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Applying Model-Based Systems Engineering to Ship Design and Acquisition through Simulation, Design of Experiments, and Operational Effectiveness Modeling

12 December 2016

Eugene Paulo, Associate Professor

Department of Systems Engineering

Naval Postgraduate School

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

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Technical Objectives

This Acquisition Research Group (ARG) sponsored project is follow-on to our recent effort supported by the Office of Naval Research (ONR). The purpose of the research was to demonstrate a methodology that leverages simulation models early in the architectural design of a ship, and that methodology is described in more detail in the technical approach section. The traditional naval architect paradigm is to design the weapon systems, radars, or any organic ship asset around the hull vessel platform instead of the platform being designed around the assets. As a result, the intended ship's operational effectiveness becomes dependent on the design of the platform, rather than on the organic assets of the ship. Simulation models allow ship designers to reverse the traditional paradigm by linking a ship's operational effectiveness to physical ship characteristics early in the life cycle. By analyzing simulations that incorporate physical design input parameters, we can identify the physical design characteristics that will result in better operational effectiveness. These physical design parameters are what define the ship's alternative configurations. Trade decisions among physical characteristics can then be based on operational effectiveness, rather than on the physical constraints of the system. For Fiscal Year 2014, this paradigm was extended by two master's student theses from within the Systems Engineering Department under the supervision of the Principle Investigator (Jaworski, 2014; Nutting, 2014).

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Technical Approach

To demonstrate this methodology, in FY12 and FY13, ONR sponsored the Department of Systems Engineering at NPS to supervise four naval officer students to apply the proposed Model-Based Systems Engineering (MBSE) design concept. While for FY14 we focused on the design of a carrier for unmanned aerial vehicles, in our work for ONR, the design concept utilizes computer simulations to model an Off-Shore Patrol Vessel (OPV) within different operational scenarios. In addition, the concept uses a ship synthesis model that dictates a feasible ship design for a given set of design parameters. The context of the design problem is to understand how different physical ship characteristics impact operational effectiveness. The MBSE design utilizes polynomial meta-model functions that act as simulation model surrogates in order to explore the trade space among several response outputs. Figure 1 illustrates the MBSE design concept proposed by the Department of Systems Engineering at NPS, based on the research effort focused on the OPV platform.

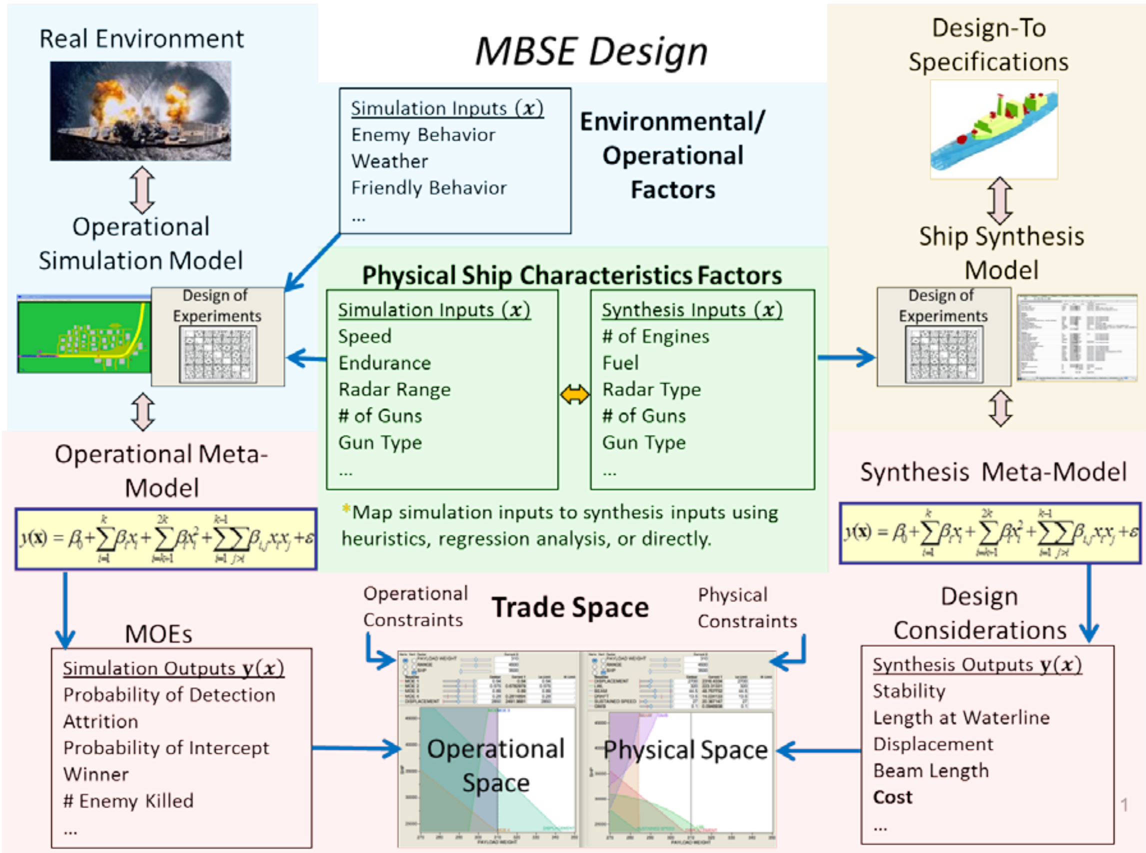

Figure 1: MBSE design concept linking synthesis physical design parameters to operational effectiveness (from MacCalman, 2013).

The left side of Figure 1 shows the linkage between the real-world operational environment, the simulation models that are an abstraction of the real environment, and the meta-models that act as surrogates to the simulations. These operational meta-models describe the dependence of the measures of effectiveness (MOEs) on physical design characteristics. The center of the figure shows the physical design characteristics consisting of measures of performance (MOPs) and physical design parameters; the physical design parameters are the decision factors that define a ship configuration and are controlled by the ship designer. The MOPs are a function of the design parameters; for example, speed is a function of the type and number of engines. Above the physical design characteristics are the environmental and operational noise factors that the designers have no control over. The meta-model response, *y*, is a vector of MOE results that are the simulation's outputs. The design matrix, *x*, contains the simulation inputs composed of the physical design characteristic decision factors and the environmental/operational noise factors.

In order to create the operational meta-models, each student performed an experimental design on their simulation model, with multiple replications on a high-performance computer cluster. We created three custom designs with a mix of continuous, discrete, binary, and categorical factors. Table 1 shows each simulation model's experimental design characteristics.

Table 1: Experimental design characteristics for the MBSE ship design problem (from MacCalman, 2013). The table shows each design's number of factors, levels, type, and the subsets of factors that have minimal correlations for either a first- or second-order model.

Maritime Interdiction Operations Design			
Number of Factors	Number of Levels	Factor Type	Factor Order (1st or 2nd)
8	300	Continuous	2nd Order
2	300	Continuous	1st Order
1	11	Discrete	
1	3	Discrete	
2	2	Binary	
1	11	Categorical	
1	3	Categorical	
Note: The 16-factor design with 200 design points has a 1st Order p_{map} = 0.047. The subset of factors that are labeled 2nd Order have a 2nd Order p_{map} = 0.048.			

Anti-Surface Warfare Design			
Number of Factors	Number of Levels	Factor Type	Factor Order (1st or 2nd)
3	200	Continuous	2nd Order
3	10	Discrete	
1	5	Discrete	1st Order
8	2	Binary	
Note: The 15-factor design with 200 design points has a 1st Order p_{map} = 0.023. The subset of factors that are labeled 2nd Order have a 2nd Order p_{map} = 0.029.			

Search and Rescue Design			
Number of Factors	Number of Levels	Factor Type	Factor Order (1st or 2nd)
11	465	Continuous	2nd Order
2	3	Discrete	1st Order
1	25	Discrete	
1	4	Categorical	
Note: The 15-factor design with 465 design points has a 1st Order p_{map} = 0.034. The subset of factors that are labeled 2nd Order have a 2nd Order p_{map} = 0.065.			

The MBSE design concept relies heavily on the accuracy of the meta-models developed from the experimental design. The designs in Table 1 provided excellent exploratory opportunities for the analyst to understand the complicated behavior of the simulation outputs. Because these designs minimize the correlation between model effects, they reduce the variance in the coefficient estimates and increase their precision by reducing model bias; these benefits may improve the fit of second-order polynomial meta-models. For an in-depth look at the simulation models, analyses, and insights gleaned from the designs in Table 1, see Ashpari (2012), and McKeown (2012). Subsequently, Kaymal (2013) examined OPV escort operations in the Straits of Gibraltar. For a more comprehensive overview of designing and analyzing large-scale simulation experiments, see Sanchez, Lucas, Sanchez, Wan, & Nannini (2012) or Sanchez & Wan (2015).

The right side of Figure 1 has the same construct as the left side, only instead of modeling the operational effectiveness, it models the ship configuration feasibility determined by the ship synthesis model. Performing a DOE to create the synthesis meta-models allows us to describe the synthesis model output's dependence on the physical design parameter inputs. The meta-model response, y, is a vector of synthesis model outputs. The design matrix, $\boldsymbol{x}$, contains the synthesis model inputs that define the ship configurations. The synthesis model outputs are design considerations that ensure that a given ship configuration (defined by the design parameters) is feasible. For example, the designer can increase the radar detection rate by maximizing the radar range with a taller mast height, which will interfere with the ship's stability (a synthesis model output). Understanding how the mast height impacts the radar detection rate, as well as the ship's stability, is important to both the operational commanders and the ship designers; a mast height that is too tall may provide excellent radar detection rates, but may render the ship configuration infeasible due to the instability it creates. Using DOE to create the operational and synthesis meta-models in tandem provides the ship designers with a way to explore the linkages between the operational MOEs and the design synthesis considerations, using mathematical functions.

The center of Figure 1, labeled "Physical Ship Characteristics Factors," shows some examples of the synthesis model inputs. These inputs may be different than the operational simulation inputs. For example, the speed of the OPV is an operational simulation input that must be mapped to the synthesis model as the type and number of engines. If an operational MOE requires a lot of speed, the ship designers can investigate how to obtain a higher rate of speed with a variety of engine types and engine numbers. Changes to the engine synthesis inputs may require changes to other synthesis inputs in order to ensure that the ship's design considerations (or synthesis outputs) remain feasible. Additionally, these synthesis input changes may result in changes in the operational MOE performance. In order to visualize how changes in design parameters impact the operational MOEs and design synthesis considerations, the MBSE design concept uses contour profilers.

At the bottom of Figure 1, labeled “Trade Space,” there are two contour profilers, one representing the operational space and the other the physical space. A contour profiler is a two-dimensional projection showing the relationships between two design parameters and a response from a polynomial, meta-model function. These projections allow the user to interactively explore how a response depends on two design parameters. The shaded areas represent constraint limits set by the user on each of the responses; as a result, the white area represents the feasible region. Within the operational space, a lower response limit may represent a threshold or minimum acceptable response the operational commanders’ desire. The limits within the physical space may be ship configuration feasibility constraints dictated by the ship synthesis model. The crosshairs within the contour profilers indicate the design parameter settings depicted along each axis. Visualizing the operational and physical contour profilers next to each other allows the user to explore different design parameter configurations, while ensuring that the ship remains feasible. As long as the crosshair remains within both the operational and physical white space (feasible region), we can find design parameter settings that will achieve the desired performance among multiple operational MOE responses. In addition, the contour profilers allow the user to understand the trade-offs that exist between responses; by adjusting the desired constraint limit of the responses, we can explore ways to increase performance in one response, while decreasing performance in another.

The operational meta-models created from the experimental designs in Table 1 were used to create the operational contour profiler in a dynamic “Dashboard” that highlights the trade-offs between three operational MOEs and five physical design considerations. Figure 2 shows the MBSE design concept contour profilers that represent the operational and physical spaces.

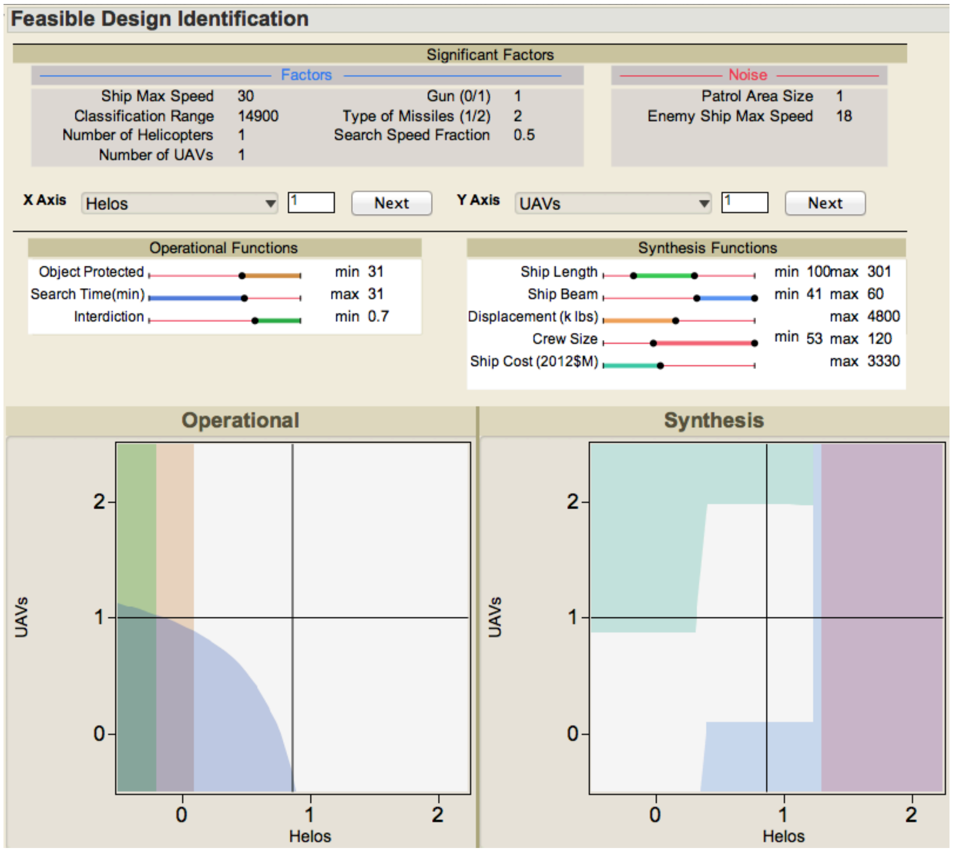

Figure 2: The MBSE design concept contour profilers (from MacCalman, 2013). The colored areas indicate infeasible ship configurations that violate the minimum and maximum constraints set at the middle of the figure, under the operational & synthesis functions.

The contour profilers in Figure 2 allow decision-makers to explore different ship configurations while ensuring it is feasible and operationally effective. There are seven physical design factors and two operational noise factors listed at the top of Figure 2; these are the significant factors within the meta-models created using the designs in Table 1. In the middle of Figure 2, there is an area that sets the minimum and maximum constraints for each of the three operational and five synthesis meta-model functions; the form of the meta-models determines the shape of the colored contours. Adjusting the constraints will adjust the colored area that indicates the infeasible region; as long as the crosshairs fall within the white space in both the operational and physical space, the ship is simultaneously feasible and effective. Because the shape of these meta-models greatly impacts the insights gleaned from the contour profilers, it is important to ensure that they are as accurate as possible in order for the MBSE design concept to be effective.

Progress Statement Summary

The following description of research progress is an extension of work from FY12 and FY13 described previously. This FY14 research, sponsored by the Acquisition Research Program (ARP), continues the use of MBSE as a means to improve both ship design and the system acquisition process by the allocation of mission capabilities to operational requirements and then to alternative physical forms. Essentially, our approach allows for acquisition decisions to be made based on the feasibility of the design in both the operational and physical domain, as both an operational effectiveness model (OEM) and a ship synthesis model (SSM) have been built for an initial proof of principle. The method is defined to support concept exploration through implementation in a dynamic “dashboard” display environment, allowing government designers, acquisition professionals, and decision-makers to explore mission-related possibilities and provide input to prospective engineering decision-makers and shipbuilders. The expectation is that this methodology is initially best suited for early concept exploration. Additionally, providing this dashboard tool to a classroom, along with the means to conduct simulation analysis in order to see the impact of changes to design decisions and/or needed capabilities, is a very possible subsequent application.

Our intent for FY14 was to apply this approach to a larger Navy vessel, rather than the OPV. This was achieved by a Systems Engineering master’s student in his thesis (Jaworski, 2014), as he focused his design and analysis on a potential carrier for unmanned aerial vehicles. We additionally examined a more formal modeling approach, and modeling language, to linking operational effectiveness to ship design through MBSE with a master’s student thesis (Nutting, 2014). Finally, this ARP project partially supported the development and dissemination of new design of experiments (DOE) approaches (Sanchez, 2014; Xing, Wan, Zhu, & Sanchez, 2015) that may benefit future studies that are focused on operational effectiveness and system design.

Jaworski's Thesis Summary

Jaworski's thesis research supported an overall NPS research effort investigating critical technologies and techniques for disseminating air wing capabilities across fleet assets. This thesis applied a model-based systems engineering (MBSE) approach to the design of an unmanned aerial system (UAS) air wing deployed in an anti-access area denial environment against a seaborne integrated air defense system (IADS). The specific research questions included the following:

- What are the functional performance drivers of a UAS air wing deployed against an IADS?
- How do variable enemy fleet IADS platforms affect anti-IADS UAS air wing performance?
- How does UAS air wing mission operational effectiveness relate to the design space of a future UAS deployment platform?

Initial document review indicated the critical need for continued U.S. Naval power projection capabilities in the face of growing near-peer competitor military development. Enemy fleet IADS present a modern challenge to continued power projection capabilities. UAS concepts were introduced as a means to combat IADS development. Initial research indicated that UAS air wings have been used as anti-IADS platforms in the past, and efforts are ongoing to develop miniature air-launched decoys with electronic warfare capability. Also, the initial research described the shift in Systems Engineering development from a document-centric approach to an MBSE approach. MBSE methods also demonstrated the link between operational effectiveness and system synthesis and served as the method for exploring the UAS research topic.

Initially, UAS model development commenced with presentation of the capability gap with regards to anti-IADS performance. Next, development of a design reference mission commenced focusing on a surface warfare scenario, describing friendly and enemy combatants and initial performance characteristics. The systems engineering model was then developed, with system context, operational activities, functional view, component view, and operational effectiveness modeled as a discrete event simulation. Model development led to the abstraction of the UAS air wing, made up of unmanned aerial vehicles (UAV), with one of three capabilities available against an IADS:

- Decoy UAVs, acting as a decoy to the enemy IADS
- Strike UAVs, capable of disabling IADS ships and associated surface to air missile inventory
- Electronic warfare (EW) UAVs, capable of degrading IADS performance

Development of the discrete event simulation allowed evaluation of the operational model under three unique experimental designs. The first examined the critical design characteristics of the UAS squadron, including UAV performance characteristics and overall UAS squadron composition. The second analyzed the effect of increased enemy IADS surface to air missile inventory on performance. The third evaluated overall performance of the UAS squadron. Analytical regression allowed development of operational meta-models of performance based on the design parameters.

With regard to research question 1, the conclusions were as follows:

- Strike UAV probability of enemy ship kill has no impact on operational performance.
- Electronic warfare effect of the EW UAVs has a greater impact on performance versus UAV speed.

With regard to research question 2, the conclusion was as follows:

- Large enemy fleets employing an IADS can be defeated with a large number of UAS and anti-ship cruise missiles.

With regard to research question 3, the conclusions were as follows:

- Using a probability of 100% IADS missile exhaustion allowed simple linear regression constructions of the IADS scenario.
- Relation of UAS air wing size to overall system operational performance is the first step to UAS deployment platform development.

Nutting's Thesis Summary

MBSE is a reaction to the increasing complexity of modern systems. The International Council on Systems Engineering (INCOSE) defines MBSE as "the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases." The formal modeling allows the use of software tools to assist in maintaining the consistency throughout the systems engineering project. This increase in automation allows systems engineers to make fewer errors and spend a greater portion of their effort on quality engineering.

Formal modeling requires a formal language. A formal language, unlike a natural language, is one that operates with explicitly defined rules. This avoids ambiguity and provides consistency. A good language for systems engineering has to be sufficiently expressive that all relevant aspects of the system and its behavior can be described, but at the same time not require years to learn.

This thesis examines modeling languages for systems engineering from the viewpoint of integrating quantitative analysis into MBSE. Two secondary topics are examined to better understand what features are desirable in modeling language for systems engineering:

- What does the process for creating a model for a quantitative analysis in systems engineering entail?
- What processes in systems engineering (as described by ISO standard 15288) are affected by language choices for quantitative modeling?

Figure 3 illustrates a process model that was created to examine what is involved in quantitative modeling for systems engineering. This model is consistent with the processes of the modeling and simulation community, and also with the stepwise refinement used in many MBSE methodologies (Robinson, 2011; INCOSE, 2008). Two key considerations resulted from this model: First, there needs to be an existing architecture in which to conduct the analysis. A simplistic view of a quantitative model is that it transforms a set of inputs into a set of outputs. Without establishing an architecture beforehand, it is unlikely that the inputs for a quantitative analysis will align with the systems engineering effort. This creates desirability for the quantitative model to be integrated into the architecture, so that creating one also creates the other, and implicitly maintains consistency between the two views.

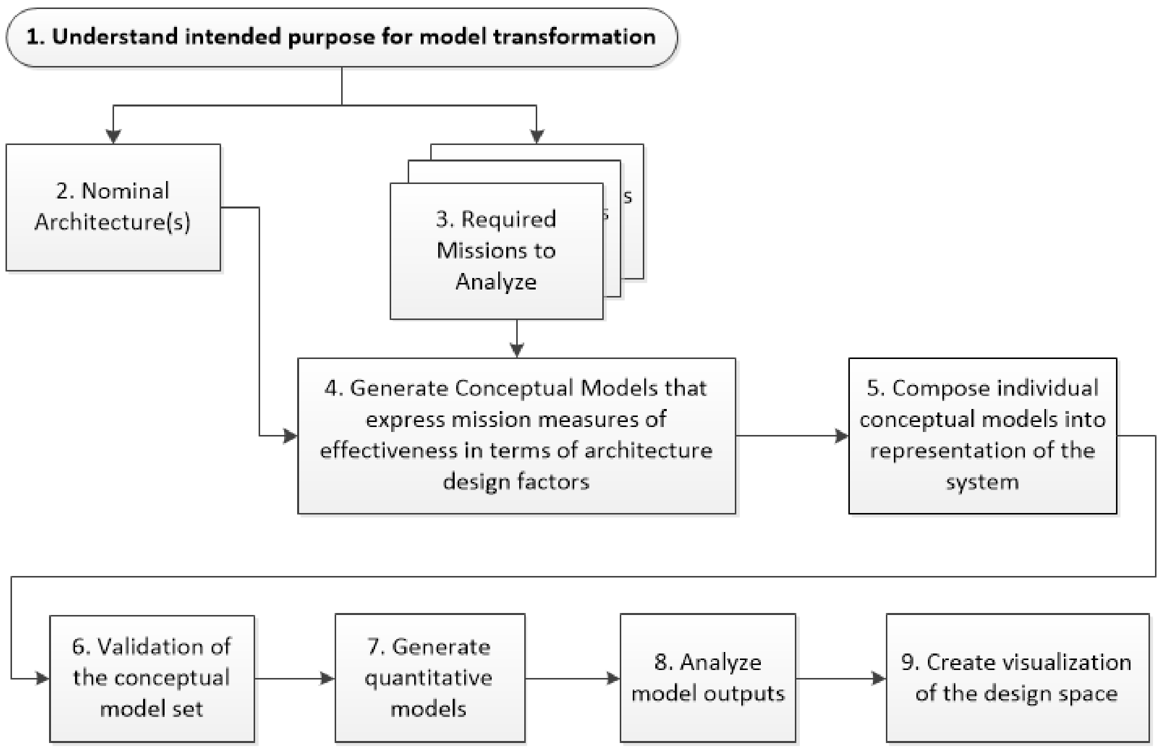

Figure 3: Quantitative Analysis Process Model

The second key consideration is in steps 5 and 6. The individual quantitative models need to be examined holistically to understand how they relate to the system. A major concern is that interactions between differing areas of functionality may be omitted due to breaking down the modeling effort into more manageable pieces; explicitly considering whether the set of conceptual models is valid provides a deliberate opportunity to assess this concern. This consideration points to the desirability of incorporating quantitative analysis into the systems model to make this step easier to conduct.

The ISO standard 15288 (Systems and software engineering—Systems Life Cycle Processes) has been adopted by INCOSE for categorizing and defining the differing processes where systems engineering is involved. Two of the processes where choice of modeling language for systems engineering and quantitative analysis are particularly important are infrastructure management and requirements engineering.

Infrastructure management has to take into consideration the capabilities and availabilities of software tools with which to conduct MBSE throughout the system life cycle. This implies that an open, or non-proprietary, language is preferable. Ideally, the language is standardized to reduce the possibility of a single software vendor making changes to the language, breaking interoperability with other software tools. Proprietary languages are at risk of the vendor exiting the market and forcing a decision on whether to maintain with increasingly obsolete tools or to undergo a costly rebuild of the system model in a different language. Additionally, the use of a proprietary language can complicate adapting custom tools between projects or throughout an industry.

The requirements engineering process benefits greatly from integration of quantitative modeling into the system model. The ability to view how a proposed requirement affects multiple aspects of the system simultaneously supports better decision-making. Furthermore, having decision-makers examine these trade-offs before setting final requirements allows the use of Richard Balling's "design by shopping" paradigm. This concept is to have decision-makers be able to examine the trade-space and understand what good designs (in terms of being Pareto optimal) look like before prioritizing the various requirements. This is a more natural decision-making sequence similar to how individuals make decisions such as buying a new car or a house, and it can lead to a better set of requirements from which to build the system.

Four important characteristics for a systems modeling language were identified: Support for interoperability and integration between multiple software tools, flexibility, support for non-fixed value parameters (such as random variables), and composability of executable architectures. Several systems modeling languages were analyzed based on these characteristics: Unified Modeling Language (UML), Systems Modeling Language (SysML), and Vitech's Schema Definition Language (SDL).

All three languages had shortcomings in supporting composability of executable architectures, due to the lack of semantics to clearly distinguish between events among different entities and internal events. They allow systems engineers to specify event sequences that are intermingled and miss possible interactions. There are approaches to resolve this limitation. The Monterey Phoenix project defines a formal language that clearly distinguishes which events are shared and which belong only to a single entity (Auguston et al., 2012). This enables automatic generation of all possible event sequences for analysis.

UML and SysML have good support for integration and interoperability with multiple tools. In addition to their specifications being open and available, both implement the XML meta-model interchange, a standard way to storing the model data to support interoperability between software tools. SysML and SDL have partial support for ISO 10303-233: systems engineering data representation, a model interchange standard for systems engineering. It only specifies a limited subset of model views and is not meant to encompass the entire system engineering modeling effort.

Both SysML and UML are flexible. Their meta-model can be adapted and extended by users to accommodate specific needs. The concept of stereotypes and extensions allows the use of specialization-type relationships that preserve the relationships of the general type of model entity.

SDL allows defining new model entities and relationships between them, providing some level of flexibility. It does not allow binding relationships between properties of different system, limiting the use of parametric relationships in the system model.

All three languages have poor support for non-fixed value properties. SysML has non-normative guidance on defining random variable datatypes, but does not provide any guidance on how to handle random variables that are defined implicitly by some sort of parametric relationship between random variables. The UML standard provides no guidance. Both languages can have ad-hoc support for random variables, but ad-hoc support by its nature is inconsistent, and for a base engineering concern such as random variables it is insufficient.

SDL has support for certain properties related to behavior models to be defined as random variables. Systemic support for arbitrary properties to be defined as random variables does not exist. The CORE MBSE tool, similar to many SysML MBSE tools, has support for scripting that can be used to create this support, but without standardization the ability to use this consistently between different tools and across projects is limited.

Design of Experiments Methodology

As previously mentioned, the use of appropriate design of experiments (DOE) methods underpins the process of constructing meta-models of both operational performance and ship synthesis. The OPV simulations implemented by Ashpari (2012), McKeown (2012), and Kaymal (2013) all ran quickly, so large-scale designs could easily be used. For example, it took less than 24 hours on a computing cluster to run 100 replications of 2048 different design points (excursions from the base-case scenario) for Kaymal's maritime escort scenario. However, for more complicated scenarios with much longer run times, it might be beneficial to reduce the computational effort required. Xing et al. (2013, 2015) examine an alternative factor screening approach, where super-saturated designs allow the analyst to examine *p* factors in *n* design points (excursions) where *n* is much less than *p.* As long as the analyst is willing to assume an upper limit on the number of truly important factors (say, at most 10% of the total factors investigated), then the “least absolute shrinkage and selection operator” (Lasso) can be used to construct optimal supersaturated screening designs. Once this screening occurs, other space-filling experimental designs can focus on the most important factors for meta-model construction. Experiments on Kaymal’s scenario, augmented with thirty additional environmental factors, are used to illustrate the new approach in Xing et al. (2013) and as the basis for a more in-depth investigation in Xing et al. (2015).

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Conclusions and Recommendations

As described above, our intent was to continue to improve the use of MBSE as a means to improve both ship design, and the system acquisition process, by the allocation of mission capabilities to operational requirements and then to alternative physical forms. Essentially, our approach allows for acquisition decisions to be made based on the feasibility of the design in both the operational and physical domain, as both an operational effectiveness model (OEM) and a ship synthesis model (SSM) have been built for an initial proof of principle. The method is defined to support concept exploration through implementation in a dynamic "dashboard" display environment, allowing government designers, acquisition professionals, and decision-makers to explore mission-related possibilities and provide input to prospective engineering decision-makers and shipbuilders. The expectation is that this methodology is initially best suited for early concept exploration. Our intent for FY14 was to apply our approach to a larger Navy vessel, rather than the OPV. This was achieved by a Systems Engineering master's student in his thesis (Jaworski, 2014), as he focused his design and analysis on a potential carrier for unmanned aerial vehicles. We additionally examined a more formal modeling approach, and modeling language, to linking operational effectiveness to ship design through MBSE with a master's student thesis (Nutting, 2014).

Recommendations for future work are centered in three areas in languages for MBSE:

- Understanding and developing the appropriate semantics for the use of black box entities in the area of parametric modeling and analysis.
- Semantics and syntax for use of random variables in properties of model entities, including those defined by relationships between random variables.
- Modeling techniques for system behaviors that make it easier to avoid specifying expected event sequences versus possible event sequences.

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