Enabling Collaborative Decision Making: A Process for Integrating Novel Systems Engineering Tools and Methods for Renewable Energy Portfolio Analysis

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Abstract. Increasingly complex problems drive systems engineers to develop novel decision making processes. The breadth of complex problems demands the interaction of various groups, each focusing on specific areas but all addressing a higher level common cause. The process brought forth in this paper integrates a series of methods, some widely accepted and others which are novel in nature. Quality Function Deployment is used to capture customer desires and focus engineering level requirements. Multi-Attribute Decision Making is used to identify system configurations when multiple and competing objectives exist, which is a situation where traditional optimization struggles. The process of surrogate modeling is introduced to rapidly access elements of modeling and simulation, a necessary step to analyze system options. The very integration of these methods enables collaborative decision making. A proof of concept is presented where each of these methods is applied to aid in the portfolio analysis of renewable energy system options for a remote off-grid site.

Introduction

Motivation. As systems engineers tackle increasingly complex problems, we struggle as a community to find and apply practical methods, processes, and proven best practices to guide and inform decisions that must be made. Additionally, in the early phases of a problem, we are quick to dismiss complex detailed engineering level analysis such as modeling and simulation in order to properly scope a plan of attack within a feasible time frame. A process is needed which includes several key facets. Given that detailed engineering analysis is traditionally both time- and resource-intensive, methods must be used to best capture customer requirements such that engineering analysis is properly and effectively directed. Additionally, it is desired to have complex, quantitative engineering level analysis inform decision making as early as possible when facing a problem, especially in the very beginning when comparatively little is known about the problem. Finally, it is expected that decision making is supported when multi-faceted problems present many competing objectives. This paper will describe a process that integrates both accepted and novel systems engineering methods to support decision making when faced with complex problems. To assist the reader with understanding this process, a practical application of these methods to addressing energy systems is discussed throughout this paper. The engineering analysis presented in this paper is an expanded discourse of methods presented by Ender *et al.* [2008] as applied to energy systems portfolio analysis.

Novelty of Approach. The application of methods described in this paper for energy systems modeling moves beyond the notion of individual component design. The approach uses elements from the field of systems-of-systems research, where each system is independently managed and operated. In this line of analysis, the capability of the integrated whole will produce results greater than sum of the individual components. An examination of whether the hybrid energy systems studied in this paper are considered a system or a system-of-systems is beyond the scope of this paper; the notion of systems-of-systems is briefly introduced because the analysis methods used in this study are born from this field of research.

Research methods conducted on capability-focused and inverse design for analysis of complex systems-of-systems [Ender, 2006; Biltgen *et al.*, 2006] will be used to identify hybrid energy solutions that meet dynamic requirements. This includes enabling inter-system requirements tradeoff analyses. Surrogate models, which are bounded equation representations of more complex tools that offer negligible loss in fidelity, are created based on trusted modeling and simulation tools. These surrogate models (in this case neural networks) can be executed thousands of times in fractions of a second, enabling rapidly resolved trade-offs that yield results that might not otherwise have been discovered with traditional means. Decision-makers are afforded a novel real-time, panoramic view of trade-offs and parametric sensitivities via advanced visualization features. The result is the ability to conduct qualitative decision-making based on rapid manipulation of quantitative modeling and simulation, initially described by Ender *et al.* [2008].

Evaluating Hybrid Power Systems. In order to put forth a novel methodology for solving complex system problems, a thorough examination is given of approaches for solving similar problems. Hybrid renewable power system designs can be evaluated with a number of methods. The most straightforward method of evaluating a system is a detailed time-series simulation, which has been used to a great extent [Lilienthal et al., 2005; Manwell et al., 1998; Borowy and Salameh, 1996; Beyer and Langer, 1996; Diaf et al. 2008; Celik, 2003]. It involves dividing a study period into discrete time steps, such as a year divided into hourly blocks. At every time step, the energy flows of the system are calculated based on load, available renewable resources, available storage state, and control logic. Simulation approaches may be easily scaled to any desired system configuration and any level of component and control detail, with arbitrarily high levels of nonlinearity. However, such approaches require time-series environmental and load information, which may not be available but can be synthetically generated.

Other approaches generally trade some level of detail for faster run-times. Statistical approaches have been used with some success to estimate the effectiveness of hybrid power systems. Techniques have been developed to estimate the loss of power supply probability for hybrid renewable systems comprising of solar, wind, and battery storage [Abouzhar and Ramakumar, 1991; *ibid*, 1993; Tina *et al.*, 2006; Karaki *et al.*, 1999]. Such methods enable the allocation of time into large discrete steps, such as a day or a month. An advantage of this method is that it produces probabilistic rather than deterministic results; to acquire the same information from a simulation could require multiple Monte Carlo runs.

A frequency domain approach has been successfully applied for power quality assessment of wind turbines [Vilar *et al.*, 2003], and in the evaluation of controllers [Uhlen *et al.*, 1994]. For such uses, computation time savings can be realized compared to a time-series approach, especially because consideration of power quality necessarily involves consideration of frequency, which implies very small simulation time steps and thus long simulation run-times.

Optimizing Hybrid Power Systems. In renewable power system design, one of the principle objectives of optimization is the selection and sizing of system components. With costs stated in terms of unit costs, and with simplified linear component and control models, the selection of component sizes has been successfully performed with a linear programming approach [Garcia and Weisser, 2006; Chen and Atta-Konadu, 1997]. This constitutes both an optimization and evaluation scheme, though fundamentally such an approach still requires the same time step resolution as a nonlinear simulation approach and is still a time-series model.

A single optimization objective can be used, such as conversion efficiency as shown by Borowy and Salameh [1996]. The most common optimization method seems to be to optimize a single economic parameter (such as overall system cost) while meeting system performance constraints (such as loss of load probability) [Kellogg *et al.*, 1996; Habib *et al.*, 1999; Muselli *et al.*, 1999; Yang *et al.*, 2007]. Multi-objective optimization has been used, with mixes of performance and economic objectives [Shi *et al.*, 2007; Anagnostopoulos and Papantonis, 2008], where solutions are sought which may not be optimal with regard to any single objective, but which are *Pareto optimal* with respect to several.

The system designer will want to select a design from somewhere along this *Pareto frontier*. However, there are two complicating factors. The first is that the final design selection, though it will be along this frontier, depends on the *relative importance* of the multiple dimensions, and this is a qualitative choice on the part of the designer or stakeholder. The second complication is that this frontier may move or change as a function of technical assumptions, constraints, or requirements. Designs which were once dominated may move to the frontier, and designs which were formerly Pareto optimal may cease to be so as conditions change. The performance of a design is a function not only of its component sizes but also of the assumptions behind it.

Driving Need: Real-Time Design Exercises. Ideally, a hybrid renewable design and optimization environment would have the following characteristics: provide sufficient description of system performance to allow selection based on multiple objectives and constraints; allow easy exploration of the entire design space (different sizing configurations); allow easy modification of assumptions, requirements, and desired outcomes; provide probabilistic results; and be usable in real-time by the designer or decision-maker.

The first goal of adequately characterizing the system will in many cases tend to favor a time-series simulation-based approach. The remainder can be satisfied through the use of a *surrogate modeling approach.* For any given system configuration and set of assumptions, a time-series simulation can adequately characterize the system; however, the desire to explore the design space and change assumptions in real-time necessitates a faster means of assessing the performance of a given system. If the designer is willing to limit the degrees of freedom of the system to the sizes of the major components and a handful of sensitivity variables, the system can be represented with regression representations of the time-series simulation.

With fast-running surrogate models of the system, an array of possibilities becomes available. The surrogates can be incorporated into a final engineering design tool that puts all necessary information in the hands of the engineer or decision-maker, and allows them to fully understand the choices available to them. Technical assumptions can be changed rapidly, requirements can be adjusted as the decision-maker gains a better understanding of the real choices available, and the relative importance of various objectives can be clarified. If desired, technical performance characteristics can be mapped to higher-level non-technical objectives through the use of dynamic

Quality Function Deployment (QFD). Rather than a report, a decision-maker can be presented with a dynamic *tool*. The results of individual simulations can even be incorporated into long-term planning exercises involving multiple years and multiple systems. In summary, a decision-maker can be presented with all the information necessary to choose one or more system configurations, with a bounty of available information and without the need to go back for more engineering analysis.

Capturing Requirements

This section will describe a method for efficiently directing engineering analysis by properly capturing the requirements or "voice" of the customer, and identifying those engineering characteristics that have the greatest impact on meeting requirements.

Quality Function Deployment. Quality Function Deployment (QFD) is a formal technique for capturing the user's requirements (voice of the customer) and mapping them to controllable product and process parameters or vehicle attributes (voice of the engineer) [Akao, 1994]. This technique includes the creation of a series of matrices showing the association between specific features of a product and statements representing the voice of the customer, and uses teamwork and creative brainstorming as well as market research to identify customer demands and design parameters. The basic structure of the QFD is shown in Figure 1. The customer requirements are listed along the vertical column on the left hand side of the QFD, and the engineering attributes are listed across the top row. The impact of each engineering attribute on each requirement is mapped qualitatively on a scale of 0 (no relationship) to 9 (strong relationship). Because these engineering attributes may have adverse impacts on various customer requirements, when used as part of the process introduced in this paper, these qualitative mappings may be positive or negative.

Each requirement is assigned an importance weighting by the user, which may be done objectively on an arbitrary scale of 0-10, 0-100, or any similar scale capturing the level of fidelity desired. The importance weighting of each engineering attribute is found by multiplying the requirements weightings vector by the impact vector of that engineering characteristic. These attribute weightings are then normalized across all of the engineering attributes, which may be used to guide a Multi-Attribute Decision Making process as described in the next section. It is important to note that there are many accepted and proven techniques for creating QFD's, including the application of the well known Seven Management and Planning Tools [Mizuno, 1988] to collaboratively develop each of the QFD regions.

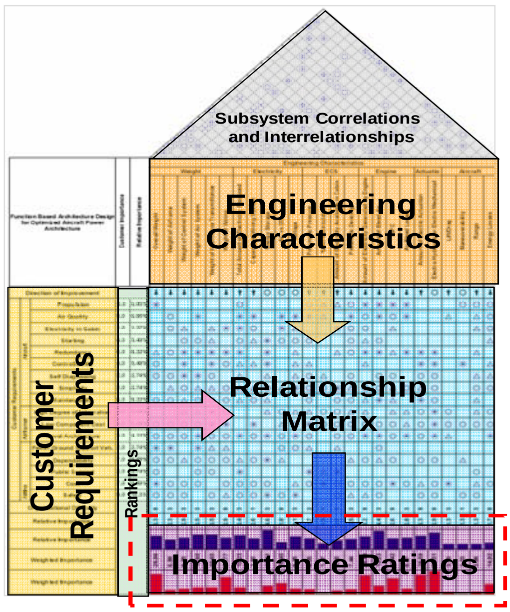

Figure 1. Quality Function Deployment

Energy Systems QFD. An example of a QFD is given in Table 1.example, which will be used throughout this study. A listing of high-level requirements is given along the leftmost column, with notional importance weightings provided. Note that many of these requirements are not measurable through traditional energy systems models (i.e. regional "energy independence" or the "maturity" of a given technology). Quantitative engineering characteristics are given along the top row. These metrics are those that are typical results of an energy systems modeling and simulation tool, such as the energy production of each source (i.e. wind turbine) and the ability to meet desired load demand (i.e. capacity shortage). Note the qualitative mappings; for example wind turbine has a strong negative impact (-9) on "ease of integration" into an existing energy system, where as it has a strong positive impact (9) on "energy independence", meaning that energy independence is more likely with increased wind turbine energy production.

		Quantitative M&S Metrics						
Requirements	*Customer Weightings*	Capacity Shortage	Renewable Fraction	Diesel Fuel Used (L)	Production wind	Production Solar	Production generator	Battery Throughput
Ease of Integration	5	0	0	-1	-9	-3	-1	-5
Reliability of Equipment	5	0	0	-1	-3	-1	-5	-5
Availability of Power	8	-9	0	0	0	0	0	0
Technology Maturity	5	0	0	0	3	2	9	2
Energy Independence	2	-9	9	-9	9	9	-9	5
Environmentally Friendly	2	0	9	-9	9	9	-9	2
TOPSIS Weighted score		0.354	0.142	0.181	0.035	0.102	0.083	0.102

Table 1. Notional Energy Systems QFD

Multi-Attribute Decision Making

With the need to address increasingly complex and multi-faceted problems, there is a strong need to incorporate methods for decision making when dealing with multiple and competing objectives. For the energy systems example, take the given problem where we wish to design a hybrid system that both provides reliable power yet minimizes fossil fuel dependency. The "optimization" of this system is completely dependant on the relative importance of those objectives, which determines which requirements will be sacrificed for others. Most optimization techniques for design are poorly suited to handle multiple and/or conflicting objectives. The design of complex interacting systems requires holistic solutions that are valid in multiple dimensions; given that requirements can impact multiple design variables, and measures of effectiveness may be conflicting. We are no longer interested in a system design that performs best in only one area, but one that is Pareto optimal among all metrics. Beginning in the 1950's and continuing through the 1970's, the U.S. Department of Defense invested heavily in the development of mathematical techniques for decision making in the presence of many attributes which are valid for a large number of complex system design processes. These are referred to as Multi-Attribute

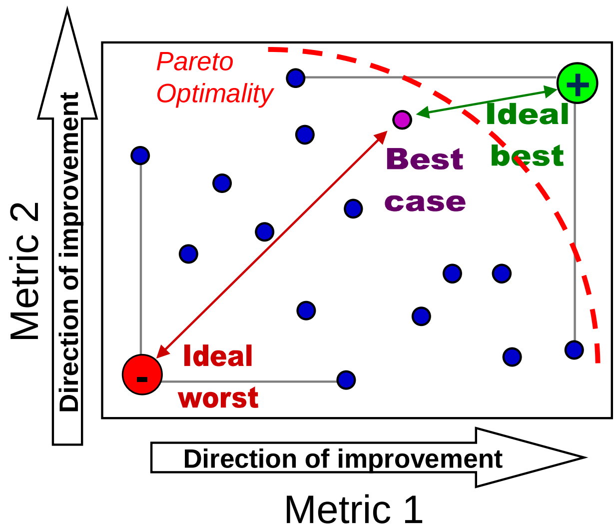

Figure 2. Evaluation of Candidate Concepts through TOPSIS

Decision Making (MADM) techniques [Yoon and Hwang, 1995].

There are many such MADM tools documented, however the Technique for Ordered Preference by Similarity to Ideal Solution (TOPSIS) will be discussed in this study [Hwang, 1981]. This uses a weighted series of criteria to identify the best and worst of each criterion and combines them into the theoretical best and worst points, as shown in Figure 2. Actual ranking is performed based on maximizing the normalized distance from the theoretical worst and minimizing the distance from the theoretical best. For the process used in this paper, these weighted series of criteria are identified through the QFD. The "points", or designs evaluated through the TOPSIS process are created through interaction with modeling and simulation, which is introduced in the next section.

Integration with Modeling and Simulation

The methods introduced in this paper, as part of an integrated decision making process, presume that system options exist to choose from, given that each of those system concepts is associated with measurable performance and cost metrics. However, it is impossible that all perturbations of options exist, or that every perturbation of potential operational uses of those options are possible to predict. For example, how would a 5% variation in available wind affect the performance of a hybrid energy system that contains wind turbines, over the course of a day or month? How would that affect the ability to meet load demand? Or for example how would a decision maker measure the amount required from another source of energy, say photovoltaics, to account for uncertainty in wind, and can this be done without adding reliance on fossil fuels? To answer those questions, we can guess, or make assumptions based on historical data. Modeling and simulation is the preferred method, but in most cases it can not be used to answer every hypothetical question. This section will focus on informing decision making through complex engineering analysis.

Modeling and Simulation Environment. The specific modeling and simulation environment needed for analysis is situated within a framework given in Figure 3 for capturing the various elements of an energy systems problem. The potential options for power generation and storage must be collected, in addition to hour-by-hour load demand and related atmospheric conditions over the course of a year. These are all used to drive the way modeling and simulation is executed, specifically described by a Design of Experiments. Response data from executing the modeling and simulation is regressed to create surrogate models that, when coupled with specific cost models, are used to assemble the integrated decision making tool. This paper will describe each of these elements; however this section will focus on the modeling and simulation effort of this process.

The authors have used HOMER as the modeling and simulation backbone behind the decision making tool set developed for this effort. HOMER is a design tool for grid-connected or off-grid power systems developed by, and available freely through, the U.S. Department of Energy's National Renewable Energy Laboratory (NREL) [Lilienthal, 2005]. Given a desired energy load profile, climate conditions such as wind patterns and available sunlight, and an array of energy sources (e.g., diesel generators, wind turbines, photovoltaic arrays, among many other options) HOMER determines the lower-cost energy solution, and provides sensitivities to changes in costs and resources. With its large database of components and performance models, HOMER significantly simplifies the design process. However, its trade space analysis has a strong reliance on a computationally intensive combinatorial design process. Furthermore, HOMER selects systems based exclusively on the levelized cost of energy of the system, and cannot rank designs based on any other criteria. However, the authors decided that the logic within HOMER could be captured in a form usable by a higher level decision making tool to make decisions based on other technical and non-technical criteria, and to aid in longer-range energy portfolio planning.

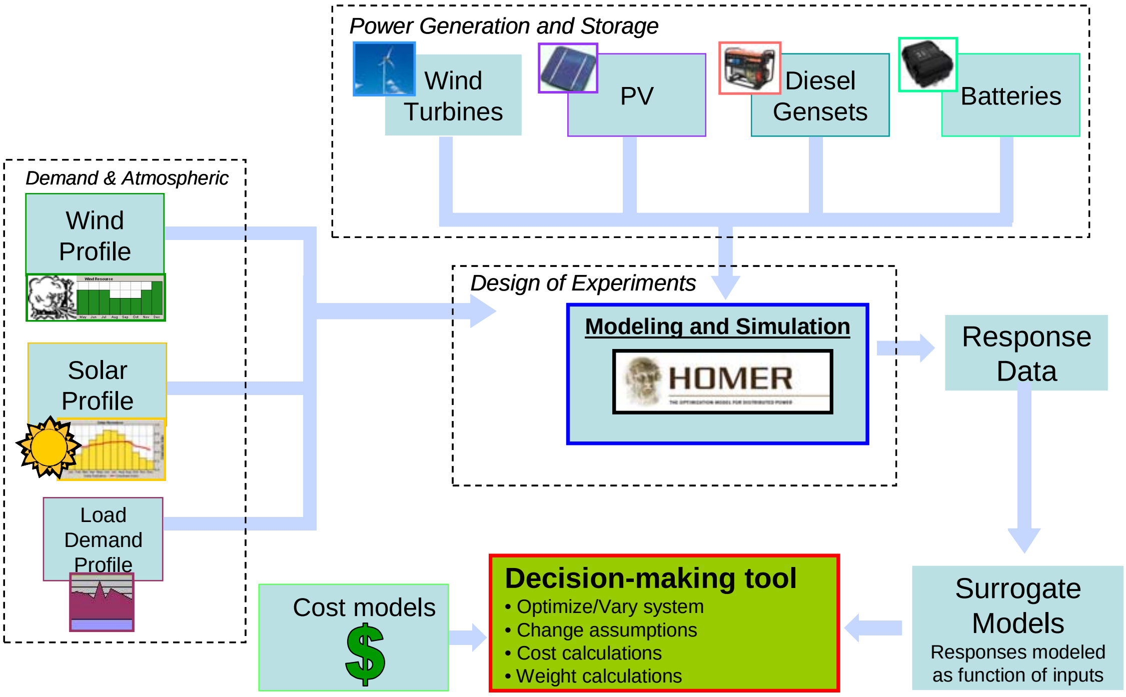

Figure 3. Energy Systems Modeling Simulation Framework

A test case was developed in order to determine the feasibility of capturing HOMER's capabilities in a tool with shorter runtimes and the ability to trade between various energy sources over a multi-year investment timeline. A notional scenario was created, using a sample load profile and sample wind and solar radiation data for a location in central Asia. The system configuration was that of a stand-alone renewable/fossil power system, with scalable/optional components. Components modeled included non-tracking photovoltaic (PV) arrays, a wind turbine with a fixed steady-state wind/power curve, a diesel generator modeled as a steady-state device, and lead-acid batteries. Sensitivity variables were also controlled, including average solar insolation, average wind speed, the hub height of the wind turbine, the efficiency of the DC to AC inverter, and the required operating reserve.

Surrogate Modeling. The primary enabler of rapid manipulation of complex modeling and simulation within a higher level analysis tool is through the use of surrogate models. Surrogate models, based on response surface methodology [Myers and Montgomery, 1995], are equation regression representations of more complex modeling and simulation tools that maintain a fairly high level of accuracy when compared to those original tools. A surrogate model is made by regressing against a set of data (Figure 4). For a very complex system model requiring time consuming computer codes to run, a structured method for data sampling with the minimum number of simulation runs (or "experiments") is needed. A statistical approach to experimental design can be useful in drawing meaningful conclusions from data. A statistical Design of Experiments (DoE) is such an approach, which plans simulation execution cases such that meaningful conclusions can be drawn.

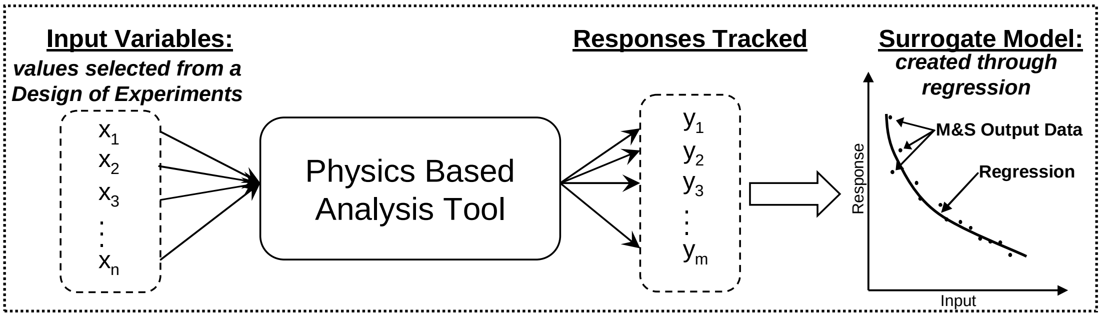

Figure 4. Surrogate Model Generation Process

These equation-based surrogate models can take most any form, based on assumptions made on the way a given response varies as a function of given variables. The most common form of surrogate models is the polynomial format. However, more complex design spaces cannot be approximated with polynomial equations, such as in a complex systems integration problem where one may not necessarily be interested in the optimization of a particular system component but on being able to quantify the interactions between the individual systems. Rather, neural networks can be used to generate surrogate models of multimodal, discontinuous, or otherwise highly nonlinear design spaces, which are commonly encountered when modeling hybrid energy systems. When used to create surrogate models, a neural network is a set of nonlinear equations that predict output variables from a set of given input variables using layers of linear regressions and S-shaped logistic functions.

The assumptions regarding how a given response varies as a function of select variables, i.e. linear or multimodal, governs the appropriate DoE to use in an analysis. For this study, a customized DoE is used which combines a Central Composite Design (CCD) used to capture the corners, a Latin Hypercube Sample (LHS) to capture multimodal effects within the design space, and a random set used for validation (but not regression).

In summary, because surrogate models are equations, albeit complex ones, they can be rapidly executed many times and provide a user the ability to access the analysis capabilities of modeling and simulation without the computational delay. Once these surrogate models are created, a design space can be explored by rapidly generating thousands of cases, each with small (but measurable) loss in fidelity from the original modeling and simulation environment.

Robust Design Simulation

Quality Engineering. The quality of a system, or its ability to meet requirements consistently, is jeopardized by uncertainty and risk. The evaluation of a design may not be driven solely by its capability to achieve specific mission requirements or remain within specific product constraints. Rather, a robust design process, or one that leads to a design that is least sensitive to influence of uncontrollable factors, is needed to balance mission capability with other system effectiveness attributes. Zang *et al.* [2002] describe those design problems that have a nondeterministic formulation, including the field of robust design, as uncertainty-based design.

In the context of an energy system that incorporates renewable sources of power production, there is a certain amount of risk created by the intermittency of the energy source. For example wind is not always available to power wind turbines, and when it is available it usually changes velocity with an element of randomness which directly applies an element of randomness and uncertainty to the power output of that wind turbine. Elements of robust design are used in this study to quantify the uncertainty of achieving certain metrics due to varying factors uncontrollable by the designer and/or decision-maker.

Uncertainty Quantification through Monte Carlo Analysis. Since the use of surrogate models enables modeling and simulation cases to be evaluated very quickly, Monte Carlo investigations comprising hundreds of thousands of runs can be conducted within several seconds on a standard desktop PC. This process enables the uncertainty quantification introduced earlier.

An example of a sensitivity study is shown in Figure 5. A given number of variables are treated as noise variables in this study, meaning that operationally the decision maker has no control over their fluctuations. As an example, atmospheric data such as the available solar irradiance and wind, as well as the price of fuel are treated as noise variables. This means that although these variables may be known in a controlled M&S environment, they are not known exactly in an operational environment. The noise variables of average wind speed, average annual solar irradiance, and fuel price are assigned distributions, and thousands of cases are run through a neural network surrogate model of levelized cost of energy. The results can be plotted in a cumulative distribution function, allowing the engineer to quickly gauge, for example, a 90% confidence upper bound on energy cost. Such methods enable the engineer to find robust solutions which offer high likelihood of success.

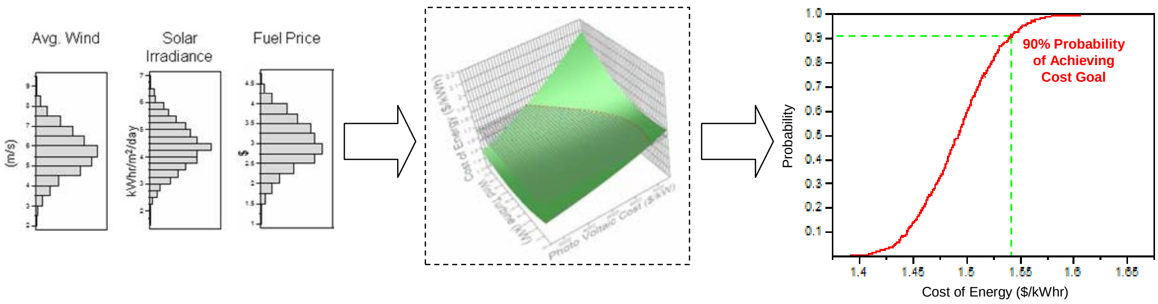

Figure 5. Uncertainty Quantification through Monte Carlo Simulation of Surrogate Models

Capability-based Inverse Design

Top-down Design. Systems engineering introduces the notion of top-down design, which as Blanchard [1991] explains, involves viewing an entire system comprised of its components as a whole functioning unit. This requires an understanding of how those components efficiently interact, with optimization of macro-level structure emphasized rather than solely focusing on micro-level system components [Chapman *et al.*, 1992]. This drives the need for having a complete identification of system requirements, and relating these requirements to specific design criteria. The goal of the systems engineer is to represent the system as a model and evaluate it through a simulation. The entire system design and development process requires an interdisciplinary effort to meet all design objectives effectively. This requires a complete understanding of the various design disciplines, and most importantly for the systems engineer, how the interrelationships between those disciplines affect overall system capability. The same conclusions can be drawn for the interrelationships of the components within a system-of-systems, where individually operated and managed systems interact to affect an overall metric.

For bottom-up design, selections are made at the lowest level, which define the capability at the next highest level. This results in one design point flowing up the hierarchy. An optimizer could be used to search the design space at each level (one level at a time) for options that do not violate constraints, and minimize/maximize a response. The top-down design approach will yield multiple combinations of variable values that meet constraints at higher levels.

The systems engineering process can be broken down into a hierarchy of decision making levels. The highest level is the overall capability level, which identifies the overall need or function that must be addressed. This system concept description is created with the intent of meeting a requirement at the overall capability level. Next below is the system level, which produces a system description, for example a performance requirement. At the lowest level is the subsystem level that produces a subsystem performance description. Baumann [2005] states that the systems engineering process is applied to each level in the design hierarchy, one level at a time. This is a "top-down, comprehensive, iterative and recursive" process and is "applied sequentially through all stages of development". It transforms needs and requirements into a set of system product and process descriptions. Figure 6 describes this systems engineering concept, showing the iteration step that must be taken across each hierarchical level [Ender, 2006]. This figure depicts an important fact about this systems engineering process: requirements are decided upon and flowed from the top-down in the design hierarchy, and at each level there must be an iteration to make sure that the design solution satisfies the requirement, one level at a time.

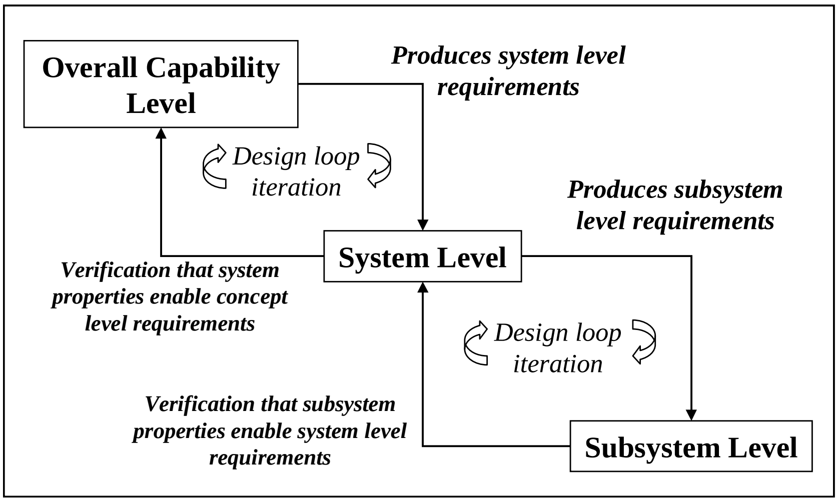

Figure 6. Systems Engineering Process with Top-Down Hierarchical Requirements Flow [Ender, 2006]

Filtered Monte Carlo through Inverse Design. According to Kuhne *et al.* [2005], "Probabilistic Design is the process of accurately accounting for and mitigating the effects of variation in part geometry and other environmental conditions while at the same time optimizing a target performance factor." However, using mathematical methods, the authors state, probabilistic design may prove to be a complex and daunting task. Using logic and graphics along with Monte Carlo simulation, Kuhne *et al.* demonstrate an alternate visual approach called a "Filtered Monte Carlo" that achieves useful probabilistic design results efficiently and simply. This method assumes the existence of a fast-running simulation model that can be called on many times, and works by populating a design space with response values obtained by running a simulation many times with randomly selected values from bounded distributions on input variables. If the output for that particular Monte Carlo simulation trial violates any response constraints defined a priori, that response is discarded. The outputs that do not violate the constraints are then plotted in a scatter plot fashion versus any of the inputs, giving the user the ability to visualize sensitivity to variation in the inputs. However, the authors note the biggest challenge to this approach is with problems with large numbers of inputs and responses (i.e. >10), which drives the need for improved visualization and data mining tools that would enable the user to simultaneously explore the design space while conducting input variation sensitivity.

Up to this point, the ability to rapidly generate point solutions has been addressed. Using surrogate models enables the generation of many point solutions very quickly. Probabilistic techniques can then be used to generate thousands of point solutions across the entire design space. This filtered Monte Carlo method is used to generate “clouds” of non-unique system solutions at the capability level. This process truly enables inverse design, where data is generated using bottom-up tools but analyzed with a top-down view; any response can be treated as an independent variable.

Collaborative Decision Making

The various methods which compose the process introduced in this paper have been applied to the informing of energy system related decision making. At this point, each of these methods will be brought together in an integration framework supporting collaborative decision making. The interactive tool developed through this research is shown for two scenarios in Figures 7 and 8. Note that high level requirements (such as ease of integration, energy independence, etc.) are shown with slide bars which control the importance weightings. These are the importance weightings which are translated through the QFD to drive the importance of the various simulation specific attributes (for example capacity shortage, diesel fuel used, etc.). The user has the ability to control the desired load demand over time, as well as to limit the amount of investment dollars over time. Assumptions such as average insolation and average wind speed may be adjusted, as well as changes in equipment purchase and maintenance costs over the life of the project (not shown). The user may change any of the inputs and re-evaluate, and in a few seconds the system will assess thousands of portfolio options through the use of surrogate models, decide which options best meet the weighted requirements through the MADM process, and select annual equipment purchases for the life of the project.

The rapid execution time of the tool, combined with the ease of adjusting requirements, budgets, and assumptions, allows a decision-maker to answer a multitude of questions without having to execute the original M&S through a number of different cases. This eliminates the lag created when the decision-maker redirects the engineering analyst. The amount of visual information available helps the decision-maker better understand the nature of the problem, and the use of adjustable non-technical requirements allows the decision-maker to treat these often un-quantified (yet still important) factors in a more formal and considered manner.

An example of use is shown in Figure 7. The user has specified a load growth profile, starting at 20 kW average in 2007 and growing to 46 kW average by 2011. The user has also specified a capital investment budget, ranging from $50,000/yr in 2007 to $230,000/yr in 2008. Most requirements are given equal weighting, but "energy independence" and "environmental friendliness" are set to zero; that is they do not factor into the decision. Under these conditions, the tool decides to purchase diesel generators, and thereafter to improve power quality with battery purchases. However, the fuel budget is large (note that in this implementation, operations costs are separate from the purchase budget, and have not been constrained).

In Figure 8, the requirements have been altered so that that "energy independence" and "environmental friendliness" are rated equally with other factors. All other assumptions and settings are kept the same. When the user selects these “greener” requirements weightings, those weightings are instantaneously sent through the QFD which reprioritizes the engineering characteristics, and in turn selects a new “best in class” through the MADM process evaluation of the surrogate model results. With the “green” requirements weightings, the tool still purchases diesel generators early on, but once a sufficient budget is available, it begins to purchase photovoltaics, batteries, and wind turbines. Noting the bottom-right plot in Figure 8, after the first year, the diesel fuel consumption drops to almost nothing.

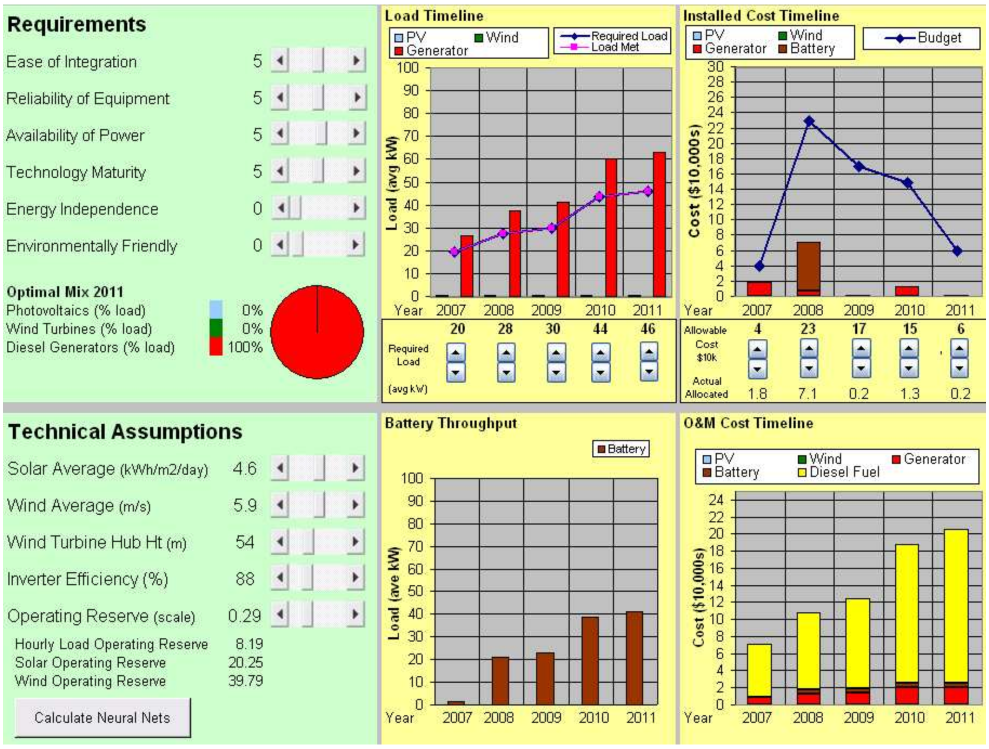

Figure 7. Integrated Framework (Scenario Favoring Fossil Fuel)

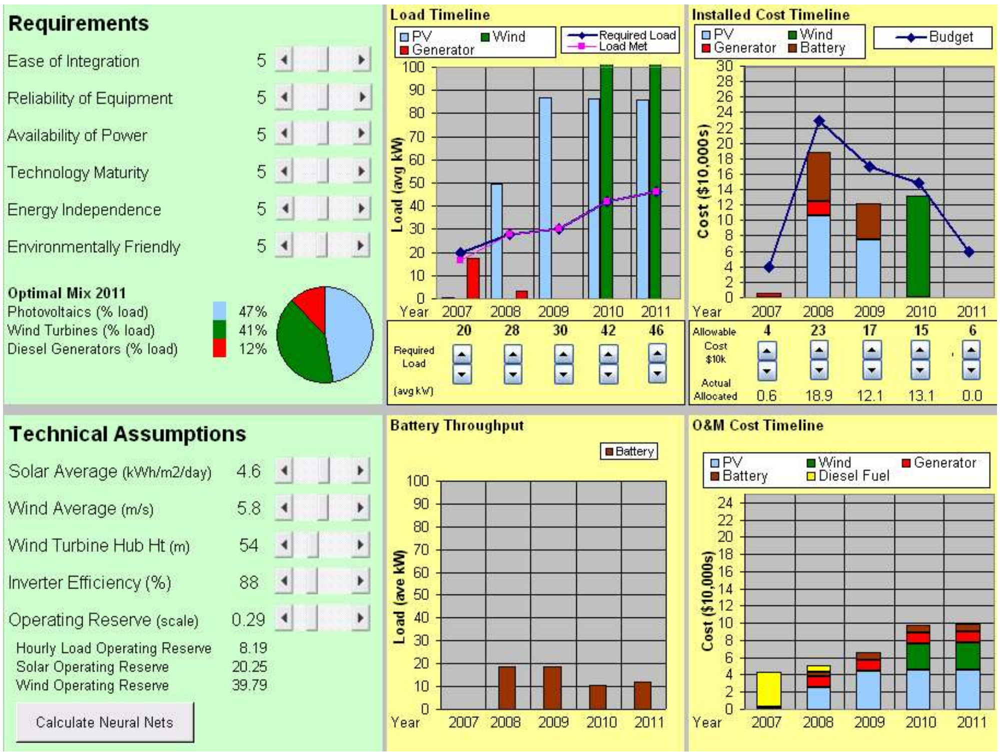

Figure 8. Integrated Framework (Scenario Favoring Renewable Energy Portfolio)

Conclusions

This paper introduced a systems engineering process that enables real-time decision making through integration with rapid modeling and simulation. It is desired to have complex, quantitative engineering level analysis inform decision making as early as possible when facing a problem, especially in the very beginning when comparatively little is known about the problem. Elements of Quality Function Deployment, Multi-Attribute Decision Making, surrogate modeling, and robust design enable qualitative decision-making based on quantitative tools. An energy systems problem is used to show the application of these methods in order to guide portfolio planning. An advisory and design tool was introduced that aids decision-makers with robust planning and implementation of effective renewable energy solutions.

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