport, these airport emissions values are then assigned to the appropriate grid cell, that is, the grid cell that contains the location of the airport. For grid cells with no airports, the grid cell emissions values are obtained via the spatial interpolation procedure [70].

The verification of the derived surrogate model is done by comparing the statistics, i.e., mean and variance, of system outputs upon propagating the emissions values corresponding to one airport group through to the APMT-Impacts AQ module using the full and surrogate model. This verification procedure is carried out with two arbitrarily selected airport groups. For the *full model* run, AEDT is run to obtain emissions values of all airports that are members of a particular group. For the *surrogate model* run, on the other hand, only the emissions values of the representative airport are computed via AEDT. The emissions values corresponding to the rest of the group members are then obtained by the means of the scaling procedure described above. These emissions values are then propagated through to APMT-Impacts AQ module to obtain the system outputs corresponding to the full and surrogate models. In this thesis, only the comparison of mean and variance of the valuations of a few health endpoints are presented, see Figure 3-6 for the comparison of mean values and Figure 3-7 for the comparison of variance. The x-axis in the figures denote the health endpoints, whereas the y-axis is for the mean or variance of the valuations. Note that some health endpoints with mean or variance that are too large or small in comparison with the values associated with other health endpoints are omitted, for a better visual clarity. The bar charts show that the derived surrogate model, which requires less computational efforts, and scaling procedure are able to provide close approximations of the results associated with the full model.

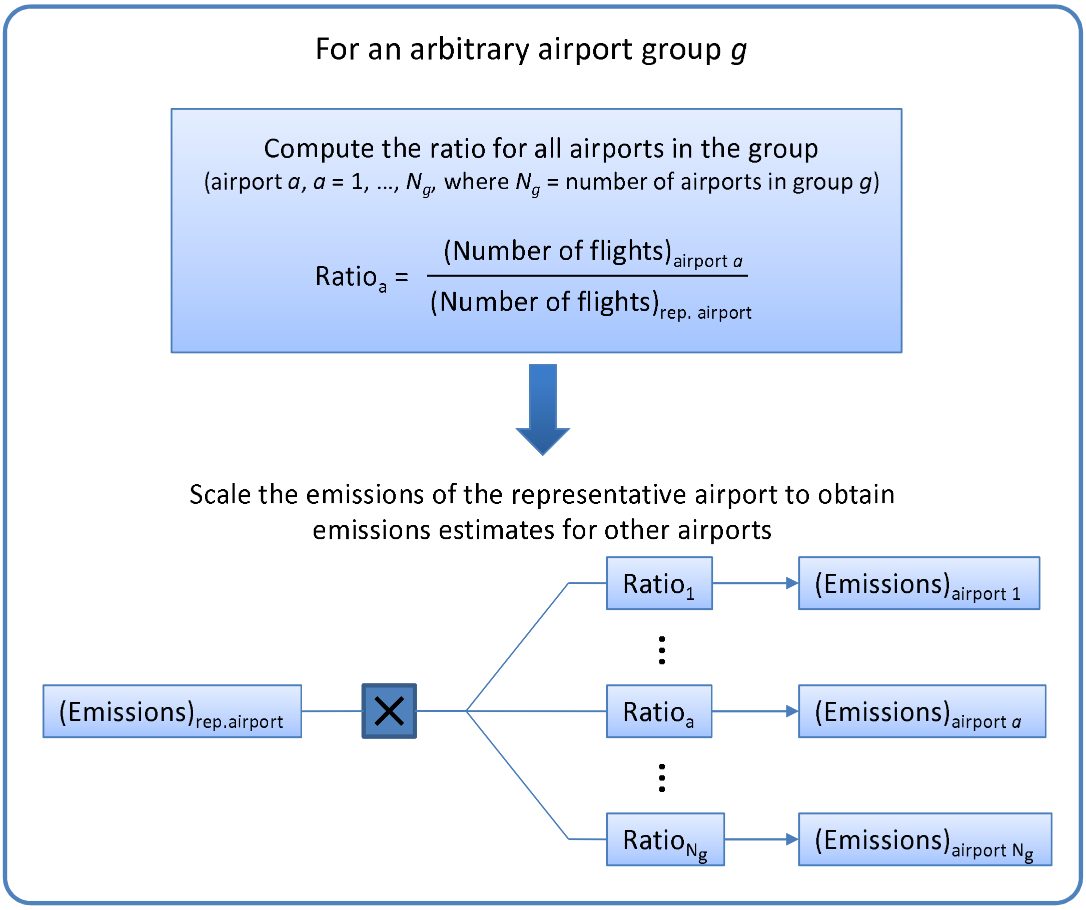


Figure 3-5: Scaling procedure to estimate emissions values of members of the airport group from those of the representative airport.

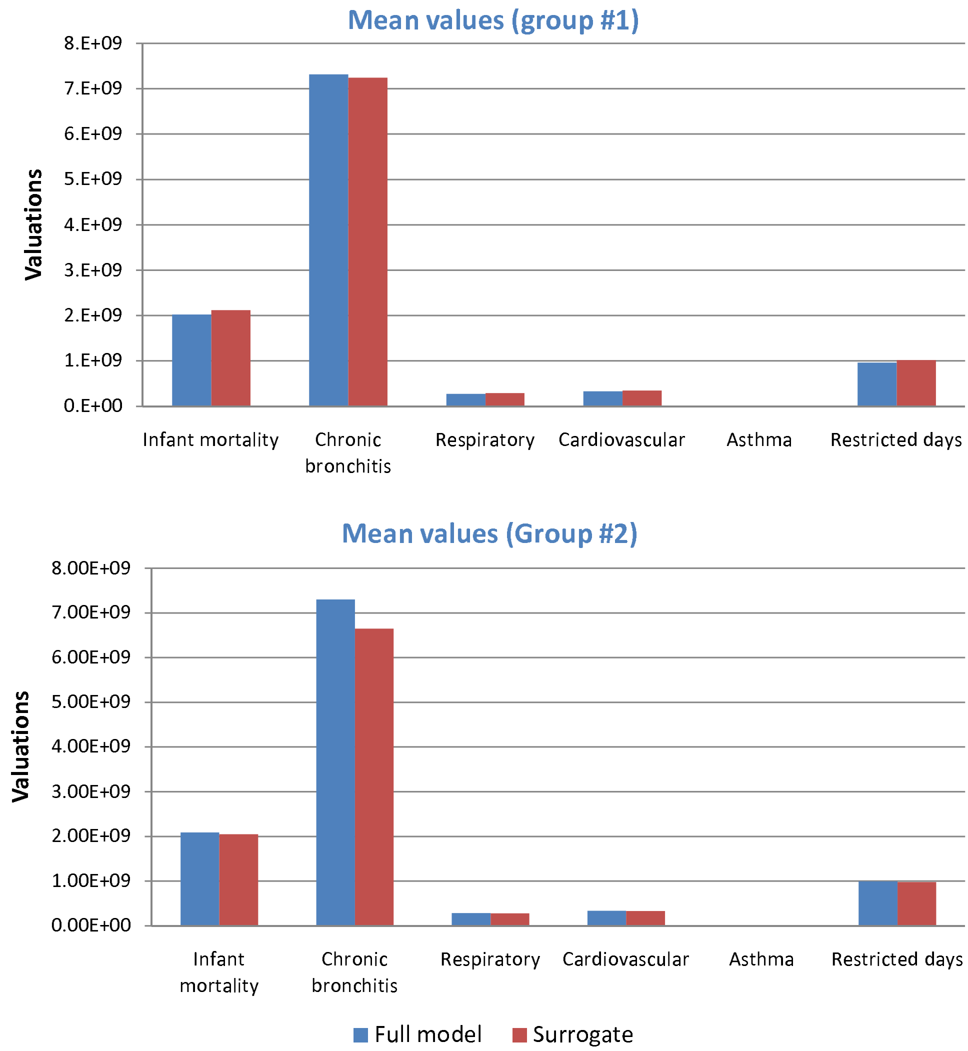


Figure 3-6: Comparison of mean values of health endpoints valuations associated with the full and surrogate models corresponding to two arbitrarily selected airport groups.

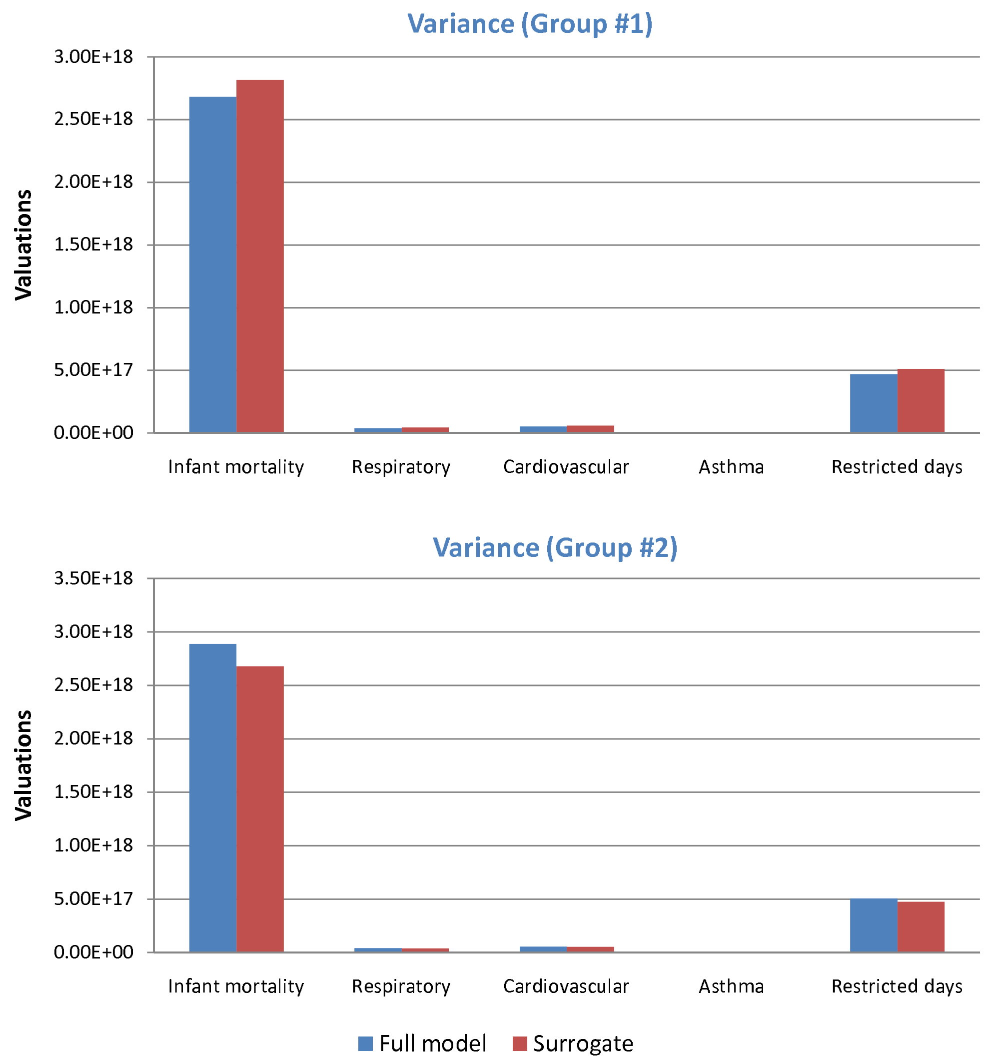


Figure 3-7: Comparison of variances of health endpoints valuations associated with the full and surrogate models corresponding to two arbitrarily selected airport groups.

3.5.3 Data Handoff Mechanism

For this analysis, the data handoff mechanism is done manually. Data format conversion is required, since emissions outputs from AEDT are available in the Microsoft SQL Server's table format. These emissions values need to be passed to the APMT-Impacts AQ module, which is developed in MATLAB, as intermediate variables. Outputs from AEDT are then converted into comma-separated values (CSV) files, a format MATLAB can read directly and use in computation, though this chosen conversion procedure is not the only available option. See, for example, the Visual Query Builder tool which is available in the MATLAB's Database toolbox.

3.5.4 Global Sensitivity Analysis

The Monte Carlo implementation of Sobol' variance decomposition method (see Section 2.2.4) is employed to estimate the total effect sensitivity indices. As part of this analysis, the important question of Monte Carlo convergence needs to be addressed. In this section, the GSA results will first be presented, followed by the discussion on the convergence study.

GSA Results

The estimated main and total effect sensitivity index values of adult mortality and total health cost are tabulated in Table 3.3 and 3.4, respectively. Results shown in these tables are obtained with 15,000 Monte Carlo trials. Although all input factors of AEDT, as listed in Table 3.1, are treated as random variables in this analysis, the sensitivity indices of outputs are only estimated to ten of them, due to the limited available computational time. The ten input factors of AEDT that are included in this analysis are the ten most significant input factors to AEDT outputs, based on the module level assessment results. The corresponding error estimates are displayed in the table as well. These error estimates provide a confidence bound around each sensitivity index value estimated via the Monte Carlo simulations; in this analysis 90% level of confidence is used. Therefore, the population sensitivity index has a 90% chance of falling in the interval of ±(error estimate) around the estimated sensitivity index value. For small sensitivity indices, that is, values that are very close to zero, the numerical error in Monte Carlo estimation procedure can result in negative values. These negative sensitivity indices are theoretically not feasible, since variance is always nonnegative and therefore sensitivity index, which is a ratio of variances, is too. The numerical error explains the negative sensitivity index values shown in Table 3.3 and 3.4. Figures 3-8 and 3-9 graphically show the negative sensitivity indices and their corresponding confidence bounds for main effect of adult mortality and total health cost, respectively. The dashed lines shown in the confidence bounds indicate the negative values, which are not valid for sensitivity indices. The actual sensitivity index value lies in the positive region of the corresponding confidence bound, although the estimated sensitivity index is negative. The main and total effect sensitivity indices of adult mortality with respect to VSL are supposed to be zero, due to the independence between VSL and adult mortality. The numerical error in the Monte Carlo estimation procedure accounts for the negative value displayed for the main effect sensitivity index.

Input factor	Main effect		Total effect	
	Sensitivity index	Error estimate	Sensitivity index	Error estimate
NO_x EI	-1.02×10^{-3}	1.34×10^{-2}	7.14×10^{-4}	1.60×10^{-2}
BADA Coeff 1	-1.08×10^{-3}	1.34×10^{-2}	5.51×10^{-4}	1.60×10^{-2}
Flaps Coeff CD	-2.07×10^{-3}	1.34×10^{-2}	1.74×10^{-4}	1.60×10^{-2}
Weight	-1.36×10^{-3}	1.34×10^{-2}	4.60×10^{-4}	1.60×10^{-2}
Jet Coeff E	-2.07×10^{-3}	1.34×10^{-2}	2.67×10^{-4}	1.60×10^{-2}
Flaps Coeff R	-2.14×10^{-3}	1.35×10^{-2}	2.09×10^{-4}	1.60×10^{-2}
Terminal Fuel Coeff 1	-1.65×10^{-3}	1.34×10^{-2}	3.69×10^{-4}	1.60×10^{-2}
Terminal Fuel Coeff 2	-2.12×10^{-3}	1.34×10^{-2}	1.19×10^{-4}	1.60×10^{-2}
Temperature	-2.10×10^{-3}	1.34×10^{-2}	8.96×10^{-5}	1.60×10^{-2}
Relative humidity	-2.18×10^{-3}	1.34×10^{-2}	6.62×10^{-5}	1.60×10^{-2}
CRF	9.96×10^{-1}	1.60×10^{-2}	1.00	1.35×10^{-2}
VSL	-2.15×10^{-3}	1.34×10^{-2}	0	1.60×10^{-2}

Table 3.3: Sensitivity index estimates and the corresponding error estimates, with 90% confidence bound, for adult mortality.

Before discussing the GSA results, it is important to note that FSC variability has not been included in this analysis. Its inclusion will alter the importance ranking of the input factors, and therefore it is prudent not to draw any conclusion before the assessment application layer integrates the FSC variability handling capability into the model. The GSA results for this SLA process show that the uncertainties in APMT-Impacts AQ module outweigh those in AEDT in the quantification of uncertainty in outputs, as deduced from comparing the estimated sensitivity indices with respect to input factors of the two modules. These results suggest that research efforts should be focused on reducing the uncertainty in APMT-Impacts AQ module inputs in order to reduce the variability of adult mortality

Input factor	Main effect		Total effect	
	Sensitivity index	Error estimate	Sensitivity index	Error estimate
NO_x EI	-6.75×10^{-3}	1.31×10^{-2}	1.46×10^{-4}	4.00×10^{-2}
BADA Coeff 1	-6.94×10^{-3}	1.31×10^{-2}	1.19×10^{-4}	4.00×10^{-2}
Flaps Coeff CD	-7.23×10^{-3}	1.31×10^{-2}	3.70×10^{-5}	4.00×10^{-2}
Weight	-6.86×10^{-3}	1.31×10^{-2}	9.47×10^{-5}	4.00×10^{-2}
Jet Coeff E	-7.18×10^{-3}	1.31×10^{-2}	5.39×10^{-5}	4.99×10^{-2}
Flaps Coeff R	-7.13×10^{-3}	1.31×10^{-2}	4.29×10^{-5}	3.99×10^{-2}
Terminal Fuel Coeff 1	-7.02×10^{-3}	1.31×10^{-2}	7.80×10^{-5}	4.00×10^{-3}
Terminal Fuel Coeff 2	-7.14×10^{-3}	1.31×10^{-2}	2.40×10^{-5}	3.99×10^{-2}
Temperature	-7.13×10^{-3}	1.31×10^{-2}	1.80×10^{-5}	4.00×10^{-2}
Relative humidity	-7.16×10^{-3}	1.31×10^{-2}	1.34×10^{-5}	4.00×10^{-2}
CRF	1.55×10^{-1}	1.43×10^{-2}	2.03×10^{-1}	3.04×10^{-2}
VSL	7.85×10^{-1}	3.29×10^{-2}	8.37×10^{-1}	1.52×10^{-2}

Table 3.4: Sensitivity index estimates and the corresponding error estimates, with 90% confidence bound, for total health costs.

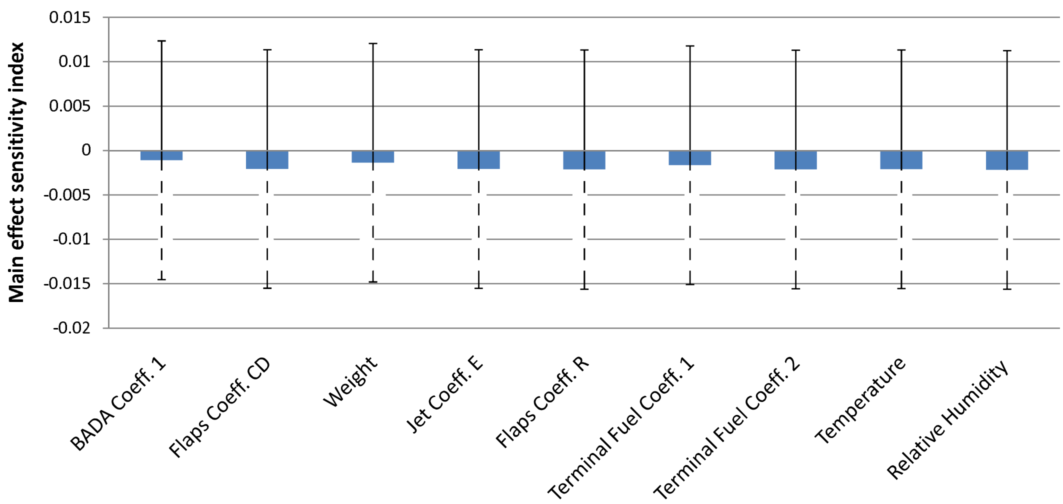


Figure 3-8: Main effect sensitivity indices and the corresponding error estimates, with 90% confidence bound, of adult mortality with respect to inputs to AEDT. The confidence interval that corresponds to negative index, which is not feasible, is indicated by dashed lines.

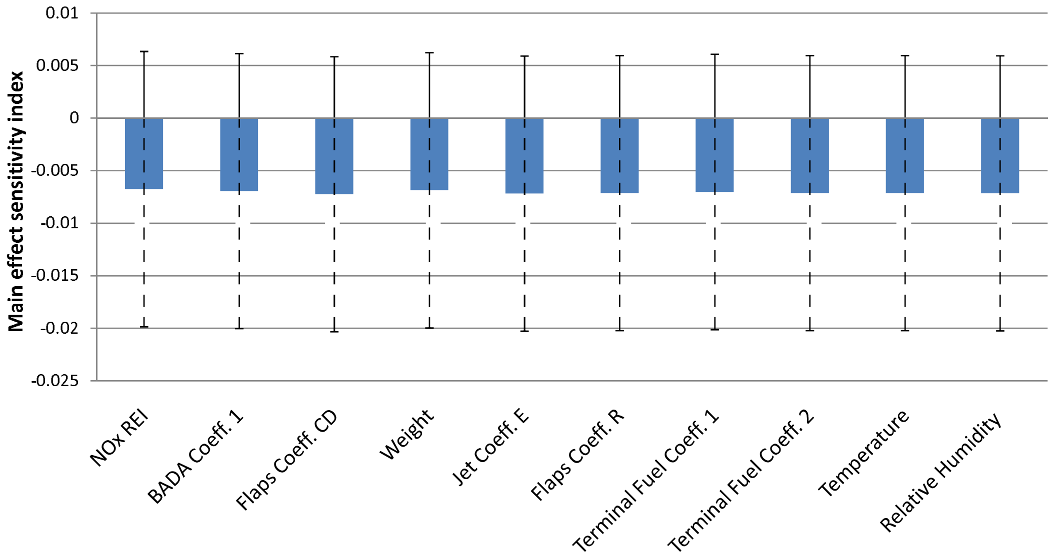


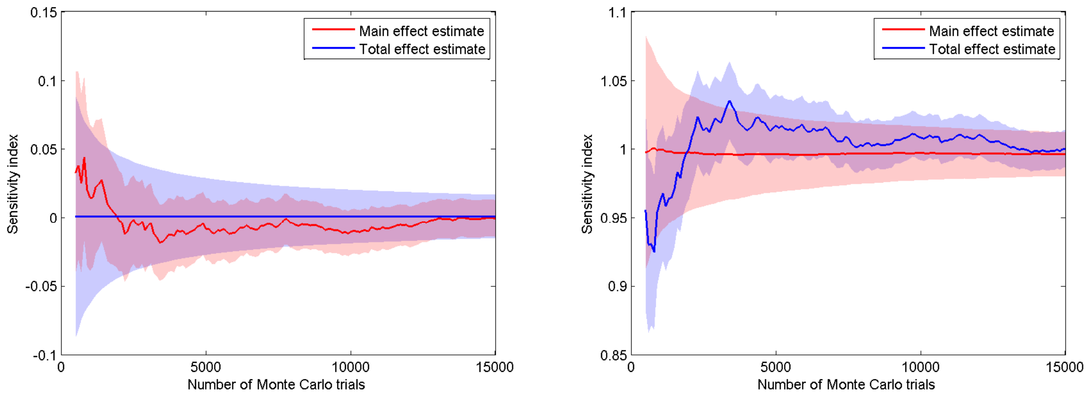
Figure 3-9: Main effect sensitivity indices and the corresponding error estimates of total health cost with respect to inputs to AEDT. The confidence interval that corresponds to negative index, which is not feasible, is indicated by dashed lines.

and total health cost.

Of the two input factors of APMT-Impacts AQ module that are considered in this analysis, only the Concentration Response Function (CRF) has an epistemic uncertainty element in it. The uncertainty in value of a statistical life (VSL), on the other hand, is categorized as an aleatory, or irreducible, uncertainty. The refinement of the uncertainty around CRF value can be obtained through a more thorough epidemiological study [7]. Based on the estimated sensitivity indices of the system outputs, this uncertainty refinement will result in a larger variance reduction in adult mortality level than the total health cost.

Convergence Study

For the convergence study performed in this assessment process, priority is given to the convergence of sensitivity index, instead of the convergence of other metrics, e.g., mean and variance as used in, for example, [1, 38]. In particular, the main and total effect sensitivity indices are estimated with increasing number of Monte Carlo trials. 500 trials are used in the first Monte Carlo simulation, and then 100 trials are added at each new simulation until a total of 15,000 trials is achieved; sensitivity indices are computed whenever new trials are added. The convergence plots for the estimated sensitivity indices are shown in Figures 3-10 and 3-11, for adult mortality and total health cost, respectively. The 90% confidence bounds corresponding to the sensitivity index estimation are shown as the shaded area. Since sensitivity indices of a particular system output to all input factors of AEDT have similar values for a given number of MC trials, only one value is displayed in the plot for clarity. Of the two input factors of APMT-Impacts AQ module, the sensitivity indices of adult mortality are only estimated with respect to CRF, since adult mortality is independent of VSL.

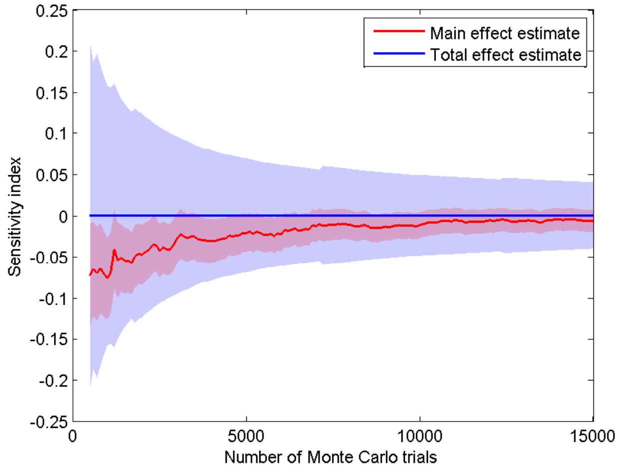


(a) AEDT inputs (b) AQ input (CRF)

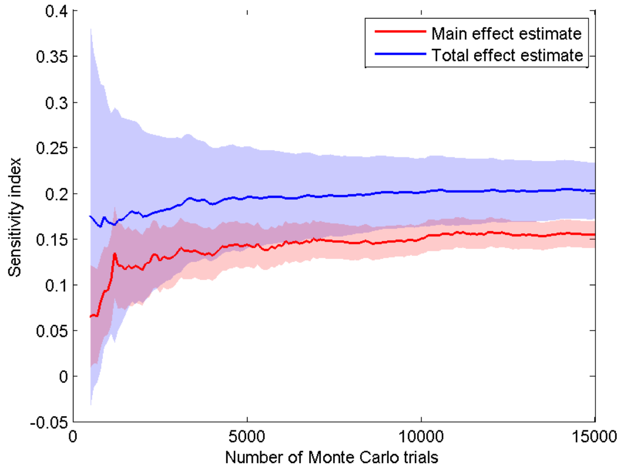
Figure 3-10: Convergence of sensitivity indices of adult mortality to input factors of AEDT and APMT-Impacts AQ module.

Figures 3-10 and 3-11 show that the estimated sensitivity indices fluctuate less with increasing number of Monte Carlo trials, and the 90% confidence bounds are narrower as well. The determination of the required number of trials for Monte Carlo simulation procedure depends on the objective of the analysis at hand. The limited computational resources can also be a deciding factor. The following discussion will focus only on the convergence of the Monte Carlo implementation of Sobol' GSA procedure in the policy- and decision-making analysis context, in particular the factor prioritization and factor fixing settings of GSA. The discussion on the important consideration in determining the required number of Monte Carlo trials, depending on the key objective of the analysis, is presented below, followed by the more specific discussion corresponding to the illustrative example used in this thesis.

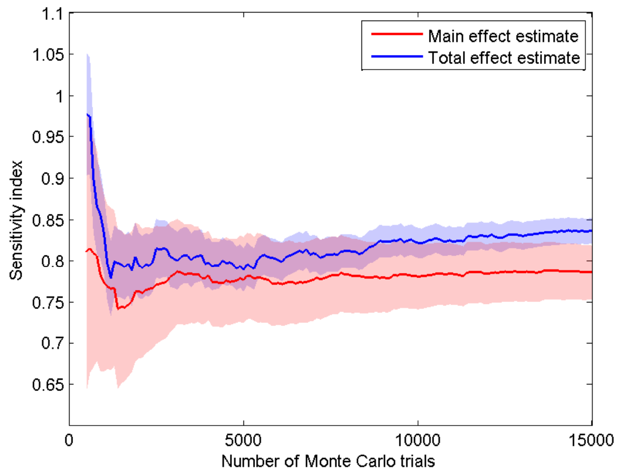
1. When the key objective of the analysis is to quantify the contribution of the uncer-



(a) AEDT inputs



(b) AQ input (CRF)



(c) AQ input (VSL)

Figure 3-11: Convergence of sensitivity indices of total health cost to input factors of AEDT and APMT-Impacts AQ module.

tainty of each input factor to the output variability

To achieve this objective, the required number of Monte Carlo trials will depend on the desired accuracy. As such, computing the confidence bound around the sensitivity index estimates, with a certain level of confidence, plays an important role. A number of Monte Carlo trials is deemed sufficient when the error estimates corresponding to all input factors achieve the desired accuracy, say, ± 0.1 with 90% level of confidence.

2. When the key objective of the analysis is to obtain the importance ranking of input factors

   The importance ranking of input factors based on their main effect sensitivity indices is relevant to factor prioritization setting. In this setting, research priority is given to input factors with highest main effect sensitivity indices. On the other hand, factor fixing setting looks into input factors with lowest total effect sensitivity indices that can be treated as deterministic variables in the model without changing the output variability significantly. When the sensitivity indices corresponding to different input factors are fairly distinct from each other, the importance ranking can be obtained with less number of Monte Carlo trials, as compared to when a high accuracy in sensitivity indices is required.

Since the focus of the analysis is to compute the contribution of input factors to output variability, the confidence bound is observed. With the desired accuracy of ± 0.1, corresponding to 90% level of confidence, 5,000 trials is deemed sufficient for the Monte Carlo simulations. If, on the other hand, only the importance ranking of input factors is desired, a handful of Monte Carlo trials are sufficient to provide policymakers with the necessary information. In factor fixing setting, policymakers can pick all ten insignificant input factors to be treated as deterministic variables, without obtaining the exact importance ranking among them. In factor prioritization setting, the importance ranking among the significant input factors can be obtained with as little as 500 Monte Carlo trials.

Chapter 4

Sensitivity Analysis of a Technology Infusion Policy

The second objective of this thesis is to *demonstrate how sensitivity analysis can be applied to policy impact analysis to identify the key drivers of uncertainty in policy impacts.* This task is accomplished by performing Global Sensitivity Analysis (GSA) on the *policy impacts* instead of on outputs pertaining to a single scenario, e.g., baseline, as presented in Chapter 3. A technology infusion policy analysis is used as an illustrative example to demonstrate the policy impact assessment process. This policy impact assessment process is performed on a system comprising AEDT and APMT-Impacts Air Quality module. It is important to note that this chapter does not intend to provide any final results that policymakers can use; rather, it only aims at providing a guideline through a simple illustrative example to perform a policy impact assessment. This chapter begins with the background and motivation on such an analysis. The description of the proposed procedure is then presented, followed by results and discussions.

4.1 Background

In the policy analysis setting, comparisons between different policy scenarios are often done by comparing the incremental changes of the policy scenarios with respect to a common baseline scenario. These changes are designated as policy impacts. Different terms, though referring to the same quantity, are used in some literature, e.g., policy effect [86], and policy minus baseline [38]. Some other policy analysis processes use a selected certification standard, instead of a baseline scenario, to which the policy scenarios are compared. For example, NASA compares future generations of aircraft to the International Civil Aviation Organization (ICAO) certification standard [80]. Some policy impact analyses performed within APMT include: uncertainty analysis to compute the variance of the difference in aviation-induced health impacts between baseline and policy [86]; sensitivity of policy impacts in the context of NO_x stringency analysis [67]; and sensitivity analysis of policy impacts in the context of economic evaluation of aviation noise [38].

4.2 Procedure

Policy impacts are computed by subtracting the model outputs corresponding to the baseline scenario from the policy outputs. The modeling of policy scenarios can be different from the baseline scenario in several ways. For example, the policy scenario may lead to changing the governing equation of the model, changing the model parameters, changing the input distributions, and/or adding new input factors to the model. Some analyses, such as GSA, involve Monte Carlo simulations that require random samples for input factors corresponding to both baseline and policy scenarios. For input factors whose uncertainty distributions remain unchanged in the baseline and policy scenarios, questions arise on whether the corresponding samples should be drawn in pairs or drawn independently. Some input factors have independent random variability between the two scenarios, and thus independent sets of random samples must be drawn. Such input factors are categorized as the *scenario-dependent* input factors. On the other hand, other input factors have a common source of uncertainty between scenarios, thus paired samples are used for both models. These input factors will be referred to as the *scenario-independent* input factors. By selecting different sampling procedures for the different categories of input factors, the modeled uncertainty of policy impacts will only account for the uncertainty corresponding to the difference between baseline and policy scenarios.

4.3 Technology Infusion Policy Impact Analysis

The technology infusion policy analysis, in the context of environmental impact of aviation, is used as an illustrative example to demonstrate the policy impact assessment process. The technology infusion policy refers to the introduction of new technology aircraft as part of the efforts to mitigate the environmental impact of aviation. A brief description of this technology infusion policy is given below, further details can be found in [80]. Specifically, the policy scenario corresponding to the year of 2040 is assumed, where the new technologies implemented in 2015, 2020, 2025 are already incorporated. Note that the mention of "system level" in [80] refers to the global or national level, specifically in terms of total energy consumption, which is different from the definition of "system level" used in this thesis. In the technology infusion policy problem, the new technology needs to reflect the desired performance, noise, and emissions improvement as regulated by the proposed policy. This technology infusion process involves the replacement of some current aircraft-engine combinations, which do not meet the desired performance, with the new "Anticipated Industry Response" technology vehicles. The emissions indices and adjusted reference fuel flow corresponding to the new vehicles are then derived, following the "Emissions Index Determination Flow" procedure, which is illustrated in Figure 2 of [80] and adapted from [43].

In this analysis, the policy impact in question is the impact of introducing the Anticipated Industry Response technology on adult mortality and total health cost caused by air quality impact of aviation. The sensitivity analysis is performed on a system comprising AEDT and APMT-Impacts Air Quality (AQ) module. The system used in the sample problem presented in Chapter 3 is employed in this analysis. The same numerical models, for both modules, are used for the baseline and policy scenarios. As mentioned, the new technology is introduced in the policy scenario by replacing some aircraft-engine combinations with the Anticipated Industry Response vehicles. This replacement affects some origin-destination routes, which are assumed unchanged for the different scenarios, and is reflected in the different fleet databases used as input to AEDT for the different scenarios. In the following discussion, the *baseline scenario* will refer to the evaluation of the aviation impact on air quality when only the current aircraft-engine combinations included in the fleet, whereas the *policy scenario* evaluations use the fleet where the aircraft replacements have taken place. The modeling for baseline and policy scenarios discussed above is illustrated in Figure 4-1. As shown in the figure, each origin-destination pair is assumed to be flown under the same atmospheric conditions, despite having different aircraft-engine combinations in the different scenarios. The emissions results from AEDT are then propagated through to APMT-Impacts AQ module, to obtain the adult mortality and total health costs corresponding to baseline and policy scenarios. Policy impacts are then computed by subtracting the baseline outputs from policy outputs.

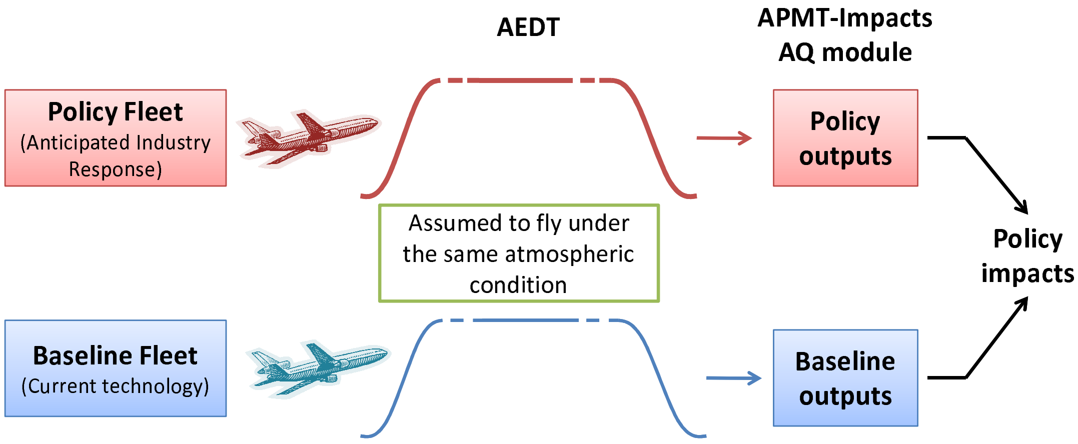


Figure 4-1: Modeling of baseline and policy scenarios in the technology infusion policy analysis.

To perform GSA on the uncertainty in policy impacts, random samples are required for the input factors of the system. To decide on the appropriate sampling procedure for each of them, the input factors need to be classified as being scenario-dependent or scenario-independent. In this analysis, the scenario-dependent input factors only include input factors pertaining to aircraft-engine combinations that are replaced in the policy scenario. Therefore, for each Monte Carlo realization, two random samples are drawn for a particular input factor, say BADA Fuel Coefficient, for the current and Anticipated Industry Response aircraft-engine combination, respectively. All other input factors are considered independent of scenario, and thus have paired samples for baseline and policy scenarios.

4.4 Results and Discussion

The main and total effect sensitivity indices of policy impacts in adult mortality and total health cost are estimated by employing the Monte Carlo implementation of Sobol' variance decomposition method. The number of trials for each Monte Carlo simulation in this analysis is 5000. The obtained sensitivity indices are tabulated in Tables 4.1 and 4.2 for the policy impacts in adult mortality and total health cost, respectively. The error estimates, corresponding to 90% level of confidence, and the summations of indices are also shown in the table.

Table 4.2 shows that the summation of main effect sensitivity indices are greater than one, which is not theoretically feasible. As discussed in Chapter 2, main effect sensitivity indices only account for the first order contribution of each input factor, thus the summation is always less than or equal to one, depending on whether higher order terms, which are always nonnegative, exist. The summation of total effect sensitivity indices, on the other hand, does not necessarily add up to one, due to the overlapping interaction terms among the indices. Recall that total sensitivity index of an input factor quantifies not only the first order (main effect) term, but also all the interaction terms involving that particular input factor. Therefore, total effect sensitivity index is always greater than or equal to the main effect, due to the nonnegativity of the interaction terms. Table 4.2 shows that some of the estimated total effect sensitivity indices are less than the corresponding main effect. Numerical errors associated with the Monte Carlo estimation procedure account for these results. Figure 4-2 graphically shows the estimated main and total effect sensitivity indices, with their corresponding 90% confidence bounds, for policy impacts in total health cost. The actual sensitivity index values can be any positive values within the confidence bound. The plot shows that despite the smaller estimates for total effect, the confidence bound corresponding to total effect sensitivity index is wider than that of the main effect. Therefore, there is a fair chance that the total effect sensitivity index is greater than or equal to the main effect. Also, there are some negative indices, which theoretically are not feasible; the discussion presented in the previous chapter regarding these negative values also applies in this case.

The results from the GSA performed on the technology infusion policy analysis show that the contribution from the uncertainties associated with input factors of APMT-Impacts Air Quality module outweigh those of input factors of AEDT. With 90% probability, all the sensitivity indices corresponding to input factors of AEDT fall below 0.1. Recall that in the estimation of sensitivity indices of the policy impacts, the input factors of APMT-Impacts AQ module pertaining to the baseline and policy scenarios are assumed to have the same variability. The fact that the uncertainties in input factors of APMT-Impacts AQ module are still dominant in determining the output variability, despite having the same random samples for both scenarios, shows that the relationship between inputs and outputs in APMT-Impacts AQ module is highly nonlinear.

Input factor	Main effect		Total effect	
	Sensitivity index	Error estimate	Sensitivity index	Error estimate
NO_x EI	4.27×10^{-2}	2.38×10^{-2}	4.97×10^{-2}	3.37×10^{-2}
BADA Coeff 1	2.68×10^{-2}	2.41×10^{-2}	2.78×10^{-2}	3.48×10^{-2}
Flaps Coeff CD	7.91×10^{-3}	2.37×10^{-2}	1.38×10^{-2}	3.50×10^{-2}
Weight	5.72×10^{-3}	2.36×10^{-2}	1.17×10^{-1}	3.23×10^{-2}
Jet Coeff E	2.42×10^{-3}	2.37×10^{-2}	5.44×10^{-3}	3.51×10^{-2}
Flaps Coeff R	5.42×10^{-3}	2.37×10^{-2}	7.14×10^{-3}	3.50×10^{-2}
Terminal Fuel Coeff 1	1.06×10^{-2}	2.39×10^{-2}	1.33×10^{-2}	3.51×10^{-2}
Temperature	-1.14×10^{-3}	2.36×10^{-2}	2.32×10^{-4}	3.53×10^{-2}
Relative humidity	-1.84×10^{-3}	2.36×10^{-2}	7.59×10^{-5}	3.53×10^{-2}
CRF	8.32×10^{-1}	3.06×10^{-2}	8.48×10^{-1}	2.49×10^{-2}
VSL	-2.19×10^{-3}	2.36×10^{-2}	0	3.53×10^{-2}
Total	0.93	-	1.08	-

Table 4.1: Sensitivity index estimates and the corresponding error estimates, with 90% confidence bound, for policy impacts in adult mortality.

Input factor	Main effect		Total effect	
	Sensitivity index	Error estimate	Sensitivity index	Error estimate
NO_x EI	2.38×10^{-2}	2.29×10^{-2}	1.25×10^{-2}	7.28×10^{-2}
BADA Coeff 1	2.30×10^{-2}	2.34×10^{-2}	6.99×10^{-3}	7.62×10^{-2}
Flaps Coeff CD	1.96×10^{-2}	2.35×10^{-2}	3.27×10^{-3}	7.57×10^{-2}
Weight	1.47×10^{-2}	2.31×10^{-2}	2.87×10^{-2}	7.55×10^{-2}
Jet Coeff E	1.85×10^{-2}	2.34×10^{-2}	1.31×10^{-2}	7.47×10^{-2}
Flaps Coeff R	1.87×10^{-2}	2.33×10^{-2}	1.74×10^{-3}	7.43×10^{-2}
Terminal Fuel Coeff 1	1.95×10^{-2}	2.36×10^{-2}	3.24×10^{-2}	7.68×10^{-2}
Temperature	1.80×10^{-2}	2.34×10^{-2}	5.73×10^{-5}	7.48×10^{-2}
Relative humidity	1.78×10^{-2}	2.33×10^{-2}	1.82×10^{-2}	7.50×10^{-2}
CRF	1.73×10^{-1}	2.59×10^{-2}	2.02×10^{-1}	5.92×10^{-2}
VSL	7.68×10^{-1}	5.29×10^{-2}	8.24×10^{-1}	2.70×10^{-2}
Total	1.11	-	1.08	-

Table 4.2: Sensitivity index estimates and the corresponding error estimates, with 90% confidence bound, for policy impacts in total health cost.

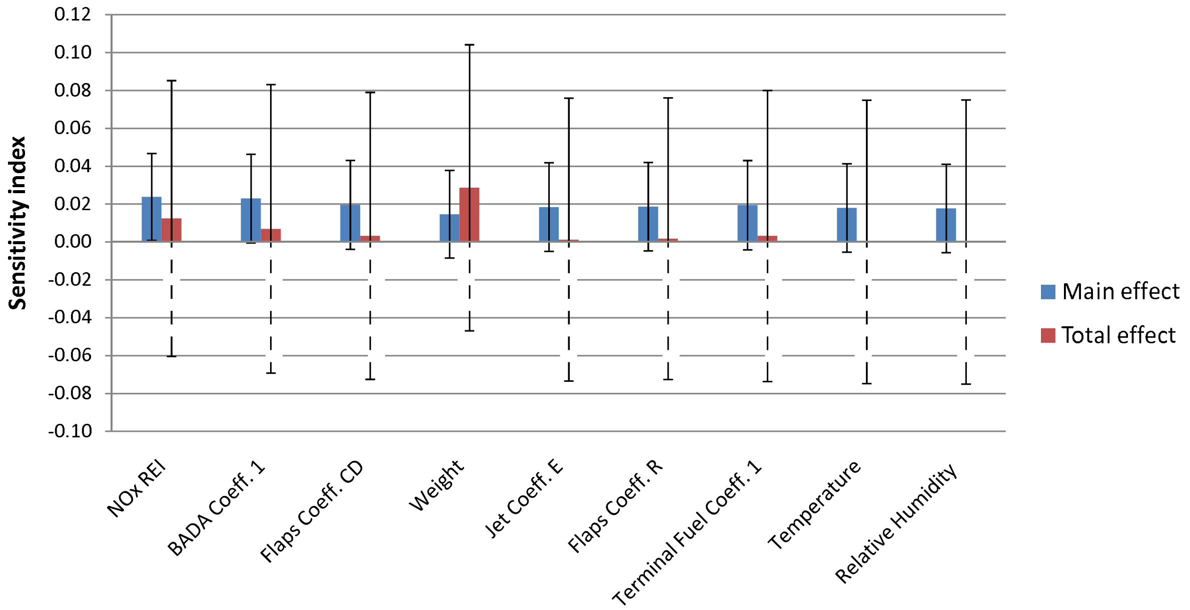


Figure 4-2: Main and total effect sensitivity indices and the corresponding error estimates, with 90% confidence bound, of policy impact in adult mortality with respect to inputs to AEDT. The confidence interval that corresponds to negative index, which is not feasible, is indicated by dashed lines.

As discussed in Chapter 2, the information on total effect sensitivity indices of an output can be used for factor fixing purposes. The insignificant total effect sensitivity indices of adult mortality and total health cost imply that the input factors of AEDT, for both baseline and policy scenarios, can be treated as deterministic variables without significantly changing the distributions of policy impacts in air quality metrics. As such, when an uncertainty analysis, i.e., to obtain the probability distribution of outputs, of policy impacts in air quality outputs is required:

- When the model and distributions of input factors are unchanged
  The uncertainty in policy impacts can be quantified by propagating the nominal values of emissions species, corresponding to the different scenarios, through to APMT-Impacts AQ module. The only input factors that are treated as random variables are those pertaining to the APMT-Impacts AQ module. The required number of runs for AEDT thus only depends on the number of scenarios, since Monte Carlo simulation is not required, which reduces the computational burden significantly. This computational gain is beneficial especially when there are a number of policy scenarios to be evaluated. The resulting distributions of policy impacts will still be representative, despite the exclusion of uncertainties associated with AEDT.

- When there are changes in the model or input distributions
  The sensitivity indices need to be recomputed. Depending on the newly computed total effect sensitivity indices, a decision can be made on which input factors are treated as deterministic variables.

Chapter 5

Conclusion and Future Work

The primary focus of this thesis is to demonstrate the use of Monte Carlo simulation and Global Sensitivity Analysis to perform system level assessment, which assesses the uncertainty of a system comprising multiple modules in an integrated manner, to support policy-making analysis. The system level assessments were performed on a baseline scenario and policy impact, in the context of aviation environmental impact analysis. This chapter presents the summary of research done to achieve the thesis objectives, followed by the conclusions from the results presented in this thesis. Some opportunities for future work will also be presented.

5.1 Summary

System level assessment is performed on a system comprising the Aviation Environmental Design Tool (AEDT) and APMT-Impacts Air Quality (AQ) module by following four key steps: defining the system structure, assessing the need to have a surrogate model, determining the required data handoff mechanism, and performing the analyses. In this particular system, AEDT passes its emissions outputs as inputs to APMT-Impacts AQ module. Surrogate models are used for both modules, to enable performing the required analyses, which are computationally intensive, within the limited available computational time. Global sensitivity analysis is performed to obtain the importance ranking of input factors, of both modules, to two selected system outputs, i.e., adult mortality and total health cost. The ranking is obtained by estimating main and total effect sensitivity indices via the Monte Carlo implementation of the Sobol' variance decomposition method. Error estimates corresponding to the indices are also computed, to provide confidence bounds for the estimation. Convergence analysis is performed as part of the global sensitivity analysis process to determine the required number of Monte Carlo trials.

The same system is used to demonstrate system level assessment in the policy impact analysis setting, using a technology infusion problem as an illustrative example. For this assessment process, global sensitivity analysis is carried out to quantify the sensitivity of policy impacts, i.e., the difference between policy and baseline outputs, to input factors of both modules. In order to correctly model the uncertainty corresponding to the difference between baseline and policy scenarios, careful consideration must be taken when selecting the appropriate sampling procedure, i.e., drawn independently or in pairs, for each input factor.

5.2 Conclusions

The results presented in this thesis show that the system level assessment process can support policy- and decision-making analyses by means of factor prioritization and factor fixing. The two system level assessment results show that the contribution of the uncertainty in the APMT-Impacts AQ module dominates the variability of both baseline outputs and policy impacts, whereas the contribution from the uncertainty in AEDT is shown to be insignificant. Based on the estimated main effect indices, the concentration response function (CRF) is the sole key driver to the variability of adult mortality, whereas the uncertainty in value of a statistical life (VSL) accounts for most of the variability of total health cost. These results suggest that future research efforts should be directed to reduce the uncertainty associated with the APMT-Impacts AQ module if reduction in the variability of adult mortality and total health cost is desired. The small total effect sensitivity indices corresponding to input factors of AEDT imply that those input factors can be treated as deterministic variables in the model without any significant effects on the output variability. Note, however, that the results presented in this thesis only pertain to specific model versions used. Any changes to the model or input factors, e.g., the inclusion of Fuel Sulfur Content (FSC) in the simulation model for AEDT, will require another round of system level assessment that may have different implications on the policy decisions.

For analyses that require Monte Carlo simulations, e.g., the global sensitivity analysis method employed in this work, the determination of the required number of Monte Carlo simulations largely depends on the objective of the analysis at hand. When only the importance ranking of input factors is required, less Monte Carlo trials are required than when the contribution of the uncertainty in each input factor to the output variability needs to be quantified with a certain degree of accuracy. In the convergence study presented in Chapter 3, 5,000 Monte Carlo trials are required to estimate the sensitivity index with ± 0.1 accuracy corresponding to 90% level of confidence, whereas 500 Monte Carlo trials are sufficient when only the importance ranking is required.

Numerical errors in the Monte Carlo simulation procedure are shown to result in negative sensitivity indices, as well as main effect sensitivity indices that are higher than the corresponding total effect, which are theoretically infeasible. It is thus important to present the confidence intervals of sensitivity indices, instead of just single-point estimates, for the assessment results to be more informative. The confidence intervals can be obtained by computing the error estimates corresponding to a certain level of confidence.

5.3 Future Work

This section presents some recommendations to have a more complete system level assessment. The system level assessment results are expected to change once FSC variability is included in the analysis, since results from module level assessment for APMT-Impacts AQ module show that FSC is one of the significant input factors to the variability of adult mortality (approximately 45% contribution) and total health cost (approximately 15% contribution). It is therefore recommended to redo the system level assessment after the capability of modeling the FSC variability is included in the AEDT model.

Several additional analyses can be performed to complete the system level assessment process. One example the distributional sensitivity analysis (DSA) that is introduced and demonstrated in [1]. In computing the sensitivity index, DSA takes into account the uncertainty in the amount of input variance that can be reduced, as opposed to GSA that assumes that an input factor can be fixed to a certain value. Another analysis can be performed to study the effect of having different nominal values of input factors to the mean and variance of outputs.

The current system level assessment only includes uncertainties in input factors that can be represented by probability distributions. This representation of uncertainty, however, is often insufficient to represent epistemic uncertainty. As such, non-probabilistic uncertainty quantification methods are required, such as evidence theory, possibility theory, or fuzzy set theory. Including the capability of handling the non-probabilistic means of quantifying uncertainty in the assessment process is thus recommended.

The numerical models that are used to demonstrate the system level assessment procedure in this thesis comprises only two modules, without any feedback loops, i.e., the intermediate variables are only propagated forward. Future research should explore the application of the system level assessment procedure on more intricate systems that have more than two modules, with more complex interaction between modules, e.g., where the passing of intermediate variables results in feedback loops in the modeling of the system.

In the context of policy impact analysis, a certain policy impact target is often specified. As such, instead of finding the key drivers to the variability of policy impacts, policy-makers are more interested in performing the sensitivity analysis pertaining only to a specific policy impacts region of interest, e.g., above or below a certain minimum or maximum bound, or within a certain range. By doing so, policymakers would then be able to answer two important questions: When the policy target is achievable, can we identify specific factors on which we should focus our research so that achieving policy target is more possible? When the introduced policy is unable to attain the specified target, can we identify the key drivers for the violation of the target, to guide us to find a more realistic target? It is thus a subject for future research focus to develop a regional sensitivity analysis method.

Appendix A

Input distributions for AEDT and APMT-Impacts AQ module

Input factor	**Dist. type**	**Dist. Parameters**
AEDT Inputs – Atmospheric factors		
Temperature	Triangular	[0.90, 1.00, 1.10]
Pressure	Triangular	[0.97, 1.00, 1.03]
Headwind	Triangular	[-0.25, 1.00, 2.00]
Relative Humidity	Triangular	[0.85, 1.00, 1.15]
AEDT Inputs – Aircraft performance factors		
Aircraft maximum stopping distance	Triangular	[0.90, 1.00, 1.10]
Aircraft thrust static	Triangular	[0.85, 1.00, 1.15]
Flaps Coefficient B	Triangular	[0.86, 1.00, 1.14]
Flaps Coefficient CD	Triangular	[0.86, 1.00, 1.14]
Flaps Coefficient R	Triangular	[0.86, 1.00, 1.14]
Jet Thrust Coefficient E	Triangular	[0.85, 1.00, 1.15]
Jet Thrust Coefficient F	Triangular	[0.85, 1.00, 1.15]
Jet Thrust Coefficient Ga	Triangular	[0.975, 1.00, 1.025]
Jet Thrust Coefficient Gb	Triangular	[0.975, 1.00, 1.025]
Jet Thrust Coefficient H	Triangular	[0.975, 1.00, 1.025]

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Input factor	Dist. type	Dist. Parameters
Propeller Thrust Coefficient (Efficiency)	Triangular	[0.90, 1.00, 1.10]
Propeller Thrust Coefficient (Power)	Triangular	[0.90, 1.00, 1.10]
Terminal Fuel Coefficient 1	Triangular	[0.90, 1.00, 1.10]
Terminal Fuel Coefficient 2	Triangular	[0.90, 1.00, 1.10]
Terminal Fuel Coefficient 3	Triangular	[0.90, 1.00, 1.10]
Terminal Fuel Coefficient 4	Triangular	[0.90, 1.00, 1.10]
Profile weight	Triangular	[0.90, 1.00, 1.10]
BADA Mach Drag Coefficient	Triangular	[0.86, 1.00, 1.14]
BADA Fuel Coefficient 1	Triangular	[0.90, 1.00, 1.10]
BADA Fuel Coefficient 2	Triangular	[0.90, 1.00, 1.10]
BADA Fuel Coefficient 3	Triangular	[0.90, 1.00, 1.10]
BADA Fuel Coefficient 4	Triangular	[0.90, 1.00, 1.10]
BADA Fuel Coefficient 5	Triangular	[0.90, 1.00, 1.10]
NPD Curve L2001	Triangular	[-1.50, 1.00, 1.50]
NPD Curve L4001	Triangular	[-1.50, 1.00, 1.50]
NPD Curve L6301	Triangular	[-1.50, 1.00, 1.50]
NPD Curve L10001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L20001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L40001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L63001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L100001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L160001	Triangular	[-5.00, 1.00, 5.00]
NPD Curve L250001	Triangular	[-5.00, 1.00, 5.00]
AEDT Inputs – Emissions Indices		
Carbon Monoxide (CO) Emissions Index (Takeoff)	Triangular	[0.74, 1.00, 1.26]
Carbon Monoxide (CO) Emissions Index (Climbout)	Triangular	[0.74, 1.00, 1.26]
Carbon Monoxide (CO) Emissions Index (Approach)	Triangular	[0.74, 1.00, 1.26]

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Input factor	Dist. type	Dist. Parameters
Carbon Monoxide (CO) Emissions Index (Idle)	Triangular	[0.74, 1.00, 1.26]
Hydrocarbon (HC) Emissions Index (Takeoff)	Triangular	[0.45, 1.00, 1.55]
Hydrocarbon (HC) Emissions Index (Climbout)	Triangular	[0.45, 1.00, 1.55]
Hydrocarbon (HC) Emissions Index (Approach)	Triangular	[0.45, 1.00, 1.55]
Hydrocarbon (HC) Emissions Index (Idle)	Triangular	[0.45, 1.00, 1.55]
Nitrogen Oxide (NO_x) Emissions Index (Takeoff)	Triangular	[0.76, 1.00, 1.24]
Nitrogen Oxide (NO_x) Emissions Index (Climbout)	Triangular	[0.76, 1.00, 1.24]
Nitrogen Oxide (NO_x) Emissions Index (Approach)	Triangular	[0.76, 1.00, 1.24]
Nitrogen Oxide (NO_x) Emissions Index (Idle)	Triangular	[0.76, 1.00, 1.24]
Smoke Number (SN) (Takeoff)	Triangular	[-3.00, 1.00, 3.00]
Smoke Number (SN) (Climbout)	Triangular	[-3.00, 1.00, 3.00]
Smoke Number (SN) (Approach)	Triangular	[-3.00, 1.00, 3.00]
Smoke Number (SN) (Idle)	Triangular	[-3.00, 1.00, 3.00]
APMT-Impacts Air Quality module inputs		
Concentration Response Function (CRF)	Triangular	[0.60, 1.00, 1.70]
Value of a Statistical Life (VSL)	Lognormal	Mean = 6.3×10^6
		Std. dev. = 2.8×10^6

Table A.1: Distributional type and parameters for input factors of AEDT and APMT-Impacts Air Quality (AQ) modules. The distributional parameters for a triangular distribution are presented in a [minimum, peak, maximum] values format.

Appendix B

List of Airport Groups

The 19 airport groups used as surrogate model in the system level assessment are tabulated below. The representative airport within each group is typed in bold.

No	**Airport code**	**Airport name**
1	**MAF**	**Midland International Airport (TX)**
2	ATW	Outagamie County Regional Airport (WI)
3	BED	Bedford Hanscom Field (MA)
4	BIL	Billings Logan International Airport (MT)
5	FAI	Fairbanks International Airport (AK)
6	GTF	Great Falls International Airport (MT)
7	HIO	Portland Airport (OR)
8	MGM	Montgomery Regional Airport (AL)
9	MOB	Mobile Regional Airport (AL)
10	OPF	Opa Locka Airport (FL)
11	PSP	Palm Springs International Airport (CA)
12	BZN	Bozeman Gallatin Field Airport (MT)
13	ILG	New Castle Airport (DE)
14	PSM	Pease International Airport (NH)

Table B.1: Airport group 1.

No	Airport code	Airport name
1	**ICT**	**Wichita Mid-Continent Airport (KS)**
2	ABE	Allentown (PA)
3	AGS	Augusta Regional Airport (GA)
4	AMA	Amarillo International Airport (TX)
5	AZO	Kalamazoo/Battle Creek International Airport (MI)
6	BHM	Birmingham International Airport (AL)
7	BMI	Central Illinois Regional Airport (IL)
8	BRO	Brownsville/South Padre Island International Airport (TX)
9	BTR	Baton Rouge International Airport (LA)
10	BTV	Burlington International Airport (VT)
11	CAK	Akron-Canton Airport (OH)
12	CID	Cedar Rapids Eastern Iowa Airport (IA)
13	CRP	Corpus Christi International Airport (TX)
14	DAB	Daytona Beach International Airport (FL)
15	DLH	Duluth International Airport (MN)
16	DSM	Des Moines International Airport (IA)
17	EGE	Eagle County Regional Airport (CO)
18	FAR	Hector International Airport (ND)
19	FAY	Fayetteville Regional.Grannis Field Airport (NC)
20	FNT	Bishop International Airport (MI)
21	FSD	Sioux Falls Regional Airport (SD)
22	GRB	Austin Straubel International Airport (WI)
23	GRK	Killeen-Fort Hood Regional Airport (TX)
24	GSO	Piedmont Triad International Airport (NC)
25	HPN	Westchester County Airport (NY)
26	ILM	Wilmington International Airport (NC)
27	JAN	Jackson-Evers International Airport (MS)
28	LAN	Lansing Capital City Airport (MI)
29	LBB	Lubbock International Airport (TX)
30	LCK	Rickenbacker International Airport (OH)
31	LSE	La Crosse Municipal Airport (WI)
32	MLB	Melbourne International Airport (FL)
33	MLI	Quad City International Airport (IL)
34	MMU	Morristown Municipal Airport (NJ)
35	OXC	Waterbury-Oxford Airport (CT)
36	PNS	Pensacola Regional Airport (FL)

Table B.2: Airport group 2.

No	Airport code	Airport name
1	**MDT**	**Harrisburg International Airport (PA)**
2	AVL	Asheville Regional Airport (NC)
3	BGR	Bangor International Airport (ME)
4	BOI	Boise Airport (ID)
5	GFK	Grand Forks International Airport (ND)
6	GPT	Gulfport-Biloxi International Airport (ND)
7	HSV	Huntsville International Airport (AL)
8	LBX	Brazoria County Airport (TX)
9	LIT	Little Rock National Airport (AR)
10	MFE	McAllen-Miller International Airport (TX)
11	MSN	Dane County Regional Airport (WI)
12	GSP	Greenville/Spartanburg Airport (SC)
13	PIA	Peoria Regional Airport (IL)

Table B.3: Airport group 3.

No	Airport code	Airport name
1	**FAT**	**Fresno Air Terminal (CA)**
2	APC	Napa County Airport (CA)
3	BGM	Greater Binghamton Airport (NY)
4	BIS	Bismarck Municipal Airport (ND)
5	CGF	Cuyahoga County Airport (OH)
6	CHA	Chattanooga Metropolitan Airport (TN)
7	CHO	Charlottesville-Albemarle Airport (IN)
8	DPA	Dupage County Airport (IL)
9	EVV	Evansville Regional Airport (IN)
10	FTW	Fort Worth Meacham International Airport (TX)
11	JAC	Jackson Hole Airport (WY)
12	MKC	Charles B. Wheeler Downtown Airport (MO)
13	PTK	Oakland County International Airport (CA)
14	APF	Naples Municipal Airport (FL)

Table B.4: Airport group 4.

No	Airport code	Airport name
1	**LEX**	**Blue Grass Airport (KY)**
2	EFD	Ellington Field (TX)
3	IXD	Olathe/New Century Aircenter Airport (KS)
4	LFT	Lafayette Regional Airport (LA)

Table B.5: Airport group 5.

No	Airport code	Airport name
1	**LGA**	**La Guardia Airport (NY)**
2	BWI	Baltimore/Washington International Airport (MD)
3	ELP	El Paso International Airport (TX)
4	FLL	Fort Lauderdale Hollywood International Airport (FL)
5	MCI	Kansas City International Airport (MO)
6	PHX	Phoenix Sky Harbor International Airport (AZ)
7	IAD	Washington Dulles International Airport (DC)
8	LGB	Long Beach Airport (CA)
9	MSY	New Orleans International Airport (LA)

Table B.6: Airport group 6.

No	Airport code	Airport name
1	**ORL**	**Orlando Executive Airport (FL)**
2	ABI	Abilene (TX)
3	ADS	Addison Airport (TX)
4	AGC	Allegheny County Airport (PA)
5	APA	Arapahoe County Airport (CO)
6	AVP	Wilkes-Barre/Scranton International Airport (PA)
7	CMI	Champaign Willard Airport (IL)
8	CPR	Natrona County International Airport (WY)
9	BCT	Boca Raton Public Airport (FL)
10	CRQ	McClellan-Pallomar Airport (CA)
11	FRG	Republic Airport (NY)
12	FTY	Fulton County
13	GON	Groton-New London Airport (CT)
14	HVN	Tweed New Haven Regional Airport (CT)
15	ITH	Ithaca Tompkins Regional Airport (NY)
16	LMT	Klamath Falls Airport (OR)
17	LNK	Lincoln Airport (NE)
18	MCN	Middle Georgia Regional Airport (GA)
19	MSO	Missoula International Airport (MT)
20	MLU	Monroe Regional Airport (LA)
21	OXR	Oxnard Airport (CA)
22	PSC	Tri-Cities Airport (WA)

Table B.7: Airport group 7.

No	Airport code	Airport name
1	**CRW**	**Charleston Yeager Airport (WV)**
2	BJC	Jeffco Airport (CO)
3	BPT	Southeast Texas Regional Airport (TX)
4	CPS	St. Louis Downtown Airport (MO)
5	BTL	W V Kellogg Airport (MI)
6	CWA	Central Wisconsin Airport (WI)
7	ERI	Erie International Airport (PA)
8	EUG	Eugene Airport (OR)
9	FSM	Fort Smith Airport (AR)
10	FXE	Fort Lauderdale Executive (FL)
11	GJT	Walker Field Airport (CO)
12	LBE	Arnold Palmer Regional Airport (PA)
13	LUK	Cincinnati Municipal Airport Lunken Field (OH)
14	MRY	Monterey Peninsula Airport (CA)
15	PDK	Dekalb Peachtree Airport (GA)
16	PNE	North Philadelphia Airport (PA)
17	PWK	Pal Waukee Airport (IL)
18	BFL	Meadows Field Airport (CA)
19	BIV	Tulip City Airport (MI)
20	BTM	Bert Mooney Airport (MT)
212	EAU	Chippewa Valley Regional Airport (WI)

Table B.8: Airport group 8.

No	Airport code	Airport name
1	**PQI**	**Northern Maine Regional Airport (ME)**
2	ASE	Aspen-Pitkin County Airport (CO)
3	BKL	Burke Lakefront Airport (OH)
4	ELM	Elmira/Corning Regional Airport (NY)
5	EYW	Key West International Airport (FL)
6	GNV	Gainesville Regional Airport (FL)
7	HTS	Tri-State Airport (WV)
8	HYA	Barnstable Municipal Airport (MA)
9	IDA	Idaho Falls Regional Airport (ID)
10	INT	Smith Reynolds Airport (NC)
11	LBF	North Platte Regional Lee Bird Field (NE)
12	LWB	Greenbrier Valley Airport (WV)
13	MKG	Muskegon County Airport (MI)
14	MSL	Northwest Alabama Regional Airport (AL)
15	MVY	Martha's Vineyard Airport (MA)
16	PFN	Panama City-Bay County International Airport (FL)
17	PKB	Mid-Ohio Valley Regional Airport (WV)
18	PWA	Wiley Post Airport (OK)
19	MFR	Medford Rogue Valley International Airport (OR)
20	ACK	Nantucket (MA)

Table B.9: Airport group 9.

No	Airport code	Airport name
1	**DTS**	**Destin-FT Walton Beach Airport (FL)**
2	HEF	Manassas Municipal (VA)
3	HLN	Helena Regional Airport (MT)
4	HXD	Hilton Head Airport (SC)
5	MOD	Modesto City-County Airport (CA)

Table B.10: Airport group 10.

No	Airport code	Airport name
1	**MHT**	**Manchester Airport (NH)**
2	ABQ	Alburquerque International Airport (NM)
3	ACY	Atlantic City International Airport (NJ)
4	AUS	Austin-Bergstorm International Airport (TX)
5	BDL	Bradley International Airport (CT)
6	BNA	Nashville International Airport (TN)
7	CLT	Charlotte/Douglas International Airport (NC)
8	DCA	Ronald Reagan Washington National Airport (DC)
9	HRL	Valley International Airport (TX)
10	IFP	Laughlin/Bullhead International Airport (AZ)
11	JAX	Jacksonville International Airport (FL)
12	JNU	Juneau International Airport (AK)
13	KTN	Ketchikan International Airport (AK)
14	LIH	Lihue Airport (HI)
15	MBS	Saginaw International Airport (MI)
16	MDW	Chicago Midway Airport (IL)
17	PVD	T.F. Green Airport (RI)

Table B.11: Airport group 11.

No	Airport code	Airport name
1	**BLV**	**Midamerica Airport (IL)**
2	DEN	Denver International Airport (CO)
3	DTW	Detroit Metro Airport (MI)
4	IAH	Bush International Airport (TX)
5	KOA	Kona International Airport (HI)
6	LAS	McCarran International Airport (NV)
7	MCO	Orlando International Airport (FL)
8	MSP	Minneapolis/St. Paul International Airport (MN)
9	OAK	Oakland International Airport (CA)
10	OGG	Kahului Airport (HI)
11	ONT	Ontario International Airport (CA)
12	PHL	Philadelphia International Airport (PA)
13	IND	Indianapolis International Airport (IN)
14	ORD	Chicago O'Hare International Airport (IL)
15	DFW	Dallas/Fort Worth International Airport (TX)

Table B.12: Airport group 12.

No	Airport code	Airport name
1	**ALB**	**Albany International Airport (NY)**
2	AEX	Alexandria International Airport (LA)
3	BFI	Boeing Field/King County International Airport (WA)
4	CHS	Charleston International Airport (SC)
5	CLE	Cleveland Hopkins International Airport (OH)
6	COS	Colorado Springs Airport (CO)
7	CVG	Cincinnati/Northern Kentucky International Airport (OH)
8	DAY	Dayton International Airport (OH)
9	GEG	Spokane International Airport (WA)
10	GRR	Gerald R. Ford International Airport (MI)
11	MYR	Myrtle Beach Airport (SC)
12	OKC	Will Rogers World Airport (OK)
13	ORF	Norfolk International Airport (VA)
14	PHF	Newport News/Williamsburg International Airport (VA)
15	PIT	Pittsburgh International Airport (PA)
16	PWM	Portland International Jetport (ME)

Table B.13: Airport group 13.

No	Airport code	Airport name
1	**OMA**	**Eppley Airfield (NE)**
2	BFM	Mobile Aerospace Field (AL)
3	BUF	Buffalo Niagara International Airport (NY)
4	CAE	Columbia Metropolitan Airport (SC)
5	CMH	Port Columbus International Airport (OH)
6	DAL	Dallas Love Field (TX)
7	FWA	Fort Wayne International Airport (IN)
8	HOU	Hobby Airport (TX)
9	LRD	Laredo International Airport (TX)
10	MKE	General Mitchell International Airport (WI)
11	PDX	Portland International Airport (OR)
12	ISP	Long Island Mac Arthur Airport (NY)
13	MHR	Sacramento Mather Airport (CA)
14	PIE	St. Petersburg-Clearwater International Airport (FL)
15	ITO	Hilo International Airport (HI)
16	PBI	Palm Beach International Airport (FL)
17	BUR	Burbank Bob Hope Airport (CA)

Table B.14: Airport group 14.

No	Airport code	Airport name
1	**MEM**	**Memphis Airport (TN)**
2	ADW	Andrews Air Force Base (MD)
3	AFW	Fort Worth Alliance Airport (TX)
4	ATL	Atlanta International Airport (GA)
5	EWR	Newark Liberty International Airport (NJ)
6	HNL	Honolulu International Airport (HI)
7	LAX	Los Angeles International Airport (CA)
8	MIA	Miami International Airport (FL)

Table B.15: Airport group 15.

No	Airport code	Airport name
1	**AOO**	**Altoona-Blair County Airport (PA)**
2	CIC	Chico Municipal Airport (CA)
3	HND	Henderson Executive Airport (NV)
4	IPL	Imperial County Airport (PA)
5	IYK	Inyokern Airport (CA)
6	MCE	Merced Municipal Airport (CA)
7	MTJ	Montrose Regional Airport (CO)
8	PIH	Pocatello Regional Airport (ID)

Table B.16: Airport group 16.

No	Airport code	Airport name
1	**LZU**	**Gwinnett County Airport (GA)**
2	JQF	Concord Regional Airport (NC)
3	JST	Johnstown-Cambria County Airport (PA)
4	OSU	Ohio State University Airport (OH)
5	DET	Detroit City Airport (MI)

Table B.17: Airport group 17.

No	**Airport code**	**Airport name**
1	**BOS**	**Boston Logan International Airport (MA)**
2	ABY	Southwest Georgia Regional Airport (GA)

Table B.18: Airport group 18.

No	**Airport code**	**Airport name**
1	**JFK**	**John F. Kennedy International Airport (NY)**
2	ANC	Anchorage International Airport (AK)

Table B.19: Airport group 19.

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