Uncertainty Quantification (UQ) in Complex System of Systems (SoS) Modeling and Simulation (M&S) Environments

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Abstract. Prevailing Modeling and Simulation (M&S) techniques have struggled to provide meaningful quantitative results in M&S of complex System of Systems (SoSs). This paper reports on systems thinking applied to "how" M&S techniques should shift to allow a next generation of quantitative tools and techniques. The imperative is to provide quantitative performance results across the constituent interfaces in a modeled architecture. Statistical and parametric methods that address Uncertainty Quantification (UQ) are presented in the light of a new paradigm in M&S using graph theory based tools and databases to allow deeper insight into the fundamental problem of interoperability modeling. A future vision is suggested that presents the opportunity for systems engineers to lead a transformation in M&S of complex SoS.

Introduction

As systems have become more complex, the modeling and simulation (M&S) of these ***s**ystem**s*** and System of Systems (SoS) becomes equally, if not more, complex. The usual M&S challenges of performance, fidelity and approximations are joined with new challenges such as emergent behavior and aleatoric and epistemic uncertainty regarding the behavior, and particularly the failure modes, in the face of uncertainty about the parameters and initial conditions with which it might be confronted in a complex, changing, and often hostile environment. The specific topic addressed by the authors in this paper is the uncertainty characterization and quantification in complex SoS M&S Environments.

The domain of SoS, and Systems of Systems Engineering (SoSE) have received much attention especially from the United States Department of Defense (DoD). Initial attention was placed on defining what is a SoS, that is when is a collection of systems a SoS. Subsequent efforts focused on defining what SoSE is and the establishment of SoSE Communities of Practice (CoP). Much of this SoS work initially focused on the notion of extending classic System Engineering (SE), processes that have been successfully used for engineering complex systems to the SoSE domain. Through review of the literature and our experiences as engineering practitioners, the authors contend that specific and quantitative tools, techniques and procedures, to define "how to" implement SoSE is missing.

The decision-maker desperately needs quantitative information from the SoSE about SoS mission goals vs. mission capability at the enterprise architecture level throughout the lifecycle. Our research and systems thinking leads us to believe that Graph theory- based approaches facilitate answer this need for quantitative SoSE. Deiotte and Garret introduced a new methodology for capturing the essence of the physical SoS, the functions executed within the SoS, the interactions between components (at both the functional and behavioral levels) and the causal nature of the SoS based on an employment strategy. Leveraging multiple graph theoretics, a Mission Level System of Systems Engineering (MLSoSE) approach provides an abstract, quantifiable method to assess the nature and quality of a SoS, addressing sensitivity, uncertainty and quality of the composition.

The foundations of graph theory spans multiple centuries back to Leonhard Euler's paper published in 1736 entitled Seven Bridges of Konigsberg (Euler, 1741). This paper related a problem of a traveling salesman who could only cross each bridge in the city of Konigsberg one time while minimizing his total travelled distance. Euler's formula relating properties of the graph (nodes, edges and faces) is said to be the origin of topology. Graphs are prolific and can be seen in all facets of science, math, nature and society. Their application to the SoS problem is bourgeoning as can be seen in the multiple graph representations of SysML, DoDAF and UML, to name a few. Authors like Garret (Garrett, Baron, Moreland, & Anderson, 2012), Marchette (Marchette, 2010), Luna (Luna, Lopes, Tao, Zapata, & Pineda, 2013) and Mortveit (Mortveit, 2008) have all applied the basic concepts of graph theory to multiple aspects of the SoS problem space. From architecture and design to analysis and Verification and Validation, graphs can be shown to be at the heart of the SoS paradigm.

The advantages of utilizing graphs for the representation, exploration and exploitation of SoSs are innumerable. Because of the flexible nature of graphs and their multiple incarnations (undirected, directed, acyclical, cyclical, etc.) graphs can be utilized to represent static and dynamic characteristics of the SoS while utilizing a standard mathematical formulation for quantitative analysis of the structure. By associating metadata to edges and nodes in the graph and transforming from one graph type to another allows engineers, architects and analysts alike to explore models of SoSs freely extracting pertinent information regarding behavior, performance, uncertainty and risks.

Additionally, there has been a large move in the past decade to utilize graphs as large, complex data stores to overcome some of the natural issues with traditional relational databases. This includes being able to associate multiple forms of information with multiple types of relationships thereby allowing the extraction of information from data in a manner that is intuitive and frank. Leveraging a graph based paradigm for SoS modeling and data bases allows interoperability far beyond the current state of the art.

The authors have had a unique opportunity to collaborate on this paradigm shift needed to enable and empower the SoSE to deliver a new level of M&S to address SoSs. We have discussed this issue with system thinkers at the INCOSE 2013 IS in a Research Session of the SoSWG. We have reached out across domains, authors and expert practitioners. As a result, we are convinced this shift has the potential for a transformation in SoSE by getting to "how." Efforts are underway to complete a graph-theory modeling tool which incorporates graph databases. Uncertainty and Uncertainty Quantification plays a central role in a new horizon for SoSE. The next section describes work accomplished on an Uncertainty Characterization and Quantification prototype targeted as a key component in near-term SoSE analyses using graph-theory based modeling techniques.

Uncertainty Quantification

Uncertainty Characterization and Quantification (UCQ) is designed to benefit a client with an M&S system[1] whose uncertainty they wish to characterize and quantify to support evaluation, management, and/or improvement of the M&S or perhaps integrating it into a multi-model synthesis. Every M&S system is based on a set of exogenous assumptions about initial conditions, environmental factors, etc. Uncertainty in the output of the M&S system is a consequence of uncertainty in the values of one or more of these exogenous assumptions. Following [National Research Council (NRC) on UQ] we refer to these uncertain exogenous assumptions as "parameters."

Uncertainty is fundamentally the potential to generate surprises, especially unpleasant surprises. At this stage in its development, UCQ focuses on one single number output from the M&S system for each unique set of parameter values the M&S system is given. We refer to this value as the quantity of interest, or QoI. [NRC 2012a] A commonly used QoI to assess the performance of a simulated missile defense system [NRC 2012a] is margin. [Helton 2009] An interceptor missile is assumed to have a kill radius such that, if the interceptor and the enemy attacking missile come within this kill radius, the attacking missile is destroyed with a positive margin equal to the kill radius, minus the distance between the two missiles. If, unfortunately, interception does not occur, the margin is then the smallest distance achieved between the two missiles, minus the kill radius.

[1] The prototype implementation includes a "Toy Problem" to take the place of a client's M&S. While much simpler than any real M&S system, the "Toy Problem" includes nonlinearity and discontinuity to ensure that UCQ for characterization and quantification of uncertainty will be effective in an environment where both the real world SOS and the M&S systems modeling it have strong digital switching elements rather than being purely analog systems that can be modeled by differential equations.

For some of the parameters whose value is uncertain, the client may have evidence to support the belief that the real-life value of the parameter will come from a specified probability distribution. In this case we refer to the parameter as aleatoric. Examples include the failure probability for individual components, the probability of a common mode failure, and the prior probabilities and likelihoods that enter into a Bayesian analysis.[2] On the other hand, there may be other parameters whose value is uncertain and nonrandom; all the user has available is a range of possibilities with no evidence to support one possibility in favor of another. Parameters subject to this kind of nonrandom uncertainty are referred to as epistemic parameters. One clear example would be the action of an enemy who makes unpredictable choices, not at random, but for reasons of his own which are not fully known to us.

We treat the client's M&S system as a black box; we do not use any classified or proprietary information about the internals of the M&S. In order to use our system, the client permits a link between it and his own M&S system, enabling UCQ to submit a specific value for each parameter, initiate a run of the simulation model, and receive back a value of the QoI. The client must also specify the range of possible values for each epistemic parameter and the probability distribution function for each aleatoric parameter.

Using this information, UCQ first creates a representative random sample using the Latin Hypercube sampling method [McKay & Conwer, 1979]. Using a geometric analogy, we refer to the vector specifying a unique value for each uncertain parameter as a point in a multidimensional parameter space.

In order to treat aleatoric and epistemic parameters consistently without discarding legitimate probability information about aleatoric parameters, or introducing spurious probability assumptions about epistemic parameters, we apply a generalized probit transformation [Bliss 1934; Cleophas & Zwinderman 2012] to replace each possible value that a given aleatoric parameter might take on with its cumulative probability in the unit interval. We also use a simple linear transformation to map the range of possible values for each epistemic parameter into the unit interval. This maps the higher dimensional space, defined by parameters expressed in natural units, to a unit hypercube. For reasons that will become apparent shortly, we refer to this unit hypercube as "batspace."

For each point in the parameter space selected by the random sampling process, UCQ queries the client's M&S system, which takes those specific parameter values, runs the simulation from start to finish, and returns the value of QoI. UCQ uses this representative random sample to output a standard statistical report of mean, standard deviation, skewness, kurtosis, and other statistics giving information about the global behavior of the QoI, as parameter values vary according to the aleatoric or epistemic information available.

Following the conventional statistical analysis, we institute an exploited search procedure in which biologically inspired agents [Brownlee 2012] ("bats") seek out areas of noteworthy performance (ANPs) [Schultz et al 1992]. ANPs come in three varieties. An Upside ANP is an area in parameter space characterized by exceptionally high values of QoI; a Downside ANP is characterized by exceptionally low values; and an Unstable ANP is characterized by rapidly changing QoI values associated with small changes in the values of the parameters.

[2] Some authors treat the latter two categories as epistemic despite the presence of a well-defined probability distribution.

An ANP is a hazard if it indicates the mere possibility of failure; it is a risk if failure has a significant degree of plausibility or probability [NRC 2009].

The database formed by aggregating all of the Upside, Downside, and Unstable ANPs forms the basis for a global characterization and quantification of uncertainty. Dempster's [1967] upper probability is a mathematical tool well suited for combining aleatoric and epistemic uncertainty without loss of information or introduction of spurious assumptions. Our approach normalizes the result of this calculation to create the membership function of an evidence-based fuzzy set of plausible values of QoI. The plausibility of failure is the highest membership of any negative value of QoI in the fuzzy set of plausible values[3]. The total uncertainty of the M&S system is quantified by the area under the membership function, the "sigma count." The global characterization and quantification of uncertainty, summarized by the two key scalar metrics quantity of uncertainty and plausibility of failure, is useful for comparative assessment of one M&S system against competing M&S systems of the same real world scenario.

We created a Toy Problem representation of an M&S system. The Toy Problem is a simple missile defense scenario that mimics the effects of aleatoric and epistemic parameters. These effects include a "kill radius" and a hypothetical "Hawaii" effect. These terms appear throughout the following explanation of the five major steps in our technical feasibility demonstration.

Step One: Consistent Treatment of Aleatoric and Epistemic Parameters. In order to treat aleatoric and epistemic parameters defined on a variety of scales of measurement in a consistent manner without losing valuable probabilistic information about the aleatoric parameters, and also without introducing spurious probabilistic assumptions about the epistemic parameters [Aven 2010], we transform the parameter vectors defined in natural units in parameter space into a multidimensional unit hypercube, referred to as batspace. Biologically inspired exploited search agents, "bats", operate in batspace to find ANPs which, when translated back to natural units in parameter space and submitted to the client's M&S system, generate areas of performance noteworthy for exceptionally high, exceptionally low, or exceptionally unstable performance.

The mapping process for an epistemic parameter is very simple. A given specific value of such a parameter in natural units is transformed into a value in the unit interval by subtracting the lower bound of the parameter's range and dividing by the width of that range. The reverse transformation is simply the mathematical inverse of that process.

The transformation of an aleatoric variable from parameter space to batspace is more complex. It uses a probit transformation [Bliss, 1934] to hold in abeyance the probabilistic information about the aleatoric variable in such a way that it can be ignored by the bats operating in batspace but restored when batspace values are transformed back into natural units in parameter space. In UCQ we transform a value in parameter space by using the probit transformation giving its cumulative probability, and we transform a corresponding point in batspace using the inverse probit transformation to find the value in natural units whose cumulative probability is that given value in the unit interval. Since the literature on

[3] The probability of failure is always less than or equal to the plausibility of failure; probability cannot be precisely quantified in the presence of epistemic uncertainty.

probit transformation is generally focused on Gaussian distributions, we use the phrase "generalized probit transformation."

These transformations can be visualized using an ordinary cumulative probability graph. Suppose that one of the parameters of an M&S is an amount of money that is normally distributed with a mean of $11 and a standard deviation of $3. If we needed to find the location in the unit interval in batspace corresponding to a dollar amount of $10, we can see it in Figure 1 by looking vertically upward from $10 on the parameter space axis and reading the value of the corresponding element of batspace as 0.37. Contrariwise, if we had a value of 0.37 in batspace and needed to find the corresponding value in natural units in parameter space, we would look horizontally from 0.37 on the vertical batspace axis and read the corresponding value of $10 in parameter space.

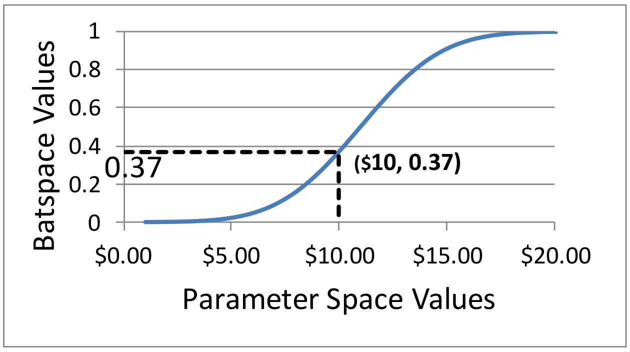

Figure 1. Cumulative Probability Graph

Since the toy problem that we used to demonstrate the performance of the prototype system for characterization and quantification of M&S uncertainty has six uncertain parameters, the parameter space and corresponding batspace in the present prototype each have six dimensions, with a seventh dimension representing the QoI. Increase in the number of dimensions is straightforward and adds only linearly to the amount of computation required.

Step Two: Standard Statistical Characterization and Quantification of Uncertainty. In this step we treat each transformed parameter in batspace as a uniformly distributed random variable. This is standard practice in Monte Carlo simulation for aleatoric uncertainties. If the transformed value in the unit interval is given a uniform distribution, the inverse transformation will give the correct probability distribution in natural units in parameter space. For epistemic uncertainties, the principle of insufficient information [Aven, 2010] is frequently used to justify the imposition of a uniform distribution. These distributional assumptions in batspace are only temporary for this stage of the analysis and will be discarded in the following stage; however they are standard practice and the statistical results of this assumption are provided to the client as a familiar set of tools for assessing M&S systems.

The Latin Hypercube sampling approach [McKay et al 1979] is a widely used method to generate a representative random sample of inputs to be used in assessing a computer simulation system. We use this method to perform a stratified random sample on the assumption of a multivariate uniform distribution discussed above.

Step Three: Search for Areas of Noteworthy Performance. The next step is to assign each sample point in the representative sample described above to a biologically inspired parallel exploited search agent. These search agents are loosely modeled as bats that use active sonar at short range to detect tiny mosquitoes by emitting chirps at varying frequencies depending on the local concentration of prey. This variation allows the bats to also use passive sonar [Bohn,1838] at longer ranges to see which other bats in their family are achieving better hunting success and fly towards those more fortunate family members on the basis of two instincts. One instinct is to approach more successful family members, and the other is to fly toward family members who are nearby. Each bat's decision-making is done in parallel, independently of the decision-making process of any other bat relying only on fellow family members' location and success.

Since there are three classes of ANPs: Upside, Downside, and Sensitivity, there are effectively three different species of bat. The concentration of the prey sought by Upside bats at any point in batspace is directly proportional to the value of QoI in the corresponding point in parameter space. Downside bats hunt for a prey whose concentration in batspace is negatively proportional to the value of QoI in parameter space. The behavior of our Sensitivity bats is least comparable to that of any real bat. These bats are motivated to fly towards nearby family members whose success rate is maximally different from theirs, whether greater or lesser.

When the bats have arrived at their next location, their position in batspace is transformed back to natural units as discussed above. This vector of parameter values is transmitted to the client's M&S system which performs a simulation run and returns the QoI. Once every bat has received the QoI value corresponding to its new location, they determine which family member to fly towards and move to a third location and the cycle continues. The current implementation of the working prototype converges within 10 or fewer iterations, except in the more complicated search for Sensitivity ANPs. The prototype has 30 bats divided into five families of six bats each; since all three species use this structure there are effectively 15 families, 90 bats in all. It is a straightforward matter to increase the number of bats, with only a linear increase in the total amount of complexity required. The result of the collection of points visited by the bats during the search is a sample which is divided into separate ANPs, one for each family for each of the three types of ANPs sought. The entire sample is used in Step Four, while the data from each of the 15 families is used separately in Step Five.

Step Four: Global Characterization and Quantification of Uncertainty. The ideal real-world system would be one that delivered excellent performance regardless of what the values of the possibilistic and probabilistic parameters happened to be. An uncertain system is one that works well in some circumstances and poorly in others. Uncertainty in a purely probabilistic or aleatory system is defined by the variance, probability of failure, and other statistical dispersion measures of the QoI across the probabilistic variations of the probabilistic inputs. Contrariwise, when all the dimensions are possibilistic, simple interval analysis [Moore et al, 1996] suffices. For the general situation of UQ for simulation models of highly complex real-world systems, neither of these standard approaches is entirely satisfactory, as discussed above. Consider an extremely simple system with just one probabilistic variable x1 which is normally distributed with mean 100 and standard deviation 10, and one possibilistic variable x2 ranging from -5 to +5 with no evidence to support any particular probability distribution. The response surface for this extremely simplified example is F(X) = x1 + x2.

In Figure 2, Graph A, the solid diamonds represent the probability density function of F(X) when x2 is equal to 0. The triangles represent the probability density function of F(X) when x2 is equal to -5. Note that pessimistic values of F(X) are more probable when x2 is negative and optimistic values of F(X) are more probable when x2 is positive.

The solid black curve is the maximum probability density of F(X) over all values of x2 for a given value of x1. It was called the upper probability by Dempster.

In 1967 Dempster proved that the probability of a partially specified event must be less than or equal to the upper probability in a mathematically defined class of situations that includes mixed models with possibilistic and probabilistic variables.

The upper probability curve can be approximated from the collection of values generated by the bats. Conceptually, we can graph each observed value of F(X) against the upper probability of the most plausible point in input space observed to generate that value of F(X), then connect the dots to draw the convex hull and a smoothed version of it.

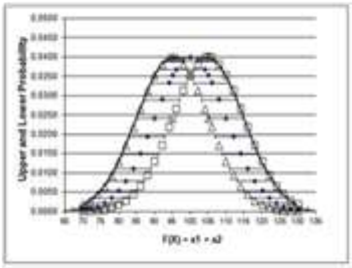	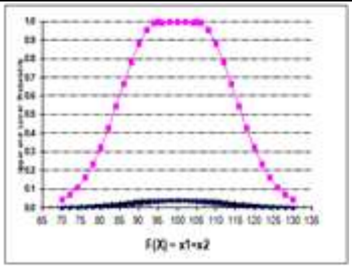	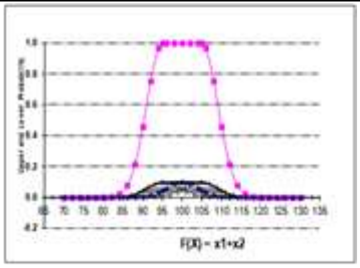
Graph A: Derivation of Plausibility	**Graph B: Set of Plausible Values, s.d. = 10**	**Graph C: Set of Plausible Values, s.d. = 4**

Figure 2. Plausibility

The area under an upper probability curve of the extremely simple function F(X) = x1+x2 is proportional to the range of the possibilistic variable but is insensitive to the variance of the probabilistic variable; similar difficulties apply to more realistic cases. Calculating a normalized plausibility by dividing each upper probability by the maximum plausibility can be used to define a fuzzy set of plausible values. The area under this curve, known as the sigma count, is positively related both to the variability of probabilistic variables and the range of possibilistic variables. This area constitutes our measure to quantify the global uncertainty of a simulation model for assessing highly-complex real-world systems. The global uncertainty of the UQ system's analysis of a given simulation model is represented by the sigma count of the plausibility membership function, which is just the area under the curve. Since it is the integral of a curve found by dividing one probability density by another, it is dimensionless, but serves to compare the total uncertainty of one model with another and, by extension, the total uncertainty of the two real-world systems being so modeled.

In a totally certain system, the graph would be a vertical line at the certain QoI value. In a totally uncertain system the graph would be a horizontal line from –infinity to +infinity and uncertainty would be infinite.

The plausibility of failure is the plausibility of the most plausible negative QoI; graphically it is the maximum height of the red area.

Figure 2, Graph B, shows the fuzzy set corresponding to the example discussed above, while Figure 2, Graph C, shows the fuzzy set arising from the same example, except with a standard deviation of only 4 for x1.

Figure 3 shows the global quantification of uncertainty for the M&S with the Hawaii effect included. The gray area represents values of QoI which are not observed, but which contribute to the total uncertainty because of the penalty value of -100. The total quantity of uncertainty for this M&S is 184.94 and the plausibility of failure is 96.14%.

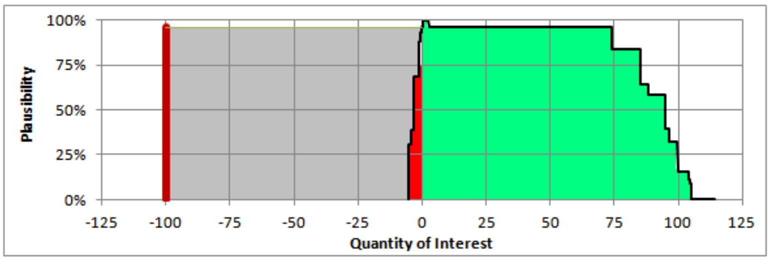

Figure 3. Evidence-Based Fuzzy Set of Plausible Values (With Hawaii Effect)

Step Five: Local Characterization and Quantification of Uncertainty. Global characterization and quantification of uncertainty is useful for comparing the overall effectiveness of competing variations of the real world SoS. [Volkert et al 2013] However, more is needed in order to achieve the full potential of characterizing and quantifying the uncertainty in an M&S system. Understanding what goes on at each individual ANP is necessary to inform the process of identifying errors and inadequacies in the simulation system in order to improve the simulation and/or to recognize opportunities to design a synergistic multi-model M&S that exploits the specific strengths and overcomes the specific weaknesses of complementary individual M&S systems. Moreover, it is through information about the various ANPs of an M&S system that the client is equipped to discover the strengths and weaknesses of the real world SoS. The following sections describe mathematical, statistical, and graphical characterization and quantification of local uncertainty in the particular area whose performance is noteworthy for high, low, or rapidly-changing values of QoI.

Mathematical Characterization and Quantification of Local Uncertainty. The local mathematical information begins with a table showing the location in parameter space of the mean values of all the parameters and of QoI for all bat families of a particular type: Upside, Downside, or Sensitivity. Following this there is a series of reports for each individual ANPs.

The first element of this series of reports is a table giving the mean, median, maximum, and minimum values of each parameter in the ANP in question, together with the mean, median, maximum, and minimum values of the QoI in the ANP. We will use the results from Bat Family 1 in the above Sensitivity search as our example shown in Table 1 below:

Table 1. Bat Family 1 Sensitivity Search

	x1	x2	x3	x4	x5	x6	QoI
mean	80	23	103	56	46	103	-22
median	81	16	100	59	52	100	14
maximum	100	100	141	100	88	141	125
minimum	14	0	94	0	0	98	-100

Statistical Characterization and Quantification of Local Uncertainty. The statistical portion of the information provided for each individual ANP begins with a stepwise quadratic regression equation fitted to the points visited by one particular bat family, with the exclusion of the first two sets of points. The resulting quadratic form potentially including all of the parameters is a meta-model of the behavior of the M&S system focused on just the neighborhood of the ANPs inhabited by that particular bat family.

A variety of statistical analysis tools can be applied to the data collected for each ANP. In our current approach a local quadratic regression for each combination of three parameters vs. QoI and reports which combinations give the best statistical predictive power.

Graphical Uncertainty Characterization and Quantification of Local Uncertainty. The three parameters with the highest collective predictive power in a local quadratic approximation for this ANP are x1, enemy aim point 1; x3, kill radius 1; and x4, attacker aim point 2. The graphical characterization and quantification of an ANP begins with an array of nine graphs. Each of the three parameters in the most predictive set of three has one row and one column in the table. The median value of the predictor in question within the given ANP is indicated by a red dot on the quadratic regression line.

Figure 4 gives the graphical characterization and quantification of uncertainty for the example ANP discussed above. Red regions in the three-dimensional space portrayed in these graphs indicate that the QoI is negative, meaning that the M&S has predicted failure of the real world SoS under simulation. Green regions indicate positive values of QoI.

The first graph approximates the QoI as a local univariate quadratic function of x1, enemy aim point 1. Since the median value x1 is already above the corresponding defending aim point x2 in the cluster found by Bat Family 1, increases within the boundaries of the neighborhood of this ANP consistently lead to more favorable values of QoI and vice versa.

The three-dimensional graph in the center, showing the local quadratic approximation of QoI as a function of x1 and x3 contains an important interaction effect. Within the local area of this ANP, performance is negative only when X1 and X3 are both low. This can be seen in the lower front right corner of the 3D graph. If X1 is high, that means in the context of this local ANP that it is close to X2; the two missiles are close together, so that a value of X3, the kill radius, within the local area of this ANP can still lead to positive QoI. Similarly, if X3 is high, the kill radius is wide enough that x1 can be in the low end of its range within this local area, relatively far away from the intercepting missile assigned to it, and still be destroyed, resulting in a positive value of QoI.

The third three-dimensional graph shows the interaction between the first enemy aim point x1 and the second enemy aim point x4 in the area inhabited by Bat Family 1. The red color is seen for high values of x1; for x4, the graph is green for values close to 50 and red for values either much higher or much lower than 50.

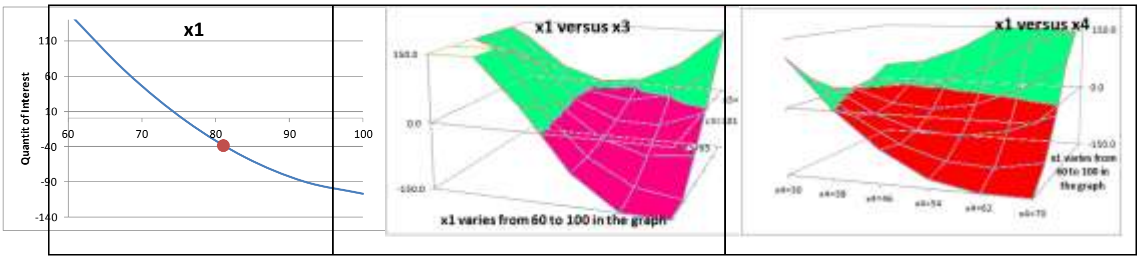

Figure 4. Graphical Characterization and Quantification of Example ANP

The second component of local graphical characterization and quantification of uncertainty consists of a graph comparable to the one for global characterization and quantification of uncertainty, with QoI on the horizontal axis and plausibility on the vertical axis. The amount of uncertainty indicated by the gray area is much larger than the area of uncertainty in the global characterization and quantification of uncertainty for the toy problem that includes the Hawaii effect. The same possibility of a penalty of -100 with one hundred percent plausibility exists in both cases, but in this local ANP, which was found by bats specifically seeking maximum sensitivity, the green area is smaller and concentrated on the most favorable end. The above example is shown in Figure 5.

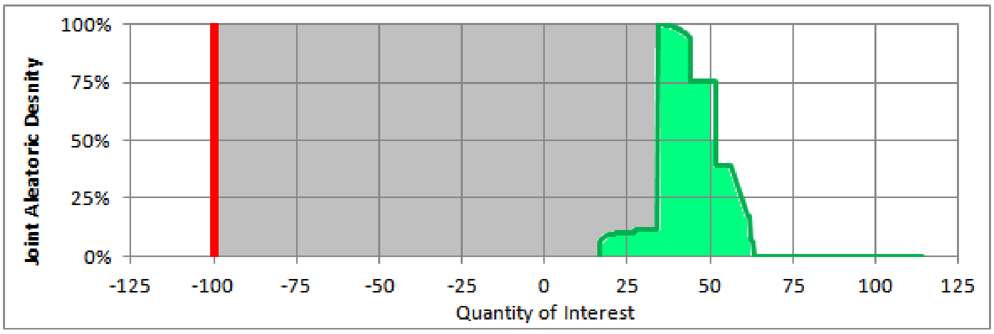

Figure 5. Plausible Instability from Sensitivity ANP 1

Summary

Uncertainty Characterization and Quantification. The goals of this project are to demonstrate feasibility of a system that will characterize and quantify the output uncertainty produced by an M&S arising from a combination of aleatoric and epistemic input uncertainties. UCQ system performs this characterization and quantification both globally and locally in terms of specific ANPs. Additionally, this system was designed to be able to be scaled up to high dimensionality in order to accommodate large models in a timely basis without requiring a super computer. Having such a tool will make it possible to evaluate and compare M&S SoS, for both evaluation and improvement as well as possible synthesis into a multi-model approach.

Our vision for UCQ is to build a web service open architecture prototype that facilitates coupling and interfacing with any number of modeling and simulation tools. A first integration in the next 24 months will be with a graph theory based architecture modeling tool. Our open architecture approach allows a service and application layer UCQ capability current complex M&S environments, even those not build on service oriented constructs. The substantial shift to graph theory based M&S in the COP will require an ability to demonstrate the value of graph theory results compared to legacy M&S systems. UCQ will serve as an initial independent variable.

Graph Theory SoS M&S. Complex SoS M&S is a fertile, undefined playing field. To the authors there is a critical need for multiple layers of both modelling and simulation that span the conceptual to the continuous. Due to the nature of the SoS (their sizes and complexities) a layered approach is necessary to be able to capture both the gross and granular characteristics of the SoS. Current techniques have proven that multiple techniques are possible and all provide useful information about Systems of Interest (SoI's) but their interactions and ability to feed one another leaves much to be desired. Our vision is one of tiered, integrated M&S tools that have the ability to perform conceptual analysis which can feed into design-level M&S and testing and ultimately to Verification, Validation and Assessment of the SoI within one seamless process. The ability to leverage common data structures and mathematics will determine the community's ability to achieve this goal. We propose the migration of all tools, techniques and procedures to a graph basis to allow this transformation and to fully reap the benefits of SoS's as they have been proposed.

Future of SoSE and Roadmap. A Confederation of small business innovative research contractors led by government change agents has taken on the challenge to demonstrate the value of the approach described in this paper. We view INCOSE as a key supporter of the systems thinking necessary to change a M&S paradigm to achieve benefits to mankind. Our reach is expanding rapidly and we find interest in many adjacent domains and enterprises. We are on a roadmap that builds a COP and conducts a series of Technical Interchange Meetings (TIMs) with invited stakeholders. The goal of these TIMs will be to advance ideas, applications and demonstrate results of "how" SoSE will conquer complex SoS M&S through UCQ.

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