33RD CONGRESS
OF THE INTERNATIONAL COUNCIL
OF THE AERONAUTICAL SCIENCES
STOCKHOLM, SWEDEN, 4-9 SEPTEMBER, 2022

SYSTEM-LEVEL IDENTIFICATION OF CRITICAL UNCERTAINTIES TO ENABLE VALIDATION EXPERIMENTS

Burak Bagdatli[1,*], Efe Y. Yarbasi[1,*] & Dimitri N. Mavris[1]

[1]Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology
[*]Authors contributed equally to this work

Abstract

Novel aircraft configurations require re-evaluation of assumptions made in analyses made in traditional design processes. Some uncertainties in the design simulations can combine and increase the risk on new aircraft programs and create critical decision points, whereas others may be less consequential and relatively easy to deal with using slight design modifications. Validation experiments aim to quantify the accuracy of the computer simulations and improve the understanding of the simulations. Such experiments can be performed to generate data to reduce the simulation uncertainty. However, given the cost and schedule impacts of physical experiments, significant care must be given for selecting only the necessary ones, i.e., the experiments that help reduce critical uncertainties. In this paper, a method for identifying and characterizing the consequences of critical uncertainties by propagation between levels of system architecture is given using the C-5M system as a canonical example. Proposed method should enable identification of points of entry for designing high-value validation experiments to reduce the overall uncertainty.

Keywords: uncertainty, simulation, design, validation

1. Introduction and Background

In the pursuit of new capabilities and missions, future military transport aircraft may look significantly different than the tube and wing configuration used today. The physical differences are driven by functional needs as unconventional configurations such as blended wing body aircraft provide increased internal volume increasing the platform's capabilities in terms of cargo capacity or mission range with additional fuel capacity. In turn the physical changes create behavioral changes in the system's operations due to new physics responses of the system that may be different to the ones commonly assumed to be correct for conventional configurations. The tightly coupled disciplines of aerodynamics and structures for wing design carry over to the fuselage design as they cannot be easily separated. Downstream components such as the tails, engine placement, landing gear integration, cargo doors and floors, fueling system, and many other systems may need to be designed with new design processes as traditional assumptions cannot be guaranteed.

The divergence from the traditional design processes require additional prototyping and testing cycles during the design of novel configurations, because the trends and historical data from previous designs that are depended upon during the conceptual design phase stop being useful. The increased reliance on physical prototyping and testing are becoming prohibitively expensive and slow down development programs significantly. Physics-based analyses and computer simulations can fill the role of physical testing as long as the simulations can be trusted and *validated* to a satisfactory degree. Naturally, all simulations and all measurements from a physical system include an error [8]. Earlier stages of an aircraft design process, where the information pertaining to the product is largely not decided upon or uncertain, will introduce uncertainty to the simulation outputs. Using physics simulations that are increasing in their fidelity over the preliminary and detail design phases, such uncertainties are reduced. For novel concepts and the use of new technologies, however; the uncertainties remain significant as a precedent may not exist at all.

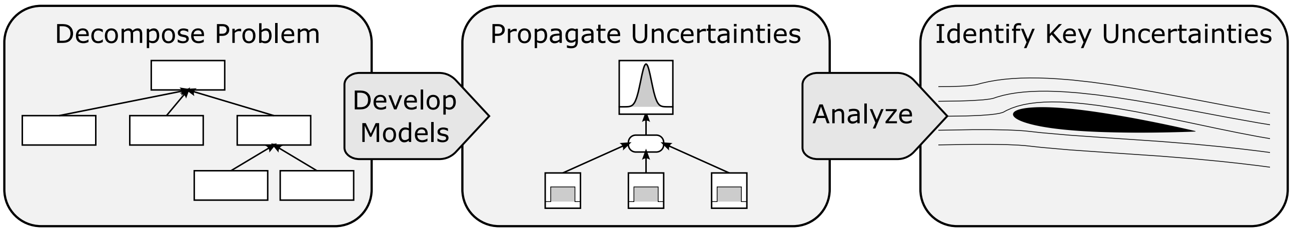

Figure 1 – Overall systems engineering process for identifying critical uncertainties

Validation experiments are performed to quantitatively assess the accuracy of the computer simulation and observe how well they represent the real world for their intended uses [8]. They are specific type of experiments in which the results obtained from (predominantly physical) experimentation *are not* assumed to be more accurate than the results obtained from the computer simulations. Their sole purpose is to see to what degree the tools represent the reality, in terms of physics phenomena and the ability of generating the same outputs. Therefore, a validation experiment is fundamentally different than other types of experiments such as phenomenon exploration or reliability tests. A validation case is a specific combination of experiment conditions that produce certain physics and measurement that are to be compared with the computer simulation. Any other combination outside of validation cases will be a *prediction*.

Putting an emphasis on computer tools is essential in the case of design of non-conventional aircraft concepts as the tools are not tried and tested. However, validating even a single tool for a wide set of conditions that will span the entire flight envelope is simply infeasible. The goal of this work is to support validation activity by identifying the set of critical conditions at which the uncertainty in predictions is significant. Later, a validation experiment can be investigated in order to reduce the associated uncertainty.

The remaining uncertainties in the simulation results are carried over to the later design stages where solutions to them may require redesign efforts. The risks that are carried forward in the program may dominate the program decisions and lead to cancellations as no one may be willing to “bet their company” as Raymer suggests at the end of the preliminary design [9]. A framework is needed to identify the critical risks in the system development caused by analysis uncertainties and trace them to the system requirements at higher levels.

Aircraft design decisions require data from multiple analyses that are usually organized around either design phases (conceptual, preliminary, and detail) or disciplines (aerodynamics, structures, handling qualities, etc.). Within a design phase the analyses are coupled together and influence each other. For example, weight calculations in conceptual design influence mission performance calculations such as the range of the aircraft which in turn influence weight calculations due to the change in fuel requirements. The coupling between analyses causes the uncertainty in one analysis to leak into another. The uncertainties must be propagated through each analysis to determine the total impact of the uncertainties in each simulation.

Some of the identified uncertainties can be reduced by replacing the offending analysis with a higher fidelity analysis. For example, early conceptual-level analyses could be replaced by higher fidelity analyses more appropriate at a preliminary design phase. Doing so will require increased computational resources as well as modifying the parameterization of the design to match the input/output needs of the new analysis. A practical mechanism for such an update that follows a systems engineering decomposition will be discussed.

Once the critical uncertainties are identified that cannot be reduced by higher fidelity analyses, physical experiments must be performed to reduce the uncertainties in the simulations by supporting them with real-world data. A conceptual flowchart is given in Figure 1. Measurement data from the physical experiments are used to validate trends and calibrate simulation results. Once the simulations are trusted, they can be used by sweeping design variables to create trends and trade-off analyses for the designs being worked on. The parametric trade-off environments can be used for uncertainty identification and propagation goals as well. Borrowing from a familiar design practice, this paper details methods used and decision support environment built for a canonical example around a well-known

Table 1 – Super Galaxy specifications[4][10]

Geometry		Weights & Mission	
Fuselage length	230 ft 10 in	Oper. empty weight	374 000 lbf
Wing span	222 ft 8 in	Max. zero-fuel weight	635 000 lbf
Wing chord root	45 ft 5 in	Max. takeoff weight	837 000 lbf
Wing chord tip	15 ft 4 in	Max. landing weight	635 850 lbf
Wing AR	7.75	Max. payload weight	261 000 lbf
Wing area	6 200 sqft	Max. wing loading	136 lbf/sqft
Wing anhedral	5°	Thrust-to-weight ratio	0.244
Wing incidence	3°	Max. load factor	2.25
Wing c/4 sweep	25°	Takeoff distance[2]	9 800 ft
Airfoils	NACA0011 & 0012[1]	Landing distance[2]	3 820 ft
Tail span	68 ft 8 in	Max. rate of climb[3]	1 725 ft/s
Horz. tail area	965 sqft	Service ceiling	35 750 ft
Vert. tail area	961 sqft	Cruise speed	490 kn (FL250)
		Stall speed	104 kn
		Max. payload range	2 980 NM
		Max. fuel range	5 620 NM

[1] Modified from standard NACA airfoils
[2] Sea level static conditions
[3] Sea level

air mobility system: the Lockheed C-5M Super Galaxy.
C-5M is one of the few mobility aircraft with enough publicly available data for modeling. Some geometric, mass, and mission data is given in Table 1 and the mission values will be used as requirements for the use case. To meet its requirements, the aircraft needs to be sized to complete a design mission consisting of different phases such as take-off, cruise, descent, and landing. For each of the design phases, different requirements may be imposed by stakeholders, e.g., “the aircraft must be able to execute a 2.25g turn at cruise conditions when fully loaded”. These requirements carefully define the capabilities that the final product should have.

2. Overall Approach

The multidisciplinary nature of aircraft design necessitates the use of multiple analyses in a convergence loop together to the outputs are consistent. While the run times of dependable high-fidelity simulations are typically significant on their own, arranging them in multidisciplinary analysis (MDA) environments exacerbates the cost due to the multiple executions necessary for convergence loops. For example, the external loads predicted by the aerodynamics calculations depend on the flight shape of the wing which in turn depends on the stress and strain calculations after loads are applied to the structure. Complicating matters further, the critical loading conditions (altitude, speed, weight, etc.) needed for design are numerous. Necessary modeling and simulation environments to simulate critical conditions can be constructed using established principles of systems engineering traced from the *mission profile* of an aircraft system.
Figure 2 shows the overall process for how the various system decompositions are leading towards a modeling architecture determination. It is important to note that all three decompositions are needed to construct the modeling architecture as the physical features of subsystems are as important as the functions they serve during different parts of the mission. The resulting decompositions lead to the modeling architecture for aerodynamics and structures shown in Figure 3. Different requirements and different modeling disciplines will necessitate in different functional architectures and certainly different physical architectures resulting in different selections of modeling tools. This paper investigates the accuracy of modeling tools used in aeroelastic wing design. Although C-5M was selected for this exercise, aircraft of other configurations can benefit from the same process.
In the example shown in Figure 3, the top row shows an aircraft concept with its subsystems. The

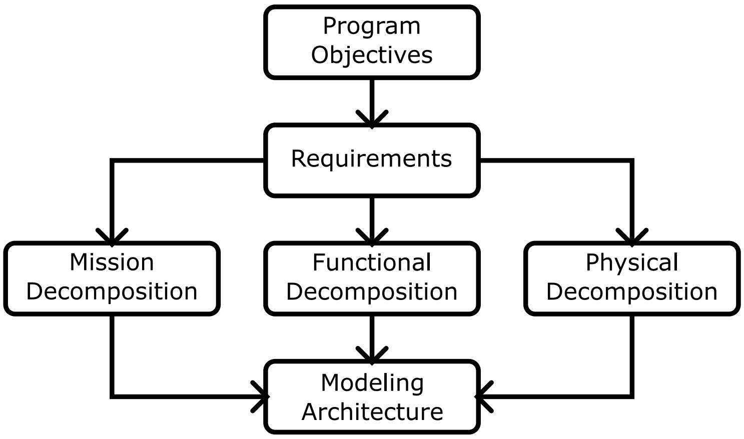

Figure 2 – System decompositions leading to modeling architecture

map of phenomena observed on the subsystems creates a link to what physics need to be captured in the simulation environment. For any design study, a fit-for-purpose simulation environment must be selected or developed if existing environments do not covert the modeling architecture. The physics can then be mapped to specific theories and potential models that make them executable on computers. In the study detailed in this paper, only grey boxes were actively used; the white boxes are given as further examples that were not investigated.

The main function of modeling and simulation in design is predicting the system's performance to a desired accuracy level for making decisions. At this stage, the final system has not taken shape yet. In fact, using the results of the simulations, it is expected to evolve to increase the stakeholders' confidence that the final design will meet its requirements. While the design matures, it passes through multiple tollgates such as preliminary and critical design reviews at which the technical feasibility and economic viability is assessed. Because details about the final design have not been decided upon and high-fidelity analyses require many parameters, early design decisions are made under significant uncertainty with low-fidelity analyses while having large influence over the system's design.

Ideally, the accuracy would be perfect throughout the design process; however, there are practical limitations on model preparation and execution times. Lower-fidelity models can provide rough estimates that may be enough to make early design decisions without being slowed down by the detailed physics calculations and the explosion of model variables they need to be run. Given that in the early phase the design does not have enough geometric fidelity, most of the detailed variables are unknown, e.g., a parametric study to define the planform will not have the same geometric resolution that is demanded by a Computational Fluid Dynamics (CFD) study. The reverse is also not feasible as the high-level of geometric fidelity will not be usable by a conceptual phase, high-level design analysis. Focusing on the physics fidelity to answer questions posed by the requirements, the demands may be different as well. For example, a drag performance determination for fuel burn studies will require a fairly high-fidelity CFD executions; however, a structural loading and stress calculations will mostly be interested in lift generation and drag fidelity is not necessary making vortex-lattice calculations acceptable. Each design phase demands a different level of accuracy from the quantitative analyses. Low and high fidelity analyses can be used in conjunction to achieve the design goals.

An aircraft is a complex system, that consists of many subsystem. The modeling of such systems often require analyses in more than one discipline. Unfortunately, most computational tools work with a single discipline. Therefore, the interactions arising from other disciplines necessitate them being carried over as external inputs and/or boundary conditions. Consistent solutions are usually found through iteration between different disciplines. A Design Structure Matrix (DSM) is typically used to describe the multidisciplinary analyses (MDA) framework. Feedback and feed forward loops are defined in DSM as well as how and which disciplinary analyses are connected.

The problem of interest in this work is the aero-structures analysis of an aircraft wing. Rapid Airframe

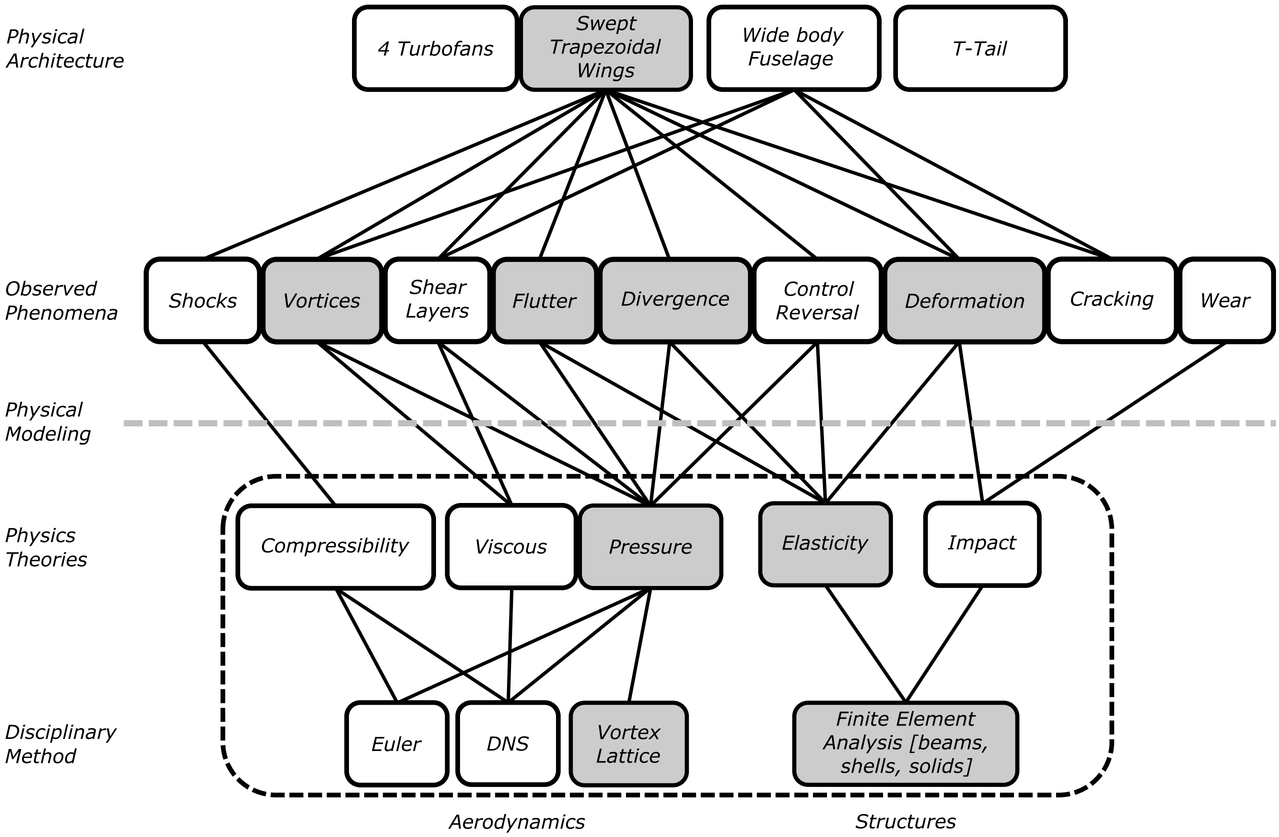

Figure 3 – Modeling architecture from an aerodynamics and structures perspective.

Design Environment (RADE) [2], an aero-structures design toolkit, was used to facilitate the MDA framework. The analyses used in the RADE toolbox for this work are:

- OpenVSP[6] for geometry generation
- Athena Vortex Lattice (AVL)[3] for aerodynamic analyses
- NASTRAN[7] for structural analyses
- HyperSizer[1] for sizing the internal structure thicknesses

Because the purpose of this study is to quantify the impacts of uncertainty in physics modeling and parameter uncertainty on the results of the design activity, selected tools form an appropriate set to demonstrate the process. For another purpose, higher fidelity tools can be implemented in the same manner albeit at a higher computational cost.

2.1 The Geometry Model

In order to calculate the aerodynamic loads, a geometry model of the Lockheed C-5M is needed. Because the entire geometry is not publicly available, was drafted in OpenVSP with some assumptions. The empennage was modeled solely for trim purposes, as the scope of this work is limited to the aero-structures analysis of the wing only. The geometry of the four engines of the aircraft is not model but they are represented as point masses and thrust vector in the analyses. It is critical to note these abstractions as they will have a significant impact on the results.

The wing box structure and mesh used to model are given in Figure 5. Single part spars, ribs and skin are located along the wing. The structural models were created using computer scripts. The internal structure, constrained by the outer mold line was represented in the OpenVSP model, and information such as the number of ribs has based on available drawings. The mid spar was removed from the analysis models to reduce the complexity of the analysis.

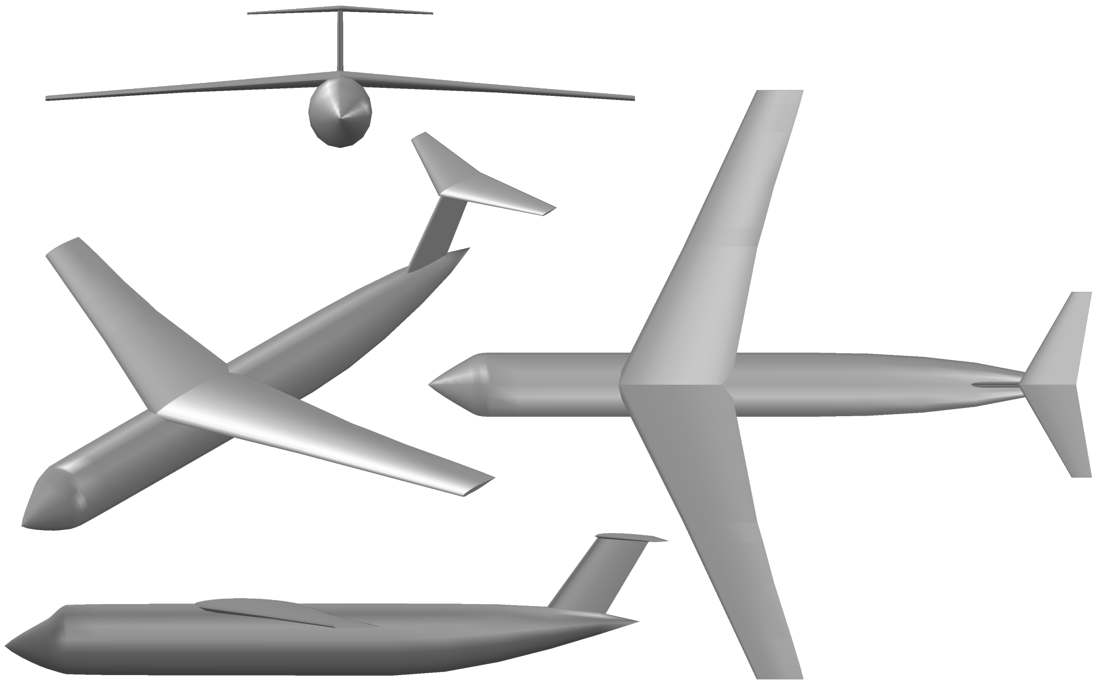

Figure 4 – OpenVSP model of the Lockheed C-5M

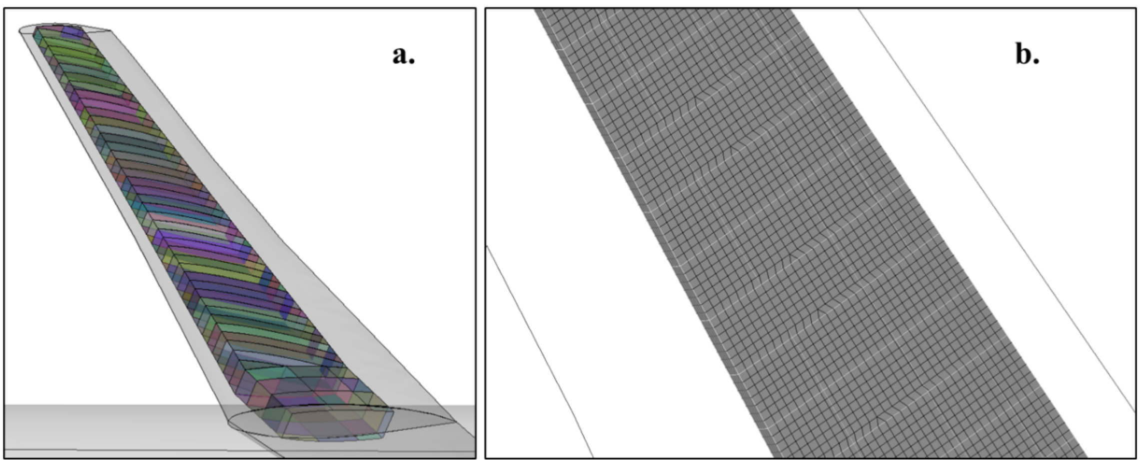

Figure 5 – Internal structure of the wing.
a. box layout b. Mesh used for structural analyses of the wing box

2.2 Design Structure Matrix

A Design Structure Matrix (DSM) provides the visual overview of multi-disciplinary design and optimization processes. Since most MDA workflows include feedback and feed forward structures, most DSM methods list the analyses on the diagonal, and the coupling attributes on off-diagonal elements. Traditionally, feed forward couplings appear in the upper triangle and the feedback couplings on the lower-triangle. Extended DSMs (xDSM) have been recently developed and present advantages over traditional DSMs such as the ability to describe the information regarding parameters passed between analyses, execution order, loops, optimization schemes and other outer-loop applications [5].
Different workflows will be described by different xDSMs. Because the calculation methodology is different, the outputs of the simulations will be different as well. In order to represent two different levels of fidelity in physics modeling, two different coupling strategies between aerodynamics and structure analyses are used in this work. These two strategies are illustrated in Figure 6. In the top xDSM, the two analyses are uncoupled, as in the displacements obtained from the structural analyses do not update the geometry in the aerodynamic analyses. In the bottom xDSM, the geometry used in aerodynamic analyses are updated, resulting in a better representation of the problem of interest at a more computational cost.
The xDSMs representing the MDA workflows used in this work are given in Figure 6. The difference between the two MDA environments is that they represent a step change in the modeling complexity. The Design of Experiments (DoE) process labeled as #1 defines the sampled points to be represented as the uncertainty in the modeling parameters. Then, aerodynamic coefficients are calculated for a specific flight condition. Based on the accuracy of the aerodynamics model, there will be an amount of uncertainty in the estimates. These coefficients are then used to calculate the aerodynamic loads acting on the wing, and they are passed to the structural analysis. Because the exact properties of the internal structures are not known, a sizing operation must be performed to estimate a realistic wingbox. The dimensions of the ribs and spars are determined by the aircraft's response to the critical flight conditions. The sizing loop terminates when the thicknesses of the internal structures converge and the loads are consistent with the external conditions. The uncertainty in the structures analysis will be fed back into the aerodynamics, potentially increasing the initial aerodynamics model uncertainties. The output of this process, the wingbox weight, will include the impact of previously introduced uncertainties. In the coupled aero-structures analysis, there is an additional MDA loop to feed the output of the structures analysis back to the aerodynamics analysis. As such, the geometry is modified according to the structural loads and a new aerodynamic load distribution is calculated. This loop continues until the loads converge. Having an extra set of iterations introduces a significant computational cost but the calculations represent an increase in the model complexity that is closer to the real phenomenon.
Decisions made in MDA problem to be solved result in different workflows leading to different xDSMs. To be clear, in the example shown on Figure 6, the component analysis tools are the same; however, the overall MDA is changing. Even if the inputs to both MDAs are exactly the same, due to the convergence loops changing, the inputs for the component analyses will be different. The selection of different component disciplinary analysis tools as well as how such component analyses are connected leads to different overall models and different solution architectures. The differences can be regarded as different abstractions of the same problem in interest and different MDA configurations will result in different model uncertainties.
In the top xDSM on Figure 6, the two analyses are uncoupled, as in the displacements obtained from the structural analyses do not update the geometry in the aerodynamic analyses. In the bottom xDSM, the geometry used in aerodynamic analyses are updated, resulting in a better representation of the problem of interest at a more computational cost. The impact of two different analysis coupling configurations will be studied in this work representing the *physics fidelity*.
The other uncertainty that will be considered is the parameter uncertainty in the inputs used to the analyses. For example, the real values of the properties of the material used in the construction of the aircraft may not be known or may be known to within a bounded range. A part of this uncertainty may be irreducible sample by sample aleatory uncertainty resulting from production or environmental conditions. Parameter uncertainties will be studied using Monte Carlo simulations on the inputs to

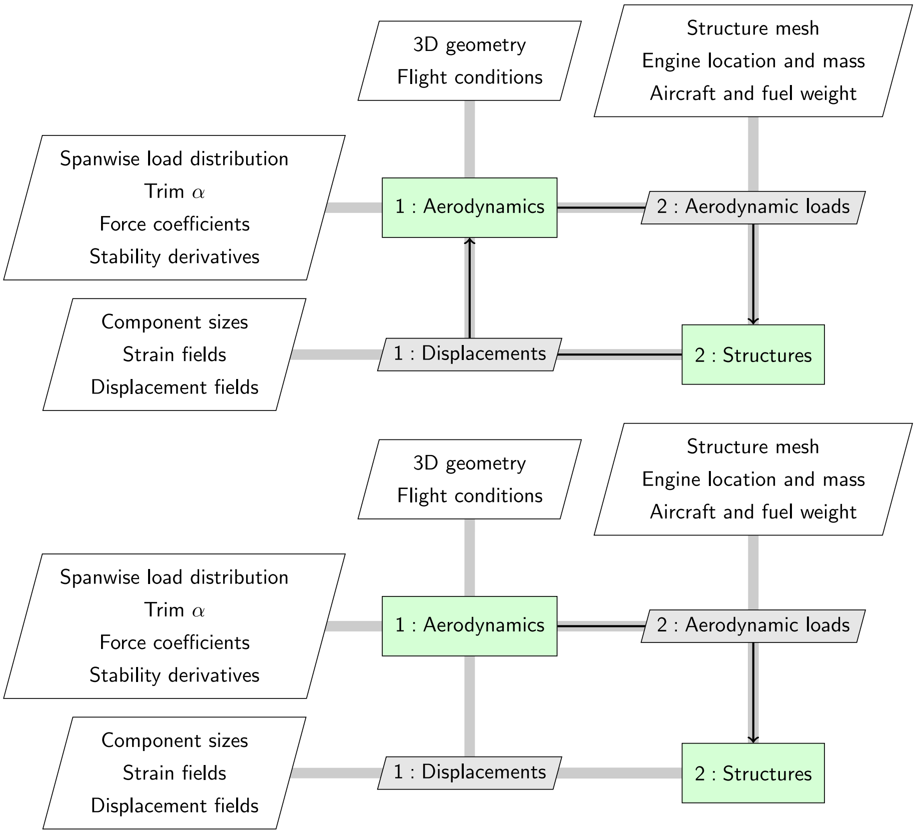

Figure 6 – Two different xDSM approaches for aeroelastic analyses. Decoupled aero-structures (top) and coupled analyses (bottom)

the MDAs.

3. Uncertainty Propagation

Typically, The computer simulations used in most engineering applications are deterministic. However, underlying calculations and solution approaches almost never exactly represent the reality of interest. Even in the case where a close-enough representation can be assumed, the parameters used in these computations are subject to real-world parameter uncertainties. Such uncertainties can be mathematically represented by sampling values from a probability distribution that defines the likelihood of parameter values. The effect of parameter uncertainties can be observed by collecting the set of outputs obtained by sampling different values from the aforementioned probability distributions. For this work ,the parameter uncertainties are propagated from a component level to the wing subsystem level and aircraft system level to quantify propagated system-level uncertainties. Investigating the statistics of system-level system response quantities (SRQs) will enable quantification of uncertainties raising from different parameters. As such, each factor can be considered as critical or trivial, depending on their impact on the system-level probability distribution. Designing validation experiments to fix accurate values for the trivial uncertainties will be a waste of time and effort. The critical uncertainties on the other hand, will have significant impact on the desired SRQ, which will make tuning the parameters in worth the effort.

3.1 Design of Experiments

Due to the practical computational budget limitations, surrogate models needed to be created and used as described earlier. In both MDAs, the processes numbered #2 and onward were used to create surrogate models by running DoEs. The surrogate models were executed in Monte Carlo simulations for uncertainty parameter sampling were then performed on these surrogate models. Running the computationally intensive analyses with limited DoEs that minimize the effort to extract trends instead of direct Monte Carlo sampling reduces the time needed for the study. For this work,

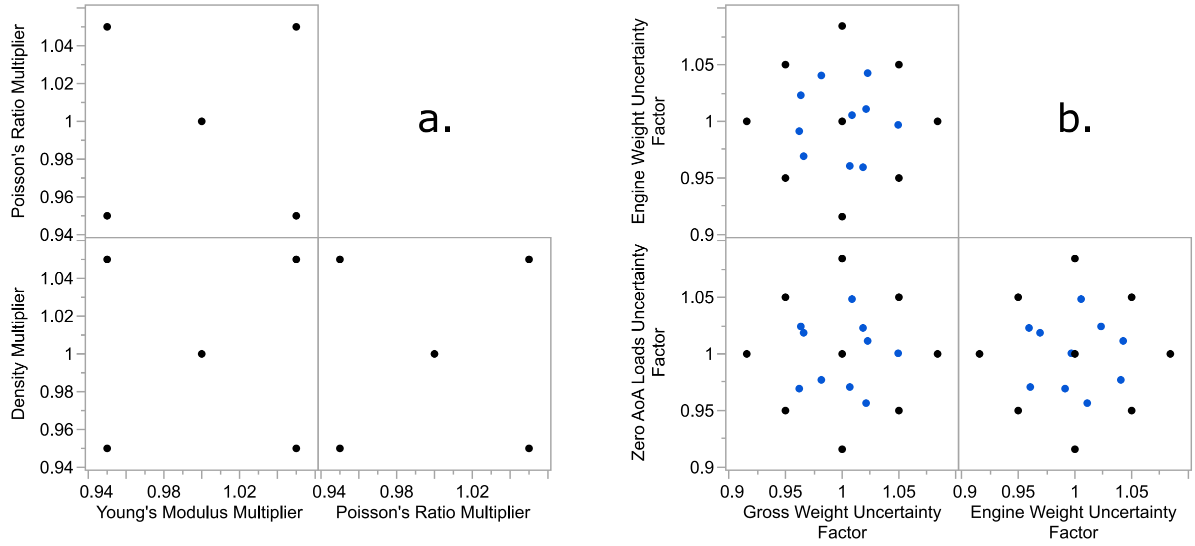

Figure 7 – DoEs used to sample uncertainty factors. A. Central Composite Design b. Full Factorial Design with a center point

parameter uncertainty factors are sampled from uniform probability density functions, representing the values in the selected range to be equally likely to be the true value. Depending on the parameter and the SME input, uniform distributions can be replaced with more appropriate distribution shapes. Six variables have been found to have more impact on the SRQs: *gross weight*, *engine weight*, *aerodynamic loads*, *Young's modulus*, *Poisson's ratio* and *material density*. These variables are sampled from two different DoEs at each run. The first three of these variables are sampled from a Central Composite Design and Minimum Potential DoEs. Material properties could not be varied continuously due the limitations of the analysis software. Therefore, the remaining three variables are sampled from a two-level Full Factorial Design with an additional center point. Two sets of DoEs were Cartesian-joined, and sampled points are used for creating surrogate models. The DoEs are illustrated in Figure 7 Because the run time for a single, convergent case was about a few hours, having more sample points was a bottleneck. 225 cases were executed in total, on four desktop computers in eight separate parallel threads in total. With a higher computational budget, more points could have been used, or surrogating the analyses could have been skipped altogether.

3.2 Quantification of Uncertainties at the Level of Consequence

The impact of uncertainty factors (i.e., sampled parameter values around a baseline) on higher level metrics are given in Figure 8. The figure illustrates the results from the analyses directly, without employing surrogate models. This chart appears noisy because it is a *marginal plot*. For example, in the first column of Figure 8, points have different sampled values from not just one but multiple uncertainty variables' probability distributions. In other words, they are the results of the simulations of varying engine weights, loads, and material properties simultaneously but plotted using only one of those variables. The limitation is due to the inability of plotting multiple dimensions effectively on a 2-D surface. Because the fine details cannot be observed, such charts are only useful in identifying strong dependencies.

Observing the trend of the fitted splines, it is seen that the impact of gross weight uncertainty is seen to be significantly larger compared to other uncertainty factors. However, gross weight uncertainty is more related to the unknowns in the early design rather than simulation uncertainty caused by unknown parameters. This fact puts an emphasis on the accuracy of the earlier design-related assumptions if one aims to reduce variability in simulation results. Furthermore, the overall impact of the uncertainty factors given in Figure 8 are as expected. Increasing material density increases the wing weight whereas an increase in Young's Modulus decreases the total weight of the aircraft as less material would be needed. Combinations of different values of design parameters create the

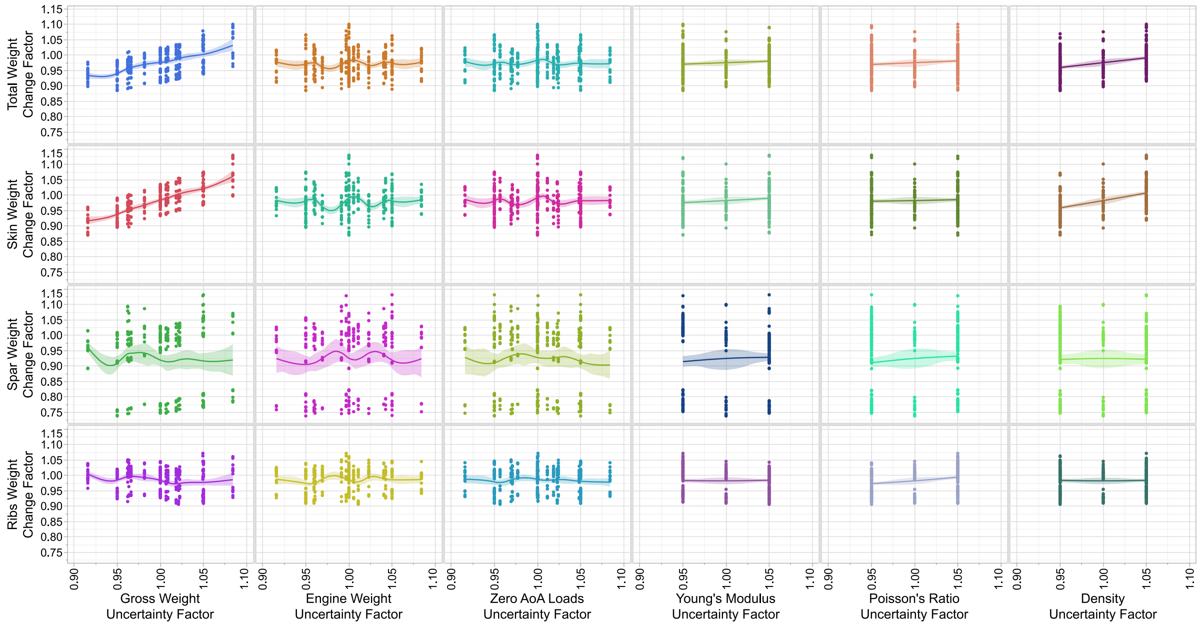

Figure 8 – Impact of uncertainty factors on mission-level metrics

vertical scatter of the results.

Figure 10 illustrates the deflection of the wing box for different load factors: *-1g* and *2.5g*; and two different types of analyses, *coupled* and *uncoupled*. The two different types of analyses represent an increase in analysis fidelity as previously presented in 6. As expected, the wing deflections are higher in the coupled aeroelastic analyses that take the local angle of attack change into account. Plotting the impact of uncertainties on geometries with real physical meaning may provide more insight as to what uncertainty or modeling choice have local impacts on the results that are probably not captured by the aggregated, higher-level metrics.

Sensitivity analyses are needed to find the impact of parameters on consequential mission-level metrics. Therefore, surrogate models are generated from the results obtained from 225 cases. In this study, polynomial regressions with up to 5th order terms are used. To reduce the needed information, a step-wise regression process was used where starting with the mean, only the most significant next term was added iteratively until a balance between fit error and regression parameter uncertainty is found. The uncertainty in the regression parameters is not related to the model parameter uncertainty. For this work, uniform probability distributions are used to sample the surrogate model. If a priori knowledge exists about the form of the possible uncertainty distribution, practitioners can use other forms of probability density functions. This part of the process is one of the critical points where information from the literature and subject matter expertise can into play to change how uncertainty probability distributions and bounds.

The prediction profilers given in Figure 11 are plotted using these surrogate models. Each plot shows their trend, as well as their relative importance. The blue bands around these plots indicate the inherent surrogate model uncertainty and not physics model parameter uncertainty. The polynomial fit error is slightly *heteroscedastic*, i.e., its variance is changing over the parameter space. As expected, the surrogate model predicts the results well in the middle region parameter space but less well near the extremes. As expected, the error bands are different for different parameters or their combinations.

Up to this point, aforementioned uncertainty parameters were related to the wing-level analyses. They can be combined with the aircraft-level analysis to complete the uncertainty propagation to the top, mission-level metrics. A similar DoE study was performed using FLOPS to determine the criticality of parameter uncertainties at the aircraft level. Among these parameters, specifically the wing weight terms can now be connected to the appropriate weight uncertainties obtained using the wing structural sizing MDA. The workflow presented in this study demonstrates the relationship

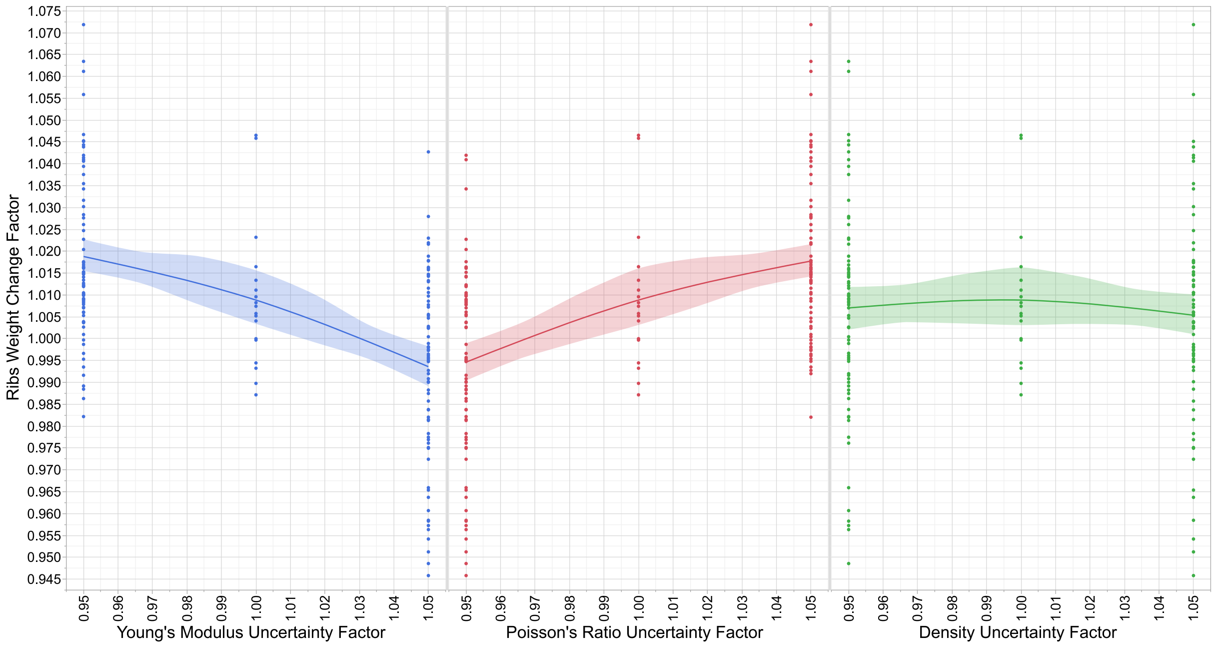

Figure 9 – Impact of wing structure material uncertainty factors on the overall wing weight

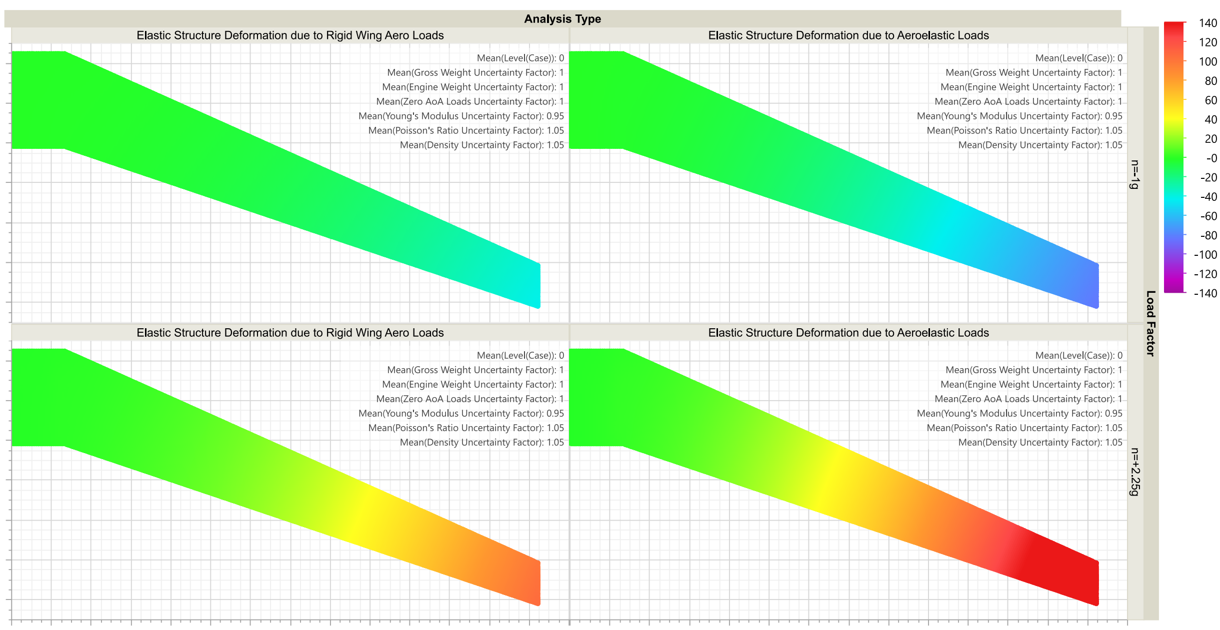

Figure 10 – Wing box deflection due to aerodynamic loads Top row: Load Factor = –1g, Bottom row: Load Factor = +2.25g. Left column: Decoupled Analysis, Right column: Coupled Analysis

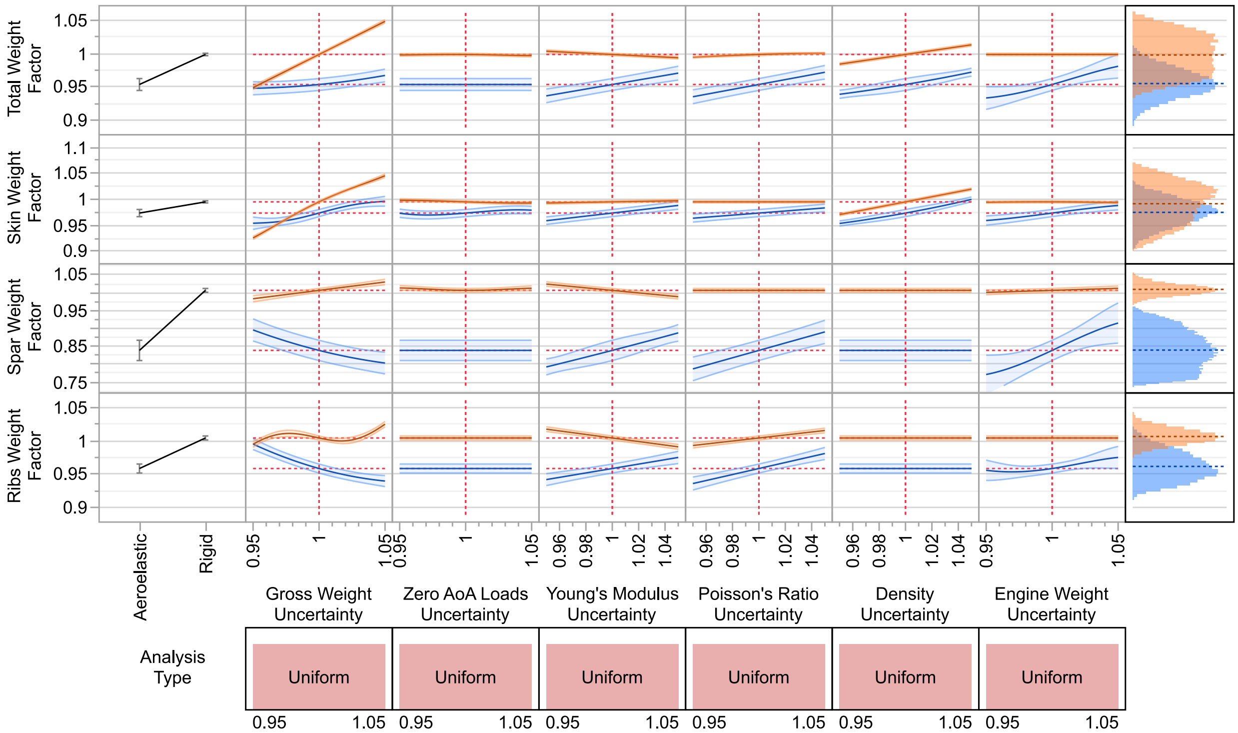

Figure 11 – Prediction profiler for parameter uncertainties (decoupled analysis in orange, aeroelastic analysis in blue)

between how uncertainties at different analyses levels can be handled, propagated and be treated. To connect additional parameters, different analyses would be needed such as ones related to CFD for the lift dependent and independent drag factors.

4. Results & Recommendations

Some uncertainties in the design simulations can combine and increase the risk on new aircraft programs and create critical decision points, whereas others may be less consequential and relatively easy to deal with using slight design modifications. To reduce the critical uncertainties, physical experiments and demonstrations can be performed to gather real-life data to fix or calibrate the simulations. Once a reasonable modeling architecture to capture the necessary physics to calculate the high-level metrics defined in the requirements is set, the modeling components are built and integrated into a multi-disciplinary analysis. Each component's input and output in the modeling architecture can be investigated for their uncertainty. With such a process, questions such as "what are the implications of predicting wing weight wrong at the conceptual level?" can be answered during design with design analyses and tools without further physical experiments, leading to the identification of *critical* uncertainties. The uncertainties can be further decomposed into smaller physical/design elements with successive multi-level analysis activities. The uncertainties in the lower-level variables can be propagated upstream with the modeling infrastructure built earlier as well as using surrogate models that can be built from the models in case their execution times are slow. Trends and other visualizations are highlighted as useful for identifying uncertainties.

Once the critical uncertainties are identified, physical experiments targeting their reduction can be designed and executed that provide the best uncertainty reduction per unit cost. Identifying critical uncertainties in design will enable the formulation of *targeted* validation experiments. If the validation is against another computational model (i.e., code validation), increasing the model fidelity to gain information about a parameter is expected to reduce the high-level uncertainties in the design goals. At the vehicle level, utilized computational tools have considerable inaccuracies due to factors such as inexact parameters, geometry abstraction, and inaccurate or uncaptured physical phenomena. In this work, the uncertainty in parameter related to the wing box weight in system-level analyses are

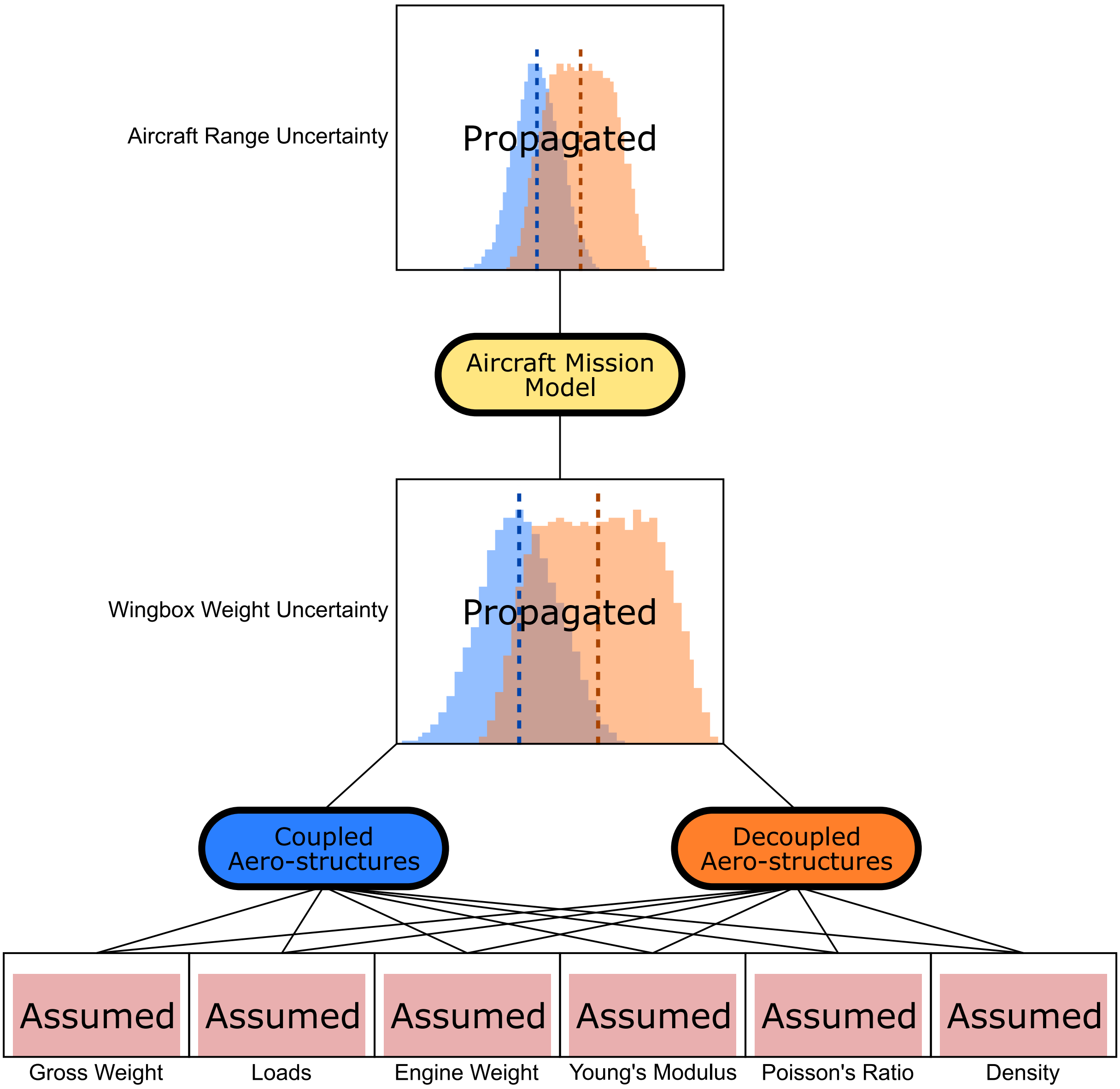

Figure 12 – Uncertainty propagation results for the two modeling scenarios with different physics fidelities

	Range Factor (Decoupled)		
Predictor	Contribution	Portion	Rank
Gross Weight Uncertainty Factor	0.215643	0.8623	1
Density Uncertainty Factor	0.024338	0.0973	2
Young's Modulus Uncertainty Factor	0.004417	0.0177	3
Engine Weight Uncertainty Factor	0.002509	0.0100	4
Poisson's Ratio Uncertainty Factor	0.001812	0.0072	5
Zero AoA Loads Uncertainty Factor	0.001356	0.0054	6

	Range Factor (Aeroelastic)		
Predictor	Contribution	Portion	Rank
Density Uncertainty Factor	0.034374	0.3015	1
Young's Modulus Uncertainty Factor	0.031687	0.2779	2
Gross Weight Uncertainty Factor	0.025300	0.2219	3
Poisson's Ratio Uncertainty Factor	0.011306	0.0992	4
Engine Weight Uncertainty Factor	0.007954	0.0698	5
Zero AoA Loads Uncertainty Factor	0.003404	0.0299	6

Figure 13 – Ordered critical uncertainties, left: decoupled analysis, right: coupled analysis

further decomposed and they are analyzed via higher fidelity physics-based analyses. Decomposed uncertainty can be propagated up to system-level metrics to reshape—and hopefully narrow—the uncertainty distributions. The results of this propagation for a single mission level metric are given in Figure 12. Although simple uniform probability distribution functions are used to sample parameter values, using two different approaches result in distinct mission level probability distributions. It is seen that both the means and the variability of the two different cases are quite different. This example can be treated as an example having two different sets of modeling assumptions in modeling and simulation environments, in this case different levels of abstraction.

Another impact of having different modeling assumptions for analyses is the ranking of the uncertainty parameters of interest. For example, the impact of previously identified uncertainty factors on the range of the aircraft are given in Figure 13. The relative importance of the gross weight uncertainty decreases as coupling between structural analyses and aerodynamic load calculations is introduced. Conversely, the parameters related to the elasticity of the material have more relative importance in coupled aero-structures analyses.

The same process used to generate the propagation in Figure 12 can be used simultaneously with other mission-level metrics. Linking the surrogate models used for wing-level analyses and surrogate models used for system-level analysis enables the propagation of uncertainty from lower levels to high-level metrics. A prediction profiler demonstrating this propagation is given in Figure 14. The distributions obtained by a specific combination of uncertainty factors can be seen in the right-most column, which can be used for comparatively assessing the impact of parameter uncertainties. It is important to pay attention to the ranges on the vertical axes. For example, the variations in the field lengths are insignificant and their trends may be misleading. However, aircraft range and fuel uncertainties are quite significant with the uncertainty parameter ranges used for the study.

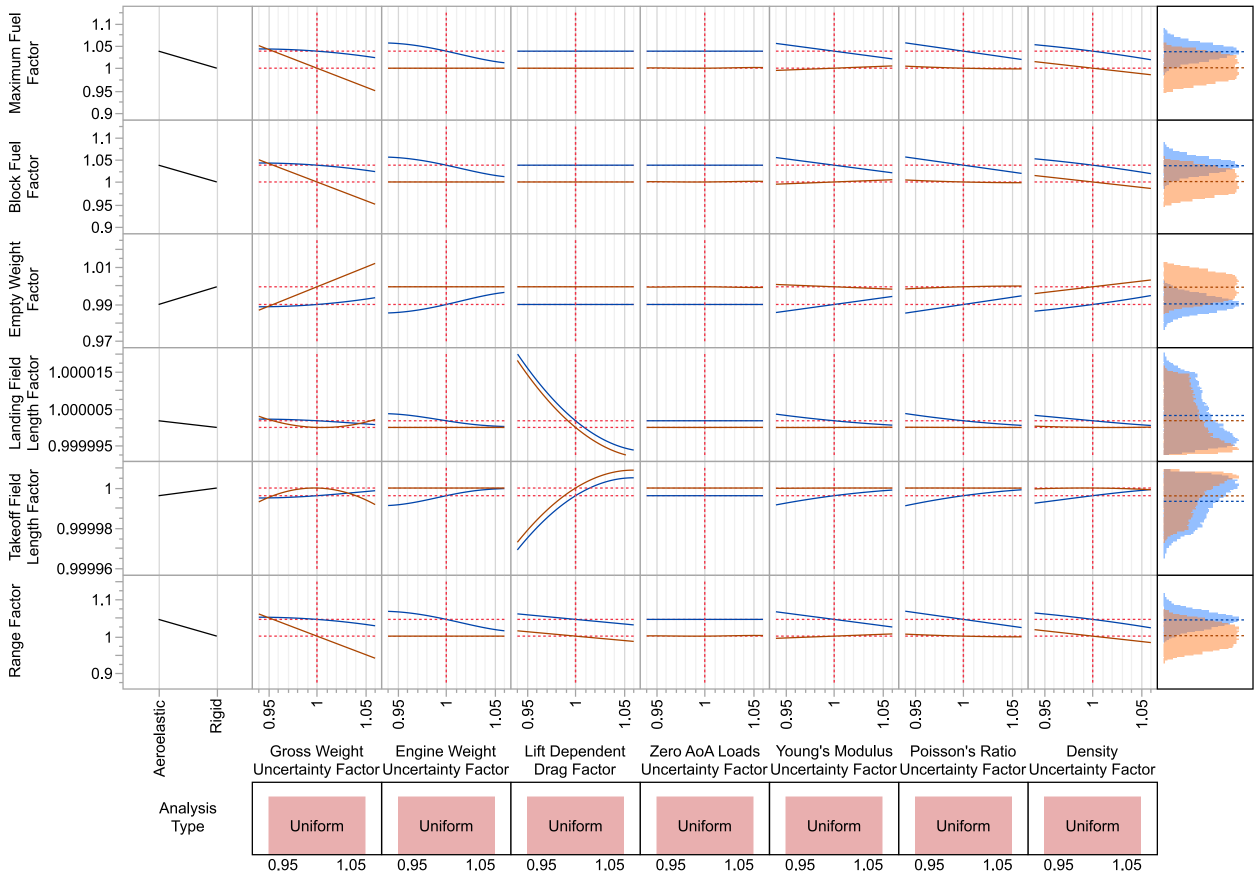

Figure 14 – Multi-level uncertainty propagation to the system-level using surrogate models

With updated data obtained from higher fidelity simulations, it might be possible to see the impact of bringing in carefully tailored validation experiments to reduce the uncertainty associated with certain parameters or models. However, it is not possible to do this for every single parameter uncertainty or abstraction used in the design, especially higher fidelity models that can capture various physical phenomena require thousands of parameters. Therefore, the capability developed in this paper should enable the program managers to identify the points of entry to design validation experiments. To reiterate, the purpose of a validation experiment is not to find a better design but to quantify the uncertainties pertaining to the model as well as understanding its limitations. Hence, the input set at which they need to be run need not to be similar to the design mission of the aircraft.
The framework described and demonstrated in this paper acts as a guidance from a utilitarian perspective. In almost no application, the expected physics phenomena are fully known, nor are their constituents, whose combinations describe a physics phenomenon. Following this model-driven framework will lead the process considering the capabilities of the candidate models and which operational conditions can be captured. The capability of this framework to identify high-value experiments that will help in reduction of overall uncertainty was demonstrated in this paper. A potential benefit of this approach is to enable and incorporate some validation experiments earlier in the design, allowing for establishing more trust in computational tools and the results they generate. More reliable and accurate results will result in time and cost savings as the likelihood of the results being scrapped out due to a requirement violation would be lower.

5. Acknowledgements

The authors recognize the valuable input provided by Nigel Taylor (MBDA), Joe Morrison (NASA), and Eric Walker (NASA) throughout the study. Their guidance was especially useful for the student teams that worked on different parts of the study creating, calibrating, and exercising the various models used to create results and visuals.

6. Contact Author Email Address

Please contact Burak Bagdatli (burak.bagdatli@ae.gatech.edu) for any inquiries about the work presented in this paper.

7. Copyright Statement

References

[1] Collier Aerospace. Hypersizer. Electronic, June 2022.

[2] J. A. Corman, N. R. Weston, C. I. Friedland, D. N. Mavris, and T. W. Laughlin. Rapid Airframe Design Environment (RADE): A Parametric, Modular, and Multidisciplinary Framework for Conceptual Phase Airframe Design. 2018.

[3] M. Drela and H. Youngren. *AVL Overview*, June 2022.

[4] B. Gunston, D. Willis, K. Munson, L. T. Peacock, P. A. Jackson, and S. Bushell, editors. *Jane's all the world's aircraft: development & production: 2013–2014*. IHS, 2013.

[5] A. B. Lambe and J. R. R. A. Martins. Extensions to the design structure matrix for the description of multidisciplinary design, analysis, and optimization processes. *Structural and Multidisciplinary Optimization 2012 46:2*, 46(2):273–284, jan 2012.

[6] R. A. McDonald and J. R. Gloudemans. *Open Vehicle Sketch Pad: An Open Source Parametric Geometry and Analysis Tool for Conceptual Aircraft Design*.

[7] MSC Software. Msc nastran. Electronic, June 2022.

[8] W. L. Oberkampf and B. L. Smith. Assessment criteria for computational fluid dynamics validation benchmark experiments. 52nd Aerospace Sciences Meeting, pages 1–27, 2014.

[9] D. P. Raymer. *Aircraft design, a conceptual approach*. American Institute of Aeronautics and Astronautics, Washington, DC, 1989.

[10] US Air Force. C-5M fact sheet, Oct. 2021.