# Integration of Uncertainty Quantification in a Model-Based Systems Analysis and Engineering Framework

Bijan Fazal*, Joanna Schmidt†, Ben D. Phillips‡, and Irian Ordaz§
*NASA Langley Research Center, Hampton VA, 23681, USA*

Kenneth T. Moore¶
*NASA Glenn Research Center, Cleveland OH, 44135, USA*

**This paper presents a technical approach to improve the confidence in the systems analysis process by integrating Uncertainty Quantification (UQ) techniques within a Model-Based Systems Analysis and Engineering (MBSA&E) framework. The MBSA&E architecture uses system models and multidisciplinary analytical solutions as central artifacts for system design and analysis. The integration of UQ enables engineers to assess and mitigate uncertainties associated with a system model, design parameters, and constraint inputs, leading to more complete design studies and better informed decision-making processes. The proposed approach leverages the strengths of MBSA&E and extends it with a UQ methodology to quantify uncertainties in the input parameters and to trace the uncertainties as they propagate throughout the system model. To demonstrate the effectiveness of an integrated MBSA&E-UQ approach, a case study involving a simplified analysis of a Transonic Truss-Braced Wing (TTBW) concept vehicle is performed. This integration enables a more comprehensive evaluation of system performance and behavior under uncertainty and a more robust approach for system design and analysis. Lastly, the paper addresses the challenges and considerations associated with integrating UQ into an MBSA&E framework.**

## I. Nomenclature

| | | |
|---|---|---|
| $A_i$ | = | the $i^{th}$ polynomial chaos expansion (PCE) coefficient |
| $a$ | = | significance level |
| $C_D$ | = | drag coefficient |
| $C_L$ | = | lift coefficient |
| $d$ | = | PCE deterministic variables |
| $F$ | = | PCE response |
| $f_{\text{NLF}}$ | = | impact of natural laminar flow on the vehicle drag |
| $g$ | = | gravity |
| $N_t$ | = | number of terms necessary for PCE model |
| $n$ | = | number of PCE variables |
| $P$ | = | number of terms in PCE model |
| $p$ | = | order of PCE expansion |
| $q$ | = | cruise dynamic pressure |
| $R$ | = | mission range |
| $S$ | = | wing reference area |
| $sfc$ | = | engine specific fuel consumption |
| $V$ | = | flight velocity |
| $W$ | = | vehicle weight |
| $\mu$ | = | mean |

*Aerospace Engineer, Aeronautics Systems Analysis Branch, AIAA Member.
†Aerospace Engineer, Aeronautics Systems Analysis Branch, AIAA Member.
‡Aerospace Engineer, Aeronautics Systems Analysis Branch, AIAA Member.
§Aerospace Engineer, Aeronautics Systems Analysis Branch.
¶Aerospace Engineer, Banner Quality Management Inc.

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| $\sigma$ | = | standard deviation |
| $\Psi_i$ | = | PCE basis functions $i^{th}$ mode |
| $\xi$ | = | PCE random variables |

## II. Introduction

Systems Engineering (SE) is an interdisciplinary approach and means to enable the realization of successful systems. It focuses on defining customer needs and required functionality early in the development cycle, documenting requirements, and then proceeding with design synthesis and system validation [1]. A Systems Engineering Transformation (SET) framework has been used by Blackburn et al. [2] to explore the interaction of mission and system models with multidisciplinary design, analysis and optimization (MDAO), airworthiness, and cost models as applied to the design of a fixed-wing unmanned aerial vehicle (UAV). A modular and complex aerospace system requires a defined architecture, logical decomposition, and interactions with sub-systems and components using model-based design and engineering techniques. Model-Based Systems Engineering (MBSE) is the formalized application of modeling to support system requirements, design, analysis, verification, and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases [1]. Previous research has been performed in linking MBSE models to MDAO analysis for air vehicle design. For instance, Aiello et al. [3] used MDAO analysis of battery usage in a Systems Modeling Language (SysML) model of a drone to satisfy mission requirements. The approaches using engineering analysis for design validation in the early lifecycle stage of a system through the joint use of MBSE and MDAO have been well documented by Chaudemar et al. [4] An agile approach to develop complex aerospace systems of interest using MBSE-based system models bridged with MDAO design models has been studied by Ciampa et al. [5]

Systems Analysis (SA) is an explicit formal inquiry carried out to identify alternative courses of action and examine the consequences of these alternatives in terms of costs, benefits, and risks resulting in a comparative framework for decision makers to make an informed choice from among the alternatives. Model-Based Systems Analysis (MBSA) is a formalized application of SA that uses physics-based design and empirical relationship models which are informed by MDAO analytical tools and methods. Ozoroski et al. [6] have explored MBSA in a multidisciplinary design and analysis (MDA) framework with multifidelity capabilities to study the acoustics and performance of supersonic concept aircraft.

In this research study, a Model-Based Systems Analysis and Engineering (MBSA&E) framework is used to couple the MBSA and the MBSE disciplines with their associated tools, methods, and models. Recent research has been done to develop integrated MBSA-MBSE frameworks and modeling workflows. The MBSE-Based Requirement Verification Framework (RVF) by Bruggeman et al. [7] ensures requirements compliance throughout aircraft design phases using a wing box use case. Workflow optimization of MBSE model parameters, MDAO problem setup, and tradeoffs using MBSE activity diagrams have been applied to a mechanical system by Habermehl et al. [8] Swaminathan et al. [9] have used the Extended Requirements-Functional-Logical-Physical (RFLP) Framework to integrate MBSE and MDAO for the design of a single-aisle transport aircraft. At NASA, a MBSA&E framework is being developed for the Advanced Air Transport Technology (AATT) Project under the Sustainable Flight National Partnership (SFNP) initiative. The MBSA&E vision is to have a systems-level, digital integration across SFNP projects, which will support the assessment, advancement, and adoption of sustainable technologies for 2030 entry-into-service subsonic transport aircraft concepts. The research objectives of the MBSA&E activity are 1) to develop an open, cross-project, cross-program, external-capable MBSA&E framework building off the Aeronautics Research Mission Directorate's (ARMD) investments and capabilities across the Advanced Air Vehicles Program (AAVP) and other programs; 2) to conduct coordinated, integrated systems analysis studies using common, open, reference and vision vehicle models; and 3) to conduct technology benefit assessments and sensitivity studies.

This work builds on related work within NASA's MBSA&E activity to demonstrate a novel approach of integrating uncertainty quantification (UQ) in the aircraft design and analysis workflow. UQ encompasses the study of the impact of uncertainties in input parameters and modeling simplifications on the outputs or responses of a process or simulation. UQ can vary in scope by including only a single model or multiple models of varying fidelity as well as experimental data. The overarching objective of UQ is to create a more robust design or evaluation process by identifying sensitivities and mitigating the potential impact of uncertainties through informed, targeted resource investments. Two main types of uncertainty are present in most simulations: model input uncertainty and model form uncertainty. Sources of uncertainty associated with the simulation input parameters are referred to as model input uncertainties, whereas sources of uncertainty associated with modeling simplifications are referred to as model form uncertainties. An important facet of UQ is the proper characterization and treatment of the simulation input uncertainties [10, 11].

This paper consists of five sections. After this Introduction, Section III describes the Transonic Truss-Braced Wing (TTBW) aircraft system model development in MBSE, the disciplinary models in MBSA, the UQ analysis model, and the cross-domain workflow. Section IV explains the TTBW case study and the derived results in terms of confidence intervals applied to the design gross mass and cost evaluations. Section V provides the impact and application of this work and its extension into future work.

## III. Approach and Implementation

The TTBW aircraft geometry used in the demonstration of this work is shown in Fig. 1. This non-proprietary configuration referred to as the TTBW Tech Collector has been developed by NASA in an effort to allow future vehicle technology studies, open publication of results, and easier collaboration with research partners outside of NASA.

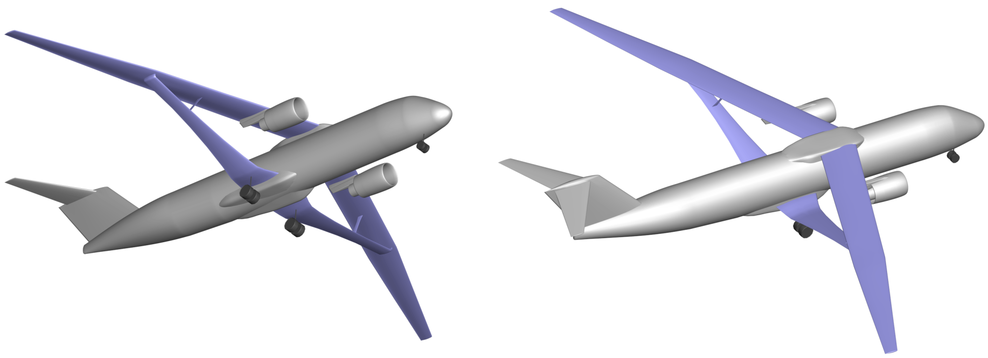


**Fig. 1 NASA Transonic Truss-Braced Wing Tech Collector concept.**

### A. Model-Based Systems Engineering

The aircraft system model was developed using industry MBSE tools, SysML, and elements of the Unified Architecture Framework (UAF). The principles of model consistency were applied to enable the system model to be reusable for different concept vehicles and extendable within an airspace system-of-systems (SoS) through project usages. The MBSE model was constructed using NASA developed and adopted systems engineering [12] and modeling practices [13], processes and requirements [14], technical standards [15], meta-model and hierarchy, model library, data classification, and model documentation. A phased approach was used in developing the MBSE model by 1) building a descriptive system, sub-system, and component level model representing physical decomposition (Fig. 2) and functional decomposition; 2) developing an executable, parametric model which enables mission and design requirements verification, system validation, and trade study analysis; and 3) coupling the MBSE vehicle system model with a multidisciplinary, physics-based MBSA model to yield an integrated modeling environment (IME) which can be used for conceptual design of advanced air vehicles infused with novel and sustainable technologies. The model to be demonstrated is the TTBW Tech Collector aircraft configuration with applied sustainable flight technologies.

The development and demonstration of these MBSE capabilities for conceptual design and mission analysis will introduce digital artifacts to support an integrated technology development of subsonic transport aircraft. The early lifecycle development path will encompass aircraft design and technology readiness of sustainable flight technologies, including all design phases and certification – digital aircraft design to digital flight test.

### B. Model-Based Systems Analysis

The multidisciplinary analysis model, shown in the design structure matrix in Fig. 3, was developed in OpenMDAO [16]. Geometry and aerodynamic performance were modeled with OpenVSP [17, 18] and VSPAERO [18], respectively. These OpenMDAO components are driven using the OpenVSP Python API and input files allow the user to declare and map OpenMDAO input/output variables and options to OpenVSP parameters. VSPAERO aerodynamic analysis was performed using a vortex lattice method with a second-order Karman-Tsien Mach correction. The mean aerodynamic chord of 9.87 ft for the wing is used as the reference length to calculate Reynolds number at the constant

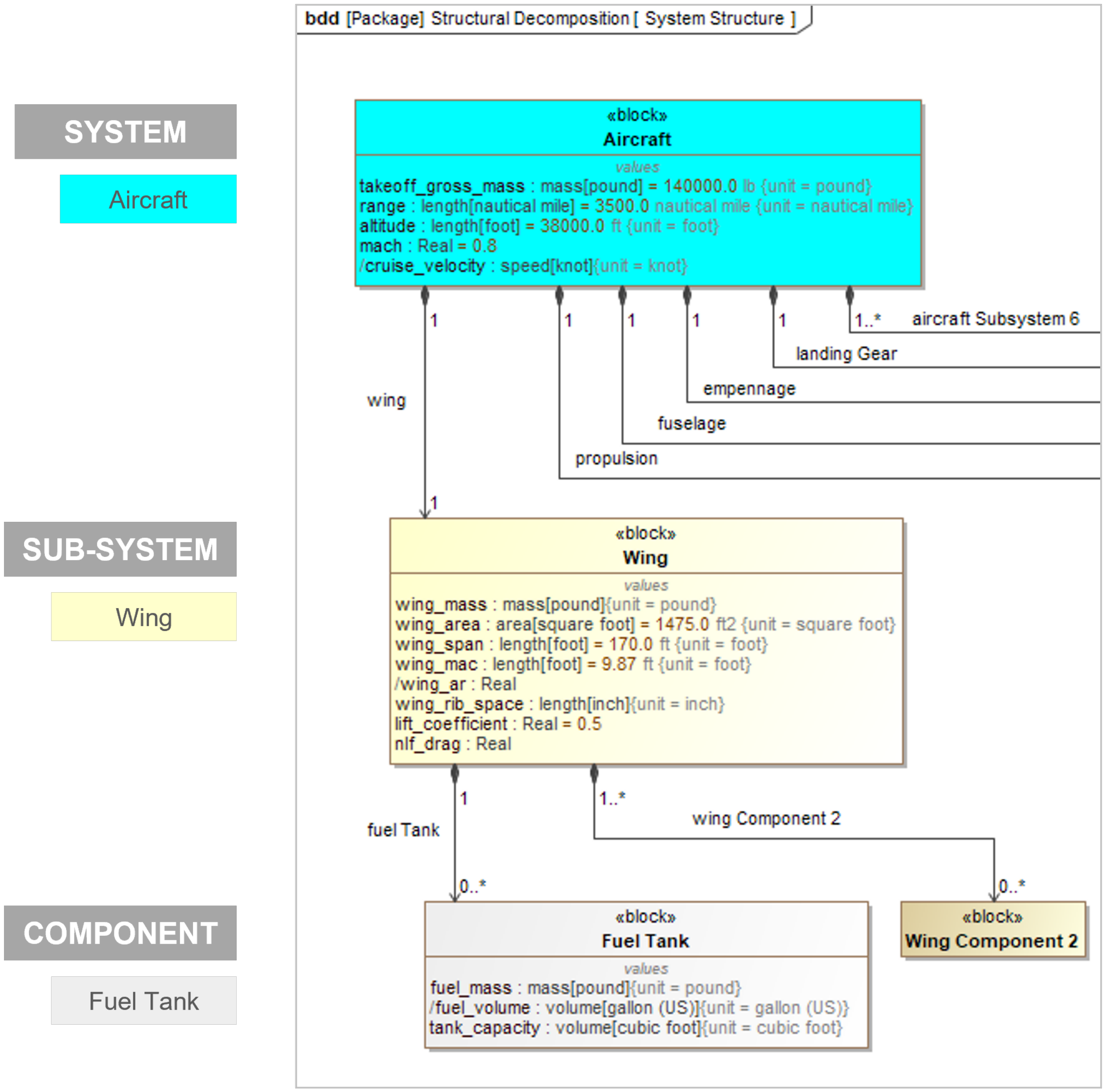



**Fig. 2 MBSE system structure.**

cruise altitude of 38,000 ft and Mach number of 0.8.

The mass of the wing, strut, and jury assembly is calculated using surrogate models based on HyperSizer [19] and Nastran [20] analysis of an aeroelastic model. In this structural model, material properties are smeared for each case to compute deflections, strains, and stresses. Finite element analysis (FEA) data are passed to HyperSizer to compute the local constraints for use in the optimization. The surrogates facilitate trade studies with respect to geometry and structural parameters such as wing aspect ratio, sweep, taper ratio, thickness-to-chord, engine mass, rib spacing, and strut attachment point. Finally, scaling factors are used to correct FEA mass to account for non-modeled structural components including aerodynamic surfaces and secondary structures.

The baseline TTBW concept is modeled using our MBSA&E framework and sized using Aviary [21]. For the demonstration study, this sized and trajectory-optimized design was used to inform a simpler model with a quicker execution time. In this model, the masses of the truss-braced wing and engines are allowed to vary but all other subsystem masses, as well as fuel burn during climb and descent, are held fixed to the baseline quantities calculated

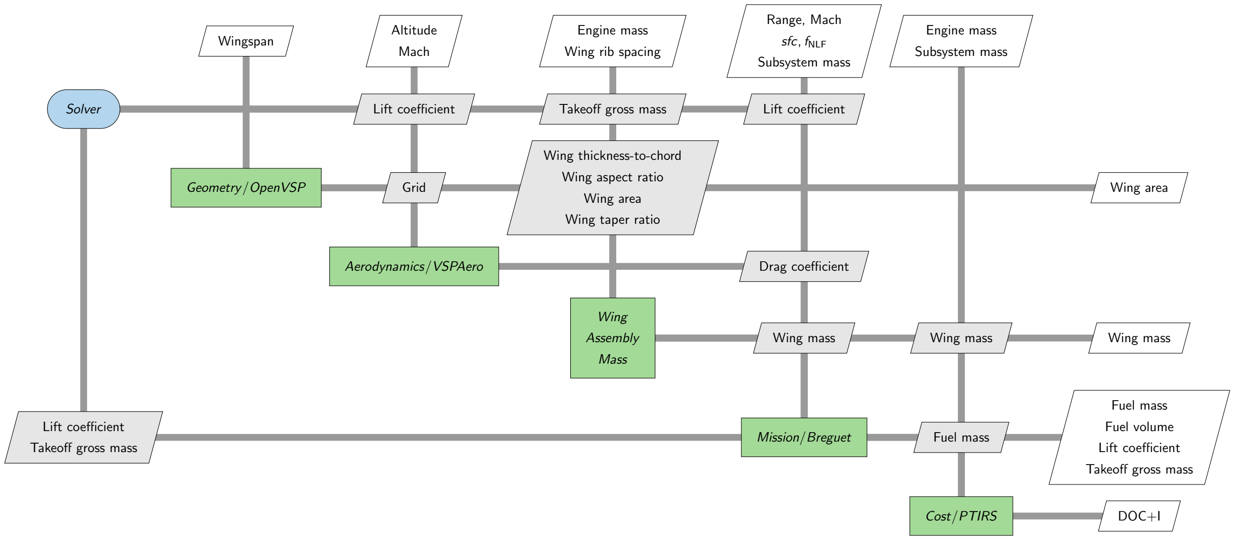



**Fig. 3 Multidisciplinary design structure matrix.**

during the Aviary [21] sizing run. For simplicity, vehicle performance during the cruise phase is modeled using the Breguet range equation, shown in Eq. (1), where $R$ is the range, $sfc$ is the engine specific fuel consumption, $V$ is flight velocity, $g$ is gravity, $\frac{C_L}{C_D}$ is the lift-to-drag ratio, and $W_i$ and $W_f$ are the cruise initial and final vehicle weights. However, note that throughout the paper, mass will be reported instead of weight. The impact of natural laminar flow on the vehicle drag is quantified with the uncertain variable, $f_{NLF}$, which applies a scaling factor to the wing profile drag. The profile drag of the wing is estimated as one-third of the total profile drag and the total profile drag is assumed to be 70% of the total drag of the vehicle [22].

$$R = \frac{1}{sfc}\frac{V}{g}\frac{C_L}{C_D}\ln\left(\frac{W_i}{W_f}\right) \tag{1}$$

This equation is rearranged to compute the change in vehicle mass, or fuel burned, during the cruise phase, as shown in Eq. (2). Here, $C_L$ is the average lift coefficient throughout the constant altitude cruise phase given by Eq. (3), $q$ is the cruise dynamic pressure, and $S$ is the wing reference area. The implicit problem is solved using a Newton solver to converge the lift coefficient in cruise and takeoff gross mass.

$$W_{fuel} = W_i - W_f = W_i(1 - e^{\frac{R}{C}}), \text{ where: } C = \frac{1}{sfc}\frac{V}{g}\frac{C_L}{C_D} \tag{2}$$

$$C_L = 0.5\frac{(W_i + W_f)}{qS} \tag{3}$$

Finally, the Economic Analysis Model from the Probabilistic Technology Investment Ranking System (PTIRS) [23] is used to calculate the Direct Operating Cost Plus Interest (DOC+I). PTIRS is a comprehensive life cycle cost model for development, production, and operations of commercial transport aircraft that can calculate DOC+I for technology-enhanced aircraft and corresponding baseline aircraft. All subsystem mass inputs to the cost model, aside from the wing, strut, and jury assembly, engine, and fuel mass, are assumed constant and set to the values of the reference vehicle.

### C. Uncertainty Quantification Analysis

The subsections below describe the uncertainty modeling methodologies and the corresponding tool used for the uncertainty quantification analysis.

### 1. *Second-Order Probability*

To propagate uncertainty through the model, the second-order probability approach outlined by Eldred and Swiler [24] for the treatment of mixed aleatory and epistemic uncertainties was employed. A flowchart of the method is shown in Fig. 4.

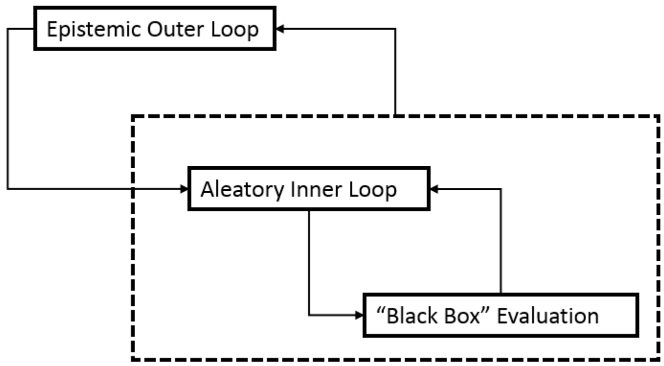



**Fig. 4 Second-order probability architecture.**

For each set of epistemic uncertainties, a cumulative distribution function (CDF) can be generated from the set of aleatory uncertainties as seen in Fig. 5. The probability box (P-Box) plot shows the family of CDF curves generated from the second-order probability approach. For a significance level of $a = 0.05$, the 95% uncertainty interval is determined by extracting the lowest response value at the 2.5% probability level and the highest response value at the 97.5% probability level from the set of CDF curves. The use of the P-Box uncertainty approach is conservative, but it is statistically justifiable for the given inputs to the simulations as no assumption is made about the distribution within the uncertainty interval.

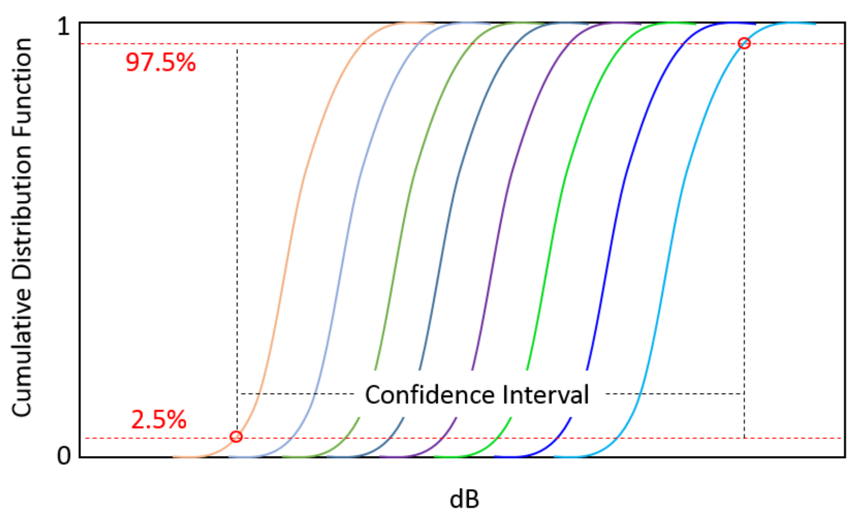



**Fig. 5 Example P-Box.**

### 2. *Point-Collocation Non-intrusive Polynomial Chaos*

Another method used in this research was non-intrusive polynomial chaos with point-collocation. Polynomial chaos is a surrogate modeling technique based on a spectral representation of uncertainty. An important aspect of spectral representation of uncertainty is that a response value or random function, $F$, can be decomposed into separable deterministic and stochastic components, as shown in Eq. (4).

$$F(\boldsymbol{d}, \boldsymbol{\xi}) \approx \sum_{i=0}^{P} A_i(\boldsymbol{d}) \Psi_i(\boldsymbol{\xi}) \tag{4}$$

Here, $A_i$ is the deterministic component and $\Psi_i$ is the random variable basis functions corresponding to the $i^{th}$ mode. The basis functions, $\Psi_i$, of each random variable are determined using the Askey key [25] and are dependent on the distribution of each random variable. The response, $F$, is a function of independent, random variables, $\boldsymbol{\xi}$, and deterministic variables, $\boldsymbol{d}$. This series is in theory an infinite series but is truncated in practice. To form a complete basis or for a total order expansion, $N_t$ terms are required, which can be computed from Eq. (5) for a polynomial chaos expansion (PCE) of order $p$ and the number of random dimensions or variables, $n$.

$$N_t = P + 1 = \frac{(n+p)!}{n!p!} \tag{5}$$

Further details on polynomial chaos theory are given by Eldred and Swiler [24]. To compute the expansion coefficients, $A_i$, a point-collocation method is used by Hosder et al. [26]. The response, $F$, is sampled at locations throughout the random variable space, and the expansion coefficients are computed with an over-determined, least squares approach. At least $N_t$ samples are needed for this procedure; Hosder et al. [26] recommend an oversampling ratio of two (i.e., $2 \cdot N_t$ samples).

*3. Uncertainty Quantification with Polynomial Chaos Expansion*

The uncertainty modeling and analysis contained in this research was performed with one of NASA's in-house uncertainty codes, Uncertainty Quantification with Polynomial Chaos Expansion (UQPCE) [27]. UQPCE is an open source, Python-based research code for use in parametric, non-deterministic computational analysis and design. UQPCE utilizes a non-intrusive polynomial chaos expansion surrogate modeling technique as outlined in Section III.C.2 to efficiently estimate uncertainties for computational analyses. The software enables the user to perform an automated uncertainty analysis for any given computational code without requiring modification to the source. UQPCE estimates sensitivities, confidence intervals, and other model statistics which can be useful in the conceptual design and analysis of flight vehicles.

### D. Cross-domain Interface

A diagram of the cross-domain interface between MBSE and MBSA is shown in Fig. 6. A set of mission instances is generated from the MBSE model based on stakeholder input and the data are exported to two text files containing 1) the mission parameter values (e.g., wingspan and cruise range) and 2) the design parameter values required to conduct system validation and verification against system requirements (e.g., total fuel mass, wing mass, wing area, and direct operating cost plus interest). The OpenMDAO component labeled MBSE driver in Fig. 6 is used to read the analysis or mission-specific aircraft design requests from the MBSE model, set up and execute the multidisciplinary problem, and return the required performance metrics of interest, which are imported back into the MBSE model. These metrics include not only a deterministic value but also a confidence interval associated with the analysis or design. Lastly, since individual mission instances are independent, both the MBSE driver and UQPCE can leverage parallel execution through Message Passing Interface (MPI) to reduce total computational time.

## IV. Demonstration and Results

The case study is explained in this section, and the final results are shown and discussed along with the impact of the development of an integrated modeling environment for conceptual aircraft design.

### A. Case Study

In this study, the goal is to demonstrate that a coupling of MBSE, MBSA, and UQ tools and methodologies improves confidence in the systems analysis and design. The mission instances are derived from a combination of system requirements for the reference TTBW concept vehicle and parametric models associated with the objective functions of minimizing weight, fuel burn, and operating cost from within the MBSE environment. Each instance corresponds to a simulated mission defined by a set of range and wingspan parameters. Table 1 shows the mission instances and their respective mission and geometry parameters.

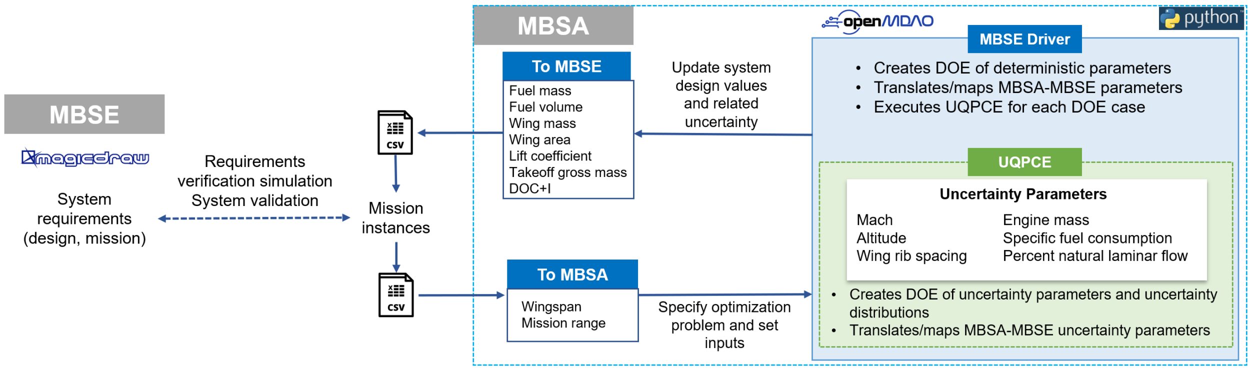



**Fig. 6 Cross-domain interface.**

**Table 1 Mission parameters from MBSE**

| Instance | Range, nmi | Wingspan, ft |
|---|---|---|
| Baseline | 3,500 | 170 |
| Aircraft 1 | 2,000 | 170 |
| Aircraft 2 | 3,000 | 175 |
| Aircraft 3 | 3,000 | 180 |
| Aircraft 4 | 4,000 | 165 |
| Aircraft 5 | 5,000 | 175 |

These parameters were passed into the MBSA environment for optimization using OpenMDAO, where deterministic and uncertain parameters were run through a design of experiments (DOE). The uncertain variables used for this case study are described in Table 2. In the UQ environment, uncertainty distributions are developed using UQPCE analysis, which is executed for each aircraft geometry and mission instance. The design parameters with related uncertainty are mapped back to the mission instances. The responses for wing area, wing mass, fuel volume, fuel mass, wing lift coefficient, gross mass, and cost are returned to MBSE for requirements verification and system validation (V&V). Note that the process is not limited to these parameters and is sufficiently general to allow passing and returning any parameter that can be mapped between MBSA and MBSE.

**Table 2 Uncertain variables**

| Input | Distribution | Parameters | |
|---|---|---|---|
| $f_{\mathrm{NLF}}$ | Epistemic | [0.0, 0.5] | |
| Mach | Uniform | [0.75, 0.85] | |
| Cruise Altitude | Gaussian | $\mu$=38,000 | $\sigma$=150 |
| Wing Rib Spacing | Gaussian | $\mu$=20 | $\sigma$=0.5 |
| *sfc* | Gaussian | $\mu$=0.4394 | $\sigma$=0.005 |
| Engine Mass | Gaussian | $\mu$=4,578 | $\sigma$=3 |

## B. Results

The application of UQ to assess the impact of uncertainty on stakeholder requirements is shown in Table 3. Each instance requires trajectory optimization to minimize fuel burn and resize the vehicle to meet the mission requirements.

The resulting key design parameters of wing area, gross mass, fuel mass and fleet direct operating cost plus interest (DOC+I) are shown for each instance. Apart from the deterministic parameter, wing area, both the mean value and confidence interval are shown. The selected uncertain parameters of gross mass, fuel mass, and DOC+I are shown in Table 3 because they correlate to the initial objective functions of mass, fuel, and cost minimization defined in MBSE. A V&V simulation is intended to compare the aircraft design to stakeholder requirements and validate the vehicle system in terms of sizing and weight constraints in a defined operating environment. A system indicator of pass or fail determines the V&V status. In this study, the V&V takes in to consideration the requirements as compared to the mean values and also assesses the requirements margin as compared to the confidence interval. The results show that the aircraft design related to the third mission instance failed the V&V because the mean cost value of $568 billion did not meet the requirement for the cost not to exceed $565 billion. The fifth mission instance failed the V&V because both its mean gross mass value of 147,000 lbm and the upper confidence interval value of 151,000 lbm exceeded the system requirement and operational bounds of 145,000 lbm.

**Table 3 Verification and validation of uncertain design parameters in MBSE**

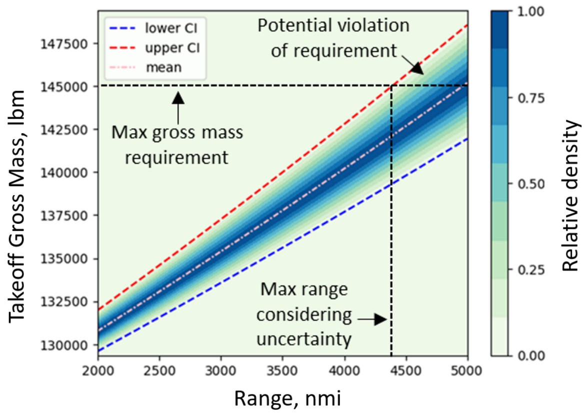
| Instance | Wing Area, $ft^2$ | Gross Mass, K-lbm | Fuel Mass, K-lbm | Fleet DOC+I, $B | System |
|---|---|---|---|---|---|
| Baseline | 1,475 | $\mu$=138, [136, 140] | $\mu$=19, [17, 21] | $\mu$=559, [559, 560] | Pass |
| Aircraft 1 | 1,475 | $\mu$=131, [130, 132] | $\mu$=12, [11, 13] | $\mu$=564, [564, 565] | Pass |
| Aircraft 2 | 1,541 | $\mu$=137, [136, 139] | $\mu$=17, [15, 18] | $\mu$=564, [563, 564] | Pass |
| Aircraft 3 | 1,607 | $\mu$=139, [138, 141] | $\mu$=17, [15, 18] | $\mu$=568, [567, 568] | Fail |
| Aircraft 4 | 1,408 | $\mu$=138, [136, 141] | $\mu$=21, [19, 23] | $\mu$=556, [555, 556] | Pass |
| Aircraft 5 | 1,541 | $\mu$=147, [144, 151] | $\mu$=26, [23, 29] | $\mu$=564, [563, 564] | Fail |

UQPCE was used to build second-order models on several responses including gross mass. The models were validated by ensuring that the order of the model was sufficient for the underlying physics and that the model mean error, signal-to-noise ratio, and distribution of error were all acceptable.

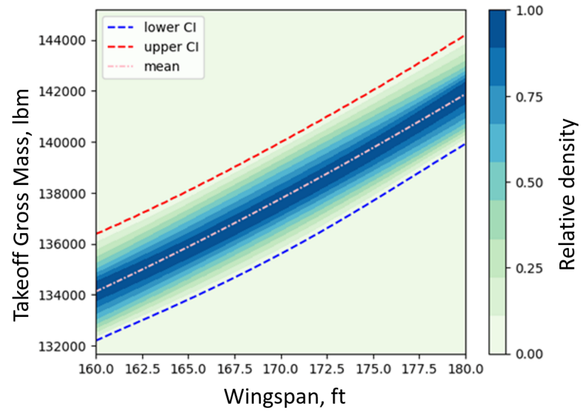
The systems analysis considers the uncertainty associated with flight conditions, structural sizing, and aerodynamic and propulsion efficiency, leading to more confidence in the assessment of system level metrics related to vehicle sizing and cost evaluations. Figure 7a shows the probability density of the uncertain response gross mass with variation in design range for the baseline geometry with a wingspan of 170 ft. The mean expected value and lower and upper 95% confidence intervals are given by the yellow, blue, and red lines, respectively. A similar uncertainty quantification plot with respect to wingspan is shown in Fig. 7b, where wingspan is varied while holding the baseline range of 3,500 nmi constant.

Figure 7a shows an increasing linear trend between mission range and takeoff gross mass. The width of the uncertain interval increases as range increases, which could be due to the epistemic uncertain parameter $f_{\mathrm{NLF}}$ and the aleatory uncertain parameter *sfc*. In Eq. 2, the range, *sfc*, and $f_{\mathrm{NLF}}$ are all in the numerator of the exponential term. Any change in *sfc* or $f_{\mathrm{NLF}}$ affects the rate of fuel consumption instead of a constant offset of fuel consumption. The change in rate with respect to range leads to a widening of the uncertain interval as range increases. Figure 7b shows a nearly linear increase in the gross mass as span increases. Both the lower and upper confidence intervals follow the same trend, increasing at the same rate as the mean.

The plot in Fig. 7a also shows the importance of uncertainty quantification when presenting analysis and design data to a decision-making stakeholder. The horizontal black dashed line in this figure shows the maximum allowable gross mass based on the requirement defined in the MBSE system model in MagicDraw. This maximum gross mass requirement is observed to intersect the mean value at a design range of 5,000 nmi, potentially leading the stakeholder to incorrectly assume that the vehicle will always be able to satisfy this requirement as long as range is less than 5,000 nmi. However, under uncertain conditions, it is possible for vehicles designed for a range of 4,400 nmi or greater to violate the maximum gross mass requirement of 145,000 lbm. This additional information can now be provided to the stakeholder through the implemented MBSE-MBSA interface, allowing more informed decisions and reducing costly future re-designs.




**(a) Uncertainty of takeoff gross mass with range.**




**(b) Uncertainty of takeoff gross mass with wingspan.**

**Fig. 7 Uncertainty quantification for vehicle sizing.**

## V. Summary and Future Work

The paper has outlined a demonstration study of integrating uncertainty quantification in the conceptual aircraft design process by coupling MBSE, MBSA, and UQ tools, methods, and models. The resulting MBSA&E-UQ framework enables an improved system design and analysis with a goal of assessing the technical feasibility and fully exploring the design space of new aircraft concepts and novel flight technologies.

This study progresses previous research by developing a working MBSA&E framework which can be applied to aircraft design and mission engineering. This work shows the benefit of using a MBSA&E framework, which is to leverage the capabilities associated with both the MBSE and the MBSA disciplines to derive a complete modeling and simulation environment for conceptual vehicle design and analysis. One of the challenges was in coupling MBSE-MBSA-UQ environments to enable the exchange of and translation of models and data. This was addressed by developing an MBSE driver which mapped MBSE-MBSA mission and design parameters to a common aircraft data dictionary and facilitated the input and output of data in each domain. For the MBSA-UQ analysis, this was addressed by updating the MBSE driver to allow parsing of uncertainty information when available, and additional software was developed to support executions of analysis models that were not inherently vectorized, as is the case with the MBSA model.

The future work will utilize the extensible MBSE system model to conduct safety, reliability, and sustainability assessments of conceptual aircraft design. Further work is planned in demonstrating the integration of MBSA&E-UQ into a digital engineering platform to expand digital aircraft design capabilities and predictive mission modeling and to create a design lifecycle thread. Lastly, the simplified systems analysis model used in this work will be updated to use Aviary for vehicle sizing and mission analysis.

## Acknowledgments

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## References

[1] *INCOSE Systems Engineering Handbook*, International Council on Systems Engineering, 2015.

[2] Blackburn, M., "Transforming Systems Engineering through Model-Centric Engineering," Tech. Rep. SERC-2021-TR-012, Systems Engineering Research Center, Hoboken, NJ, August 2021. URL `https://sercproddata.s3.us-east-2.amazonaws.com/technical_reports/reports/1657127968.A013_SERC%20WRT%201036_Technical%20Report%20SERC-2021-TR-012%2Bcov.pdf`.

[3] Aiello, O., Kandel, D. S. D. R., Chaudemar, J.-C., Poitouz, O., and de Saqui-Sannes, P., "Populating MBSE Models from MDAO Analysis," *IEEE International Symposium on Systems Engineering (ISSE)*, 2021. https://doi.org/10.1109/ISSE51541.2021.9582519.

[4] Chaudemar, J.-C., and Saqui-Sannes, P. D., "MBSE and MDAO for Early Validation of Design Decisions: a Bibliography Survey," *IEEE International Systems Conference (SysCon)*, 2021. https://doi.org/10.1109/SysCon48628.2021.9447140.

[5] Ciampa, P. D., Nagel, B., and Rocca, G. L., "A MBSE Approach to MDAO Systems for the Development of Complex Products," AIAA Paper 2020–3150, June 2020. https://doi.org/10.2514/6.2020-3150.

[6] Ozoroski, L. P., Geiselhart, K. A., Padula, S. L., Li, W., Olson, E. D., Campbell, R. L., Shields, E. W., Berton, J. J., Gray, J. S., Jones, S. M., Naiman, C. G., Seidel, J. A., Moore, K. T., Naylor, B. A., and Townsend, S., "Initial Multidisciplinary Design and Analysis Framework," NASA TM–2010-216711, 2010.

[7] Bruggeman, A.-L. M., van Manen, B., van der Laan, T., van den Berg, T., and Rocca, G. L., "An MBSE-Based Requirement Verification Framework to support the MDAO Process," AIAA Paper 2022–3722, June 2022. https://doi.org/10.2514/6.2022-3722.

[8] Habermehl, C., Höpfner, G., Berroth, J., Neumann, S., and Jacobs, G., "Optimization Workflows for Linking Model-Based Systems Engineering (MBSE) and Multidisciplinary Analysis and Optimization (MDAO)," *Applied Sciences*, Vol. 12, No. 5316, 2022, pp. 1–24. https://doi.org/10.3390/app12115316.

[9] Swaminathan, R., Sarojini, D., and Hwang, J. T., "Integrating MBSE and MDO through an Extended Requirements-Functional-Logical-Physical (RFLP) Framework," AIAA Paper 2023–3908, June 2023. https://doi.org/doi.org/10.2514/6.2023-3908.

[10] Walker, E., Hemsch, M. J., and West, T., "Integrated Uncertainty Quantification for Risk and Resource Management: A NASA Langley Perspective (Invited)," *53rd AIAA Aerospace Sciences Meeting*, AIAA, 2015. https://doi.org/10.2514/6.2015-0501.

[11] Oberkampf, W. L., and Roy, C. J., *Verification and Validation in Scientific Computing*, Cambridge University Press, New York, NY, 2010.

[12] "NASA Systems Engineering Handbook," NASA SP-2016-6105 Rev 2, 2016.

[13] "NASA Systems Modeling Handbook for Systems Engineering," NASA HDBK-1009, 2022.

[14] "NASA Systems Engineering Processes and Requirements," NASA NPR 7123.1D, 2020.

[15] "NASA Standard for Models and Simulations," NASA STD-7009A, 2016.

[16] Gray, J. S., Hwang, J. T., Martins, J. R. R. A., Moore, K. T., and Naylor, B. A., "OpenMDAO: An Open-Source Framework for Multidisciplinary Design, Analysis, and Optimization," *Structural and Multidisciplinary Optimization*, Vol. 59, 2019, pp. 1075–1104. https://doi.org/10.1007/s00158-019-02211-z.

[17] Hann, A., "Vehicle Sketch Pad: A Parametric Geometry Modeler for Conceptual Aircraft Design," AIAA Paper 2010-657, January 2010. https://doi.org/10.2514/6.2010-657.

[18] McDonald, R. A., and Gloudemans, J. R., "Open Vehicle Sketch Pad: An Open Source Parametric Geometry and Analysis Tool for Conceptual Aircraft Design," AIAA Paper 2022-0004, January 2022. https://doi.org/10.2514/6.2022-0004.

[19] *HyperSizer User's Manual, Book 2: Analytical Method and Verification Examples*, Collier Research & Development Corp., Hampton, VA, September 1998.

[20] "The NASTRAN theoretical manual," Nasa, 1981.

[21] Gratz, J., Kirk, J., Recine, C., Jasa, J., Aretskin-Hariton, E., Moore, K., Caldwell, D., Lyons, K., Schnulo, S., Falck, R., Schilling, H., Olson, E., Pham, D., Jiang, X., Murri, S., Margolis, B., Hendricks, E., Gray, J., Naylor, B., Phillips, B., Garcia, J., Marfatia, K., and Wrenn, G., "Aviary: An Open-Source Multidisciplinary Design, Analysis, and Optimization Tool for Modeling Aircraft with Analytic Gradients," AIAA Paper Pending, July 2024.

[22] Somers, D. M., "Design of a Slotted, Natural-Laminar-Flow Airfoil for a Transport Aircraft," NASA CR-2019-220403, August 2019.

[23] Frederic, P., Bezos-O'Connor, G. M., and Nickol, C., *Cost Analysis Approach in the Development of Advanced Technologies for Green Aviation Aircraft*, John Wiley & Sons, Ltd, 2016, pp. 1–13. https://doi.org/https://doi.org/10.1002/9780470686652.eae1078, URL https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470686652.eae1078.

[24] Eldred, M., and Swiler, L., "Efficient Algorithms for Mixed Aleatory-Epistemic Uncertainty Quantification with Application to Radiation-Hardened Electronics; Part I: Algorithms and Benchmark Results," Tech. Rep. SAND2009-5805, Sandia National Laboratories, September 2009.

[25] Xiu, D., and Karniadakis, G. E., "The Wiener–Askey Polynomial Chaos for Stochastic Differential Equations," *SIAM Journal on Scientific Computing*, Vol. 24, No. 2, 2002, pp. 619–644.

[26] Hosder, S., Walters, R. W., and Balch, M., "Point-Collocation Nonintrusive Polynomial Chaos Method for Stochastic Computational Fluid Dynamics," *AIAA Journal*, Vol. 48, No. 12, 2010, pp. 2721–2730.

[27] Phillips, B. D., and Schmidt, J. N., "UQPCE v0.3.0," https://github.com/nasa/UQPCE, 2023.