PROBABILISTIC ANALYSIS OF AIRCRAFT MANEUVERS
USING MULTI-FIDELITY AERODYNAMICS DATABASES
AND UNCERTAINTY QUANTIFICATION

A DISSERTATION
SUBMITTED TO THE DEPARTMENT OF AERONAUTICS AND ASTRONAUTICS
AND THE COMMITTEE ON GRADUATE STUDIES
OF STANFORD UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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March 2021

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Introduction

Engineering design is a predictive discipline involving the estimation of the future real-world behavior of an object that may only exist as a thought in the brain, as a sketch on paper, or more recently, as a file on a computer. The design process starts with a definition of requirements that must be fulfilled by the object in question. It ends with the manufacturing of prototypes that, hopefully, confirm the fulfillment of those requirements. Depending on the complexity of the object, the interim can be as short as a few hours due to the advent of rapid prototyping techniques such as additive manufacturing, or as long as multiple years involving thousands of hours of engineering work.

Those hours are spent predicting real-world behavior of an object that doesn't physically exist yet. Numerous analysis techniques progressing from basic back-of-the-envelope calculations, through computational numerical simulations, to prototyping and experimental testing of sub-systems, are employed in this endeavor. Due to the intricacies of real-world physics, almost none of these techniques are perfect. Each method has some uncertainty associated with its predictions that must be taken into account by the engineers employing them. Quantifying these uncertainties can be highly specific to the method in question.

The word *fidelity* is used to refer to how closely a method can mimic real-world behavior. High-fidelity methods are better at predicting real-world behavior, whereas low-fidelity methods employ simplifications that introduce uncertainties into the analyses. As an example, consider estimating the weight of an object. A low-fidelity method would be to pick up the object and try and estimate the weight based on how heavy it feels. Factors such as personal bias, left vs. right hand usage, and muscle soreness, would contribute to the uncertainty in the estimate. A high-fidelity method would be to use a weighing scale, that is accurate up to one milligram, to measure the weight. Direct measurement introduces significantly fewer sources of uncertainty and the weight would be accurate up to 0.5 milligrams.

Fidelity comes at a cost. This is to be expected. If high-fidelity analyses were less expensive than low-fidelity ones, there would be no reason to use low-fidelity analyses. Continuing with the weight estimation example, the only cost of the low-fidelity method is the time taken to pick up and estimate the object's weight. The high-fidelity method incurs the additional cost of the weighing scale. Cost minimization is

often a priority, and a mix of low- and high-fidelity analyses are needed. Greater emphasis is placed on lower-fidelity methods in earlier stages of the design process, where rough estimations are sufficient to base design decisions upon. This emphasis transfers to higher-fidelity methods as the design progresses and more certainty in performance metrics is required before the significant investment of creating a prototype, is made.

This dissertation focuses on combining results from analyses of varying fidelity to create a superior prediction of the real-world behavior of an engineered object. These predictions incorporate the uncertainties inherent in the analyses to create a probabilistic representation, rather than a single, deterministic result. A method to quantify the uncertainties due to modeling simplifications, in particular computational fluid dynamics (CFD) simulations, is implemented and validated. Finally, statistical analysis that allows for explicit calculation of the likelihood of meeting/failing a particular design requirement is presented. The engineered object of choice to showcase real-world impact of the work, is an aircraft. It represents one of the most complex, engineered objects and it requires years of development to design. Standard industrial analysis techniques are employed. The design requirements are real-world flight certification tests created by the Federal Aviation Administration (FAA) that are in use today.

1.1   Motivation

Aircraft design is a complex, non-linear, multi-disciplinary problem that requires many years, and thousands of hours of engineering to solve. An aircraft is composed of numerous sub-systems that work together to make flight possible. The sheer size, complexity, and number of parts, make aircraft manufacturing a very long and expensive process. It is imperative that all aspects of the aircraft's real-world performance are thoroughly investigated before the manufacturing step is taken in the design process. While historical experience in designing previous aircraft is useful, in order to push the boundaries of performance, more precise analyses are required.

The rapid improvement of computational capabilities in the recent past has increased the use of computer simulations to predict various aspects of the aircraft's real-world behavior in a virtual setting. Coupled with advances in the understanding of the underlying physics of these phenomena, this has led to the development of computer simulations of varying sophistication and computational cost that can describe the relevant quantities of interest (QoI) at different levels of fidelity. These simulations allow for the critical assessment of engineering designs significantly earlier in the design process than what was previously possible with purely experimental design campaigns. These analyses have been used in for aerodynamic shape optimizations [2, 11, 35], structural optimizations [5, 41, 70], and more recently, combined aero-structural optimizations [10, 30].

While these simulations can use simplifying assumptions that introduce uncertainties in their analyses, they have, nevertheless, significantly improved the ability to predict the satisfaction of performance-based design requirements, such as range, passenger capacity, and weight, early in the design process. But performance-based metrics are not the only design requirements on an aircraft. Governing bodies, such as

the Federal Aviation Administration (FAA), set stringent flight certification requirements that test for the air-worthiness of an aircraft [62]. These are fundamentally different from performance-based requirements as the outcome is binary, either the aircraft passes or fails the test. Consequently, the ramifications of not meeting the certification requirements are worse than not meeting performance-based requirements. *Flight certification* suggests that these tests can only be performed with a full-scale prototype but learning from the trend of an increased reliance on computational analyses, virtual representations of the aircraft design can be put through simulated air-worthiness testing to provide estimates for the likelihood of passing or failing a requirement.

The current methodology involves building a virtual representation of the aircraft using aerodynamic databases that contain the force and moment coefficients experienced by the aircraft across its expected flight envelope. These databases are created using a single information source and at specific milestones during the design process. They do not contain any information about the uncertainties introduced due to the particular information source that is used. Simulating a flight certification maneuver using these databases yield a single deterministic outcome. Such a result belies the uncertainty that are present in the database and wrongly assumes a 100% certainty in the force and moment coefficient data that populates the database. With rigorous handling and propagation of these uncertainties, the deterministic result can be converted to a more realistic likelihood of success or failure.

The objective of this work is to perform statistical analyses on simulations of flight certification maneuvers for commercial aircraft. This is achieved by tackling the problem on multiple fronts. A method to quantify the uncertainties arising from modeling assumptions in the widely used Reynolds-Averaged Navier-Stokes (RANS) computational fluid dynamics (CFD) simulations is presented, implemented, and validated. This data, along with other data and uncertainties from other information sources, is incorporated into aerodynamic databases that utilize multi-fidelity models to create a stochastic representation of the aircraft's potential performance. These models are sampled to create hundreds of individual representations of the databases that have small variations as a result of the uncertainties in the underlying data. These samples are used to propagate the uncertainties through the flight simulation of a current air-worthiness test maneuver. Statistical analysis of the results of these maneuver simulations yields the likelihood of an aircraft passing or failing the given test maneuver.

This enables the consideration of flight certification metrics earlier in the aircraft design process. It also allows for the assessment of the adequacy of the planned control systems. Quantification of the risks involved with failing a certification maneuver equips the engineers with the necessary information required to mitigate them.

1.2 Uncertainty Quantification

Computer simulations and real-world experiments alike, carry some inaccuracies in their predictions. The field of uncertainty quantification (UQ) does exactly as the name suggests; it provides methodologies to

efficiently characterize, propagate, and, in some cases, minimize uncertainties that plague analyses. UQ has been adopted for a wide range of applications including modeling climate change [37, 60], understanding uncertainties in numerical simulations [23, 53, 64], and even predicting the economic effects of COVID-19 [3]. The benefits of UQ are realized when the process is taken one step further and the quantified uncertainties are used to make better decisions [42]. Information on the underlying uncertainties of analysis techniques can be used to make better medical decisions [4], create reliable and robust designs [21, 32, 59], and create safer autonomous driving algorithms [9, 20, 69]. This work aims to propagate uncertainties in design analyses through flight simulations to calculate the likelihood that an aircraft will succeed or fail in meeting flight certification requirements.

Uncertainties are often divided into two categories: aleatoric and epistemic. Aleatoric uncertainties arise due to natural variation in the parameters that describe a situation. Epistemic uncertainties arise due to incomplete knowledge of the situation. To exemplify the differences between the two categories, consider a ball being thrown multiple times using the same amount of force. Slight changes in the wind direction and speed will result in slight differences in the distance that the ball travels. The uncertainty in the distance travelled due to this natural variation in the wind, is aleatoric. It can be quantified by throwing the ball thousands of times, recording each distance, and calculating statistical information, such as the mean and standard deviation, about the result. These uncertainties are easier to quantify, through methods such as Monte Carlo simulations [24, 50] and polynomial chaos expansions [54, 56], but are irreducible. Now consider that to remove the effects of natural variation, the same ball throw is simulated using simple calculations employing Newtons laws of motion. The calculated distance is the same every time, but there are simplifications in the equations, such as ignoring wind resistance, that introduce uncertainty in the result. These simplifications reflect the lack of knowledge that defines epistemic uncertainties. Contrary to aleatoric ones, epistemic uncertainties are reducible (through better modeling/measurement) but are difficult to calculate and propagate as they are extremely problem-dependent [22].

Analyses of varying fidelity are used in this work. There are uncertainties associated with each. For some techniques, the uncertainties are provided by subject matter experts (SME) that rely on historical data and their experience in using the analyses. Explicit quantification of epistemic uncertainties is performed for one commonly used analysis technique: Reynolds-averaged Navier-Stokes (RANS) computational fluid dynamics (CFD) simulations. Specifically, the uncertainties introduced due turbulence models and numerical error due to insufficient discretization, are quantified.

1.2.1 Turbulence Modeling Uncertainty

The Navier-Stokes equations are a set of non-linear partial differential equations that describe the motion and behavior of fluids. Computational fluid dynamics (CFD) is the field of study that involves the use of computers and numerical analysis techniques to solve the non-linear Navier-Stokes equations to simulate the flow of a fluid over a domain of interest. This is made more difficult due to turbulence, which is a state of fluid flow that is characterized by chaotic, small-scale fluctuations in the density and velocity of the fluid. The

range of length, and time scales that need to be resolved through spatial, and temporal discretization make it computationally intractable to solve exactly, i.e. without any simplifying models. Most flows of engineering interest are plagued by turbulence. The difficulty in solving these flows exactly has paved the way for the development of a hierarchy of solution techniques that trade computational cost for prediction accuracy.

The most widely used method in industry is the Reynolds-averaged Navier-Stokes (RANS) simulation. Steady RANS simulations are very computationally efficient and can be used for expensive undertakings such as iterative aerodynamic shape optimization [11, 39, 47], and aircraft database generation [68]. The computational efficiency comes at the cost of modeling inaccuracies. The simulations assume that the flow is steady (no time-dependent variation in flow), and require simplifying turbulence models that aggregate the effects of the turbulent eddies that would be present in the flow.

The inadequacy of turbulence models in predicting certain flow features has been well documented [65]. These models have various parameters and constants that are calibrated using canonical flow conditions such as the flow over a flat plate. Cheung et al. in [12] treat these parameters as random variables and use high fidelity data from direct numerical simulations (DNS) to learn posterior distributions for these parameters. Similarly, Dow et al. in [16] use DNS data to solve an inverse RANS problem to determine the eddy viscosity field that would result in a flow field closest to the DNS data. Both methods lean on DNS that are computationally expensive and limited to simple geometries such as flat plates [33], and channels [45, 48].

This work focuses on the eigenspace perturbation methodology [18, 34] which is a physics-based UQ method that does not require any high-fidelity information and can provide uncertainty estimates by running 6 RANS simulations. This has been applied to wind-engineering [27] and to perform design optimizations under uncertainty [51]. Chapter **??** details this methodology, provides various validation cases, and explores the relationship between uncertainty introduced by turbulence models and the numerical errors introduced due to insufficient discretization.

1.2.2 Numerical Discretization Error

Turbulence models are not the only source of uncertainty in RANS CFD simulations. Solving continuous equations on a discrete domain creates numerical discretization error. In RANS CFD simulations, the continuous RANS equations that define fluid flow are solved on a discrete domain known as the mesh or grid. Numerical discretization error is classified as an epistemic uncertainty as it can be reduced by increasing the number of discrete points in the domain. As the discretization increases and the grid spacing tends towards 0, the numerical error approaches 0 as well. This is the basis for the "Grid Convergence Study" method for quantification of numerical discretization error [1]. This is an important tool used in the verification and validation (V&V) of CFD codes and turbulence models [63].

Section **??** delves into the details of quantifying numerical discretization error. It goes on to explore its relationship with the turbulence modeling uncertainty estimate by applying both uncertainty quantification techniques to two benchmark simulations: a 2D NACA0012 airfoil, and a 3D ONERA M6 wing.

1.3 Multi-Fidelity Analysis

During the course of the typical aerospace design process, different kinds of performance analysis tools are used at different stages. Low-fidelity computer simulations accept lower accuracy for faster computations. They are useful at the very early stages of the design process, when the geometry of the aircraft is not well defined and is subject to significant change. For example, AVL [17] solves the incompressible potential flow equations, which takes mere seconds, and can rapidly explore a large multi-dimensional design space changing variables like number of engines, or wing placement [7, 8]. These are often replaced by higher-fidelity techniques, such as RANS CFD simulations, as the design progresses and more details of the design are finalized. Experimental data, normally obtained through a costly wind-tunnel test, typically provides the most accurate representation of the phenomena analyzed. It is obtained late in the design process as expensive prototypes of subsystems need to be manufactured.

Instead of discarding the low-fidelity simulation data when higher-fidelity data is available, there exist methods to combine data from multiple fidelity levels to better represent the quantities of interest (QOI). Multi-fidelity extensions to popular surrogate modeling techniques have been developed. Polynomial chaos expansion (PCE) [6, 56], which is a popular technique for sensitivity analysis [13, 66], can be used to combine multi-fidelity information by learning an additive correction on the low-fidelity data [55, 57]. Gaussian processes (GP) [43, 49, 61], popular for its direct estimation of the error in its modeling, combines multiple information sources by learning additive and multiplicative corrections on low-fidelity data [38]. This correction of the lower-fidelity data f_{i-1} to a higher-fidelity f_i is represented as

$$f_i(\mathbf{x}) = \rho_i f_{i-1}(\mathbf{x}) + \delta_i(\mathbf{x}), \tag{1.1}$$

where ρ_i is a constant multiplicative term and $\delta_i(\mathbf{x})$ is the additive term. These are sometimes referred to as bridge functions [31]. Note that multi-fidelity PCE neglect the multiplicative term $\rho_i(\mathbf{x})$ in their corrections. One disadvantage of using GP vs. PCE is that the GP assumes a Gaussian distribution for across the uncertainty intervals. PCE can handle different probability distributions, but the superior multi-fidelity handling, and the direct error estimation of the GP regression makes multi-fidelity GP the tool of choice.

Multi-fidelity GP have been used extensively in aerospace applications [44, 50], modeling oil reservoir production and pressures [38], hydrodynamic simulations [29], and biological tissue growth [46]. Numerous extensions to the framework have been proposed. Ghoreishi et al. introduced the ability to have non-hierarchical information sources by relating each fidelity level to the highest fidelity, as opposed to each other [25]. This is unnecessary in the context of aircraft design as there is a well-defined hierarchy based on the physics that is modeled. Perdikaris et al. [58] significantly improved prediction capability by using deep Gaussian processes [15]. The significant computational cost and the loss of a Gaussian posterior precludes its use in this effort. Han et al. [31] proposed the use of gradient information to improve predictive capability. Unfortunately, gradient information is only available for RANS CFD simulations through the use of adjoints [35], not the other information sources.

This work does employ important improvements to the multi-fidelity GP process that were proposed by Gratiet [28]. Reformulation of the equations significantly reduced the computational cost of processing the GP by splitting the data into the individual information sources. This results in the inversion of smaller matrices which is more computationally efficient. He also extends the multiplicative term to be a function of $\mathbf{x}$, as opposed to a constant. Section **??** presents these equations in detail and extends them for use with noisy data for design sets that are not nested.

1.4   Aerodynamic Databases

Aerodynamic databases are a representation of the aircraft's behavior in-flight. It contains all the forces and moments that are experienced by the aircraft as a function of the aircraft's configuration (control surface deflections), orientation (angle of attack, angle of sideslip), and operating conditions (dynamic pressure, mach number, altitude). Calculating these forces and moments at various points in its operating envelope are paramount to predicting real-world performance Most aerodynamic analyses, be it computational or experimental, are geared towards creating a database that catalogs these values as a function of the aircraft's orientation and operating conditions.

The industry standard is to have a lookup-table that is populated by data from aerodynamic analyses that are performed during the design process. They get updated as the design progresses and the results from the higher-fidelity analysis techniques, replace the lower-fidelity data. The forces and moments are described as multi-dimensional functions depending on, up to, 5 input variables: angle of attack, sideslip angle, mach number, dynamic pressure, and altitude. Often only a subset of the 5 input variables are used. Discrete analyses in this multi-dimensional domain provide data points that are used to interpolate values between analysis locations. These databases are deterministic and have no characterization of the uncertainties present in the analysis techniques.

Engelund et al. [19] created databases for the Hyper-X scramjet using wind tunnel data to analyze and predict the expected behavior before flight testing was performed. Keshmiri et al. [40] used a mixture of CFD analyses and wind tunnel experiments to create aerodynamic databases for the generic hypersonic vehicle. Instead of having a lookup table, the coefficients were described using analytic polynomial functions of arbitrary order. Databases for the Mars Pathfinder aerodynamics that were created using CFD data by Gnoffo et al. [26] were validated using flight measurements and were found to be accurate within reason.

Each of these previous works have created deterministic expressions of the databases There is no quantification of the uncertainties that affect the analyses that are used. Previous work by Wendorff et al. [68] introduces the concept of probabilistic aerodynamic databases that uses multi-fidelity data and its associated uncertainties in a Gaussian Process regression framework to create a non-deterministic representation of the database. Using a combination of sensitivity and uncertainty analysis, an adaptive sampling technique was developed to find the best location to perform the next analysis to minimize the uncertainty in the objective function at minimum analysis cost. This was extended to include physics-based uncertainty quantification

for the RANS CFD simulations [52].

The current work follows from this and extends the databases from exclusively describing longitudinal dynamics to include lateral-directional information as well. The databases are concerned with the force coefficients of lift, drag, and side-force, C_L, C_D, and C_{SF} respectively, and the moment coefficients of pitch, roll, and yaw, C_m, C_l, and C_n respectively. These coefficients are treated as functions of the angle of attack (α) and angle of sideslip (β). The databases are divided into two parts, the aerodynamics databases that describe the bare airframe aerodynamics, and the controls databases which describe the effect of controls surface deflections. Simple linear combinations of the two are used to determine the final forces and moments that are experienced by the aircraft. The generic coefficient C_i is calculated as a function of α, β, and the control surface deflections δ_j as

$$C_i\left(\alpha, \beta, \delta_1, ..., \delta_N\right) = C_{i0}\left(\alpha, \beta\right) + \sum_{j}^{N} C_{i_{\delta_j}}\left(\alpha, \beta, \delta_j\right), \tag{1.2}$$

where $i0$ refers to the bare airframe coefficient and $C_{i_{\delta_j}}$ refers to the incremental effect the control surface δ_j on coefficient C_i:

$$C_{i_{\delta_j}}\left(\alpha, \beta, \delta_j\right) = C_i\left(\alpha, \beta, \delta_j\right) - C_{i0}\left(\alpha, \beta\right). \tag{1.3}$$

Deflections of the ailerons, rudder, elevator, flaps, and spoilers are used.

Chapter **??** delves into the details of creating multi-fidelity aerodynamics and controls databases using multi-fidelity GP regression. This creates probabilistic databases that can be sampled to create hundreds of individual databases have slight variations due to the uncertainties present in the underlying data. AVL simulations, RANS CFD simulations, and wind and water tunnel experiments provide three different information sources of increasing fidelity. The required data is generated and databases are created for the generic T-tail transport (GTT) aircraft [14].

1.5 Certification by Analysis

To be able to fly a new aircraft design, it needs to go through rigorous air-worthiness testing to ensure it is safe and can perform predictably in a variety of different situations. In the US, these tests are defined and carried out by the Federal Aviation Administration (FAA) [62]. They occur at the very end of the design process, once a functional full-scale aircraft is built. Failing a certification test at this stage would require a redesign that would be incredibly expensive. To prevent this from occurring, factors of safety are employed to account for potential uncertainty and error in the design analyses. The quantification of uncertainties in analyses can replace arbitrary safety factors with the explicitly calculated design margins required to account for the errors. This is the cornerstone of reliability based design processes [32].

Certification by analysis (CbA) purports that the passing of certification requirements can be done using purely simulation-based analyses. It is the logical conclusion to the current trend of an increased reliance

on computer simulations for design analysis. With the maturing of simulation procedures, it has garnered interest from the aerospace community. To achieve this, simulation would have to be as accurate, if not more accurate, than what is possible with flight testing. There are many required improvements to simulation capabilities [65] that will take years to develop. In the interim, the effects of uncertainties on flight performance predictions and predicted performance in flight testing can be quantified. This provides aircraft designers with a method to estimate the likelihood that a design will pass or fail a certification test.

1.5.1 Uncertainty Propagation

A common method for uncertainty propagation is to perform a Monte Carlo analysis. This is a brute-force method of characterizing the effect of input uncertainties on an output quantity of interest (QoI) [36, 67]. It involves running multiple deterministic calculations where input variables are randomly sampled from their respective probability distributions. The results are analyzed to determine the effect of the variation in the input variables on the posterior probability distribution of an output quantity of interest (QoI). In the context of this work, the deterministic calculations are the flight simulations, the input values are the aerodynamics and controls databases, and the QoI is the success/failure of the certification test.

A significant advantage of using GP regression to represent the probabilistic aerodynamic databases is the ability to take deterministic samples of the database. Each sample is a potential candidate aircraft that could explain the data that is used to create the databases. They represent aircraft that have slightly different performance from each other. These differences respect the uncertainty associated with the underlying data. Since multi-fidelity GP regression is used to model the databases, the input probability distributions are Gaussian. The flight simulation does not represent a linear transfer function, therefore the posterior probability distribution of the QoI is arbitrary. As such, cumulative density functions are used to describe the posterior probabilities.

1.5.2 Aircraft Maneuver Simulation

Aerodynamic databases contain all the information needed to perform high-fidelity flight simulations. With multi-fidelity aerodynamics and controls databases, a virtual representation of the GTT aircraft can be flown through real-world flight certification maneuvers. With the help of industry experts at The Boeing Company, a maneuver was picked from the FAA's *Flight Test Guide for Certification of Transport Category Airplanes* [62]. Within Chapter *5.3 Directional and Lateral Control* of the guide, the *Lateral Control: Roll Capability §25.147(d)* maneuver was chosen. The testing procedure is paraphrased as:

1. Airplane starts in a trimmed state for steady straight flight at maximum takeoff speed.

2. Establish a steady $30°$ banked turn.

3. Roll the airplane to a $30°$ bank angle in the other direction.

4. Aircraft must have sufficient roll authority to perform the $60°$ change in bank angle in no more than 11 seconds.

5. The aircraft must be able to do this with one engine inoperative, specifically the one that makes this maneuver more difficult.

This part of the work leans heavily on the expertise of the The Boeing Company in flight simulation and control law mixing. Due to proprietary and patent restrictions, exact implementation of the flight simulation code is unavailable but enough information is provided to outline the simulations' overarching methodology and workflow. This maneuver is simulated using a 5 degree of freedom (DOF) flight simulator that is used by The Boeing Company in their design processes. Details of the maneuver simulation process are discussed in Section **??**.

1.6   Contributions

This thesis establishes a framework to perform virtual flight testing of an aircraft early in the design process. While the focus is on aircraft design, the principles of multi-fidelity modeling and uncertainty quantification, and certification testing can be applied to any design problem that requires significant analysis.

Starting with UQ, Chapter **??** delves into the eigenspace perturbation methodology to quantify epistemic uncertainties introduced by turbulence models into RANS CFD simulations. The methodology is implemented in an open source CFD solver, SU2, to enable its widespread use in the research community. It is validated on a bevy of test cases that range from commonly used benchmark flow conditions, to those of specific aerospace interest. The relationship between turbulence modeling uncertainty and numerical disctretization error, another common source of uncertainty in CFD simulations, is investigated. The UQ methodology is applied to two aircraft, the NASA Common Research Model and the Generic T-tail Transport, to create aerodynamic databases with physics-informed uncertainties.

Since CFD is not the only analysis technique used in the aircraft design process, Chapter **??** presents multi-fidelity Gaussian processes (GP) that are used to combine data from different information sources. Existing equations for multi-fidelity GP regression are extended to use noisy data when design sets are not nested. Multi-fidelity aerodynamic databases are modeled using these equation, with AVL simulations as the lowest fidelity level, RANS CFD simulations with quantified uncertainties as the middle-fidelity, and wind tunnel experimental data as the highest fidelity. The benefits of multi-fidelity data fusion are elucidated using one-dimensional aerodynamic databases created for the NASA CRM aircraft. This is extended in Chapter **??**, where the first comprehensive, multi-fidelity, multi-dimensional aerodynamics and controls databases that represents a full-configuration aircraft's lateral and longitudinal dynamics are presented. These are created for the generic T-tail transport aircraft.

With all aspects of an aircraft's performance defined, Chapter **??** delves into the simulation of a FAA flight certification maneuver that is used to test the air-worthiness of commercial jets. The Monte Carlo method is

used to propagate the uncertainties in the design analyses through the flight simulation. The effect of the input uncertainty on the aircraft maneuver is analyzed and a probability of succeeding/failing the certification test is explicitly quantified. The virtual flight testing is also performed using databases based on lower-fidelity data, representative of what would be available at earlier stages in the design process. By quantifying the likelihood of success/failure of a flight certification maneuver, potential problems in the aircraft design can be identified and the risk of failure can be mitigated.

These contributions are discussed in further detail in Chapter **??**. Potential avenues for future research are presented as well.

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