UNCERTAINTY QUANTIFICATION FOR CAPABILITY-BASED SYSTEMS-OF-SYSTEMS DESIGN

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Abstract

Computational simulation tools, once trusted to a select few individuals with powerful computers and "mystical" codes are now becoming commonplace in biomedicine, geospatial analysis, predictive social network studies, materials science, and engineering design. While analysts have traditionally been able to focus on the mastery of a single discipline, the US Department of Defense's recent shift to capability-based acquisition places an increasing focus on systems-of-system interoperability. This requires engineers and analysts to have working knowledge of a number of tasks, and the complexity endemic to this problem set complicates the use of simulation-based methods. Furthermore, in many cases, simulation tools are executed in a deterministic manner (as dictated by requirements for expediency and clarity of presentation); however, a quantification of uncertainty is often useful in assessing risk and understanding the limitations of a design. A number of complex issues arise in the quantification of the myriad sources of uncertainty in systems-of-systems problems. This paper summarizes some of the recurring and emerging challenges in uncertainty quantification for systems-of-systems design and highlights recommendations to address them where possible.

1 Introduction

"*There are known unknowns. That is to say, there are things that we now know we don't know. But there are also unknown unknowns. There are things we do not know we don't know*"

Former U.S. Secretary of Defense Donald Rumsfeld
February 12, 2002

Uncertainty, literally, the lack of what is known, is a concept that is central to the world around us and pervasive in the design of aerospace systems. Engineering design can be thought of as the application of scientific and mathematical principles to make rational decisions that guide the creation of products or processes. The purpose of design is therefore to narrow a quasi-infinite constrained opportunity space to the handful of rational decisions that meet a set of requirements or fulfill a need. The concept of uncertainty confounds the engineer's ability to reliably differentiate between the many alternatives in this space and identify the "correct" defining parameters with confidence.

Since the introduction of the Rumsfeld-directed Joint Capabilities Integration and Development System (JCIDS) in the summer of 2003, the U.S. aerospace community has been increasingly faced with a new challenge: engineering complex systems to purposefully provide joint capabilities in uncertain future environments [1]. Engineering efforts that traditionally focused on a small, well-defined set of physical phenomena and used models validated against precise scenarios were confronted with the need to extend systems engineering methods to large-scale "systems-of-systems." This shift induces new challenges that must be addressed by a mix of proven and nascent methods.

To be sure, this expansive topic cannot be definitively addressed in any single work. This paper focuses primarily on the application of probabilistic methods for uncertainty quantification in the aerospace multidisciplinary design optimization community and summarizes challenges that have co-evolved with the impetus toward capability-based systems engineering over the last several years.

2 Types of Uncertainty

There are many different ways of classifying uncertainty for a variety of applications:

- Objective vs. Subjective [2]
- Vagueness vs. Ambiguity [3]
- Epistemic vs. Aleatory [4], [5]
- Parameter vs. Model [6], [7]

Choi provides a detailed overview of these types of uncertainty and Talley categorizes the various classes in a taxonomy with relevance to systems-of-systems applications [8], [9]. Of the classifications mentioned above, the final two distinctions are more applicable to this discussion.

Epistemic uncertainty, from the Greek *episteme* meaning "of or pertaining to knowledge" is defined by Oberkampf as "any lack of knowledge or information in any phase or activity of the modeling process" [10], [11]. This type of uncertainty is also called *reducible* because its impact can be minimized by gaining additional information about the system or its environment. Engineering design is concerned with gathering knowledge through experiments and studies that quantify and reduce the impact of epistemic uncertainty.

Aleatory uncertainty, whose Latin root *āleātor* (meaning *gambler*) pertains to random chance and may only be quantified statistically. Also referred to as *irreducible uncertainty*, this type cannot be reduced by the addition of more knowledge. The natural variability of the physical properties of the system or its environment typify sources of aleatory uncertainty. In engineering design, this type of uncertainty is usually represented by a random variable or a probability distribution.

The division by these two classes is not clear-cut. Haukaas notes that aleatory and epistemic uncertainty may not be treated disjunctively because aleatory uncertainty is often also pervasive in variables which are traditionally dominated by epistemic uncertainty [8], [12].

An additional classification popular in the literature is the distinction between *parameter uncertainty* and *model uncertainty*.

Parameter uncertainty, also referred to as natural uncertainty or data uncertainty, is related to the lack of knowledge about the model parameters (inputs). Systems design is often concerned with parameter uncertainty, as the specification of values for design parameters "closes" the design problem. One of the major focuses of Taguchi's robust design method is on parameter design, that is, the determination of design factors under uncertainty [13].

While parameter uncertainty is related to the physical parameters themselves, *model uncertainty* refers to lack of knowledge about the relationships between parameters and the underlying phenomenologies. According to Choi, model uncertainty "is due to lack of understanding of physical phenomena (ignorance) and the use of simplified structural models and probabilistic models (errors of simplification)" [8].

When designs are created based on historical data, the focus of uncertainty quantification is almost exclusively in the realm of parameter uncertainty since the underlying models are semi-empirical and well-understood. As conceptual design requires knowledge of untested physics, implements advanced technologies, or adds degrees-of-freedom for which few models exist, model uncertainty may begin to dominate. Unfortunately, as explained below, for certain types of problems the impact of model uncertainty can become overwhelming.

3 History of Uncertainty Quantification in Robust Design

For most of the early 20th century, aerospace design was largely a *craft*. Practiced by hobbyists and artisans, knowledge gained on aerospace disciplines came largely through experimentation and flight test. Scientific advancement in the nascent field was largely focused on the discipline level and was isolated rather than integrative. Following World War II, the scientific principles behind flight were steadily codified. Educational programs grew into discipline-focused practices and knowledge transfer shifted from a solely apprentice-based paradigm to one based on both application and theory. In the time period from 1950-1980, design was largely thought of as a *practice* which integrated the disciplines. Decisions were made based on testing, experimentation, and reliance on historical data and personal experience.

Digital computers proliferated as desktop engineering tools in the mid-1980's and the iterative practices for aircraft design began to take the form of deterministic computer software. The phrase "design tools" gradually began to refer to sizing routines and CAD packages as opposed to T-squares and French curves. Many discipline-level models were integrated to form the first mature aircraft design tool suites. For example, in the 1970s, NASA Ames research center began to develop the AirCraft SYNThesis (ACSYNT) tool, a conceptual design aid that integrated modules for aerodynamics, propulsion, mission performance, and eventually geometry [14], [15]. In the early 1980s, NASA Langley introduced the FLight OPtimization System (FLOPS), a multidisciplinary design tool for predicting overall aircraft performance, weight, cost, and environmental factors [16], [17]. Both of these tools are deterministic, iterative, semi-empirical design aids that automate the workflow of synthesis and sizing while incorporating some disciplinary analyses. The notion that one could perform a conceptual design process in hours to days using a handful of computers was new and exciting. By the late 1980s, the concept of *design-as-a discipline* was beginning to take hold[1].

Around this time, the confluence of design tools, Moore's Law, and the growing popularity of Taguchi's robust design methods gave birth to the notion of performing practical probabilistic aircraft design. Codes which had previously been used to perform deterministic trade studies could be modified to quantify uncertainty by wrapping their "namelist" input files within a probabilistic simulator that fed user-specified distributions into the tool one case at a time. The resultant outputs represented probability distributions that could be used to ascertain the technical feasibility and economic viability of proposed aircraft concepts across a user-defined range of uncertainty on the parameter assumptions.

Also in the early 1990s, designers saw utility in linking multiple discipline-level design tools with automated synthesis and sizing routines such as FLOPS and ACSYNT. Software tools such as iSIGHT by Engineous software entered the market. Originally

[1] As evidenced by the increased numbers of design-related textbooks and the proliferation of "design-oriented" academic programs around this time.

developed by Dr. Siu Tong, under funding from General Electric Corporation from 1979-1983, Engineous began to commercialize iSIGHT in 1996 [18], [19]. After incubation at Virginia Tech in the 1980's, Phoenix Integration was founded in 1995 to commercialize the ModelCenter software as a visual environment for integrating design tools and performing trade studies. These Process Integration and Design Optimization (PIDO) tools provided engineers with an off-the shelf software package that replaced the manual integration process pejoratively referred to as "sneaker net" by which the outputs from one tool were manually handed off to another engineer or "thrown over the wall." While deterministic trade studies were the norm in the early 1990s, it was not long before computers were powerful enough to allow the aforementioned probabilistic wrapping of the suite of design tools to become practical. During this era, the term *multidisciplinary design optimization (MDO)* was popularized[2] to refer to the ability to integrate and optimize multiple disciplinary tools and perform uncertainty quantification across a range of input parameters.

The desire for increasing integration of more disciplinary tools was quickly stymied by the *curse of dimensionality:* the tendency for problems to become exponentially harder as variables are added. Disciplinary tools were developing, maturing, and proliferating around the community at record speeds and the advancement of computing power could not keep up with the development of tools and methods.

Beginning in 1995, Schrage, Mavris, and their colleagues promulgated the concept of IPPD through robust design simulation [20], [21]. Central to this concept is the cross-fertilization of the *response surface equation (RSE)* technique from the field of applied mathematics and agriculture. While the concept began to be applied in isolated instances throughout the 1970s and 1980s (notably by Healy, Kowalik, and Ramsey in 1975), Mavris and Schrage advanced the notion that one could build practical and accurate approximations of physics-based design tools using the software and methods matured in the intervening time [23], [24]. Demonstrating the viability of the concept using an integrated engine/aircraft design suite for NASA's High Speed Civil Transport (HSCT), Bandte, Mavris, and Schrage demonstrated the viability of quickly performing accurate deterministic design using RSEs [25]. With a dramatic increase in speed exchanged for a slight degradation in accuracy. It was a logical step to reintroduce the concept of probabilistic systems design, only this time, the probability distributions were executed through *surrogate models* (in the form of RSEs) created from the original suite of tools. Around the same time, the Boeing Corporation began developing a set of mathematical techniques that would eventually be known as *Design Explorer* in partnership with Rice University [26]. Design Explorer uses adaptive surrogate models based on the Kriging approach for design and optimization [27]. (In 2004, the tool was licensed to Phoenix Integration and included in ModelCenter) [28].

As the thirst for expansion continued, the curse of dimensionality again reared its ugly head: this time, in the difficult of creating surrogate models with large dimensionality. Koch et. al. explored the dimensionality problem for multidisciplinary, multiobjective problems and examined the use of Kriging and compromise design [29]. In 1997, the Southwest Research Institute's "Fast Probability Integration" (FPI) tool was examined to abandon the RSE-based approach by alternatively approximating the Monte Carlo Simulation (MCS) [30]. After extensive experimentation, it was determined to be more practical to simply reduce the degrees of freedom to the canonical set of variables most significant to the variability of the set of responses using the ANOVA statistical technique [31]. This constrained the dimensionality of RSEs but made probabilistic multidisciplinary design possible.

In 1998, Daberkow and Mavris also explored the feasibility of artificial neural networks as surrogate models but deemed the additional burden in their creation impractical when there was only a slight discernable advantage over polynomial surrogates for the class of problems studied [32]. However, as a harbinger of things to come, the pair noted that appropriately trained neural networks are likely to yield better approximations as the dimensionality and complexity of the problem increase. Other types of surrogate models including radial basis functions and Kriging models were implemented for other aerospace applications and met with success [25-29].

As previously mentioned, a majority of the mathematical techniques matured during this era were focused on the quantification of parameter uncertainty. For well-posed problems, model uncertainty is either considered to be negligible or is treated as aleatory uncertainty. This categorization is appropriate when:

- Physics and phenomena are well understood
- Proven, validated design tools exist
- Assumptions can be stated and/or proven
- Simulation tools are non-noisy and repeatable
- Problem setup approaches do not vary widely across practitioners with similar backgrounds
- Educational programs are available that provide training and produce practitioners that can address the requisite design issues

By the end of the 20th century, the concept of aircraft design-as-a-discipline provoked less consternation from disciplinary traditionalists. Many challenges in tool integration, design optimization, and uncertainty quantification were largely "solved" by the explosion of new methods development in the late 1990s and the methods development community was well-poised to address a new set of challenges that lurked just around the corner.

[2] Though introduced twenty years earlier, the term proliferated during this time.

4 The Shift to Systems-of-Systems

The downturn in commercial aviation following the events of September 11, 2001 had impacts on the development of new methods in aerospace academics. Industry sponsors limited expenditures on new technologies and methods as their order backlog dwindled. The turmoil in the US aeronautics sector was further exacerbated by President Bush's January 2004 announcement of a new vision for space exploration. From FY 2000 to 2007, the budget for NASA aeronautics activities has been reduced by nearly 30%[3] [38].

On the other hand, defense spending during the same time period has increased dramatically. The Philadelphia Stock Exchange defense index fund which represents the top 18 defense companies, has risen 150% from 2002 to 2007 and the spending as a percentage of US GDP has trended upwards from 3% to 4% between 2000 to 2007, though not nearly to the thirty-year high of the Reagan administration (6.2%)[4]. Simply put, this dramatic shift in resources has redirected methods development research toward the defense sector. As opposed to the tightly coupled problems endemic to commercial aircraft design, the defense establishment is more concerned with the design of "systems-of-systems" (SoS). These large-scale complex systems are often comprised of geographically distributed, loosely coupled independent systems that reconfigure dynamically both physically and temporally[5]. DoD acquisition guidance is concerned with the acquisition of SoS and their integration into the larger DoD enterprise for the purpose of accomplishing joint warfighting missions, providing joint capabilities, and achieving joint effects.

To address uncertainty quantification for SoS, the logical step was to synthesize the lessons learned to date: integrate the system-level design tools in a PIDO framework, generate surrogate models, and perform probabilistic analysis using MCS. In 2004, the US Air Force Research Laboratory (AFRL), Pratt and Whitney, and Raytheon funded a collaborative study to demonstrate an integrated design environment of a propulsion system and a weapon in support of a Long-Range Strike (LRS) military campaign simulation [39]. In this study, the aforementioned approach met with significant difficulties as it was not possible to create RSEs of sufficient accuracy to reliably approximate the integrated suite of design tools. The source of error was traced to significant discontinuities in the military campaign simulation which were not erroneous, but rather, functions of the nonlinear nature of combat. To account for this phenomenon, the concept of using artificial neural networks as surrogate models was revisited.

The artificial neural network (ANN) technique can trace its origin to a 1943 article by neurophysiologist Warren Mc-Culloch and mathematician Walter Pitts entitled "A Logical Calculus of Ideas Immanent in Nervous Activity" [40]. As in biological systems, a single neuron can be connected to many other neurons to create very complex networks of structures. Artificial neural networks have found widespread application in pattern recognition and classification, control processes, artificial intelligence, optical character recognition, autonomous robots, and the development of adaptive software agents. Their ability to model processes also makes them ideal for regression tasks, especially those with discontinuous or highly non-linear responses.

As illustrated by Biltgen in Fig. 1, the application of a neural network to a system-of-systems problem generally results in a higher value for the coefficient of determination (R^2), a better fit in the actual-by-predicted plot, and a distribution of error that approximates the standard normal. This is due to the ability of the neural network to capture the nonlinearities and discontinuities present in combat models which are required to accurately *simulate* the operation of the system *and its environment*.

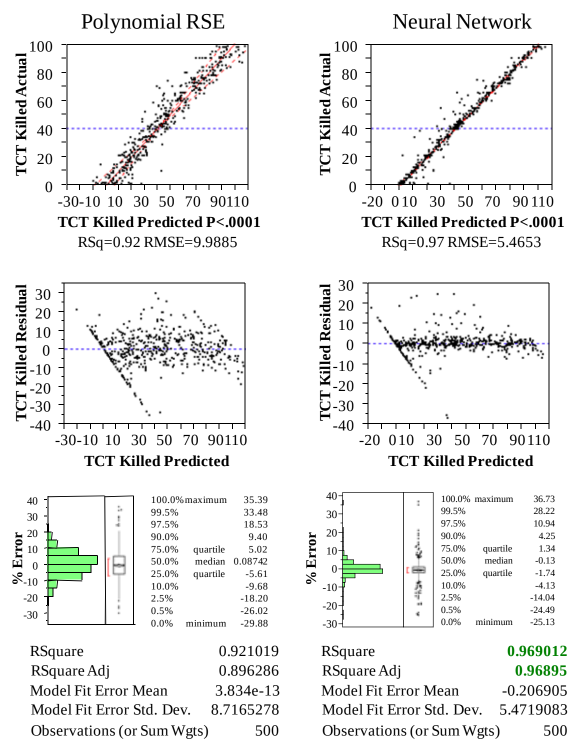

Fig. 1. Comparison of Polynomial RSEs and Neural Networks for a System-of-Systems Problem [41].

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[3] NASA's budgeting practices have changed from direct to full-cost to direct since the late 1990s, making a precise evaluation of the budget situation difficult. The President's budget request for FY 2009 (direct) is $593.8 M.

[4] 4% of US GDP is approximately half-a-trillion dollars.

[5] The US DoD also uses the term "families-of-systems," (FoS) which are "a set of systems that provides similar capabilities through different approaches to achieve similar or complementary effects" [1]. One illustrative example of a FoS is the pantheon of manned aircraft, unmanned aircraft, satellites, and ground-based special forces that are capable of tracking moving targets (one FoS, several SoS and systems). The distinction between FoS and SoS is not germane to this paper.

One of the major difficulties in using neural networks for parameter uncertainty quantification is the need for *extremely accurate* surrogate models.

RSEs for well-behaved system level problems can often be created with an R^2 value on the 0.999 level. When applied to the same problems, neural networks typically perform about the same; however, when extended to systems-of-systems problems, even the neural network technique may have a dramatically lower R^2 even when multiple network topologies and long training times are used. While these surrogates provide interesting insight into SoS-level trends and enable identification of sensitivities to design parameters, Fig. 2 illustrates the large discrepancies encountered when MCS is used on surrogates of less authoritative accuracy.

In this example, a simplified operations analysis code of a "Scud-hunt" time-critical strike mission is used [41]. The dependent variable in each of the nine plots shown is the percentage of time critical targets (mobile Scud missile launchers) destroyed and the independent variable represents uncertainty on the attacking aircraft's sensor range due to environmental, operational, and electronic warfare concerns. The charts answer the question "what is the probability of killing a target on this mission" under the operational circumstances which confound the ability to precisely define how far the aircraft can see (sensor range). To demonstrate the use of ANNs, a uniform distribution was used across the sensor range parameter on three separate neural network models of the same data. The three rows represent different levels of increasing accuracy in the ANNs with the lower-left plot most closely approximating the actual analysis. Non-linearities due to the complexities of military combat (which appear in the actual code) are accurately captured by the 21 node ANN that has an R^2 of 0.9633. On the other hand, when compared to the 9-node neural network and the 3 node neural network with R^2 values of 0.8121 and 0.7419 respectively, the nonlinearities are lost. Note also that this example includes only the impact of uncertainty due to variability in the specification of a single parameter: "sensor range."

The second column illustrates the uncertainty analysis results when a second uniform distribution is added to examine the joint probability outcomes across sensor range and friendly speed (the speed of the attacking aircraft). Here, the bottom center plot illustrates in red the impact of a single variable (from the lower left plot). The "fuzziness" around the red line depicts the additional variability due to the second parameter. Using the 21-node ANN, the maximum uncertainty in the estimation of targets killed is approximately 5-10% across the range of inputs while the 3-node ANN has a maximum variability of up to 40%, illustrating the need for very accurate surrogates[6].

Moving from left to right, it is also evident that even within a model of a given accuracy, the addition of multiple probability distributions on the inputs obviously creates compounding uncertainties on the responses. Even when highly mathematically accurate surrogates (or even the true models themselves) are used, the problem of uncertainty quantification now becomes a problem of visualization and understanding. Most traditional engineering texts contain plots that more closely mimic the left-side of Fig. 2: they are simplified "partial derivatives" illustrating the impact of a response due to a single factor. As one moves to the right and adds more variables to the exploratory study, the "fuzziness" in the outputs more closely resembles a "total derivative." It quickly becomes

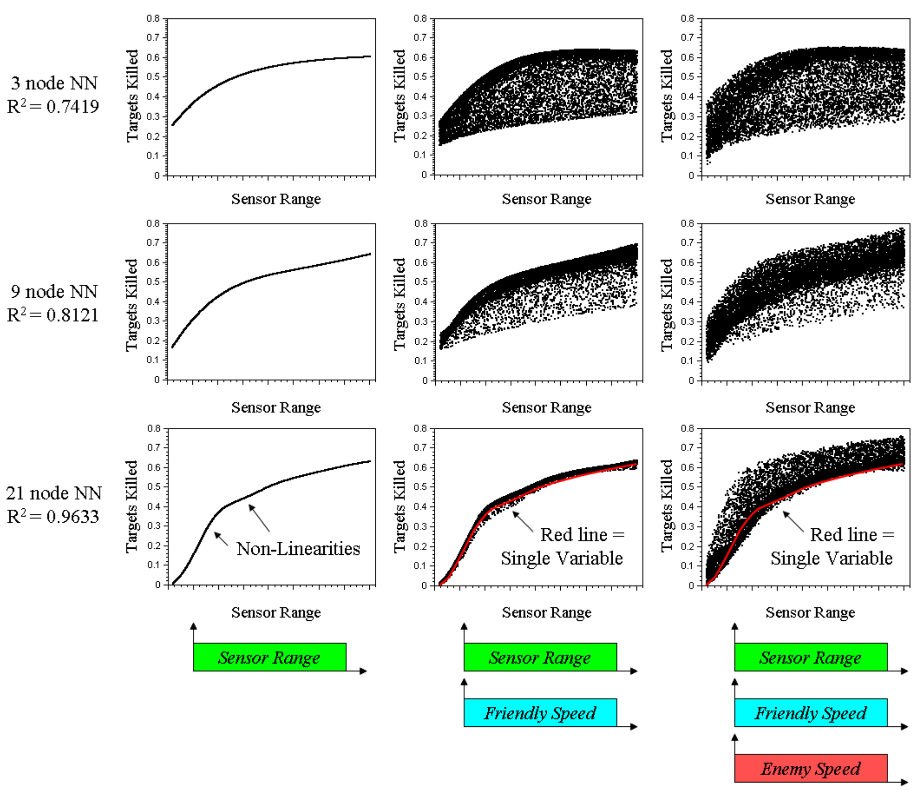

Fig. 2. Comparison of Neural Network Accuracy and Impact of Multiple Variables.

[6] It should be noted that many designers are unwilling to accept a 5-10% uncertainty and that the surrogate technique appears ill-suited for this application. This is not precisely true as *exceptionally large ranges* of uncertainty (tens of miles on sensor range and hundreds of knots on aircraft speed) were used to create illustrative and comparative examples. In practice, much more refined ranges would likely be used.

very difficult for engineers to understand the significance of impacts when all variables are changing simultaneously.

In systems-of-systems problems the curse of dimensionality not only refers to the ability to compute accurate uncertainty-bounded solutions in realistic time frames, but also the ability to then visualize, understand, and make decisions regarding the generated information. As Marsaw et. al. note, the use of probabilistic methods across multiple input variables drives the need to shift from two-dimensional bivariate plots to a multi-dimensional visualization environment which "consists of a matrix of bivariate scatterplots showing all parameters simultaneously" [42]. The multivariate environment for the ANN-enabled 2004 Air Force Research Laboratory technology study is shown in Fig. 3. Here, output measures-of-effectiveness are shown in the upper leftmost area of the plot and independent variables are shown with decreasing class significance in the SoS hierarchy as one moves down and to the right.

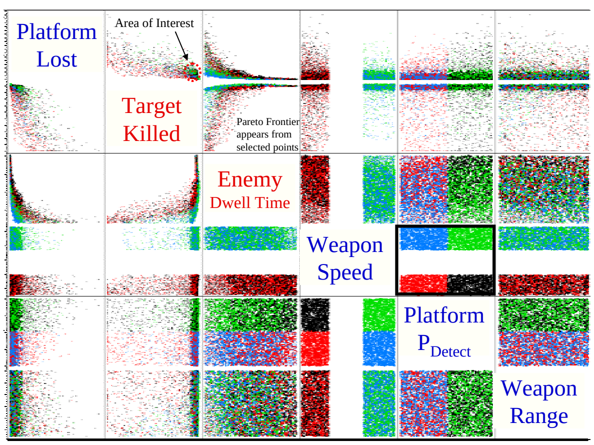

Fig. 3. Multivariate Plot for the 2004 Air Force Research Laboratory Study.

Techniques such as dynamic linking of data points, dynamic filtering based on design assumptions, color coding, and manipulation of histograms and scatterplots are all used to "slice" the data in different ways. While such an environment provides a wealth of information, much research is needed on the concise presentation of this type of information in a format easily interpretable by decision makers.

5 Uncertainty in Assumptions and Model Validation

Though the integration of aircraft design tools with operations analysis models provides the means to trace the impact of system-level technology parameters to capability-level measures-of-effectiveness, this research highlighted the social disconnect that engineers have with the difficulty of simulating system operations. For systems design problems (models based on physics), the assumption space is relatively well-defined. Terms like "straight and level flight", "clamped beam", "inviscid", and "low speed" all have a set of parameters tacitly associated with them. In SoS design, the assumption space includes phrases like "intermittent communications", "hostile threat environment", "forward presence", and "off-board sensing" to name a few. These phrases carry with them *ambiguous* assumption sets; engineers and analysts from different backgrounds set up the problem differently depending on how they interpret these phrases. Consequently, solutions vary widely due to misrepresentation of the operational assumptions. In system-level problems, these sources of *model uncertainty* were largely neglected; however, for systems-of-systems design problems, the influencing aspects of the operating environment (and its uncertainty) often dominate the impacts on capability-level measures-of-effectiveness. Varying these assumptions probabilistically is often not practical as the multiple assumption sets often require different discrete setups, compounding the complexity of the analysis task exponentially. Currently, there is no well-defined taxonomy of assumptions for systems-of-systems analysis in the aerospace community. Decision makers often focus on the variables they know (lift, drag, fuel consumption) while harmonization of the model parameters that often dominate these technical factors is often much more critical. As systems engineering moves firmly into the realm of systems-of-systems, engineers and managers must be careful not to confuse the unfamiliar with the unimportant.

Another challenge facing the community is the perceived need for "verified," "validated," or "accredited" models. The definition of these terms is as follows [43][7]:

- **Verification:** "The process of determining that a model implementation and its associated data accurately *represents the developer's conceptual description* and specifications."
- **Validation:** "The process of determining the degree to which a model and its associated data are an *accurate representation of the real world.*"
- **Accreditation:** "The *official certification* that a model, simulation, or federation of models and simulations and its associated data are acceptable for use for a specific purpose."

It is a US DoD policy that "models and simulations used to support major DoD decision-making organizations and processes… shall be accredited for that specific purpose" [44]. The accredited models typically used for these purposes include monolithic simulations that take days or weeks to run and often center around one or several inflexible point scenarios. They usually represent present-day or near-term systems exercising known capabilities in well-studied operational environments.

Recently there has been much work on topics such as agent-based modeling, constructive simulation, discrete

[7] Emphasis added.

event simulation, system dynamics, graph theory, network theory, real options, Petri nets, and other techniques for modeling cognition (behaviors), networks, emergence, deep uncertainty, complexity, and other irregular disciplines which dominate these types of problems. To date there are few *structured methods* which deal holistically with these disciplines, and based on the definitions above, models are usually verified, sometimes validated, and seldom accredited.

The operations analysis, modeling and simulation, and aerospace design community have long been focused on the precise specification of performance metrics using validated or accredited phenomenology models. In a traditional application, MCS is used to quantify uncertainty around these points and allows decision makers to understand the risk of certain courses of action.

On the other hand, the cognitive science and exploratory analysis communities have tended to focus on broad-brush, low-fidelity, high-speed models designed to provide insight into a wide range of potential outcomes. Many network models and military simulations now rely more extensively on behaviors of human-simulating agents than the system-simulating physics-based codes. Simply running a MCS around these unvalidated (and in some cases unvalidatable) models does not tend to reveal accurate or useful results primarily because *the parameters related to model uncertainty cannot be defined a priori*. Customers cannot always state assumptions and requirements clearly at the study onset because of the inherent uncertainty in even the problem statement. Simulation efforts therefore often take a "build-observe-tweak-observe" iterative development approach to model construction and portray a "hand-waving" attitude toward validation.

This disconnect appears to arise from the need for systems-designers to venture into the operations analysis community to comply with the mandate for capability-based acquisition. The shift unfortunately necessitates a broad understanding of many different systems and phenomena. For example, aircraft designers often have extensive knowledge of flight physics but little understanding of how threat surface-to-air missile systems perform (much less how they are typically integrated or operated as a network).

A framework for understanding the VV&A needs of the simulation tools with respect to the decisions it will be used for is needed. This framework should advise the simulationist on the type of model required and the assumptions that must be defined (or uncertainty-bounded) to support the required decisions. Analysts must then work with decision makers and other experts to bound the parameters defining model uncertainty. This necessary but oft-overlooked step is needed before any simulation or surrogate can be reliably constructed to study the impacts of parameter uncertainty and determine the values of design parameters.

6 "New" Challenges

The emergence of systems-of-systems as a focus of design and systems engineering activities seems to identify several "new" sources of uncertainty:

- Scenarios assumptions ambiguous and evolving
- Measures of Effectiveness are difficult to define
- The operational characteristics including strategy and tactics are unknown
- Physical phenomena are focused more on interactions with the environment and other systems
- Validation needs are not straightforward
- Problem setup approaches vary widely across different experts (even within the same field)

In reality, these are not new effects. While traditional systems design focuses on uncertainty due to natural or parameter uncertainty, ***capability-based systems-of-systems design must be more concerned with model uncertainty.*** In fact, parameter uncertainty and in many cases the parameters themselves at each individual system level have a negligible contribution to the overall variability of the capability-level response. This realization highlights the fundamental challenge of this new era, as few of the aforementioned factors can be handled by simply using a Monte Carlo Simulation.

Engineering problems are often solved through scientific reductionism by recognizing the dominant impacts of a physical phenomenon and summarily simplifying the requisite models. It is not clear where this reduction-based approach loses the "essence" of the complexity that is under study. The interesting, interrelating, and "game changing" behaviors in systems-of-systems are the ones which must be modeled.

The acquisition community will also have to come to grips with the fact that models are often unvalidated and are sometimes unvalidatable. Concept of validation breaks down when considering unknown systems, and exercising unknown functions in an unknown environment. For the present, an understanding of bounds and insight into relationships may be the limits of the analytical craft. Precise quantification of uncertainty due to so many factors that dramatically change the topology of the modeling environment may be unachievable for some time.

That is not to say that these issues are not being addressed across various communities; however, in many instances, these disparate stakeholders have yet to come together, cross-fertilize best practices, and harmonize an approach to studying systems-of-systems problems. The same impasse is encountered each time a new layer of complexity is included in the model of the world. This complexity is always addressed in time through the development of new tools, techniques, and skills.

The various challenges outlined in this paper related to uncertainty quantification for capability-based systems-of-systems design and analysis are summarized in relation to traditional system-level challenges in Fig. 4.

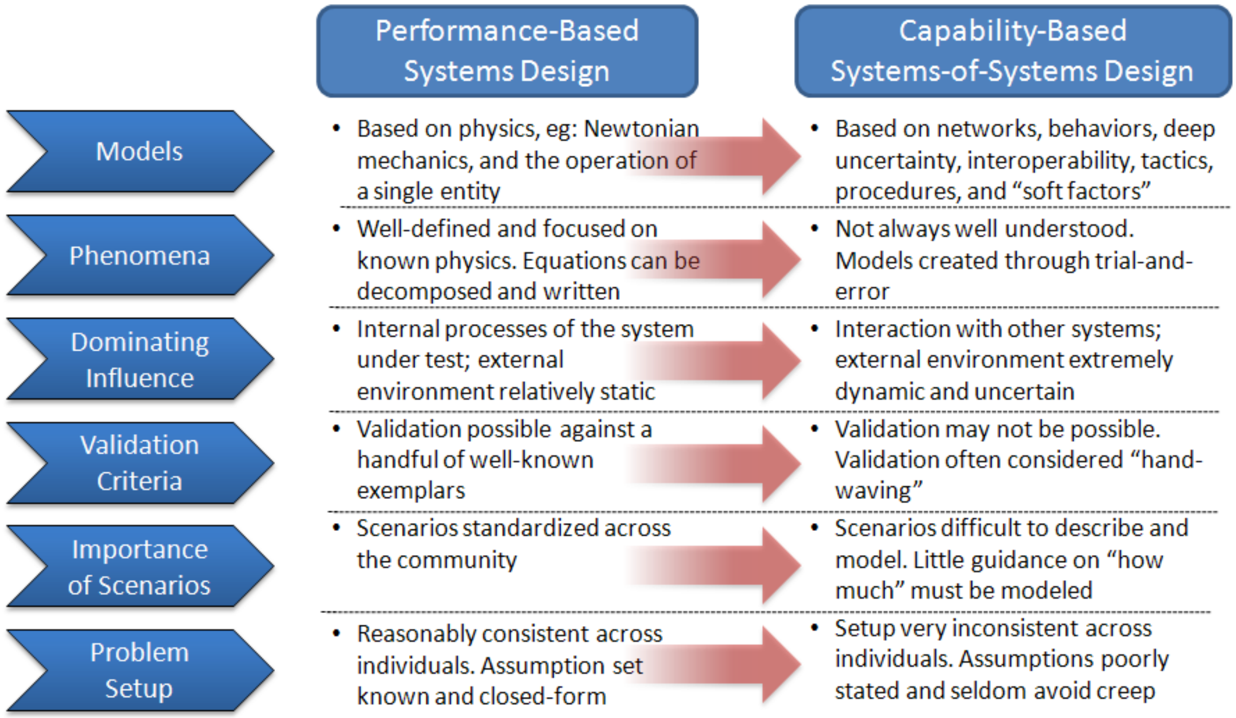

Fig. 4. Comparison of Performance-Based Systems Design and Capability-Based Systems-of-Systems Design.

7 Summary and Conclusions

The maturation of disciplinary science and the emergence of *design-as-a-discipline* allowed the physics of the aerospace domain to be understood, taught, and modeled. Over the past several years, these methods have been linearly extended to address the problems classified as "systems-of-systems," which in many cases are dominated more by the interactions between systems than the parameters of the systems themselves. This poses several challenges for uncertainty quantification in aerospace design as the methods and techniques were primarily developed to quantitatively evaluate parameter uncertainty as opposed to model uncertainty. Model uncertainty tends to dominate systems-of-systems problems resulting from a variety of sources, not the least of which stems from the inability to crisply define the system interrelationships, operating environment, and assumptions of the problem. In fact, for these classes of systems, the environment and the interactions between systems are often more significant on the overall response than the system design parameters themselves.

While it appears new sources of uncertainty have been uncovered as this field evolves, the sources are not new, merely more dominant than they had been considered in the past. Methods for quantifying uncertainty for unvalidated models are needed (if such a concept is even useful or makes sense). Engineers and decision makers must also learn to collaboratively develop models and understand the sources of and bounds on uncertainty. A process for defining ambiguous scenario assumptions at pre-defined "checkpoints" is likely needed to avoid the tendency of assumptions to co-develop with results until the simulation is "overcalibrated" to a familiar and uninteresting solution.

As shown in this work, for the aforementioned reasons, the quantification of uncertainty in systems-of-systems is not merely as simple as "throw a Monte Carlo around it" or "figure out the right distribution to use." Engineers need intelligent ways of quickly focusing on the important parameters, which unfortunately may include many factors outside their traditional purview.

The use of probabilistic methods combined with surrogate models for uncertainty quantification is only advised when the predictive model very closely approximates the actual code. Settling for lower levels of accuracy than traditionally recommended for polynomial surrogates is appropriate only for insight-providing design space exploration studies. The lack of fit appears to be due to more than the neural network topology, training algorithms, and training time. New methods for narrowing the model uncertainty associated with scenarios, assumptions, and behaviors are needed in conjunction with statistical techniques for improving the fit of the ANN-based surrogates.

Finally, as the size and complexity of systems-of-systems problems increases, new visualization techniques that inform and do not overwhelm the decision maker are sorely needed. The difficulty in understanding the problem domains will only continue to increase as new layers of complexity are considered non-negligible in the study of systems-of-systems.

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The statements in this work and conclusions therein are those of the author and do not necessarily reflect the official position of the Georgia Institute of Technology or the United States Air Force Research Laboratory.

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