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FORMULATION OF AN EXPERIMENT SELECTION METHODOLOGY FOR UNCERTAINTY REDUCTION AND APPLICATION TO ACTIVE FLOW CONTROL

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Abstract

Many technologies have the potential to alleviate concerns related to the environmental impact of commercial aviation. However, there is considerable uncertainty surrounding the impacts that integration of these technologies will have on future aircraft. In this paper, the foundation is established for a physical experiment selection methodology that aims to maximize the reduction of uncertainty and the maturation of technologies. Throughout the methodology formulation, a case study is described for an active flow control technology currently under development.

1 Introduction

Commercial aviation forecasts continue to predict increased passenger traffic and fleet expansion, and concerns about the environmental impact of the commercial aviation sector have grown accordingly. Many public and private organizations have set aggressive goals to address these concerns. For instance, the National Aeronautics and Space Administration (NASA) Environmentally Responsible Aviation (ERA) project has been established to simultaneously meet goals, shown in Table 1, for noise, emissions, and fuel burn. Reconfiguration and optimization of traditional vehicle architectures is likely not sufficient for achieving these goals; thus, the maturation of advanced vehicle concepts and enabling technologies is being pursued.

Table 1 NASA ERA system-level metrics and goals (adapted from Ref. [1])

Technology benefits[1]	N+2 (2020)
Noise (cum. below stage 4)	-42 dB
LTO NOx (below CAEP6)	-75%
Cruise NOx[2]	-70%
Aircraft fuel burn[2]	-50%

[1]Referenced to a Boeing 777-200 with GE90 engines
[2]Relative to 2005 best in class

One of the technologies that has been identified with the potential to alleviate environmental concerns, in addition to other integration issues, is active flow control (AFC). Although scientific AFC research has been ongoing since Prandtl's suction flow control experiments over 100 years ago [2], few production vehicles currently operate with these technologies. Most of the vehicles are military aircraft that employ boundary layer control for wing lift augmentation. For example, the Mikoyan-Gurevich MiG-21 has an internally-driven boundary layer control system, and the Boeing C-17 Globemaster III uses externally-blown flaps. Traditional boundary layer control devices utilize steady suction or blowing to control the time-averaged flow state, whereas modern AFC devices control flow instabilities. One of the primary benefits of the modern AFC devices, from an integration viewpoint, is that they are typically more energy efficient than boundary layer control devices.

Unlike boundary layer control devices, modern AFC devices are relatively immature; the shift from laboratory settings to real-world aeronautical applications began around the year 2000 [3]. Due to the immaturity of modern AFC devices, system-level integration effects are not well-understood. If uncertainty surrounding these effects is not reduced during modern AFC technology development programs, then vehicle integrators will face additional risk when the technologies are adopted.

Uncertainty surrounding technology integration effects can be reduced by gaining knowledge from the "right" physical experiments. For any advanced technology development program, justification of investments is usually based on the premise that uncertainty in performance, cost, and schedule will be reduced [4]. These investments should not be squandered by selecting experiments that result in minimal uncertainty reduction. Technology readiness levels (TRLs) are used as a figure of merit for assessing and communicating the maturity of novel technologies, and they provide vague guidelines for the experimental demonstrations that must occur to "graduate" each maturity level. However, TRLs do not explicitly capture the uncertainty reductions that complement maturation. A physical experiment that satisfies the qualitative requirements of a given TRL does not necessarily guarantee that significant uncertainty reduction will be attained.

Choosing the "right" physical experiments is challenging. Many combinations of options such as experimental facility, variable settings, and geometry can be proposed. Decision makers (DMs) need a way to evaluate each of the proposed experiments based on uncertainty reduction, resource requirements, maturation, and other criteria. Adding to the difficulty, some of the criteria may be conflicting. As an example, the most inexpensive experiment to perform will likely not provide the most uncertainty reduction.

In an ideal technology development program, physical experiments will be optimally selected to reduce uncertainty and increase maturity so that the full potential of the technology can be exploited. The research presented in this paper provides an important contribution that is necessary to enable this vision: formulation of an experiment selection methodology for reducing uncertainty surrounding the integration impacts of immature technologies.

The next section of this paper provides background information about the case study and the relationship between uncertainty and knowledge. Then, key elements of the proposed methodology are presented along with application to the case study. Finally, the last section ends with a summary and the future direction for research. Note that, throughout the rest of this paper, modern AFC devices will be referred to with the initialism *AFC*.

2 Background

Continuing with the AFC theme set by the motivation for this research, section 2.1 introduces an AFC technology that is currently under development by NASA and its partners. This technology is used as a case study for the proposed methodology. Then, section 2.2 discusses uncertainty, knowledge, and understanding in the technology development context.

2.1 Technology for the case study: the AFC-enhanced vertical tail

A commercial transport drag reduction approach that is currently being investigated in the NASA ERA project is to use AFC actuators installed just upstream of the rudder hinge line to enable vertical tail (VT) area reduction. This can be accomplished by controlling rudder flow separation to enhance the side force generated by the VT during critical flight situations, such as asymmetric power at takeoff. The AFC device that is being used for actuation is called a sweeping jet. This is a type of fluidic oscillator that produces a pulsed jet when supplied with pressurized fluid [5]. A typical sweeping jet actuator configuration is depicted in Fig. 1. The jet that enters the main cavity of the sweeping jet attaches to one

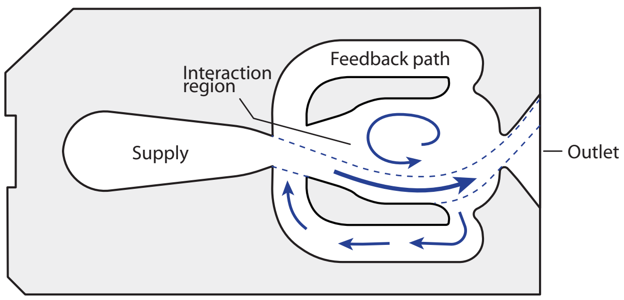

Fig. 1 Sweeping jet actuator that is installed just upstream of the rudder hinge line (from Ref. [5]).

side of the cavity wall, due to the Coanda effect [6]. Then, the pressure in the adjacent feedback loop increases. The higher pressure forces the jet to the opposite cavity wall, and the same process repeats cyclically. For separation control applications, the sweeping motion of the jet is important for effectiveness. This is because, in addition to the jets injecting momentum to the flowfield, the sweeping motion of adjacent jets promotes the formation of streamwise vortices that remove low-momentum fluid from the boundary layer and supply it with high-momentum fluid from the outer region [7]. An additional benefit is that the sweeping motion enables larger spacing between actuators than non-oscillatory jets with the same effectiveness.

The sweeping jet actuator was developed more than 50 years ago at the Harry Diamond Laboratories and was originally used in analog computers and fluidic amplifiers [8]. More recent investigations have been conducted to explore the use of sweeping jets for aeronautical applications (e.g., [8, 9, 10, 11]). The actuators have been tested at full scale on an isolated Boeing 757 VT, where a 20–30% side-force enhancement was demonstrated at conditions similar to takeoff and landing [12]. Results from the full-scale experiments are being used to determine optimal actuator placement and supplied mass flow rate for flight experiments on Boeing's ecoDemonstrator 757 aircraft.

Although VT area reduction would reduce the weight and drag of an aircraft, installation of an AFC system in the VT would degrade performance as well. A power distribution architec-

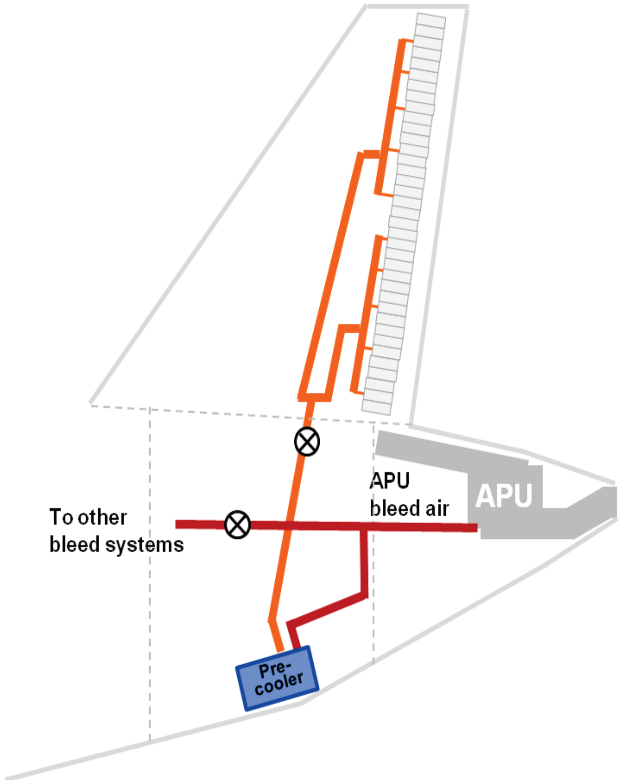

Fig. 2 AFC power distribution architecture designed by Boeing (from Ref. [13]).

ture is required to deliver pressurized air from a source, such as an auxiliary power unit (APU), to the sweeping jet actuators. An example of an AFC architecture is shown in Fig. 2. As seen in the figure, flow supply lines would be routed from the APU bleed point to the sweeping jet actuators. Since the hot bleed flow from an APU may transfer too much heat to the aircraft structure, a pre-cooler would be required. Additional components such as these would add weight to the vehicle. There would also be a fuel burn penalty due to operating the APU for takeoff and landing segments of the mission. Other concerns include increased costs, increased complexity, reliability, and noise. However, the current application scenario being considered for this technology is to install it only on some members of a commercial transport family. The VT of a commercial transport family is typically the same area for all family members and sized for the shortest member; thus, members with longer fuselages carry VTs with non-optimal areas. The use of AFC actuation will enable the VT to be sized for the longest family member.

2.2 Uncertainty, knowledge, and understanding

As a technology matures, its success is determined by DMs who must balance and mitigate the uncertain costs and benefits of introducing the technology to a vehicle development program. With this context in mind, the authors follow Nikolaidis [14] in defining uncertainty indirectly from the definition of certainty. Nikolaidis defines *certainty* as the condition of possessing all knowledge that is needed to choose the action with the most desirable consequences. Uncertainty can then be defined as the gap between certainty and a DM's present state of knowledge. This concept is illustrated in Fig. 3a.

Uncertainties are often categorized using a taxonomy that has been developed by the risk assessment community [15]:

- *Aleatory uncertainty*: uncertainty due to inherent randomness
- *Epistemic uncertainty*: uncertainty due to lack of knowledge

An example of a source of aleatory uncertainty is Young's modulus of a material. Although Young's modulus is reported as a constant, there is variability between material samples due to the manufacturing process. The inherent randomness in Young's modulus can be reduced by improving the manufacturing process, but sources of aleatory uncertainty are often treated as irreducible. The term "epistemic" comes from the Greek "episteme", meaning knowledge; hence, epistemic uncertainty can be reduced by acquiring additional knowledge. An example of an epistemic source of uncertainty is a calibration parameter in a deterministic computer model of a physical system. The value of the calibration parameter, such that the model predictions will match reality, is uncertain. After obtaining data from physical experiments, discrepancies between the model predictions and the system behavior can be minimized using a calibration process. Aleatory (irreducible) and epistemic (reducible) uncertainties are the components of a DM's total uncertainty, as shown in Fig. 3b.

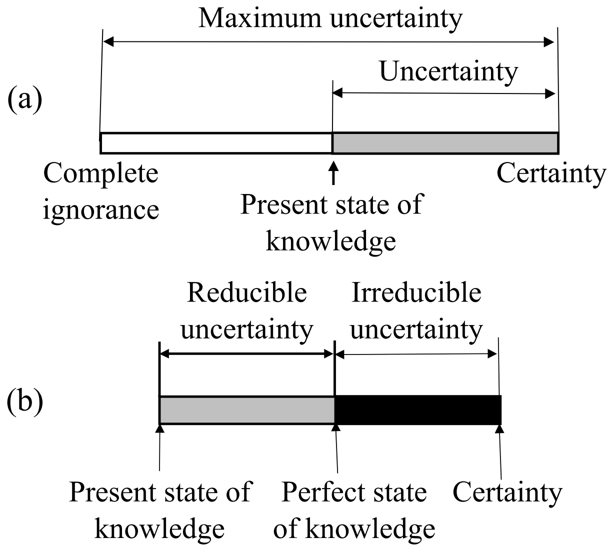

Fig. 3 Depiction of the definition of uncertainty (adapted from Ref. [14]).

Mathematical representation, or characterization, of uncertainties depends on the categorization. The most common mathematical form used for aleatory uncertainty is a probability distribution function (PDF). There is disagreement among researchers about what mathematical form epistemic uncertainties should take. Some, such as Oberkampf and Roy [15], argue that epistemic uncertainties should not be endowed with any probabilistic structure and should instead be represented as intervals. O'Hagan and Oakley [16], among others, argue that probability is adequate for describing any type of uncertainty. Rational arguments have been offered in support of both approaches, and both representations are frequently used in the literature. This suggests that there is not necessarily a correct choice for all problems. There is also a mixed aleatory/epistemic type of mathematical representation. As an example, assume that the aleatory uncertainty source mentioned previously, Young's modulus, is characterized as a normal distribution with mean μ and standard deviation σ. One may not know the precise values of μ and σ; thus, they are epistemic uncertainties.

The definition of epistemic uncertainty may lead one to ask, "What types of knowledge should be acquired during a technology development program?" Epistemology, the study of knowledge, provides philosophical views that can help answer this question. Although there are various kinds of knowledge, such as knowing how to do something or knowing someone by acquaintance, epistemologists typically focus on *propositional knowledge*, also referred to as knowledge-that [17]. Propositional knowledge requires that a subject knows a proposition. For example, one may express propositional knowledge of an AFC impact on an aircraft as, "I know that the cruise drag reduction achieved by implementing the active flow control technology is two percent." The particular knowledge that is of interest in this research is scientific knowledge, which is propositional knowledge generated by the scientific method. Scientific experimentation also generates information that promotes *understanding*. Many epistemologists consider understanding to be a type of knowledge, namely, knowledge of causes. Whether understanding is propositional in nature is debatable. Nevertheless, propositional knowledge (knowledge-that) alone is not sufficient for technology development; understanding is required not only for uncertainty reduction but also to improve performance.

3 Proposed methodology

Selection of physical experiments for a technology development program requires informed decision making. A formal decision process for intelligently selecting from a set of alternatives is required. The top-down design decision support process, developed by Mavris et al. [18], provides a foundation for this purpose:

1. Establish the need
2. Define the problem
3. Establish value objectives
4. Generate feasible alternatives
5. Evaluate alternatives
6. Make decision

In order to evaluate alternatives based on multiple criteria, modeling and simulation (M&S) is employed to quantify metric values. In this research, *metrics* are figures of merit that characterize the impacts of technology integration and attributes of the physical experiments. A way to quantify uncertainty in the metrics is also needed. A process extracted from steps commonly found in the M&S-based uncertainty quantification (UQ) literature is used as a basis:

1. Identify sources of uncertainty
2. Characterize uncertainty
3. Propagate uncertainty
4. Analyze impacts
5. Reduce uncertainty

The proposed methodology for selection of physical experiments, shown in Fig. 4, is a fusion of the top-down design decision support process and the generic UQ process. Each step is described in the following sections.

3.1 Definition of the need and the technology (step 1)

It is assumed that the need for the technology has been established prior to the start of the development program. But, the need must be well-defined so that the objectives of the development effort can be aligned with the system-level goals. System-level analysis should be used to establish the need by demonstrating that the vehicle concept is not technically feasible using conventional technology. Metrics that describe the performance gap, in addition to the performance goal values, need to be tracked during technology development.

Defining the technology involves specifying the vehicle architecture and the integration approach. This information is essential for later steps. A diagram of the vehicle with the integrated technology and a description of the physical principles that characterize the technology facilitate communication of this information. The engineering design literature also led the authors to a system decomposition approach. There are two types of decomposition commonly utilized in the design of complex systems: physical and functional [19]. A physical decomposition is a schematic diagram that illustrates the system subassemblies and components and how the parts

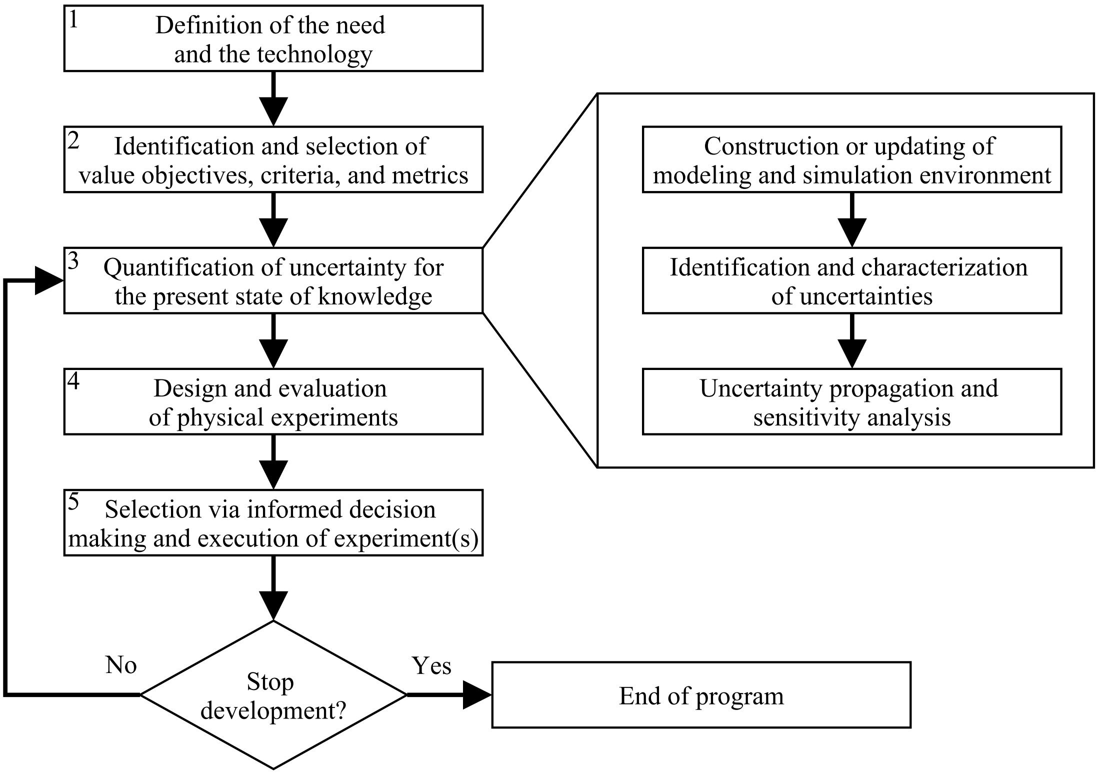

Fig. 4 Proposed methodology for selection of physical experiments.

connect. A functional decomposition results in a diagram called a function structure. This diagram uses function blocks to represent transformations done by the system components, with flows of information, energy, material, etc., indicated by arrows. Since a physical decomposition is more appropriate for understanding the nature of technology integration, it is incorporated in this methodology. As seen in the following example for this step, the physical decomposition can also be used to clearly show metrics at all levels of the system hierarchy.

3.1.1 Step 1 case study

The need for the AFC-enhanced VT technology has been defined by NASA. In the first phase of the ERA project, a large technology portfolio was explored, with system-level analysis, for enabling advanced vehicles to meet the goals in Table 1. As part of the second phase of the project, a subset of technologies was selected for development. To contribute to the 50% fuel burn goal, one of the technologies selected was the AFC-enhanced VT. In addition to fuel burn, NASA has identified total vehicle drag during cruise as a key performance metric for this technology. One drawback of this technology is that the actuators will produce noise during operation, so it is important to track the degradation to the ERA noise goal as well.

To guide subsequent steps, basic physical principles that govern the operation of the AFC-enhanced VT are described in section 2.1 and Boeing's diagram of a representative aircraft with the integrated AFC system is shown in Fig. 2. A physical decomposition, shown in Fig. 5, has been created based on this information. The light green boxes contain aircraft components and the light blue boxes contain metrics tracked at the level of the green box that they flow into. Directional arrows have been used in this diagram to indicate the flow of information from the technology level to the system level. At the top, relevant ERA goals are listed: noise and fuel burn. Four levels were defined for the system hierarchy: ERA goals, component groups, components, and component breakdown. Below the ERA goal level, the groupings are similar to an

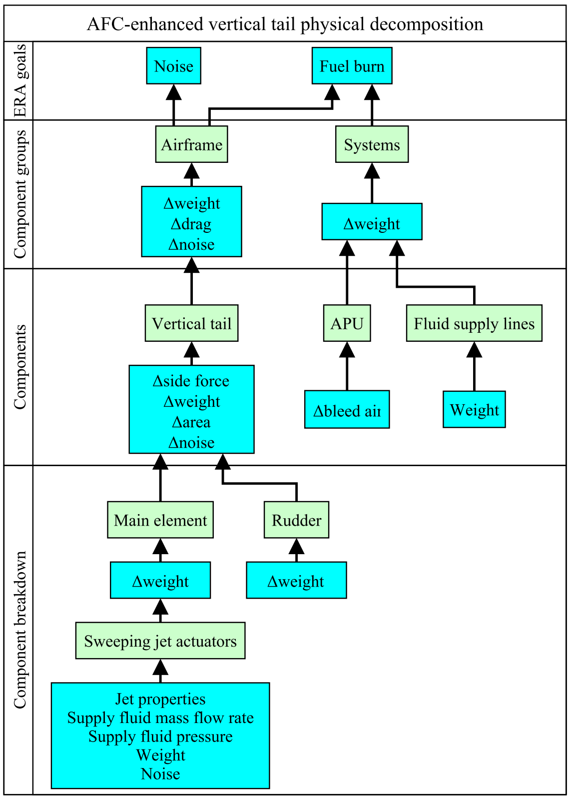

Fig. 5 Physical decomposition for the AFC-enhanced VT technology.

aircraft weight breakdown. This type of breakdown was selected for the physical decomposition because it is exhaustive and can be used to represent the system components at any desired level of detail.

3.2 Identification and selection of value objectives, criteria, and metrics (step 2)

The purpose of this step is to select which criteria will be used to evaluate the set of possible physical experiments based on the objectives and constraints established by DMs. Although objectives will vary from one development program to another, there are a few that will likely be common for all: uncertainty reduction, maturation, and performance improvement. Constraints should include budget, schedule, and the availability of experimental facilities.

System-level performance improvement is quantified using metrics defined in step 1. Assuming that the M&S capability is available, system-level analysis can be employed to identify important disciplinary impacts associated with infusing the technology. A vetted approach for rapidly modeling technologies at the system level is the use of "k-factors". These are dimensionless, multiplicative values that operate on disciplinary input parameters in computer codes. As an example for demonstrating the concept, consider the k-factor-modified Breguet range equation, rearranged for calculating fuel burn, for flight at constant velocity V_∞, thrust-specific fuel consumption c_t, and lift-to-drag ratio C_L/C_D:

$$W_f = k_{W_0} W_0 \left[1 - \exp\left(-\frac{k_{c_t} c_t R}{\frac{k_{C_L} C_L}{k_{C_D} C_D} V_\infty} \right) \right] \qquad (1)$$

where W_0 is the gross weight of the aircraft with full fuel tanks, W_f is the weight of fuel used during the mission of range R, and k_i is a k-factor for variable i. To simulate the impact of an aerodynamic technology such as AFC on fuel burn, the k-factors on the lift and drag coefficients in Eq. (1) would be set to particular values. A sensitivity analysis provides an indication of how much each k-factor contributes to variability in the system-level metrics. k-factors with the largest impacts are the ones that should be identified as important metrics since reducing uncertainty in these will maximize uncertainty reduction in the system-level metrics. The chosen metrics are also used to quantify performance improvement at the technology level. A notional example of a graphical approach to sensitivity analysis and k-factor selection is illustrated at the top of Fig. 6. The lines within each box are "slices" of the system-level metrics at a point in the k-space. k_2 and k_3 have been circled because they contribute more to variability in the Ms than k_1.

To quantify the knowledge gained from experimental observations, an uncertainty reduction measure is required. A frequently used measure for probabilistic assessments is variance reduction. Entropy measures, borrowed from information theory, have also been applied. Based on an analysis of the uncertainty literature, Bjorkman [20] concluded that an entropy measure is a better option than variance. Bjorkman provides multiple valid reasons for preferring entropy. But, since employing both does not in-

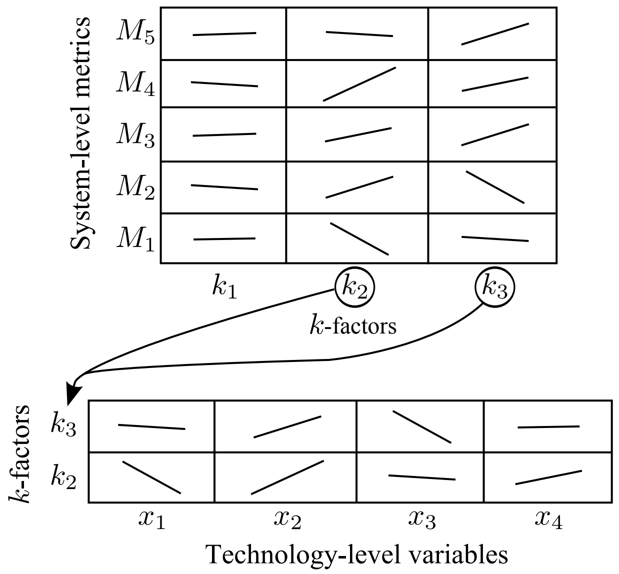

Fig. 6 Notional graphical sensitivity analyses at the system level (top) and the technology level (bottom). Important k-factors are selected for further investigation during the technology development program.

cur any substantial computational penalties, the authors of this paper suggest doing so. If non-probabilistic methods are used to characterize epistemic uncertainties, then alternative uncertainty reduction measures must be derived.

The most prevalent approach for representing the maturity achieved by an experimental activity is a TRL scale. TRL definitions have been proposed by multiple organizations around the world. Selection of a particular scale and the determination of whether a better alternative exists is outside the scope of the work presented in this paper. But, at least one measure of maturity should be chosen for use in this methodology. Selection of the best metrics for cost, schedule, and availability are also outside the scope of this work.

After DMs choose metrics that are crucial for evaluating the physical experiments, individual metrics or functions of metrics become the *criteria* for the decision process. If so desired, DMs can place subjective weights on each of the criterion to represent relative importance. The criteria and associated weights are used in later steps.

3.2.1 Step 2 case study

NASA's objectives for development of the AFC-enhanced VT naturally include uncertainty reduction, maturation, and the attainment of performance goals. Schedule and budget constraints have also been established.

Mooney et al. [13] conducted a system-level analysis to quantify the manufacturing, operational, and combined net present value for a mid-size aircraft with the AFC-enhanced VT technology. A method for modeling the performance impacts was used that is similar to the k-factor approach. Results from sensitivity analyses indicate that the drag reduction achieved by implementing the technology is the primary contributor to uncertainty in combined net present value. Other important performance impacts identified are detriments in thrust-specific fuel consumption and weight. All three qualify as important metrics and are carried forward, similar to k_2 and k_3 in Fig. 6.

NASA selected all of the physical experiments for the second phase of ERA using a set of diverse criteria. For brevity, the process is not discussed in this paper.

3.3 Quantification of uncertainty for the present state of knowledge (step 3)

Before uncertainty reduction that is achieved by alternatives can be predicted, an uncertainty benchmark must be determined. As stated previously, M&S is required for UQ in this methodology. Construction or updating of the M&S environment is the starting point for this step before UQ can be carried out.

3.3.1 Construction or updating of modeling and simulation environment

Products from defining the technology in step 1 and metrics identified in step 2 guide construction of the M&S environment. The physical decomposition, explanation of the governing physics, and diagram of the integrated technology should be used to ensure that all germane phenomena are captured. Assuming that the k-factor approach is utilized for system-level modeling, additional

M&S capability should provide quantification of the important k-factors. An example of this is shown in the notional sensitivity plot at the bottom of Fig. 6.

It is essential for the computational cost of the M&S environment to be affordable. This is because uncertainty propagation techniques necessitate a large number of evaluations. Considering the computational appetite of many physics-based computer codes, researchers often leverage the power of design of experiments and surrogate models. For example, response surface methodology [21] is frequently used to generate statistical models, which can be evaluated virtually instantaneously, of computer codes in lieu of executing the code itself. If high-fidelity codes such as computational fluid dynamics are not used to model the physics, then an alternative approach is to build statistical models from any existing experimental data.

3.3.2 Identification and characterization of uncertainties

Identification of sources of uncertainty involves determining where uncertainty in the metrics of interest stems from. Many of the important sources are identified by enumerating variables at all levels of the system hierarchy that are uncertain. This exercise is facilitated by an understanding of how a given technology integrates with a vehicle concept; thus, the products of step 1 are useful for this task as well. The use of M&S for quantifying metrics introduces *model form uncertainty*, which is due to assumptions made in the modeling of physics [15]. Another prevalent source is measurement uncertainty.

Once the sources of uncertainty have been identified, they must be characterized. As discussed in section 2.2, aleatory uncertainties are typically represented with PDFs, and there are two primary options for epistemic uncertainties. DMs and analysts must decide how to represent epistemic uncertainties. One advantage of using the probabilistic approach is that it enables Bayesian inference, which is discussed in the last step of the methodology. Assigning probability distributions or intervals to each source is not a trivial task, as one must translate one's own beliefs and/or the beliefs of others to mathematical language. For aleatory sources, the distribution shape can be estimated based on existing experimental data. If this information does not exist, a distribution shape can be assumed and updated if and when data are generated. Expert elicitation methods, such as O'Hagan's SHELF [22], should be employed for specifying PDFs in this step. But, once a sensitivity analysis is carried out in the propagation step, the analyst may determine that some sources of uncertainty are not important no matter what distribution is assumed.

3.3.3 Uncertainty propagation and sensitivity analysis

It is known from probability theory that any function of a random variable is also a random variable; thus, when uncertain inputs to an M&S environment are characterized as random variables, the outputs from the environment are also random variables. As an example (adapted from Ref. [23]), consider a deterministic computational model that maps an input from the real number line into an output from the real number line: $y = g(z)$. Suppose that an analyst has characterized z as an epistemic or aleatory source of uncertainty with a given PDF $f(z)$. Now, z is treated as a random variable, which is denoted by Z. The uncertain output from the computational model is denoted by Y, which is also a random variable. Obtaining the cumulative distribution function (CDF) and PDF of the model output Y is the objective of uncertainty propagation. The CDF of Y is calculated as follows:

$$\begin{aligned}\mathbb{P}(Y \leq y) &= \mathbb{P}(g(Z) \leq y)\\ &= \mathbb{P}(g(Z) \in (-\infty, y])\\ &= \mathbb{P}(Z \in g^{-1}(-\infty, y])\\ &= \int_{g^{-1}(-\infty,y]} f(z)\, dz \end{aligned} \tag{2}$$

Once the CDF has been computed, the PDF is found by differentiating the CDF. The structure of most M&S environments requires that the integral in Eq. (2) be computed numerically. If it is not possible to modify the computational codes within the environment, then a non-intrusive propagation method must be selected. Non-intrusive propagation methods include simulation-based, such as Monte Carlo simulation; local expansion-based, such as a Taylor series; most probable point-based, such as the first-order reliability method; functional expansion-based, such as polynomial chaos expansion; and numerical integration-based, such as full factorial numerical integration [24]. If epistemic uncertainty is characterized with intervals, then propagation will result in a probability box instead of one CDF for each output. Other propagation methods exist for this type of characterization, such as second order Monte Carlo. Many M&S environments are treated as black-box-type functions, and this limits the choice of propagation methods to non-intrusive. As previously mentioned, surrogate modeling techniques can be employed to enable computationally expensive uncertainty propagation. The highest accuracy and most expensive methods involve Monte Carlo simulation, which should be used for propagation, if computational resources allow.

In addition to the propagation task, a sensitivity analysis is conducted during this step. Sensitivity analysis can be local or global. An example of a local sensitivity analysis is computing the partial derivatives of a computational model's outputs with respect to the input variables at a given point in the input space. When inputs are uncertain, it is useful to understand which input sources of uncertainty are the largest contributors to uncertainty in the outputs, and this is what a global sensitivity analysis can reveal. There are many available techniques for global sensitivity analyses such as scatterplots and variance-based measures [25]. A notional example of the results from a variance-based technique is shown in Fig. 7. An important result of sensitivity analysis is a ranking of epistemic and aleatory uncertainty sources based on their contribution to the system-level metric uncertainties.

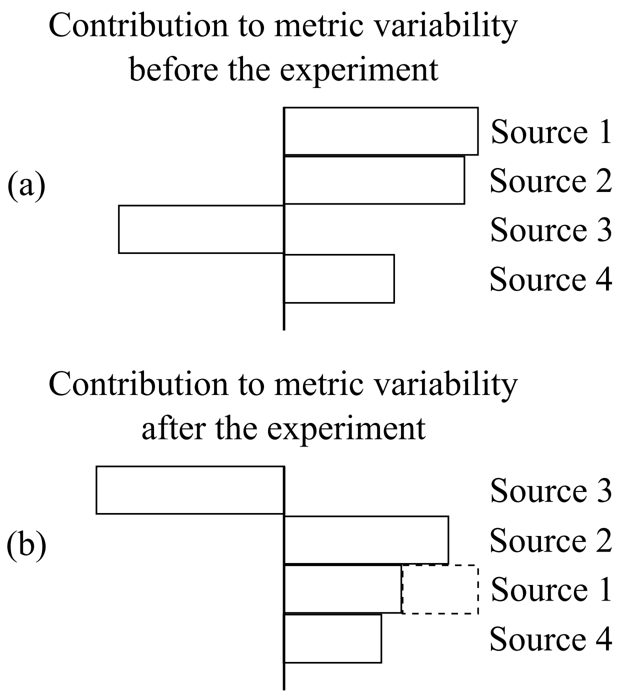

Fig. 7 Notional variance-based sensitivity analyses for ranking the importance of sources of uncertainty. A physical experiment reduces the epistemic uncertainty surrounding source 1.

3.3.4 Step 3 case study

The premier suite of aircraft system-level analysis tools currently employed for the ERA project is called the Environmental Design Space (EDS) [26]. EDS is a physics-based, integrated, multidisciplinary M&S environment that consists of core modules originally developed by NASA. The current EDS modeling capability for the AFC-enhanced VT technology is at the components level and up in Fig. 5. Additional M&S tools are being brought in to capture behavior at lower levels.

Both probabilistic and non-probabilistic approaches to characterize epistemic uncertainty are being considered for the case study. The authors are working closely with NASA subject-matter experts to elicit distributions and ranges for sources of uncertainty. In addition to identifying sources of uncertainty from the physical decomposition, shown in Fig. 5, measurement uncertainties and uncertainties associated with modeling have also been identified. Upon completion of the M&S envrionment, uncertainties at the technology level will be propagated to metrics of interest, such as aircraft cruise drag, weight, thrust-specific fuel consumption, and fuel burn.

3.4 Design and evaluation of physical experiments (step 4)

In this methodology, it is assumed that physical experiments are designed and proposed by technologists, but they must be aware of information from previous steps in order to produce relevant experiments. Of particular importance is the definition of the technology. This is because physical experiments should be designed with system-level constraints in mind. For example, pneumatic or electrical power availability for AFC actuation will be limited on an aircraft; thus, it is not always useful to collect experimental data under the assumption that any resources available in the laboratory should be used to demonstrate significant performance benefits. This is especially true when the cost of experimentation is exorbitant. Another key result that can guide the experimental design is the ranking of uncertainties, by importance, for critical metrics, as seen in Fig. 7a. Technologists should also be informed of the criteria that DMs will use to evaluate the experiments.

Once experiments are designed, all criteria can be determined for each. Criteria representing objectives such as maturity, cost, and schedule are relatively straightforward to estimate before any experiments are selected and conducted. Criteria associated with performance improvement and uncertainty reduction after the experiment are more complicated to predict *a priori*. Researchers such as Sankararaman et al. [27] have proposed the use of Bayesian inference for this purpose, but determination of the most appropriate approach for this methodology is part of current research activities.

3.4.1 Step 4 case study

Two of the experiments for the AFC-enhanced VT have been performed: a sub-scale wind tunnel experiment and a full-scale wind tunnel experiment. These experiments are being studied retrospectively to understand the logic behind their design. Lessons learned are being applied to predict uncertainty reduction and performance improvement for the full-scale flight experiment. Data for quantities such as cost, schedule, and TRL are also available for use in applying this methodology to a real program.

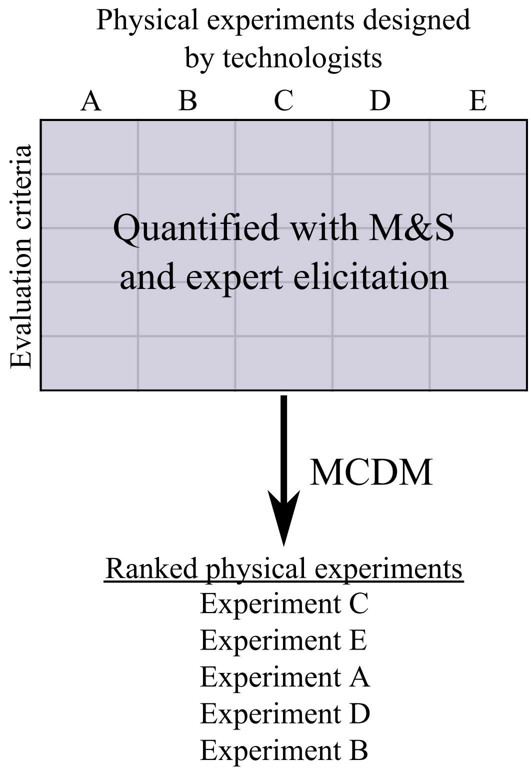

Fig. 8 Notional depiction of the decision process for selecting physical experiments.

3.5 Selection via informed decision making and execution of experiment(s) (step 5)

The objective of this step is to find the best compromise physical experiment(s). The word "compromise" is used here because it is usually the best type of solution that can be found in multi-criteria problems. Conflicting criteria, such as uncertainty reduction and cost, result in trade-offs of performance in each. A plethora of multi-criteria decision-making (MCDM) tools exist for aiding DMs in finding the best alternative. Most of the MCDM methods incorporate DM-supplied criteria preferences in the form of weights. No one MCDM technique is available that is guaranteed to work well for all problems, but multiple approaches to selecting an MCDM method, such as expert/intelligent systems, are designed for facilitating selection. The result of employing an MCDM tool is a ranking of alternatives, as shown in Fig. 8. As part of the planned research for evolving this experiment selection methodology, MCDM methods will be investigated and the most suitable options chosen.

After an experiment or set of experiments is selected and executed, DMs must determine whether another experimentation iteration will be done. If the feedback loop in Fig. 4 is followed, step 3 is carried out again to update uncertainty with the recently acquired knowledge from experimentation. Updates to the M&S environment may be warranted, and new sources of uncertainty could be uncovered. The experimental data should be used to update the form of epistemic uncertainty sources. If PDFs are used for characterization, a logical approach is to employ Bayesian inference. The goal of Bayesian inference is to update prior knowledge of a distribution parameter of interest using the observed data. The updated distribution is attained by applying Bayes' theorem:

$$\underbrace{\pi(\theta|D)}_{\text{posterior}} = \frac{\overbrace{f(D|\theta)}^{\text{likelihood}}\overbrace{\pi(\theta)}^{\text{prior}}}{\underbrace{m(D)}_{\text{marginal}}} \tag{3}$$

The likelihood function summarizes information from the experimental data D. The parameter θ is not directly observable, but it is inferred. For example, if the data are generated by a normal distribution, then θ could be the mean of that distribution. The prior PDF represents the DM's knowledge about the parameter θ before the experimental data are observed, and the posterior PDF represents the updated knowledge about the parameter after observing the data. The marginal distribution can be thought of as a normalizing constant, once the prior is specified and the data are observed, which ensures that the posterior is a proper PDF. Results from updating with Eq. (3) can be used to produce a new sensitivity analysis, which will likely demonstrate a different prioritization of uncertainties, as seen in Fig 7b. This information can then be leveraged for another round of experiment selection and execution by following steps 4 and 5.

3.5.1 Step 5 case study

In future work, MCDM techniques will be used to simulate the selection of AFC-enhanced VT physical experiments. Results will be compared with the process used to determine which experiments to conduct in the ERA project. Input from NASA DMs will be valuable for vetting the results of applying this methodology.

4 Summary and future direction

In order to accelerate the reduction of uncertainty surrounding the impacts that technologies will have on future aircraft, physical experiments must be carefully selected. As a contribution toward enabling an optimal technology development program, a methodology for strategic selection of physical experiments has been proposed. An AFC technology applied to the VT of a commercial transport been presented as a case study throughout the methodology formulation.

Additional research is necessary to mature the experiment selection methodology. In particular, future work will focus on four components: the prediction of uncertainty reduction and performance improvement before an experiment is conducted, selection of the most appropriate sensitivity analysis methods, selection of suitable MCDM techniques, and the updating of uncertainties after an experiment is conducted.

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References

[1] Guynn, M D, Berton, J J, Tong, M T, and Haller, W J. Advanced single-aisle transport propulsion design options revisited. *13th AIAA Aviation Technology, Integration, and Operations Conference*, Los Angeles, CA, AIAA Paper 2013-4330, 2013.

[2] Prandtl, L. Über Flüssigkeitsbewegung bei sehr kleiner reibung. *Proceedings of the Third Inter-*

national Mathematical Congress, Heidelberg, Germany, pp. 484–491, 1904.

[3] Williams, D R and MacMynowski, D G. Brief history of flow control, *Fundamentals and applications of modern flow control*, edited by R D Joslin and D N Miller. AIAA, Reston, VA, pp. 1–20, 2009.

[4] Mankins, J C. Technology readiness and risk assessments: a new approach. *Acta Astronautica*, Vol. 65, No. 9-10, pp. 1208–1215, 2009.

[5] Cattafesta, L N and Sheplak, M. Actuators for active flow control. *Annual Review of Fluid Mechanics*, Vol. 43, No. 1, pp. 247–272, 2011.

[6] Coanda, H.. Device for deflecting a stream of elastic fluid projected into an elastic fluid. U.S. Patent No. 2,052,869, September 1, 1936.

[7] Woszidlo, R.. Parameters governing separation control with sweeping jet actuators. Ph.D. Dissertation, Department of Aerospace and Mechanical Engineering, University of Arizona, Tucson, AZ, 2011.

[8] Seele, R, Graff, E, Lin, J, and Wygnanski, I. Performance enhancement of a vertical tail model with sweeping jet actuators. *51st AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*, Grapevine, TX, AIAA Paper 2013-0411, 2013.

[9] Phillips, E and Wygnanski, I. Use of sweeping jets during transient deployment of a control surface. *AIAA Journal*, Vol. 51, No. 4, pp. 819–828, 2013.

[10] Tewes, P, Taubert, L, and Wygnanski, I. On the use of sweeping jets to augment the lift of a lambda-wing. *28th AIAA Applied Aerodynamics Conference*, Chicago, IL, AIAA Paper 2010-4689, 2010.

[11] Seele, R, Tewes, P, Woszidlo, R, McVeigh, M A, Lucas, N J, and Wygnanski, I J. Discrete sweeping jets as tools for improving the performance of the V-22. *Journal of Aircraft*, Vol. 46, No. 6, pp. 2098–2106, 2009.

[12] Warwick, G. Boeing, NASA test active flow-control tail. *Aviation Week*, November 14, 2013, `http://aviationweek.com/awin-featured-story/boeing-nasa-test-active-flow-control-tail` [cited 26 June 2014].

[13] Mooney, H P, Brandt, J B, Lacy, D S, and Whalen, E A. AFC-enabled vertical tail system integration study. NASA/CR-2014-218168, 2014.

[14] Nikolaidis, E. Types of uncertainty in design decision making, *Engineering design reliability handbook*, edited by E Nikolaidis, D Ghiocel, and S Singhal. CRC Press, Boca Raton, FL, 2005.

[15] Oberkampf, W L and Roy, C J. *Verification and validation in scientific computing*. Cambridge University Press, New York, 2010.

[16] O'Hagan, A and Oakley, J E. Probability is perfect, but we can't elicit it perfectly. *Reliability Engineering & System Safety*, Vol. 85, No. 1-3, pp. 239–248, 2004.

[17] Hetherington, S. Knowledge. Internet Encyclopedia of Philosophy, `http://www.iep.utm.edu/knowledg/` [cited 30 June 2014]".

[18] Mavris, D N, Baker, A P, and Schrage, D P. IPPD through robust design simulation for an affordable short haul civil tiltrotor. *American Helicopter Society 53rd Annual Forum*, Virginia Beach, VA, 1997.

[19] Dieter, G E and Schmidt, L C. *Engineering design*. 4th ed., McGraw-Hill, New York, 2009.

[20] Bjorkman, E A. Test and evaluation resource allocation using uncertainty reduction as a measure of test value. Ph.D. Dissertation, School of Engineering and Applied Science, George Washington University, Washington, D.C., 2012.

[21] Myers, R H, Montgomery, D C, and Anderson-Cook, C M. *Response surface methodology: process and product optimization using designed experiments*. 3rd ed., John Wiley & Sons, Hoboken, NJ, 2009.

[22] O'Hagan, A. SHELF: The Sheffield Elicitation Framework, `http://www.tonyohagan.co.uk/shelf/index.html` [cited 24 June 2014].

[23] Grimmett, G R and Stirzaker, D R. *Probability and random processes*. 3rd ed., Oxford University Press, New York, 2001.

[24] Lee, S H and Chen, W. A comparative study of uncertainty propagation methods for black-box-type problems. *Structural and Multidisciplinary Optimization*, Vol. 37, No. 3, pp. 239–253, 2008.

[25] Saltelli, A, Ratto, M, Andres, T, Campolongo, F, Cariboni, J, Gatelli, D, Saisana, M, and Taran-

tola, S. *Global sensitivity analysis: the primer*. John Wiley & Sons, Chichester, England, 2008.

[26] Kirby, M R and Mavris, D N. The environmental design space. *26th International Congress of the Aeronautical Sciences*, Anchorage, AK, ICAS 2008-4.7.3, 2008.

[27] Sankararaman, S, McLemore, K, Mahadevan, S, Bradford, S C, and Peterson, L D. Test resource allocation in hierarchical systems using Bayesian networks. *AIAA Journal*, Vol. 51, No. 3, pp. 537–550, 2013.

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