QUANTITATIVE FIDELITY MANAGEMENT AND SELECTION OF PHYSICS-BASED MULTIDISCIPLINARY DESIGN ENVIRONMENTS

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Keywords: *physics-based modeling, model fidelity, probabilistic analysis*

Abstract

Computer modeling and simulation environments are used widely in engineering disciplines for the design of next generation systems. Detailed physics-based models can add unwanted complexity to the overall modeling environment, so there is a need to be able to select the appropriate model with an adequate amount of fidelity. The methodology developed in this research provides a way to manage the fidelity and facilitate down-selection from a provided set of potential models through quantitative assessments. The concept of model form uncertainty is utilized to represent model fidelity, and an existing system-level physics-based modeling environment enables the quantitative assessments of additional potential model combinations. The methodology is demonstrated on a case study inspired by the recent shift in aviation towards environmentally conscious aircraft systems.

1 Introduction

Advancements in the field of computer science over the past 50 years have led to the use of computer models and simulations for engineering problem solving[13]. Modeling and simulation provides many benefits, such as the ability to conduct a large number of assessments over a short period of time, a safer testing alternative for live experiments with potential consequences, and identification of system shortcomings before live tests are conducted[5]. In the same manner that a prototype is considered a ‘model’ of a real, full-scale system and a wind tunnel experiment a ‘simulation’ of an actual flight test, an analytical, mathematical representation is also a model, and the use of a computer based environment to create data a ‘simulation’ [3].

The fundamental makeup of models can range from those that are empirically based upon a historical database to physics-based mathematical representations. Empirical models can only predict behavior of systems within the limits of their design space. However, when attempting to assess a system design that introduces a phenomenon that has not been previously characterized, engineers must instead develop and utilize physics-based models due to the lack of historical data. For example, when aggressive aircraft performance goals are set, next generation systems are designed to push the envelope through the integration of advanced technologies onto new, unconventional configurations. When it is anticipated that the performance of these complex systems will introduce new, uncharacterized phenomena, a physics-based formulation will be required.

Unlike empirical models, physics-based models explicitly depend on the laws of nature, which are characterized through mathematical formulas and integrated together to provide a quantitative representation of the physics that govern the system. However, the true form of a model representing a system under development may not be known, which causes uncertainty to exist with respect to how accurately the chosen model properly represents the system under assessment. This type of uncertainty is called model form uncertainty, and it is a type of epistemic uncertainty[12]. The amount of model form uncertainty that exists in a modeling environment is a function of the amount of detail put into each tool within the model and the amount of data available to characterize the system. As new data about the system becomes available, the model is calibrated to meet the observed performance characterized by the experimental data. Models that are represented with a great amount of detail should have a decreasing amount of model form uncertainty as they are continuously re-calibrated throughout the system's development. Model form uncertainty and model fidelity are inversely correlated. Model fidelity is defined as a measure of the realism of a model or simulation. Therefore, as model form uncertainty decreases, the perceived model fidelity will increase.

During design, modeling environments are used to provide information that can be used for decision support. Figure 1 displays a generic, top-down decision support process that can be used as a framework for making design decisions. Within this process, models are used during the "Evaluate alternatives" step to provide information about each of the design alternatives. Engineers desire information that has limited uncertainty, which makes high fidelity modeling environments attractive. However, a high fidelity physics-based environment that represents each aspect of a system in great detail can become increasingly complex, especially when it is a multidisciplinary system. Increasing complexity can result in an increase in the amount of time and computational resources required to run a single simulation, which can hinder the usefulness of the model to engineers. Therefore, engineers require a way to select appropriate physics-based modules to create a modeling and simulation environment that has an adequate fidelity level without over-complicating the environment and contributing to an unnecessary increase in execution time.

The research presented in this paper provides a methodology for quantitatively assessing different combinations of physics-based models by

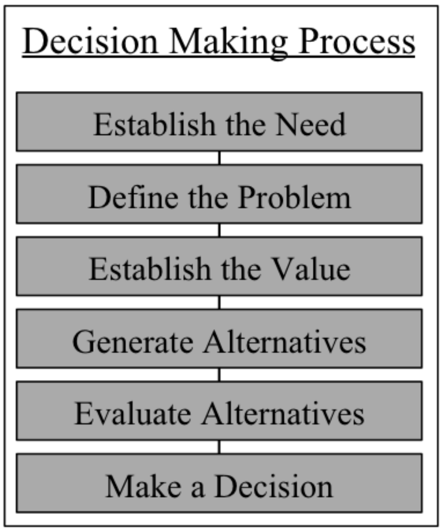

Fig. 1 : Generic top down decision making process.

utilizing an existing, baseline physics-based environment, surrogate models, and a technology forecasting technique. The quantitative assessment will provide information on the combined complexity of each alternative and the ability of each alternative to provide results within a desired precision level. This information will then be used to conduct trade-offs between complexity and fidelity and enable the down-selection of a final modeling environment. The methodology is based upon the assumption that model form uncertainty can be used as a surrogate for model fidelity, and the representation of model form uncertainty can be used to aid model fidelity prioritization. Additionally, execution time will be used as a surrogate for model complexity.

2 Background

The methodology developed in this research relies on two enabling techniques: surrogate modeling and a technology forecasting technique called the k-factor approach. The following subsections will provide information about both techniques.

2.1 Technology Forecasting Technique

Forecasting is the process of predicting a view of the future. Technology forecasting refers to determining the impact a technology will have on a system's performance before it is fully realized and can be measured[8]. There are two different types of forecasts: exploratory and normative. Normative forecasting techniques are top-down assessments where an objective with an unknown feasibility is provided and the goal of the forecast is to work backwards from the provided objective to determine what is required to make it feasible[8]. Alternatively, exploratory forecasting techniques are bottom-up assessments that are based upon extending past trends into the future along an expected progression path[8].

Performing a quantitative technology forecast requires the quantitative representation of the technologies under assessment. Twiss, however, acknowledges that representation of technologies in a quantitative manner is not trivial, especially if the physics governing the technology has not been properly characterized or is not well understood[17]. A technique that facilitates technology forecasting in a system modeling environment was developed and is referred to as the technology k-factor approach[11, 7]. The k-factor approach represents technologies, or potential impacts of technologies, in a system modeling environment as defined delta's with respect to a current system baseline. The k-factors directly modify computed metrics during the analysis, which enables the technology benefits and penalties to be included in the simulation. The technology k-factors provide a way to simulate the technology benefits or penalties in a generic way [11, 8, 7].

$$W_{fuel} = \left[(k_{W_{empty}} * W_{empty}) + W_{payload}\right] \left[exp\left(\frac{Range * k_{TSFC} * TSFC}{V} * \frac{k_{C_D}}{k_{C_L}} * \frac{D}{L}\right) - 1\right] \quad (1)$$

Equation 1 displays fuel weight for a fixed range mission as a function of the intermediate metrics aircraft empty weight (W_{empty}), payload weight ($W_{payload}$), thrust specific fuel consumption ($TSFC$), and aircraft lift and drag. This equation demonstrates how the technology k-factor modeling approach can be implemented. The terms k_{TSFC}, k_{C_L}, k_{C_D}, and $k_{W_{empty}}$ are used to represent technologies that could potentially impact the intermediate metrics.

2.2 Surrogate Modeling

Surrogate models, or metamodels, are approximations of a complex analysis model [11, 16]. Hence, they can be described as a model of a model [16]. Surrogate models are based upon the original models, therefore the physics-based relationships between the inputs and outputs will be retained. They are, however, less complex than the original analysis model but still accurate to a certain degree. The reduced complexity can lead to faster simulation times and less computational expense.

There are many different types of surrogate models, including Response Surface Equations (RSEs) and Artificial Neural Networks[11, 9]. RSEs are polynomial regressions of the model outputs as a function of the model inputs. They are developed by using a Design of Experiment (DOE) technique to sample the inputs within their valid ranges and then regressing the simulation outputs as a function of the inputs. The ability of the RSE to capture interactions of the input variables depends on the order of the model. For example, a quadratic regression model, or second order RSE, will capture linear effects, quadratic effects, and two-variable interactions[9].

Artificial Neural Networks (ANN), another type of surrogate model, are models that are inspired by the central nervous system and used heavily in the discipline of machine learning. ANNs map inputs to outputs by developing a network of hidden nodes, or neurons, which mimics a biological neural network. There can be many layers of hidden nodes, and the number of layers depends on the complexity of the phenomena being modeled. Determination of the nodes, and their weightings, is done by utilizing a set of training data. In general, ANNs provide a better representation of systems with non-linear behavior than RSEs.

3 Technical Approach

The quantitative fidelity management methodology developed for this research provides a way to perform trade-offs between model fidelity and model complexity of integrated design environments. The methodology leverages the capabilities provided by surrogate modeling and the technology k-factor approach to enable quantitative assessments of all model combinations, which facilitates down-selection of the final modeling environment. Development of the methodology was done by following the generic top-down decision support framework previously discussed and presented in Figure 1. Similarly to the manner the decision support framework is used to determine the final design of a system, it can also be followed to choose the modeling environment most appropriate for system design support.

An integrated modeling environment is created to meet specific modeling needs with respect to system design. The goals of the environment must be enumerated and explained before different potential models can be assessed and compared. The goals can be provided in the form of metrics the environment should be able to quantify. Multidisciplinary models are capable of tracking a variety of metrics that capture the performance at multiple levels of the integrated system; therefore, the most important metrics with respect to the design process must be identified and selected to track the progress. Therefore, the first step of the methodology is:

- **Step 1:** Identify responses of interest

Next, the tools that will facilitate the assessment of the potential model alternatives should be identified and prepared. It was established that the technology k-factor modeling approach provides a way to quantitatively represent technology impacts within an existing modeling environment. The k-factors can be seen as calibration parameters because they alter the outputs the modeling environment produces for a given set of inputs by acting on intermediate metrics. Additionally, uncertainty can be added to the system assessment through probabilistic k-factors, which would cause the outputs of the modeling environment to also be probabilistic. Therefore, the k-factor concept provides a way to introduce uncertainty into a model.

The ability to add uncertainty into an existing environment through the k-factor approach can be leveraged for the fidelity management methodology. In the context of model fidelity, the k-factors can be used to represent the fidelity of different alternative models, or sets models, before they have been integrated and exercised. Based upon this observation, the k-factors in an existing, baseline modeling environment are utilized within this research to represent the model alternatives under assessment and are referred to as k'-factors.

Utilizing k'-factors to represent model alternatives requires that a baseline modeling environment that quantifies the appropriate responses and has relevant k'-factors built into its modules exists. Once this baseline environment and the k'-factors have been identified, the model then must be exercised to obtain the information required to assess the model alternatives. The number of alternative models, or the number of model combinations, under consideration may be large. This implies the simulation time of the baseline modeling environment may need to be decreased, which can be achieved via surrogate models. It was previously established that surrogate models are created by formulating a DOE that captures the design variables ranges, conducting the simulations, and utilizing the resulting data to establish the mathematical relationships. Likewise, surrogate models of the responses of interest can be fit as a function of the identified k'-factors. This will enable a set of functions that retains the physics-based relationships between the k'-factors and responses and decreases the time it will take to evaluate the alternatives.

This information leads to the next three steps of the methodology:

- **Step 2:** Obtain baseline modeling environment
- **Step 3:** Identify potential k'-factors and enumerate acceptable ranges
- **Step 4:** Formulate surrogate models

Next, before the alternative models are evaluated, it is important to determine what value metrics will be used to facilitate model comparisons. It has been established that the primary trade-off under consideration is between the fidelity and the complexity of the integrated modeling environment. For this research the fidelity of the integrated modeling environment will be quantified through the amount of error surrounding the responses, where small error values correspond to a high fidelity environment. The complexity of the environment will be quantified through the computational effort, which will be measured in terms of execution time. A small execution time corresponds to an environment with a low complexity. Fidelity and complexity goals for the integrated environment can be set in terms of the error and execution time, which is Step 5 of the methodology.

- **Step 5:** Establish environment fidelity and complexity goals or thresholds

Once the value has been established for the alternative models, the models themselves and their defining characteristics should be enumerated. The alternative models are mapped to the k'-factors according to the intermediate metrics each model calculates. Therefore, each model should be mapped to one or more k'-factors. After the mappings are completed, the fidelity and complexity of each individual model should be captured. The fidelity, or model form uncertainty, of each model is represented by an error margin applied to the relevant k'-factors, which can later be translated into a probability distribution function, The complexity of each model is represented by an execution time. This leads to the following methodology steps:

- **Step 6:** Identify all model alternatives and their corresponding error and execution times

- **Step 7:** Map alternative models to identified k'-factors

Next, the model alternatives are evaluated. Comparison of the potential models is facilitated by propagating the k'-factor uncertainty distributions to the identified responses through the surrogate models. This enables a probabilistic representation of the responses as a function of the uncertainty of each model or model combination. Once this is completed for each model combination, the probabilistic information can be used to capture the fidelity of each simulated environment. There are various ways the probabilistic results can be displayed, and this research utilizes the prediction profiler approach to demonstrate the sensitivities of the responses to the uncertainty in each of the k'-factors. The concept of a prediction profiler will be discussed in the next section.

The resulting fidelity and complexity information for each combination of models is used to perform trade-offs and enable a down-selection to a final integrated environment. It will be demonstrated through the case study implementation that a dynamic scatterplot assessment was created to enable on-the-fly trade-off assessments for the potential model combinations. Finally, the information provided by the prediction profiler and scatterplot will be used to aid the down-selection of the final environment based on the enumerated fidelity and complexity goals for the integrated environment. Therefore, the final steps of the methodology are as follows:

- **Step 8:** Obtain probabilistic assessment results for each response

- **Step 9:** Conduct trade-offs between complexity and fidelity

- **Step 10:** Down-select final environment

Figure 2 visually summarizes each of the enumerated steps of the fidelity management methodology.

4 Methodology Implementation

The fidelity management methodology outlined in the previous section has been applied to a case study inspired by the current goals of the the aerospace industry, which are related to diminished environmental impacts. The motivation for this shift comes from a variety of statistics dealing with projected air travel growth [2, 1], increased fuel prices[15, 2], atmospheric emissions effects [1, 15, 10], and community

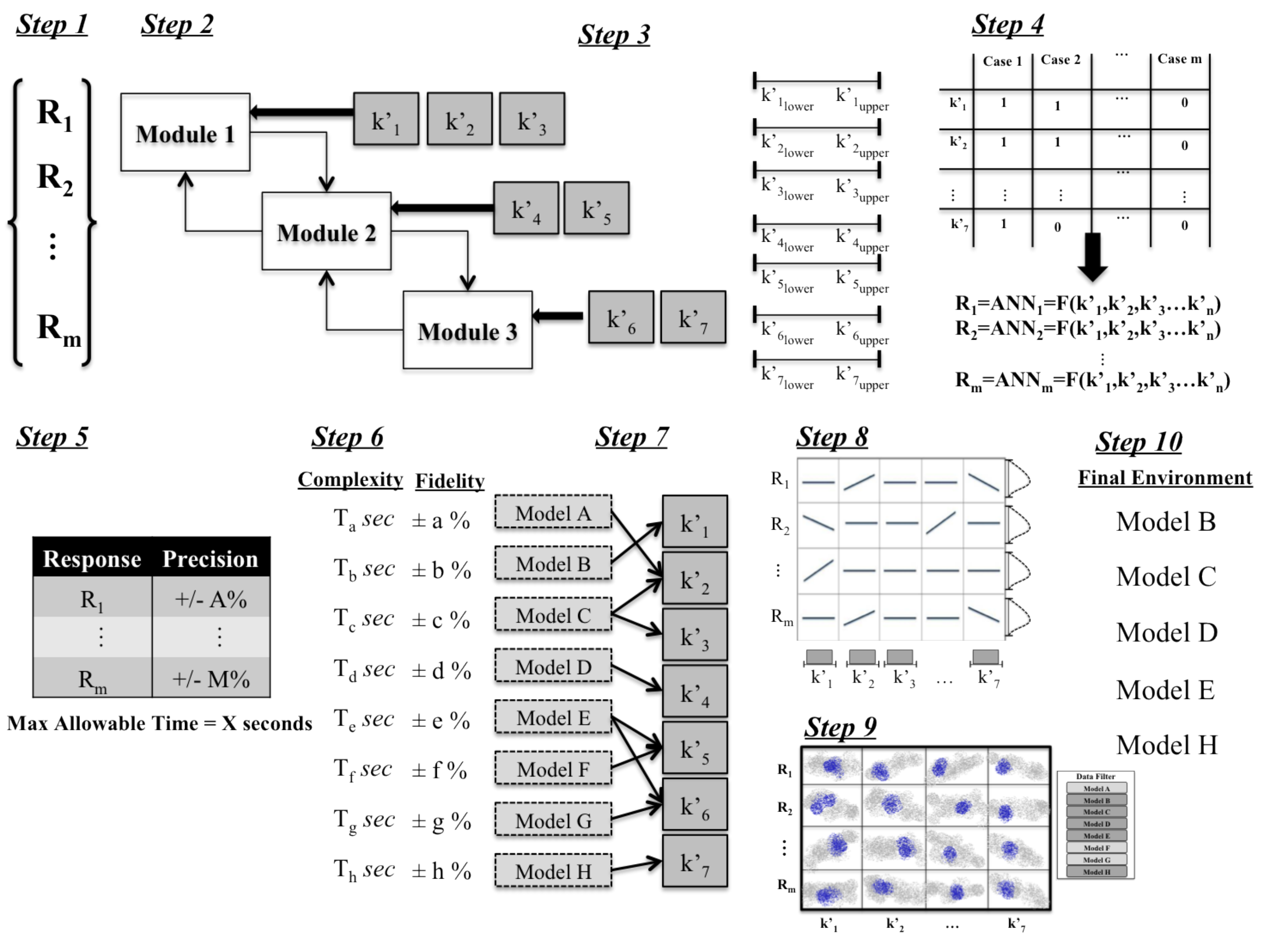

Fig. 2 : Fidelity management methodology depiction.

noise concerns[4]. Government entities have acknowledged the air travel environmental problem and plans have been put in place to undertake them. Specific goals were outlined in the 2010 National Aeronautics Research and Development Plan (NARDP) for near term (2015, or N+1), mid term (2020, or N+2), and far term (2025, or N+3) time frames to guide future research plans. Government agencies, such as the FAA and NASA, have responded to these goals by forming three separate technology research and development programs aimed at targeting each of the three time frames: the FAA's Continuous Lower Energy, Emissions and Noise (CLEEN) project, NASA's Environmentally Responsible Aviation (ERA) project, and NASA's Fixed Wing (FW) program. Figure 3 displays the goals for each program.

The following subsections provide an implementation of the enumerated methodology and discuss all relevant results.

Technology Benefits	N+1	N+2	N+3
Noise (cum below Stage 4)	- 32 dB	- 42 dB	-52 dB
LTO NOx Emissions (below CAEP 6)	-60%	-75%	-80%
Cruise NOx Emissions (rel. to 2005 best in class)	-55%	-70%	-80%
Aircraft Fuel/Energy Consumption (rel. to 2005 best in class)	-33%	-50%	-60%

Fig. 3 : Environmental goals for N+1, N+2, and N+3 timeframe.

4.1 Step 1

Identify responses of interest

The responses selected to track for this research were chosen because of their relation to the environmental objectives displayed in Figure 3. Three responses were chosen and they are as follows: vehicle operating empty weight in pounds (OEW), mission fuel weight in pounds, and approach noise is decibels.

4.2 Step 2

Identify and obtain baseline modeling environment

For a baseline modeling environment, the Environmental Design Space (EDS) was chosen because of its capabilities and its availability. EDS is a modeling and simulation environment developed for the FAA and is based on well-established NASA modules[6]. Each of the modules within EDS are partial physics-based formulations, and altogether they enable the assessment of source noise, exhaust emissions, and performance of both current aircraft vehicle systems and future aircraft systems with new, emerging technologies[14]. The modules within EDS are:

- **Numerical Propulsion System Simulation (NPSS)**
- **Compressor Map Generator (CMPGEN)**
- **Weight Analysis of Turbine Engines (WATE)**
- **Flight Optimization System (FLOPS)**
- **Pressure and Temperature Correlations (P3T3)**
- **Aircraft Noise Prediction Program (ANOPP)**

The modules are integrated through the object-oriented NPSS coding language to enable automated information passing. Figure 4 displays the overall architecture and demonstrates how the information flows within the environment. Additionally, EDS is capable of assessing various vehicle classes and configurations. The vehicle model utilized for this research is a large single aisle seat class (150 passenger) tube and wing aircraft system with a 2960 nmi design range. The model is representative of approximately a 1995 era aircraft.

4.3 Step 3

Identify potential k'-factors and enumerate acceptable ranges

Five calibration parameters within EDS were identified for the case study k'-factors. Table 1 provides the names of the k'-factors, the metric within EDS they alter, and their allowable ranges. These parameters were selected for the case study because of their relationship to the responses identified in Step 1. Factors FRFU, FRWI, and FCDO are applied by being multiplied directly with the baseline model value of their affected metrics. In contrast, VCTE and Fan_ Deff are absolute scalar changes, meaning the parameter value is is added directly to the baseline model metric value.

Table 1: EDS k'-factors for case study.

k'-factor	Affected metric	Min Value	Max Value
FRFU	Fuselage weight	0.7	1.0
FRWI	Wing weight	0.75	1.0
FCDO	Parasite drag	0.8	1.0
VCTE	Trailing edge camber	0.2	0.3
Fan_ Deff	Fan efficiency	-0.008	-0.005

4.4 Step 4

Formulate surrogate models

A space filling DOE was generated over the k'-factor ranges provided in Table 1 and the corresponding EDS simulations were performed. Due to the complexity of the EDS environment, ANNs were fit for each of the three responses. It was determined that the ANNs retained the relationships between the k'-factors and responses, which is demonstrated through the R^2 values provided in Table 2.

Table 2: Artifical Neural Network R^2 statistics.

Response	R^2 Value
OEW	0.99909
Fuel Weight	0.99636
Approach noise	0.99423

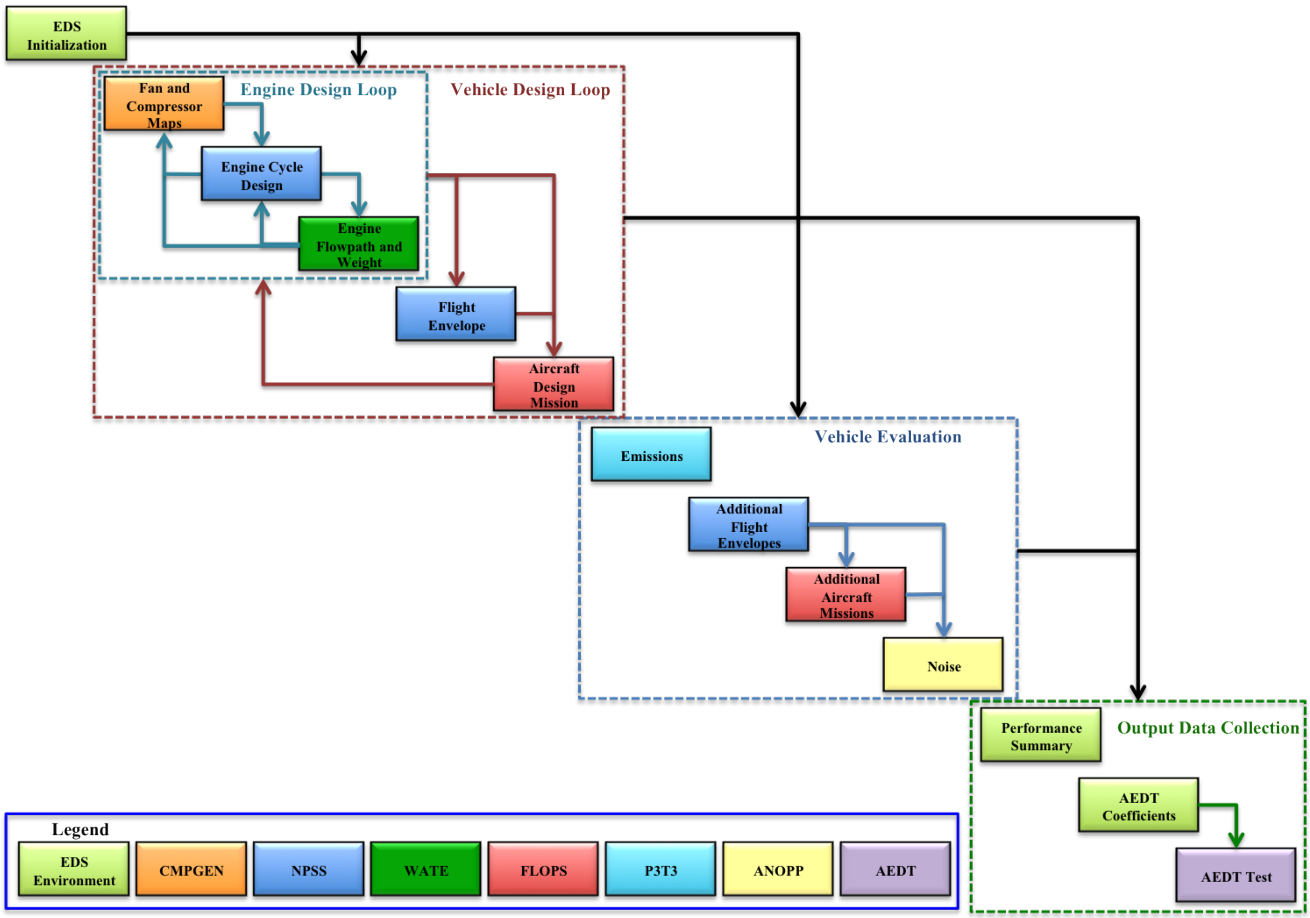

Fig. 4 : Environmental Design Space.

4.5 Step 5

Establish environment fidelity and complexity goals or thresholds

Desired fidelity, or precision, thresholds were enumerated for each of the three responses. The precision thresholds are $\pm4.5\%$ for OEW, $\pm0.5\%$ for approach noise, and $\pm4.5\%$ for fuel weight. A threshold for complexity, or execution time, was not explicitly set. Instead, the goal for the case study is to choose a combination of models that meets the defined fidelity goals while minimizing the execution time.

4.6 Step 6 and Step 7

Identify all model alternatives and their corresponding error and execution times

Map alternative models to identified k'-factors

Eleven potential models were selected for the case study. Note that these models do not actually exist, but were created for the case study to demonstrate the methodology. Metadata that defines the fidelity and complexity characteristics of the models were also created. The metadata was defined in a manner that ensures a range of fidelity and complexity combinations exists. Two model alternatives each were mapped to FRFU, FRWI, FCDO, and Fan_ Deff, while three alternative models were mapped to VCTE. Table 3 displays the models, their corresponding metadata, and the k'-factor mappings. map to the k'-factors.

Table 3: Model alternatives and their fidelity and complexity metadata.

Model	k'-factor mapping	Fidelity	Complexity (sec)
A1	FRFU	±6%	148
A2	FRFU	±14%	9
B1	FRWI	±5%	221
B2	FRWI	±12%	12
C1	FCDO	±5%	602
C2	FCDO	±2.5%	221
D1	VCTE	±4%	518
D2	VCTE	±11%	15
D3	VCTE	±17%	6
E1	Fan_ Deff	±10%	20
E2	Fan_ Deff	±18%	5

4.7 Step 8

Obtain probabilistic assessment results for each response

Uniform distributions were characterized for each of the k'-factors based off the ranges used for surrogate generation. The uncertainty was propagated through the surrogate models using a 10,000 case Monte Carlo simulation to provide probabilistic characterizations of the three responses. Figure 5 depicts the input distributions for the k'-factors and the output distributions for the three responses.

The uncertainty propagation enables identification of the k'-factors that drive the uncertainty in each of the responses for the given input ranges. Figure 5 also displays the results of this sensitivity analysis in the form of prediction profilers for each combination of the three responses and five k'-factors. The prediction profiler displays the prediction traces for each k'-factor, which are defined as the predicted response in which one factor is changed while the others are held at their current values[8]. The impact of the k'-factors can be determined by observing the magnitudes and directions of the slopes. It is observed that both FRFU and FRWI have strong impacts on all three responses in comparison to the other k'-factors. Additionally, it appears that VCTE has a relatively low impact on the three responses.

4.8 Step 9

Conduct trade-offs between complexity and fidelity

In order to compare the probabilistic results for all potential modeling combinations, an environment that is dynamic and parametric was required. Therefore, an interactive scatterplot platform was created that provides a filtering mechanism for the Monte Carlo simulation results. Each point in the scatterplot is characterized by a vector of inputs, which is a value of each k'-factor, and a vector of outputs, which is the response values calculated by the surrogates. The filter enables the selection of sets of points that have common characteristics, which further enables identification of trends within the data. Figure 6 provides a depiction of the platform with all sampling results displayed. The axes for the scatterplot are in terms of percent error instead of absolute value as they were for the prediction profiler. The expected value, or mean value, of the input and output distributions displayed in Figure 5 were used as the baseline value for the ± percentages. The scales for all y-axes and all x-axes are consistent to enable a visual comparison of the amount of error present.

Each of the 10,000 points from the Monte Carlo simulation were characterized by the combination of models they represent. The sampled values for the k'-factors for each data point were used to create these characterizations. The appropriate model combination for each point was chosen by identifying the highest fidelity model that could achieve the sampled percent error for each k'-factor. Table 4 displays information on two data points to demonstrate how the percent error values for the k'-factors were used to assign model combinations.

Once model combinations were assigned for each point, the integrated complexity for each combination was calculated by summing the execution times for all models in the combination. The execution times were then used for color-coding the scatterplot, as seen in Figure 6. Recall that high execution times correspond to high complexity.

After the interactive platform was created,

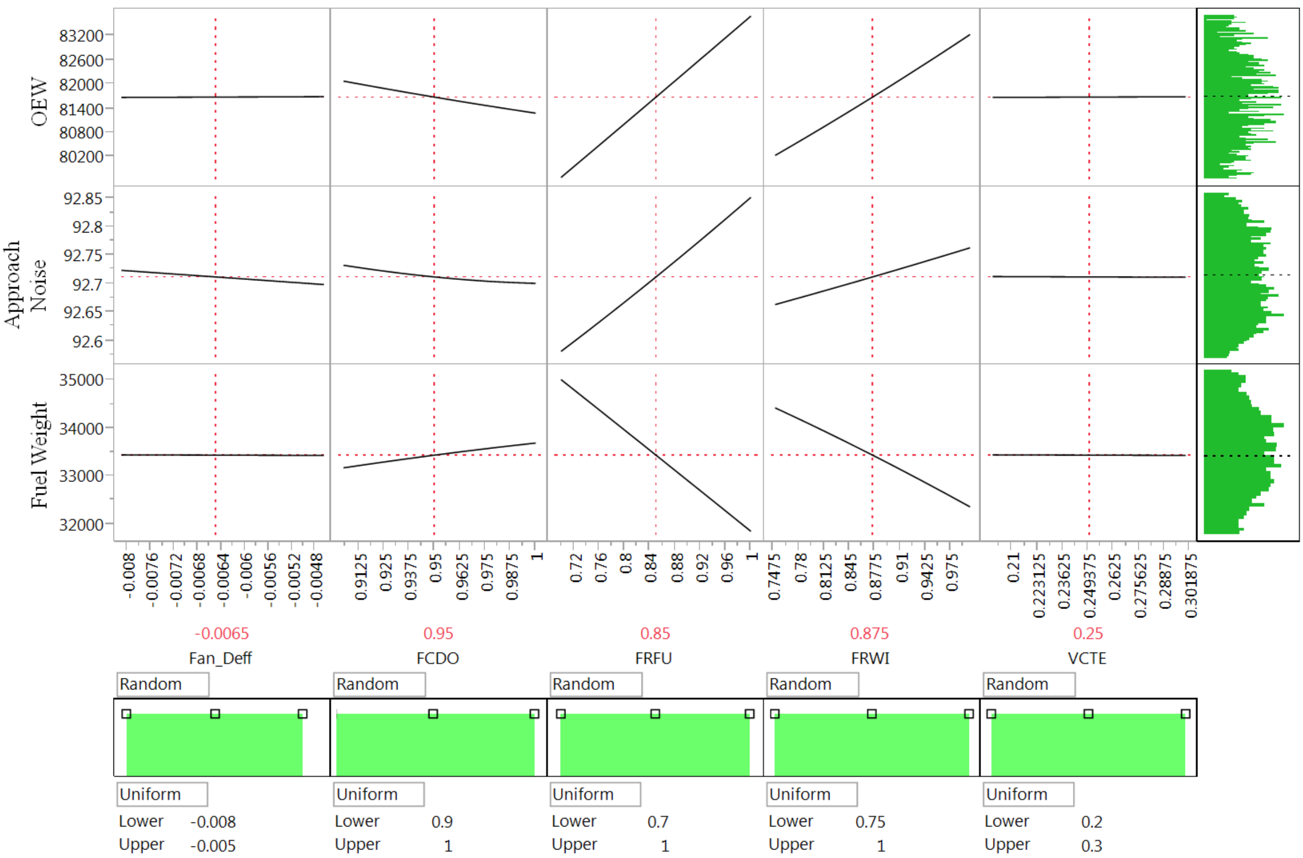

Fig. 5 : Prediction profiler and Monte Carlo simulation results.

it was exercised to asses the complexity-fidelity trade-off for the potential model combinations. Figure 7 depicts one way the platform was exercised. First, the precision thresholds established in Step 5 for each of the three responses were overlaid onto the scatterplot, which enables visual identification of points that fall within the thresholds and points that exceed the thresholds. The scenario shown on the left side of Figure 7 displays all points that map to the the model combination *A1-B1-C1-D1-E1*, which is the combination with the highest fidelity. It is clear that all points fall within the precision thresholds for all three responses; however, the dark red coloring of the points is indicative of a high execution time. Indeed, this combination of models has the highest execution time, which is 1,509 seconds or approximately 25 minutes. In contrast, the scenario shown on the right side of Figure 7 displays all points that map to the model combination *A2-B2-C2-D3-E2*. This corresponds to the combination with the lowest combined fidelity and complexity. It is observed that the points fall outside the error thresholds for the responses; however, the execution time has been reduced to 253 seconds or approximately 4 minutes.

4.9 Step 10

Down-select final environment

The models enumerated in Table 3 correspond to a total of 48 possible model combinations that could be selected. The probabilistic platform shown in Figure 6 and Figure 7 provides an informative look at the fidelity and complexity of each potential combination, but assessing each combination may be too cumbersome. Therefore, for the sake of demonstrating down-selection a subset of combinations was selected. Selection of the subset was done by considering the sensitivity results shown in Figure 5 and the metadata in Table 3. As previously stated, FRFU and FRWI both have strong impacts on the responses. Therefore, it is assumed that having a low-fidelity representation of both will cause the precision

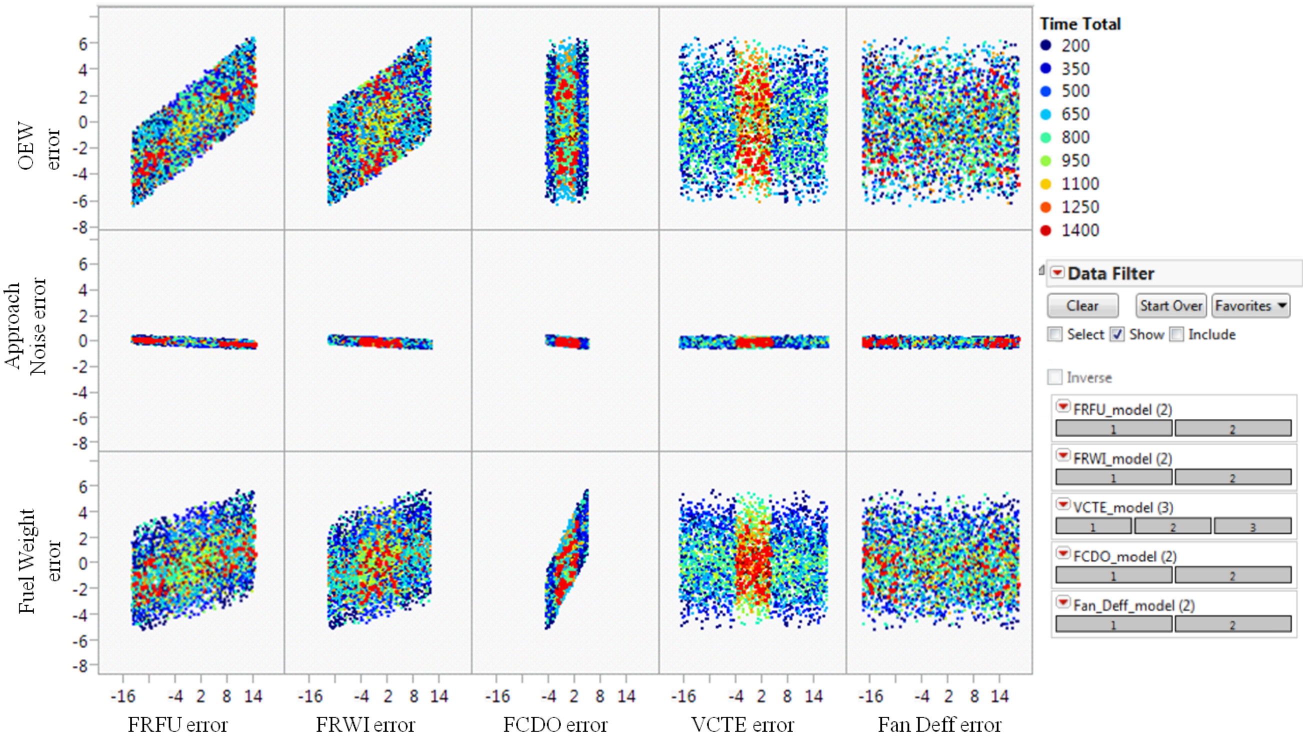

Fig. 6 : Scatterplot matrix colored by execution time.

Table 4: Example of how model combinations were assigned for each data point.

	Point 14	Point 335
% FRFU	-6.4	-5.6
FRFU Model	A2	A1
% FRWI	8.9	11.0
FRWI Model	B2	B2
% FCDO	2.2	-3.6
FCDO Model	C1	C2
% VCTE	0.2	11.7
VCTe Model	D1	D3
% Fan_ Deff	-5.3	11.6
Fan_ Deff Model	E1	E2

goals to not be met. Additionally, it was noted that VCTE appears to have a weak impact on all responses. This would imply a low-fidelity representation is appropriate, especially if there is a large savings in execution time. Observing the metadata for VCTE's model alternatives shows that choosing model *D3* over model *D1* would provide a time savings of 512 seconds, which is significant.

Based upon these observations, model *D3* was selected for all combinations considered. Additionally, all combinations include the pair *A1-B2* or A2-B1, which ensures that either FRFU or FRWI will be represented with the highest fidelity option. Finally, all potential combinations of models for FCDO and Fan_ Deff are considered. Therefore, these assumptions create a subset of eight combinations out of the original 48. They are defined as follows:

1. *A1-B2-C1-D3-E1*
2. *A1-B2-C1-D3-E2*
3. *A1-B2-C2-D3-E1*
4. *A1-B2-C2-D3-E2*
5. *A2-B1-C1-D3-E1*
6. *A2-B1-C1-D3-E2*
7. *A2-B1-C2-D3-E1*
8. *A2-B1-C2-D3-E2*

The probabilistic platform was used to analyze each of the enumerated combinations. The

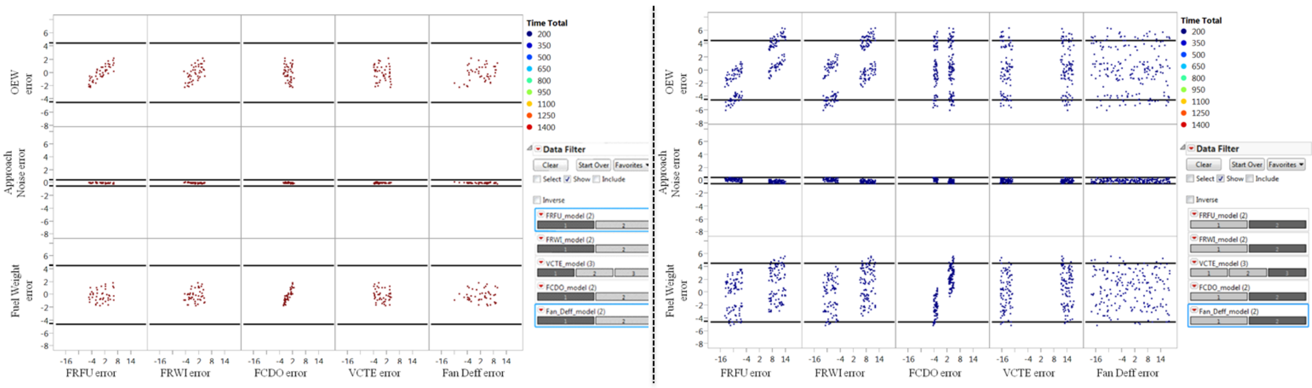

Fig. 7 : Demonstration of the probabilistic model comparison environment.

maximum observed error for each response was identified for each combination, as well as the overall execution time. Figure 8 displays the results for OEW error, Figure 9 displays the results for approach noise error, Figure 10 displays the results for fuel weight error, and Figure 11 provides the execution times. The error goals for OEW, approach noise, and fuel weight are plotted on the corresponding figures to identify which combinations exceed the allowable error range. It is observed that all combinations meet the 0.5% allowable error for approach noise. For fuel weight, Combination 3 and Combination 8 exceed the 4.5% allowable error. Combination 2, Combination 3, and Combination 4 are able to meet the 4.5% allowable error for OEW. Therefore, only two combinations out of the eight in the subset are able to simultaneously stay within the allowable error thresholds, and they are Combination 2 and Combination 4.

Recalling the goals set in Step 5, the objective is to select an integrated environment that meets the provided precision goals and minimizes execution time. Therefore, the final down-selection between Combination 2 and Combination 4 is made by comparing their execution times. As seen in Figure 11, Combination 4 has a significantly lower execution time than Combination 2. The exact time for Combination 4 is 392 seconds and the exact time for Combination 2 is 773 seconds. Therefore, Combination 4 would be selected because it provides a 381 second savings in execution time while still enabling the precision goals to be met.

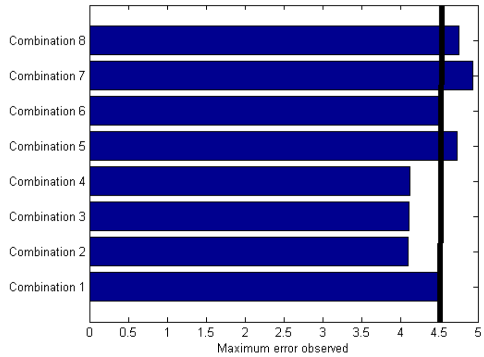

Fig. 8 : Maximum observed OEW error for each model combination.

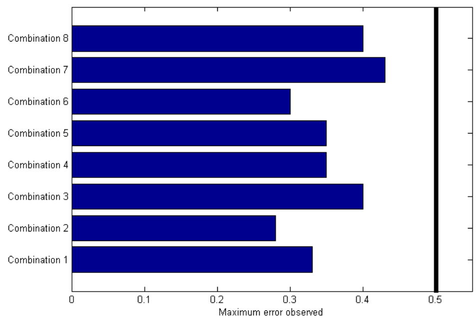

Fig. 9 : Maximum observed approach noise error for each model combination.

5 Conclusions

Modeling and simulation will continue to be used in the future for the design of next generation systems, and these models will become increasingly complex as more modeling effort is put into them. Models that become over-complex will result in execution times that hinder their usefulness; conversely, models that do not include enough detail about the system under assessment will produce simulation results surrounded by too much uncertainty. Therefore, there is a need to be able to identify areas of the system that should be represented by high-fidelity analysis codes to minimize wasted effort and produce results that are surrounded by a limited amount of uncertainty.

A method that facilitates the quantitative management of model fidelity and complexity has been presented and demonstrated. The capabilities provided by mature enablers have been synthesized to provide the opportunity to produce quantitative fidelity assessment results. It has been demonstrated through the defined case study that the method presented in this research can help engineers determine parts of the system where high fidelity representation is most needed.

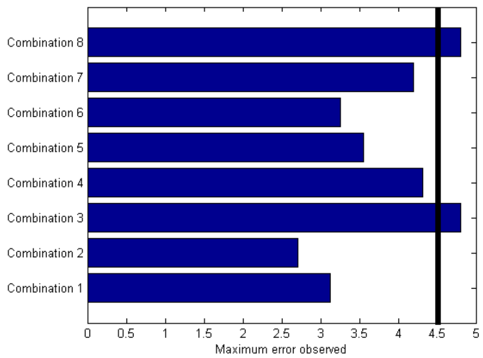

Fig. 10 : Maximum observed fuel weight error for each model combination.

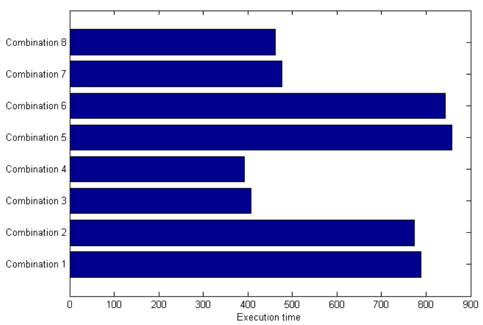

Fig. 11 : Integrated execution time for each model combination.

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