Risk-Based Treatment of Uncertainty in Trade Space Exploration: Application via Monte Carlo Simulation on a Manned, Mini-Submersible Model

by

Nicholas Andrew Dadds

B.S., Systems Engineering
United States Naval Academy, 2008

Submitted to the Department of Mechanical Engineering
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Author ……………………………………………………………………………………………
Department of Mechanical Engineering
May 11, 2018

Certified by………………………………………………………………………………………
Benjamin Lane
The Charles Stark Draper Laboratory, Inc.
Thesis Supervisor

Certified by………………………………………………………………………………………
Daniel Frey
Professor of Mechanical Engineering
Thesis Supervisor

Accepted by………………………………………………………………………………………
Rohan Abeyaratne
Chairman, Department Committee on Graduate Students
Department of Mechanical Engineering

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Abstract

In design, modeling and simulation are commonly used to answer questions of interest as it is both inefficient and expensive to physically build and evaluate numerous possibilities. Any modeling effort aims to build the simplest model while capturing the real-world trends appropriately. When modeling highly complex systems or pushing technological bounds, variables in the model will possess elements of uncertainty. In a trade space approach, different design combinations may exhibit different uncertainty profiles. Omitting uncertainties in the modeling effort can bias design combinations in the overall trade space in terms of capability and cost as well as misrepresent the value of tradeoffs between designs. Therefore, if the uncertainties are not represented, the decision-maker is accepting an unknown level of risk when selecting a design.

This thesis proposes that uncertainty in early stage design is not well represented, despite its playing a major role in a system's ultimate success. This research explicitly accounts for uncertainty in model inputs via probability distributions instead of simply applying "best estimate" deterministic values. These distributions are sampled via Monte Carlo simulation to generate uncertainty profiles for different design combinations, thereby increasing the validity of the model outputs. This approach for capturing the implications of uncertainty in early stage design allows for a more accurate representation of design risk. Ultimately, the deterministic design points in the trade space are quantitatively and qualitatively evaluated against the design points incorporating uncertainty. Understanding that model outputs can only ever be as good as model inputs, the exploration of the effect of uncertainty on the design trade space is important.

An example of Trade Space Exploration for the conceptual design of a manned, mini-submersible is used to demonstrate an approach for quantifying and visualizing uncertainty to inform decision-making. This case study suggests that visualizing risk at the system level in a typical performance versus cost context is valuable.

Thesis Supervisor: Daniel Frey
Title: Professor, Department of Mechanical Engineering
Thesis Supervisor: Benjamin Lane
Title: The Charles Stark Draper Laboratory, Inc.

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List of Acronyms

AoU- Area of Uncertainty

AWF- Acquisition Workforce

BBP- Better Buying Power

BCA- Budget Control Act

CER- Cost Estimating Relationship

CNO- Chief of Naval Operations

CONOPs- Concept of Operations

DAS- Defense Acquisition System

DoD- Department of Defense

EEC- Entrance and Exit Criteria

FC- Fuel Cell

LCP- Lockout Chamber Pressurization

LI- Lithium Ion

LIO- Lock-In/Lock-Out

LOA- Length Overall

MATE- Multi-Attribute Tradespace Exploration

MBE- Model Based Engineering

MCS- Monte Carlo Simulation

MOP- Measures of Performance

MSA- Materiel Solution Analysis

MWC- Mid Water Column

OMOP- Overall Measure of Performance

PDF- Probability Density Function

PERT- Program Evaluation and Review Technique

R&D- Research and Development

RDT&E- Research, Development, Test, and Evaluation

SCR- System Concept Review

SME- Subject Matter Expert

SRR- System Requirements Review

TMRR- Technology Maturation and Risk Reduction

TRL- Technology Readiness Level

TSE- Trade Space Exploration

USD(AT&L)- Under Secretary of Defense for Acquisition, Technology, and Logistics

USSOCOM- U.S. Special Operations Command

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Chapter 1 Introduction

In recent history the Department of Defense (DoD) has regularly found itself under immense fiscal pressure. Under this pressure, the DoD Acquisition Workforce (AWF) is charged with maintaining current platforms and weapon systems while also designing future platforms and weapon systems. Continuing to provide capability to the warfighter in a strained fiscal environment is a challenge the DoD AWF is facing. With the release of Better Buying Power (BBP) 3.0 in 2015 the Under Secretary of Defense for Acquisition, Technology, and Logistics (USD(AT&L)) stressed the importance of understanding and mitigating risks in order to successfully develop affordable capabilities [1]. The Chief of Naval Operations (CNO) reiterated these views last year by highlighting the importance of pursuing solutions that are achievable "at a reasonable risk, an identifiable risk, and at a cost that we can control" [2]. These sentiments by DoD and Navy leadership acknowledge the importance of identifying and assessing the risks associated with future capabilities to achieve affordable solutions.

1.1 Motivation

The importance of identifying and assessing the risks associated with future capabilities motivates this thesis. This thesis demonstrates how the implications of uncertainty in a conceptual design trade space can be captured and communicated to better inform requirements and decision-making. While uncertainty analysis has many forms, this thesis focuses on an approach to illuminate the risks associated with endogenous uncertainties related to the technical performance of maturing systems, their associated costs, and the associated value of their performance [3]. The concepts and combinations of Model Based Engineering (MBE) and Trade Space Exploration (TSE) support the DoD effort of providing the warfighter superior capabilities at affordable costs. The implementation of these concepts, along with uncertainty analysis, improves the ability of the DoD AWF to identify and assess design risks earlier in and continuously through the DoD Acquisition Life Cycle. With Materiel Solution Analysis (MSA) being the earliest phase in the Defense Acquisition System (DAS), this phase represents the area of focus for this research since the early identification and management of risk relates favorably to successful program outcomes [4].

Ultimately, this research can be deconstructed into three parts. The first part was familiarization with the topics of MBE, TSE, and uncertainty analysis. The second part was identifying the high-level frameworks for TSE and uncertainty analysis and highlighting where they fit within the DAS. Specifically, within the MBE design and acquisition framework proposed by Stepanchick [5]. The third part applies TSE, along with a risk-based treatment of uncertainty, to the conceptual design of a manned, mini-submersible. The aim of part three is the assessment of risk as it pertains to various design solutions in terms of performance and cost.

1.2 Research Outline

Chapter 2 begins with a brief history of the pressurized situation the DoD is operating within. Chapter 2 continues by introducing concepts involved in the early stage design environment of the DoD and discusses how these techniques efficiently support DoD goals. Chapter 2 closes with a short overview of the DAS phases. Chapter 3 presents the frameworks associated with the concepts of MBE, TSE and uncertainty analysis and incorporates them into the MSA phase of the DAS. This high-level framework is followed by the steps to setup for and conduct uncertainty analysis. Chapter 4 provides a comprehensive application of the approach laid out in Chapter 3 in the conceptual design of a manned, mini-submersible. Chapter 5 provides conclusions and recommendations.

Chapter 2 Background

2.1 Department of Defense Program Complexity

The DoD AWF is responsible for developing, procuring, and maintaining highly complex systems for the nations armed forces. These complex systems include platforms, such as the new Ford Class Carrier, and weapons, such as the Aegis Ballistic Missile Defense system. Not only are the platforms and weapons themselves complex, but so too are the environments where they are expected to operate. These environments span from the undersea to the space domain and in some instances the systems are also required to operate across the full spectrum. Unfortunately, for the DoD, as system complexity has grown so has cost [6].

2.2 Department of Defense Budget History

The fiscal environment, as it pertains to the DoD, experienced a shift over the last 8 years. The end of the 20th century and beginning of the 21st century saw DoD budgets grow steadily [7]. The budget growth was in concert with increasing system complexities and operational tempos. The pinnacle of the DoD budget occurred in 2010 as it approached 700 billion dollars [7]. After 2010, the DoD budget declined slightly and has since stabilized around a figure of 600 billion dollars annually [7]. The flattening of the annual DoD budget required the AWF to figure out how to continue providing advances in capability while maintaining costs; or as then USD(AT&L) Carter put it, decision-makers needed to start “doing more without more” [8]. The preceding discussion is highlighted in Figure 2-1 [7].

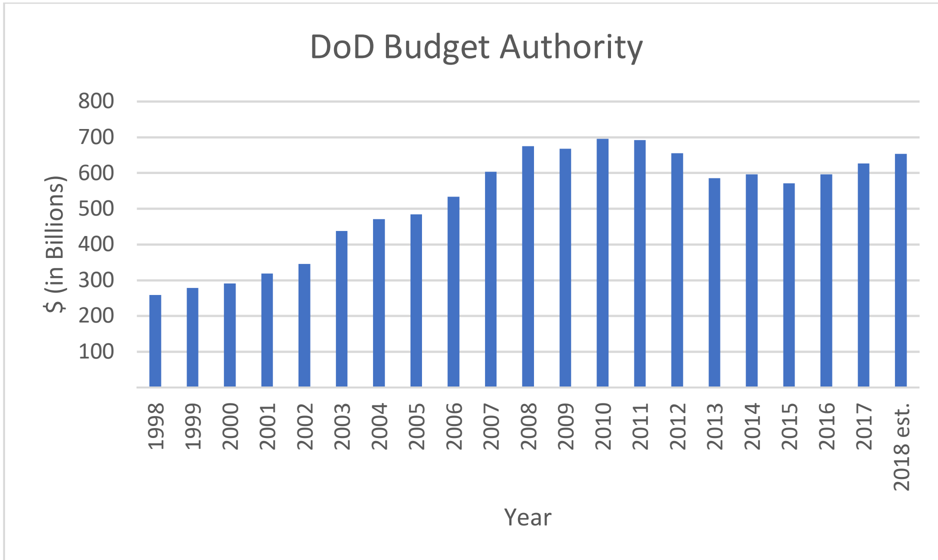

Figure 2-1: Annual DoD Budget Authority

2.3 Budget Pressure on the Department of Defense

The fiscal environment of the last 8 years put considerable downward pressure on the DoD budget. DoD leadership recognized that the budget trend of the early 2000's was unsustainable and began taking action. This action came in the form of an initiative known as BBP. The introduction of BBP came in 2010 and focused on restoring affordability and efficiency in defense spending [8]. BBP 2.0 followed two years later, in 2012, reemphasizing affordability and value as tenets of DoD programs. In the release of BBP 2.0 USD(AT&L) Kendall alluded to an era of limited resources for the DoD presumably because of congressional legislation from the prior year [9].

Along with the DoD affordability initiative, at a higher level, Congress took their own action in 2011 due to concerns with deficit levels and the approaching debt limit [10]. The action taken by Congress is known as the Budget Control Act (BCA) of 2011 [10]. The legislation, as written, presented two obvious concerns for the DoD [10]. The first factor affecting the DoD was the imposition of annual required discretionary defense spending limits [10]. The second factor was added budget reductions on top of the initial spending limits, which began in 2013 [10]. A third, and unforeseen, issue resulting from the legislation was that DoD programs were unable to anticipate either their funding level or funding timing, or both [2]. The difficulty in anticipating funding levels is exemplified in Table 1 [10]. The strained fiscal environment places significant pressure on DoD programs.

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
BCA 2011 Projections	555	546	556	566	577	590	603	616	630	644
Actuals	555	518	520	521	548	551	*TBD*	*TBD*	*TBD*	*TBD*

Table 1. Defense Budget Authority Limits Under the BCA by Year (in Billions of nominal dollar)

2.4 Adversarial Pressure on the Department of Defense

To further complicate the strained fiscal environment, the DoD also recognized an advancement in the capabilities of potential adversaries [1]. This recognition is exemplified in the release of BBP 3.0 in 2015. While the affordability efforts from BBP and BBP 2.0 remained, BBP 3.0's clear focus was on innovation and technical excellence [1]. In BBP 3.0 the USD(AT&L) ties the technological superiority of the DoD to effective research and development (R&D) programs. Figure 2-2 displays this shift in focus with an upturn in the DoD Research, Development, Test, and Evaluation (RDT&E) budget [7]. The RDT&E budget is used to pursue and validate promising technologies in support of the armed forces. The CNO reemphasized the pressures on the global stage the following year with the release of *A Design for Maintaining Maritime Superiority* [11]. The CNO addresses the speed at which competitors are increasing their capabilities and the subsequent pressure their advances place on the armed forces [11]. The challenge to the DoD AWF is to continue developing and fielding technological superior solutions to counter future threats.

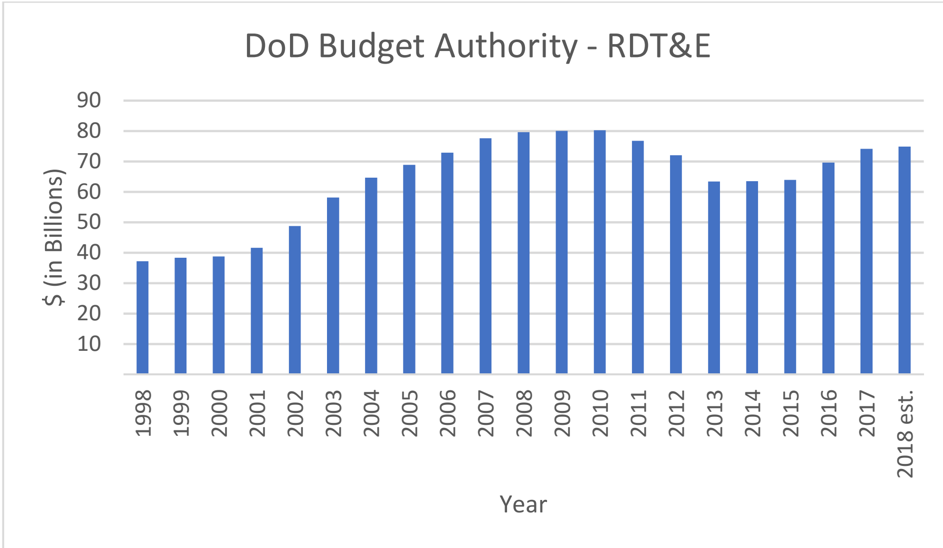

Figure 2-2: Annual DoD Budget Authority for RDT&E

2.5 Model Based Engineering

The two objectives of the prevailing environment have historically been in direct contrast for the DoD. As system complexities have increased, development timelines have grown, and costs have followed suit [6]. In an effort to counter this trend the DoD, along with industry partners, began investigating a MBE approach to acquisition [6]. Although additional upfront costs are necessary for MBE implementation, the existence of models earlier in the acquisition lifecycle can be leveraged to better understand, and therefore inform, requirements [6]. Early requirements insight is critical in a cost constrained environment because "more than anything else, requirements drive costs" [9].

MBE is an approach to design in which models from multiple engineering disciplines are integrated and refined throughout the design process [6]. Integration across technical domains in a common, model-based environment is advantageous to a document-based approach [12]. A model-based approach replaces the design teams disparate mental, and/or actual, models with a synthesized view of the system [12]. With a group understanding of the problem the design team can focus more effort on development [12]. A document-based approach can leave considerable room for interpretation, especially across multiple engineering disciplines, and often leaves coordination and verification until later stages of design [12]. An early introduction of MBE in the acquisition process benefits all engineering disciplines on a design team, which continues to grow with system complexity [6]. Figure 2-3 depicts the MBE design team perspective [13].

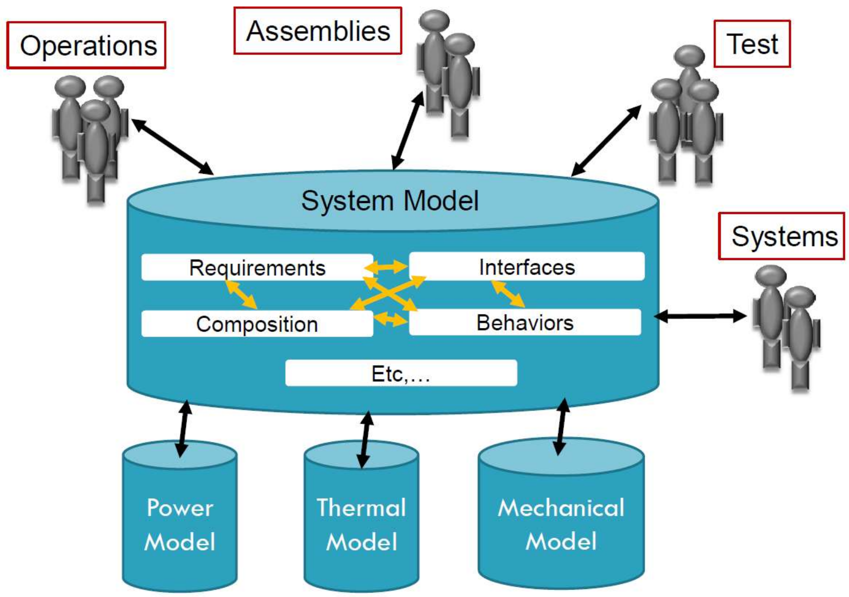

Figure 2-3: MBE Design Team Perspective

The introduction and integration of descriptive, design, and computational models earlier in the acquisition life cycle is beneficial [6]. The descriptive model outlines the initial requirements and coordination information from the system perspective [12]. The convergence to a system view aligns the various disciplines of the design team [12]. The descriptive model enables coordination of design and computational models, which provides an early understanding of how subsystem changes influence system performance [6]. Observing how changes propagate through the system enables the continuous verification of requirements and instills greater confidence in the design [6]. Continuous verification of requirements reduces expensive rework and helps to identify, and therefore avoid, gold plated solutions [6]. Model integration allows for an objective evaluation of the system under design.

In summary, MBE supports the efficient communication of design teams and enhances knowledge earlier in design. A MBE approach equips decision-makers with more information when they have the greatest ability to influence program costs. These early insights are critical for a decision-maker seeking to produce complex systems in a cost constrained environment. These relationships are depicted in Figure 2-4 [14].

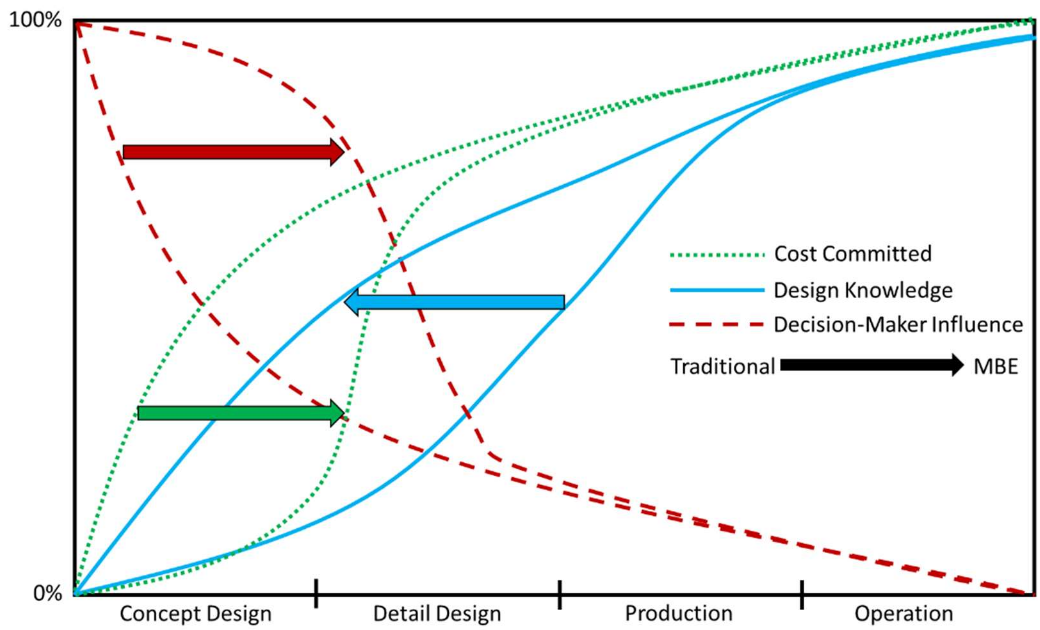

Figure 2-4: MBE Benefits vs. Traditional Design

2.6 Trade Space Exploration

In addition to the previously mentioned benefits of MBE, the incorporation of models earlier in the DoD Acquisition Life Cycle also enables TSE. The idea behind TSE is that for a needed capability there exists a vast set of possible design solutions [15]. TSE is therefore the process by which the solution space is examined [16]. A key contribution of TSE is that design solutions are not evaluated in isolation. Instead, TSE highlights the tradeoffs between design solutions, typically expressing the impacts on a performance versus cost basis [16]. Where MBE enables an objective evaluation of the system early in design, TSE enables an objective evaluation of the system alternatives.

The TSE process affords designers and decision-makers a better understanding of the underlying tradeoffs between design solutions and the cost of requirements [17], [18]. There are several references regarding how to conduct TSE, but the general steps follow:

1) Establish the Need
2) Define the Problem
3) Define Value
4) Generate Feasible Alternatives
5) Evaluate Alternatives
6) Make Decision

These steps were adapted from the Multi-Attribute Tradespace Exploration (MATE) process [17]. Stakeholders decompose the need into measurable performance metrics and assign value to them [17]. Designers identify options which address the need, within the problem constraints, and these options, when combined, represent the solution space [17]. Every design solution is assessed via a performance and cost model [17]. The performance and cost models map the design options to the performance attributes, thereby generating the data to populate the trade space [17]. An overview of the TSE process is captured in Figure 2-5 [19]

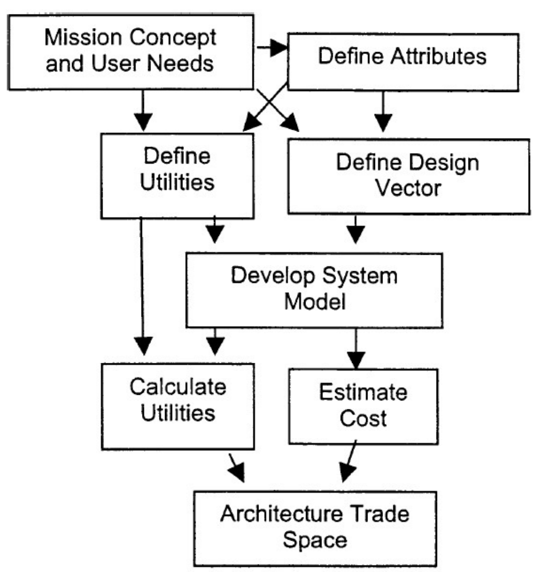

Figure 2-5: MATE Process

The introduction of TSE early in the DoD Acquisition Life Cycle is advantageous. As previously discussed, and shown in Figure 2-4, the decisions made in the conceptual design phase lock in a significant portion of program costs [17]. With this in mind, the careful consideration of the solution space is extremely valuable [17]. The trade space approach results in the identification of efficient design solutions in terms of stakeholder value [17]. This efficiency is defined by the problem constraints at a given point in time [17]. The efficient designs are said to exist on the Pareto Frontier and are Pareto Optimal [17]. Said another way, the efficient designs are non-dominated by other design alternatives [17]. This discussion is displayed in Figure 2-6.

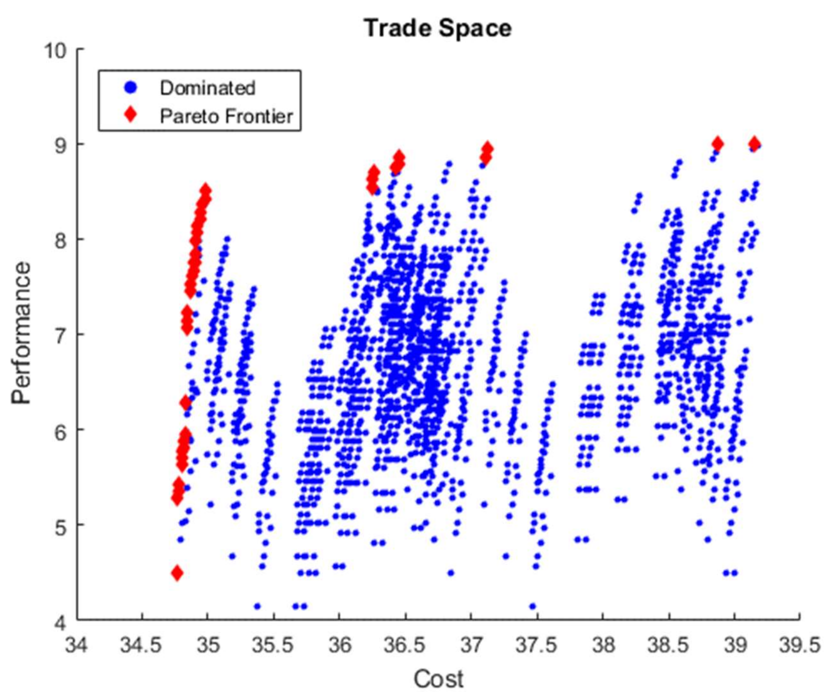

Figure 2-6: Trade Space Representation with Pareto Frontier Identified

In summary, TSE supports efficient and effective communication between designers and decision-makers by quantifying the tradeoffs between competing designs [16]. TSE therefore identifies the most valuable designs to the decision-maker. If implemented early in the DoD Acquisition Life Cycle, TSE further increases decision-maker knowledge when they have the greatest ability to influence program costs. As previously mentioned, these early insights are critical for a decision-maker seeking to produce complex systems in a cost constrained environment.

2.7 Defense Acquisition System

With the preceding discussion emphasizing the importance of both risk identification and decision-making in early stage design it is warranted to briefly introduce the DAS phases. The overall goal of the DAS is to deliver capabilities which fulfill warfighter needs [20]. The DAS consists of five phases with each phase having an objective in support of the overall DAS goal. The five phases of the DAS are Materiel Solution Analysis (MSA), Technology Maturation and Risk Reduction (TMRR), Engineering and Manufacturing Development, Production and Deployment, and Operations and Support [20]. The DoD Acquisition Life Cycle is shown in Figure 2-7 [4].

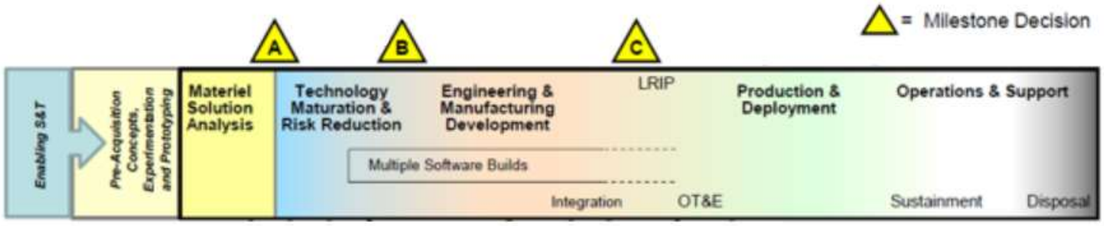

Figure 2-7: DoD Acquisition Life Cycle

As mentioned earlier, the focus area for this research is the MSA phase as it is the earliest phase in the DAS. The objective of the MSA phase is identifying the most promising technology that can meet the user need [20]. Within the current DoD environment, the most promising technology must be characterized by both its performance and cost. This research suggests that the objective of the MSA phase cannot be accomplished without also explicitly accounting for uncertainty.

Chapter 3 Framework and Method

3.1 Framework

Stepanchick [5] presents a framework for how the DoD can transition to a MBE approach to acquisition using the current acquisition process as a baseline. Through documentation reviews and interviews he identified where current processes could benefit from better MBE deliverables and tailored existing requirements to support a model-based perspective [5]. Similar to current DoD acquisition processes, the tailored requirements were tied to entrance and exit criteria (EEC) of design reviews [5]. The two design reviews applicable to the MSA phase are the System Concept Review (SCR) and System Requirements Review (SRR). Figure 3-1 leverages the MBE framework, proposed by Stepanchick [5], to highlight where and how uncertainty analysis can be incorporated into the MSA phase. The uncertainty analysis approach presented in Figure 3-1 leverages work from Walton [21] where uncertainty analysis is inserted between the generation and selection stages in the conceptual design of space systems [21]. The MBE framework for all phases of the DoD Acquisition Life Cycle is found in Appendix C.

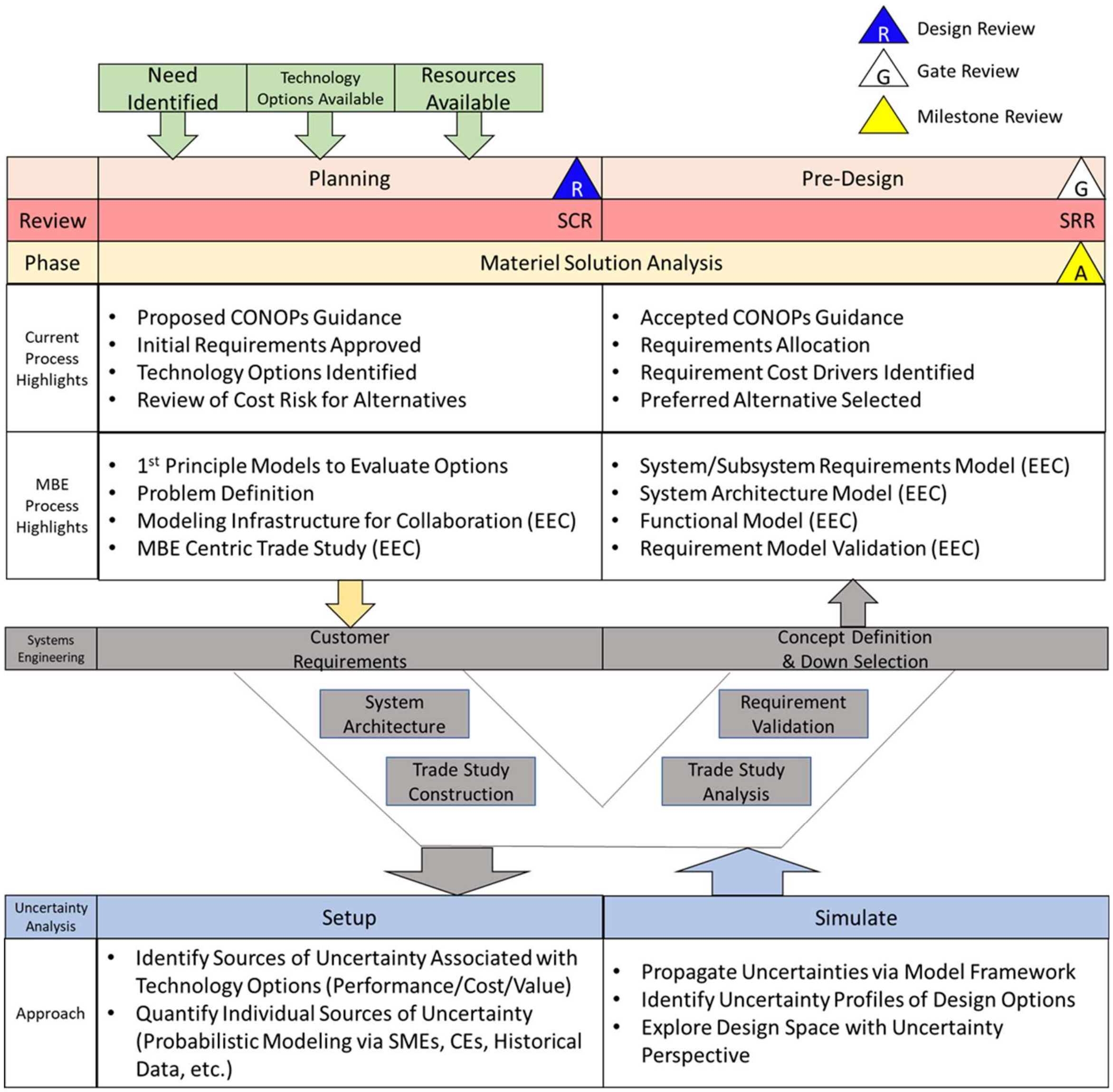

Figure 3-1: MBE/DoD Acquisition/Uncertainty Analysis Framework

3.2 Method

The following section describes both the approach to setup for and conduct uncertainty analysis. The setup resembles a TSE approach, which begins with the identification of a need and ends with the identification of designs of interest, upon which uncertainty analysis is applied. Although shown starting at the end of setup, uncertainty analysis can begin as soon as potential sources of uncertainty are identified and ends with an evaluation of the results. It is important to note at the outset of this process that while laid out in a serial fashion, many sequences of steps can be iterative if needed, as well as steps themselves.

3.2.1 Problem Setup

Prior to conducting uncertainty analysis, several inputs are needed. The inputs that precede uncertainty analysis are as follows:

1) Need Identification
    a. In DoD acquisition the need for the MSA phase comes in the form of an initial capabilities document [20]. Generally speaking, the need describes the product or capability to be delivered to the customer or user.
2) Stakeholder Identification
    a. While the need describes the product or capability to be delivered, the end user is oftentimes not the only stakeholder. Additional stakeholders can control the resources and/or impose additional constraints on the project [17]. These factors provide substantial influence over the project. In DoD acquisition the stakeholders typically include the requirements and acquisition communities, in addition to the end users.
3) Stakeholder Requirements
    a. As shown in Figure 3-1, entrance into the MSA coincides with approval of initial requirements. Although the product or capability was previously identified, requirements further refine the boundaries of the project. Some examples of these constraints could be weight limits, budget caps, and/or minimum speeds.
4) Performance Attribute Identification
    a. Since the stakeholders have substantial influence on the project it is necessary they are involved in this step. By having the stakeholders identify the performance attributes they are providing a clear articulation of the project objectives and identifying how success is measured [17].
5) Establish a Value Function
    a. Assuming individual performance attributes are defined by acceptable ranges from minimum to maximum, the next step entails determining how the varying

levels of success are valued. For example, if we assume more power is always better, does this scale linearly from minimum to maximum, is an S-curve more appropriate, or does the value of more power diminish with every unit of power gained. Additionally, assuming a design with multiple performance attributes, if stakeholders wanted both power and payload, but a design only has the capacity for more of one, which is valued more.

   b. There are multiple methods for establishing a value function:
      i. Analytic Hierarchy Process [22].
      ii. Utility Theory [23].

6) Design Variable Identification [17]
   a. Ultimately a system will be built to satisfy the need identified. This step involves decomposing the system to identify the subsystem and component options that support fulfilling the objective. The designers are responsible for identifying the feasible subsystem and component options that will form the system [17]. The different combinations of these options create the trade space.

7) Model Formulation [24]
   a. This step involves creating the modeling and simulation environment for the analysis and requires input from multiple parties such as the designers, modelers, and cost estimators. The modeling framework needs to receive inputs from the design variables and produce outputs in terms of the performance attributes.
   b. In early stage design these models often include:
      i. First Principle Models
      ii. Parametric Models
      iii. Performance Models
      iv. Cost Models

8) Trade Space of Deterministic Model Outputs
   a. Once model formulation is complete all design variable combinations are simulated constituting a full factorial design of experiments.

9) Identify Promising Designs for Uncertainty Analysis
   a. As the number of design variables and the options within design variables increase, the size of the trade space expands. Assuming DV design variables each

with O options the size of the resulting trade space is O^{DV} [21]. A subset of the full trade space is necessary for the follow-on analysis to reduce computational time and minimize the difficulty of assessing results [25].

b. In a trade space approach there are various methods to down select deterministic designs for follow on analysis. A few are described below:
    i. Pareto Optimal designs are those that exists on the Pareto Frontier and are said to exhibit strong dominance over alternative designs. In a multi-objective design, it would be impossible to improve in one objective without degradation in another objective for a Pareto Optimal design [26].
    ii. Fuzzy Pareto Optimality is a concept introduced by Smaling [27] in which additional designs that do not exist on the Pareto Frontier remain in the solution set for follow on analysis. The fuzziness of the designs selected is determined based on a subjective factor K, which sets a specified inclusion distance from the Pareto Frontier [27].
    iii. Heuristics can also be used to identify designs of interest by SMEs and stakeholders.
c. The case presented in the next chapter uses a combination of Pareto Optimality and heuristics to capture the Pareto Optimal designs for all "families of designs" characterized by uncertainty.
    i. With the sources of uncertainty identified prior to trade space down selection and the hypothesis that unique design combinations will exhibit unique uncertainty profiles this method proves effective.
        1. The uncertainty profiles provide insight to conclude that the trends observed for the selected designs can be expected for the familiar designs not analyzed.
            a. Dominated designs will remain dominated.
        2. The uncertainty profiles will display the deterministic design bias in terms of the objectives and highlight the tradeoffs between designs with uncertainty accounted for.

3.2.2 Uncertainty Analysis

The approach for identifying, characterizing, simulating, and quantifying the effect of uncertainty in a concept design using probabilistic methods is discussed below. Applying this approach produced the foundation for quantifying and visualizing the implications of uncertainty in an early stage design trade space. The general steps that constitute uncertainty analysis are as follows:

1) Major Sources of Uncertainty Identified
    a. Understanding that a model is a simplification of the real environment, assumptions will inevitably be made during the modeling process. The deterministic assumptions should be documented and validated by designers, subject matter experts (SMEs), cost estimators, and stakeholders prior to proceeding with down selection. In the event consensus cannot be achieved, these parameters are prime targets for further investigation.
    b. With model formulation complete, modelers can perform a sensitivity analysis on model parameters, which will assist in identifying design metrics that have significant impact on model outputs.
        i. The high impact design metrics provide insight as to where the design team should focus their efforts for identifying sources of uncertainty within the design variables [21]. For example, in the mini-submersible design discussed in the next chapter, volume was identified as a high impact metric whereas weight was not. Therefore, while some uncertainty existed in terms of the weights of different Energy Source options, the uncertainty associated with the energy densities was significantly more important to capture in the modeling effort.
    c. In addition to identifying uncertainties with high impact potential it is also important to identify uncertainties that assist in differentiating between design alternatives [21].
    d. Supporting the above discussion regarding the omission of the less significant weight uncertainties, the modeling effort would become intractable if every source of uncertainty was identified and modeled [21]. It is important to aggregate

uncertainties to minimize computational complexity while still accurately representing tradeoffs between designs.

i. Another example from the mini-submersible design helps illuminate this idea. In early stage design it is conceivable that both the supporting infrastructure and energy density for the Energy Source options aren't exactly known. Rather than modeling both uncertainties, an assumption is made for the system infrastructures, which don't contribute to energy available, while the energy density uncertainties are explicitly modeled. This approach captures the essence of both uncertainties. It is both less computationally intensive to model the energy density uncertainty than the system infrastructure uncertainty and easier to implement in the model framework.

2) Characterize Uncertain Variables [24]

a. The characterization of the uncertain variables is a collective effort from designers, SMEs, and cost estimators. Each uncertain variable is modeled using a probability density function (PDF) via historical data, market research, SME opinion, and cost estimator opinion [24].

i. The probabilistic modeling of variables can take many forms depending on the type of variable being represented.

1. Gaussian distributions can be used to represent many natural phenomena with reasonable results.
2. Uniform distributions can be used when a range of outcomes are possible, but the probability of any outcome within the range is identical [24].
3. The Gumbel, Frechet, and Weibull distributions are extreme value distributions and useful if attempting to model rare events. The Weibull distribution is also often used in reliability modeling [24].
4. The Beta-PERT distribution is a modification from the Beta distribution and discussed in the next chapter as it is the distribution used in the case study.

3) Create Framework for Efficient Sampling and Simulation (Optional)

a. This step is discussed in detail in the next chapter as it is highly subjective to the model setup and sources of uncertainty.

4) Run Monte Carlo Simulation (MCS) & Collect Data [24]

a. For each sample in the simulation run every uncertain variable will generate a value from its PDF, but prior to running the simulation an assessment needs to be made regarding the relationships between the uncertain variables. This assessment determines whether any dependencies exist between uncertain variables.

i. For example, if two uncertain variables exist for a design variable option, such as cost and performance, then it is necessary to determine does performance depend on how much money is spent, or does how much money is spent determine the level of performance? If the answer is yes, then 1 random number is generated and used to sample the PDFs of both uncertain variables. If the answer is no, then an independent random number is generated for each uncertain variable and used to sample their respective PDFs.

b. The simulation generates thousands of design variable input combinations and their associated output realizations [28]. A larger simulation run results in a smoother output distribution, but a greater computational expense [24]. The typical MCS flow chart is shown in Figure 3-2 [3].

i. The number of samples should be enough to generate stable results in repeated simulation runs [28].

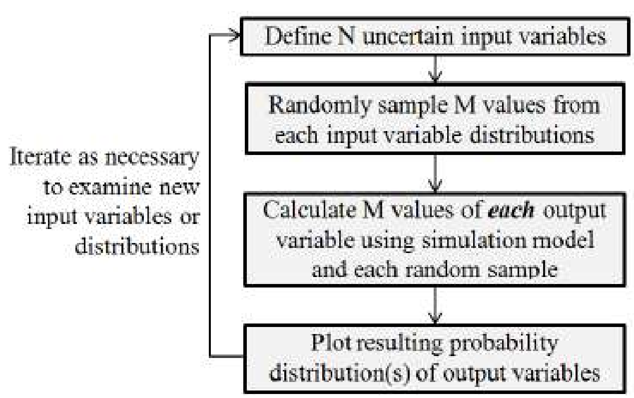

Figure 3-2: Monte Carlo Simulation Flow Chart

5) Generate Sample Statistics for Data
    a. The design combinations are no longer represented as a single point in the trade space. The design combinations are now represented by a collection of points, also known as a point cloud. The sample statistics collected for the follow-on analysis are the point cloud centroids, the point cloud X and Y ranges, and the point cloud boundary area, defined as Area of Uncertainty (AoU).
6) Plot Results
    a. Deterministic with Uncertainty Point Cloud.
        i. This is the raw output data from the MCS.
    b. Deterministic with Point Cloud Boundary Area.
    c. Deterministic vs. Uncertain Centroid.
    d. Percent Confidence in Relation to Uncertain Centroid.
    e. Uncertain Centroid Performance/Cost vs. AoU.
        i. The X and Y Ranges of the Monte Carlo point cloud affect the value of this plot since one of the objectives could be contributing a disproportionate amount to the AoU.
7) Evaluate Results
    a. The last step is to assess the design alternatives using uncertainty as a central decision criterion along with performance and cost [21].

The outputs of uncertainty analysis serve to inform the SCR and SRR. In a MBE approach the models, assumptions, and uncertainty profiles can be refined and updated to form the design baseline in the follow-on phases of the DAS. As technologies are matured, the uncertain variable PDFs can be updated for risk monitoring. Additionally, the models, assumptions, uncertainty profiles, and results can be databased for reuse on other projects and shared across programs. The database can also serve as a reference for decision rationale.

Chapter 4 Case Study: Manned, Mini-Submersible

4.1 Background

The mini-submersible model presented in this case study was adapted from a concept design group project known as JAWFISH [29]. While several modifications were made to the original model in support of this research, the major adaptation was the incorporation of a Fuel Cell (FC) option as an Energy Source subsystem tradeoff. The FC model originated from a prior year concept design group project known as SUBLET [30]. The following discussion does not cover every detail of the mini-submersible model, but only highlight the portions necessary for clarity in this paper. Further information regarding the JAWFISH and SUBLET projects can be found in their respective reports.

4.2 Mini-Submersible Overview

The mini-submersible consisted of a cylindrical pressure hull with spherical end caps and an external fairing. The pressure hull was segmented into three distinct compartments. Forward, a pilot compartment that consisted of the control and navigation systems and supported two crew members, a pilot and co-pilot. Amidships, a lockout chamber which supported the Lock-In/Lock-Out (LIO) of up to 5 divers at a time. Aft, a transport compartment that supported divers and cargo storage. Figure 4-1 shows the general layout of the mini-submersible.

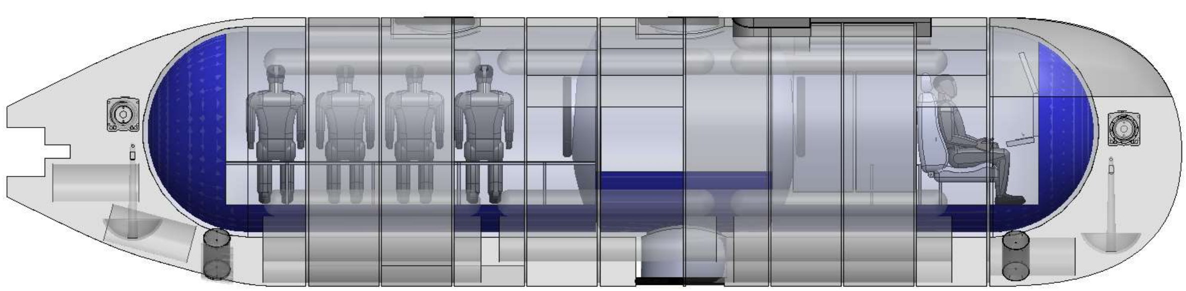

Figure 4-1: Mini-Submersible Overview

4.3 Problem Setup

4.3.1 Need Identification

The projects purpose was to produce a feasible mini-submersible design with the capability of externally mating to and launching from a larger host submarine. This concept is shown in Figure 4-2. The mission concept of the mini-submersible was as follows: transport divers from a host submarine to a mission area in a dry atmosphere environment, lockout divers and remain on station (loiter) while the divers conduct their mission, retrieve divers upon mission completion, and transit back to the host submarine. The mini-submersible needed to provide the capability to lockout and retrieve divers in the middle of the water column. This will be referred to as Mid Water Column (MWC) LIO for the remainder of this paper.

Figure 4-2: Mini-Submersible Concept

4.3.2 Stakeholder Identification

The project stakeholders included U.S. Special Operations Command (USSOCOM), Naval Special Warfare Command, and Naval Sea Systems Command. The program manager for Maritime Undersea Systems at USSOCOM was the project sponsor and overall decision-maker.

4.3.3 Stakeholder Requirements

Initial requirements were set by the project sponsor and refined via input from the other stakeholders. The problem posed by the project sponsor was to determine how much capability could fit in a defined footprint. The footprint was a cylinder of length 42.2 feet and diameter 9 feet. The footprint was the key constraint on the design trade space. Capability in this project was defined by the payload, endurance, and mission flexibility of the mini-submersible. The initial set of requirements are provided in Table 2.

Category	Notes	Metric	Threshold	Objective
Crew Size	Includes 2 Pilots	People	6	11
Cargo Volume		Cubic Feet	20	40
Range	Roundtrip	Nautical Miles	60	300
Loiter Time		Hours	24	36
LCPs	@Depth 190ft		1	4
MWC LIO			Yes	Yes

Table 2. Initial Flexible Requirements

4.3.4 Performance Attribute Identification

The Measures of Performance (MOP) were also defined by the project stakeholders. The MOP and their associated mission areas are provided in Table 3.

Measures of Performance	Mission Area
Crew Size	Payload
Cargo Volume	Payload
Range	Endurance
Loiter Time	Endurance
Lockout Chamber Pressurizations	Mission Flexibility
% of Missions Accessible	Mission Flexibility

Table 3. Measures of Performance and Associated Mission Area

4.3.5 Establish a Value Function

The value metric for this project was defined as Overall Measure of Performance (OMOP). To establish the value criteria the design team surveyed the project stakeholders, which included pilots and divers (both former and current), to define weighting metrics (Wi) across MOP as well as utility functions ($MOPi(X)$) from threshold to objective values for individual MOP. It is important to note that the underlying assumption in this formulation is that MOP contribute independently to OMOP [16]. Equation 1 shows the formulation of OMOP.

Equation 1: OMOP

$$OMOP = \sum_{i=1}^{N} Wi \times MOPi(X)$$

The last caveat to the value formulation is that separate weighting metrics across MOP were elicited for LIO missions versus Non-LIO missions. This caveat was due to stakeholders expressing that they valued MOP differently depending on the mission type. The stakeholders projected that over the life of the platform 70% of missions conducted would involve LIO operations while the remaining 30% would focus on intelligence, surveillance, and reconnaissance. The weighting metrics for MOP are shown in Figure 4-3.

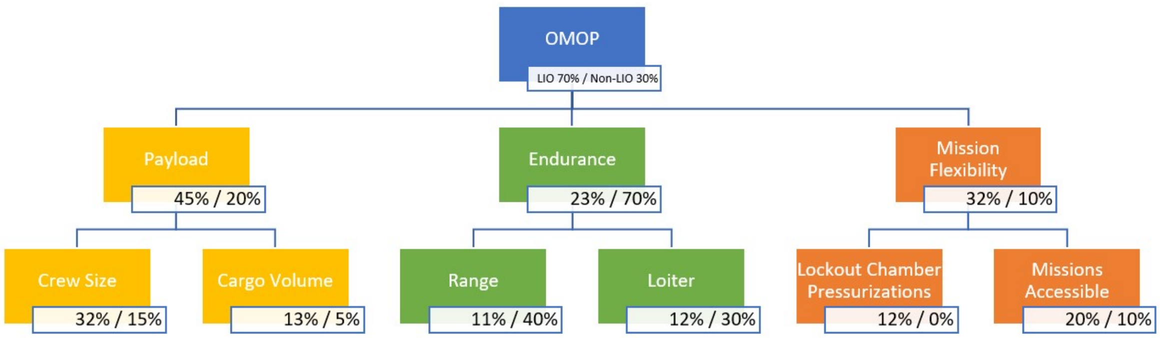

Figure 4-3: OMOP Weighting Metrics

The Energy Source subsystem affects OMOP through the Endurance mission area. Based on the design combination, a set amount of energy is needed to satisfy the Loiter requirement and the energy remaining determines the achievable Range. The MWC LIO subsystem affects OMOP through the Mission Flexibility mission area. The MWC LIO subsystem option determines the percentage of missions accessible for a given design. The rationale behind this performance attribute follows. The project stakeholders desire 100% Mission Accessibility for the mini-submersible. An anchoring system allows access to a total of 50% of desired missions, 20% exclusively. A hovering system allows access to a total of 70% of desired missions, 40% exclusively. 30% of missions are accessible via either option and having both a hovering and anchoring system allows access to 90% of missions. 10% of missions are currently inaccessible with the technology available. Figure 4-4 displays this breakdown.

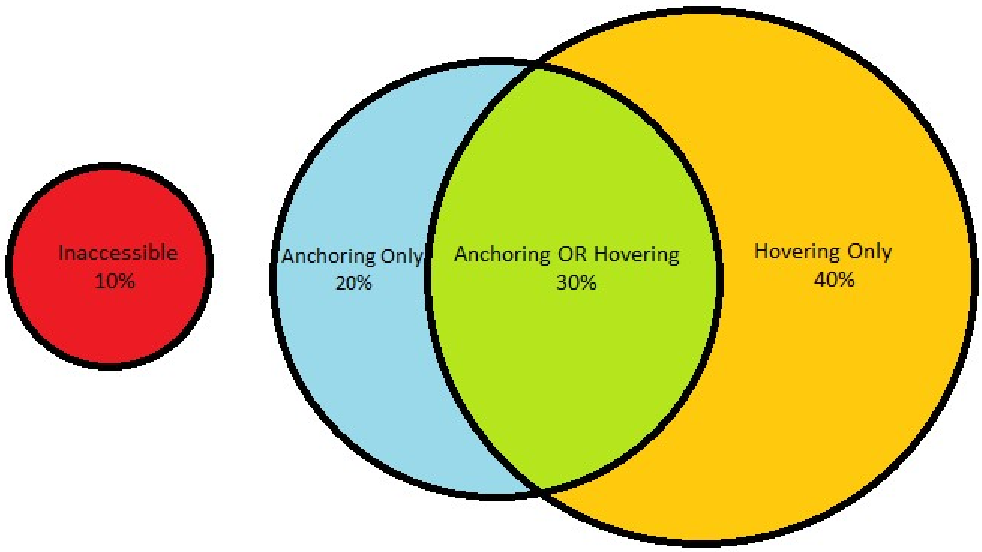

Figure 4-4: Percentage of Missions Accessible

The utility functions for individual MOP are flexible and can be defined as desired by the stakeholders. The utility functions are anchored using the threshold and objective values provided in the initial requirements. Threshold values are set to zero utility and objective values represent maximum utility for a given performance attribute. For discrete performance attributes, such as Crew Size, the utility defined by the stakeholders directly relates to the level of performance achieved. For continuous performance attributes, such as Range, stakeholders define utility for a few discrete performance levels from threshold to objective and then a line of best fit is calculated to produce a utility value for all performance levels. An example of the utility function for Crew Size is shown in Figure 4-5.

Crew Size (including 2 Pilots)

	Crew	Utility
Threshold	6	0
	7	2
	8	4
	9	6
	10	8
Objective	11	10

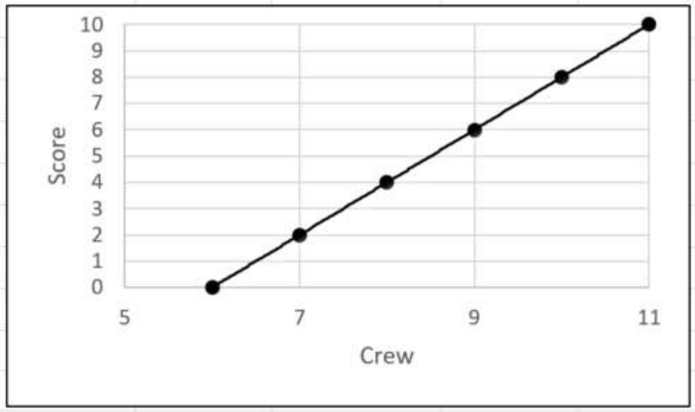

Figure 4-5: Utility Function Example for Crew Size MOP

4.3.6 Design Variable Identification

The key design variables for the mini-submersible were the options for the Energy Source subsystem, either a Lithium Ion (LI) battery or a Fuel Cell, and the options for the MWC LIO subsystem, either an Anchoring system, a Hovering system, or Both. The system decomposition is shown in Figure 4-6. The possible combinations of the two subsystems are shown in in Table 4.

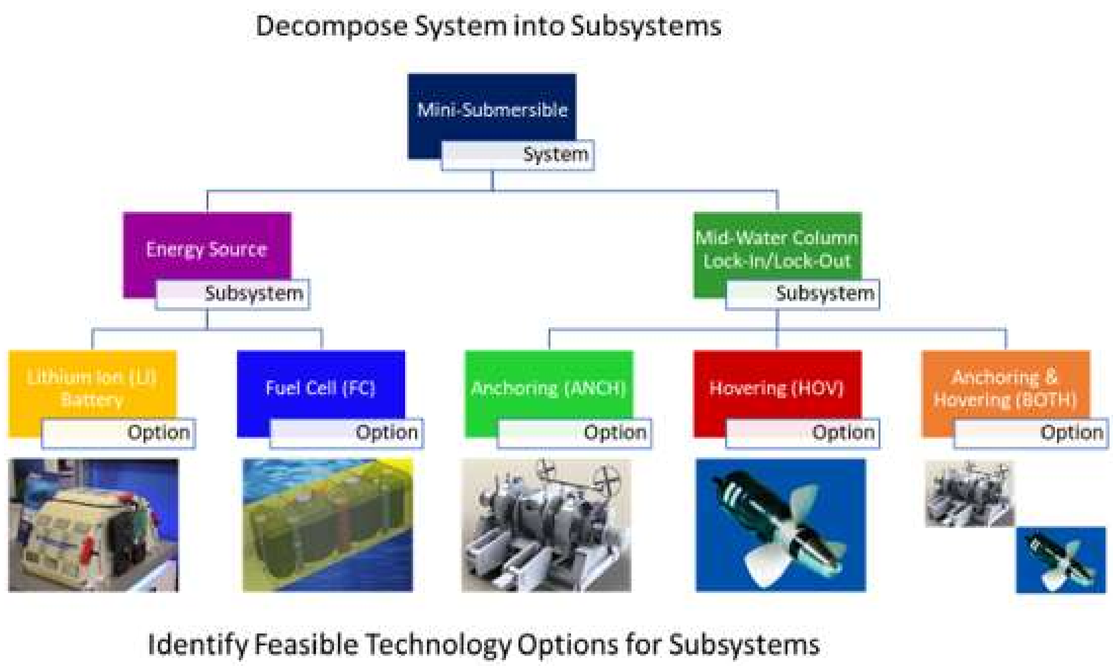

Figure 4-6: System Decomposition into Tradeable Options

		MWC LIO Subsystem		
		Anchoring	Hovering	Both
Energy Source Subsystem	Lithium Ion (LI)	LI / Anchoring	LI / Hovering	LI / Both
	Fuel Cell (FC)	FC / Anchoring	FC / Hovering	FC / Both

Table 4. Combinations of Key Design Variables

The other design variables that contributed to the creation of the trade space were Crew Size, Cargo Volume, Loiter Time, Lockout Chamber Pressurizations (LCPs), and Length Overall (LOA). Note that the structure of this problem resulted in overlap between some performance attributes and design variables. The basis for this overlap is briefly summarized for clarity. Crew Size and Cargo Volume represent the payload of the vessel, but also affect the design by requiring additional dry atmosphere volume. Loiter Time represents a portion of the vessels endurance, but also affects the design by requiring additional energy during the loiter period for Hovering or Both MWC LIO options. LCPs represent a portion of the vessels mission flexibility, but also affect the design by requiring additional high-pressure air tanks. The options for all design variables are shown in Table 5.

Design Variable	**Options**
Energy Source Subsystem	<Lithium Ion, Fuel Cell >
MWC LIO Subsystem	<Anchoring, Hovering, Both>
Crew Size	<6, 7, 8, 9, 10, 11>
Cargo Volume	<20, 30, 40>
Loiter Time	<24, 27, 30, 33, 36>
LCPs	<1, 2, 3, 4>
LOA	<39.083, 40.625, 42.167>

Table 5. Design Variable Options

4.3.6.1 Key Design Variable Tradeoffs

4.3.6.1.1 Energy Source Subsystem Tradeoffs

A brief discussion of the tradeoffs between the options for the Energy Source subsystem follows. The FC option requires more system infrastructure than the LI option due to the FC pressure vessel. That being said, the FC option still provides a higher energy density than the LI option. The cost of the FC option also scales differently than the LI option. All FC options have an initial cost for the purchase of the power plant plus the additional cost of the oxygen and hydrogen tanks [30]. The cost of the LI option simply scales linearly from zero in dollars per kilowatt-hour [30]. The cost model, described in more detail in the next section, also factors in development cost in the form of a cost estimating relationship (CER) to account for less mature technologies. This CER is baselined at 1 for LI options as this technology has been proven on a manned mini-submersible in a representative environment. The FC option incurs a cost penalty in this respect.

4.3.6.1.2 MWC LIO Subsystem Tradeoffs

A brief discussion of the tradeoffs between the options for the MWC LIO subsystem follows. Although the Hovering option is equipped with larger thrusters, the Anchoring option still requires more volume due to the forward and aft anchor systems. The size of the anchor systems forward and aft also places a tighter restriction on the pressure hull length when compared to the Hovering option due to the limited footprint. Additionally, the Hovering option requires more energy during MWC LIO operations and the subsequent loiter period while the Anchoring option only requires energy for hotel loads. The cost model also includes additional software and energy costs for the Hovering option whereas the anchor system costs are included for the Anchoring option. The Both option includes the combination of positives and negatives from Anchoring and Hovering.

4.3.7 Model Formulation

4.3.7.1 Overview

The modeling approach began by decomposing the mini-submersible design and requirements into sub-models. A baseline amount of equipment was required for every design combination regardless of the design variable inputs. Sonar and navigation equipment, a propulsion motor, propeller, and control surfaces are examples of items common to all designs. Additionally, first principle sub-models were created to determine the amount of energy, oxygen, high-pressure air, and variable ballast required to satisfy each design combination with respect to the design variable inputs. The structure model was driven by the Crew Size and Cargo Volume design variables to determine pressure hull characteristics. Specifically, the transport compartment stack length grew to accommodate divers and cargo. The outputs from the first principle models, structure model, and design variables served as inputs to the parametric weight and buoyancy models as well as the geometric volume model. Three feasibility checks followed to determine if the design combination was conceivable within the required footprint. Failing any feasibility check removed the design from the trade space. If the design combination was conceivable, the achievable range was determined based on the Energy Source subsystem and the amount of external volume remaining. Failing to meet the threshold range requirement also removed the design from the trade space. If range met or exceeded the threshold requirement, the design combination was costed and an OMOP was calculated. Figure 4-7 shows an overview of the model formulation.

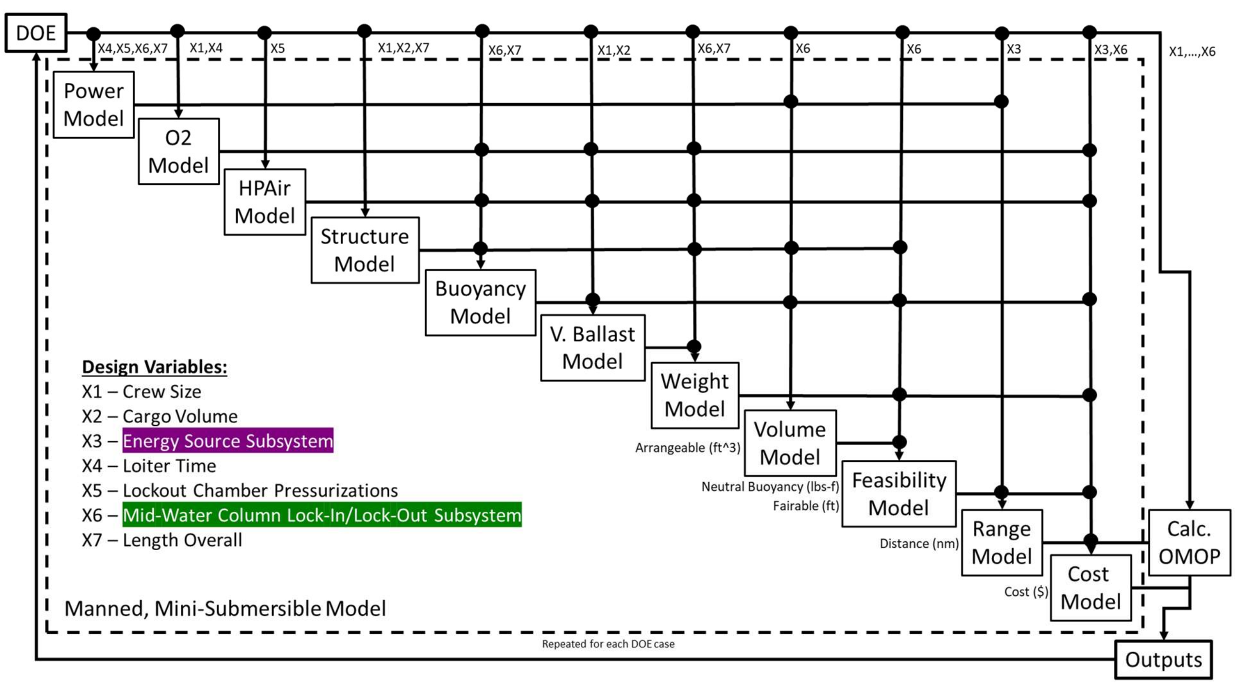

Figure 4-7: Mini-Submersible Model – System Perspective

In summary, the mini-submersible model first calculates the amount of equipment and consumables required based on the input set of design variables. Next, the model determines if the design combination is feasible within the volume limited footprint. Then, the model determines if enough volume remains to meet the threshold range requirement. Finally, cost and OMOP are calculated for feasible designs. Detailed flow charts of the sub-models are found in Appendix A.

4.3.7.2 Feasibility Constraints

A feasible design is defined by the four checks described below:

1) Arrangeable – All equipment and consumables required for the design combination fit within the envelop volume. The envelop volume is the space contained by the outer fairing, shown in Figure 4-8.
2) Neutral Buoyancy – With all equipment and consumables added, enough volume remains between the fairing and the pressure hull to achieve neutral buoyancy through the full spectrum of loading conditions.
    a. This volume allows for the addition of lead (weight) or syntactic foam (buoyancy) to achieve a relationship manageable by the variable ballast system.
3) Fairable – The relationship between the length of the fairing and the pressure hull is such that the pressure hull can be faired with respect to typical mini-submersible values. Figure 4-8 illustrates this concern.
4) Range Threshold – Range greater than or equal to 60 nautical miles.

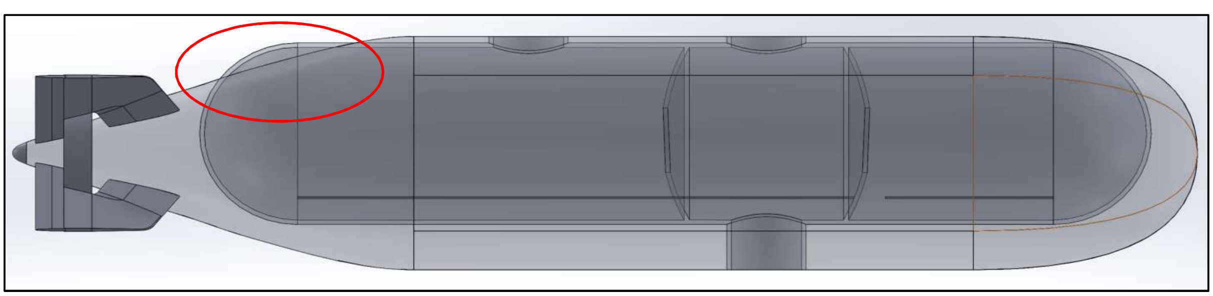

Figure 4-8: Infeasible Variant Removed from Trade Space – Not Fairable

4.3.7.3 Cost Model

In terms of DoD cost estimating, the cost model for the mini-submersible most closely resembles an engineering cost [29]. A cost of required components common across all design combinations forms the Fixed Cost. A weight-based approach assuming HY-80 steel forms the cost of the structure. Other variable costs include energy, oxygen tanks, high-pressure air tanks, and ballast. The costs of the Energy Source and MWC LIO subsystems are also subjected to a development cost CER, as mentioned in section 4.3.6.1, prior to their addition to Variable Cost. Equation 2 summarizes the formulation of Variable Cost. Fixed Cost and Variable Cost are then summed and multiplied by a cost factor consisting of CERs accounting for tax, shipping, labor, integration, and assembly to estimate a production cost [29]. Equation 3 summarizes the formulation of Total Production Cost.

Equation 2: Variable Cost

$$\begin{aligned} VariableCost = [&Structure + \ O2\,Tanks + HPA\,Tanks + Ballast \\ &+ (Energy\ Source\ Subsystem\ \times Development\ CER) \\ &+ (MWC\ LIO\ Subsystem\ \times Development\ CER)] \end{aligned}$$

Equation 3: Total Production Cost

$$Total\ Production\ Cost = (Fixed\ Cost + Variable\ Cost)\ \times Production\ Cost\ Factor$$

4.3.8 Trade Space of Deterministic Model Outputs

The trade space for the feasible mini-submersible designs is shown in Figure 4-9. Each point represents a unique combination of the design variables previously discussed. The assumptions for the uncertain parameters in the deterministic model are representative of the mean, or expectation, of the uncertain distributions, which are defined later.

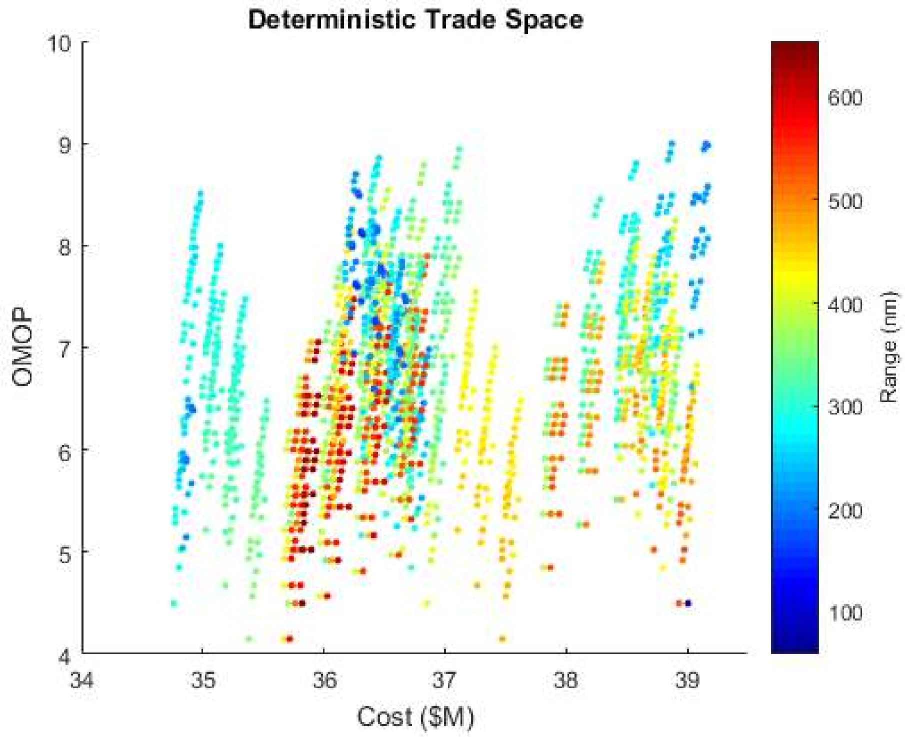

Figure 4-9: Deterministic Trade Space

4.3.9 Identify Promising Designs for Uncertainty Analysis

The approach for identifying promising designs was to capture all design combinations on the Pareto Frontier and ensure each of the six design combinations comprising the Energy Source and MWC LIO subsystems were represented in the follow-on uncertainty analysis. MATLAB was used to achieve this by identifying and recording the designs which exhibited strong dominance on the Pareto Frontier. Once recorded, the identified layer of the Pareto Frontier was removed, and the next set of Pareto Optimal designs was identified and recorded. This was conducted until each Energy Source and MWC LIO design combination was represented. This outcome was achieved on the third iteration. Figure 4-10 displays the outcome of the first iteration.

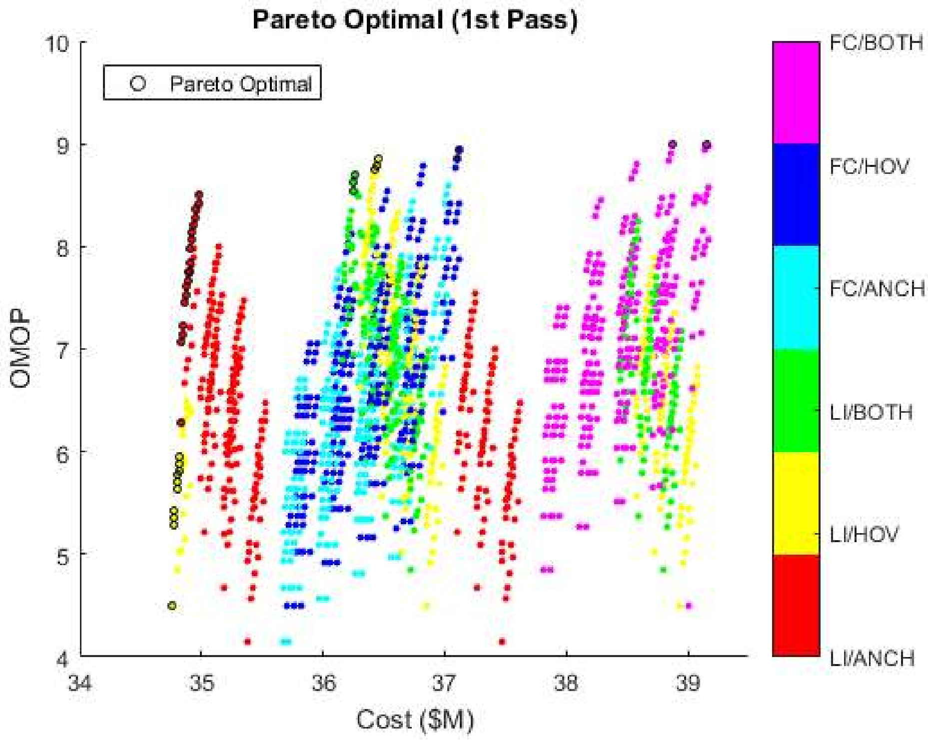

Figure 4-10: Key Design Variable Combinations with First Layer of Pareto Optimal Designs Selected

4.4 Uncertainty Analysis

At the end of Model Formulation, a one factor at a time sensitivity analysis was conducted on model assumptions to investigate which assumptions had the greatest impact on feasibility, OMOP, and cost. As expected in this volume limited design, the three key contributors were, pressure hull diameter, external volume permeability (volume external to the pressure hull reserved for manufacturability and free flood space) and energy density. The common theme across these three parameters was they all focused on the efficient use of volume. This analysis assisted in determining which sources of uncertainty were of greatest concern.

4.4.1 Identify Major Sources of Uncertainty

In this case example the major source of uncertainty was identified to be the energy density of the energy sources. The second source of uncertainty was based on the anticipated performance of the MWC LIO subsystem options, in terms of percentage of missions accessible. As discussed in the previous section, the cost model also factors in a development CER. Since cost estimating is oftentimes more of an art than a science, uncertainty is also accounted for in the development CERs applied in the deterministic analysis. These cost uncertainties are included for the LI energy source, the FC energy source, the Anchoring system, and the Hovering system. The Anchoring and Hovering system cost uncertainties are also carried into the Both option.

As discussed in multiple references, TSE works best when treated as an iterative process of discovery [15], [31]. As designers and decision-makers begin understanding underlying design tradeoffs new insights are gained, including insights regarding value functions [31]. While not the focus of this paper, it is an important part of the overall process as this can affect both weightings between MOP as well as the individual utility functions for MOP. This situation occurred during the JAWFISH concept design. The design team performed an initial assessment of the Hovering capability and discovered some limitations regarding wave orbital energy below the ocean surface. This feedback was provided to the project stakeholders, but the JAWFISH design team did not revisit how the stakeholders valued Hovering or explicitly account for the new insight. Nonetheless, during down selection, the uncertainty in Hovering performance strongly influenced the stakeholders final selection of a Fuzzy Pareto Optimal Both design instead of a Pareto Optimal design. This situation motivated explicitly accounting for performance uncertainty in the Hovering option. This performance uncertainty is carried into the Both option as well.

While other sources of uncertainty could be included, the selections above made the problem interesting enough to apply the process. The parametric analysis of weights, buoyancies and volumes was based on high fidelity historical data from two prototype mini-submersibles. This reason, coupled with the application of standard design/build and service life allowance margins, which hedge against uncertainty in these areas, influenced the decision to leave these items out of the uncertainty analysis. The projected shorter lifespan of 10 years, compared to 30 years for typical DoD weapon systems and platforms, and a highly specific mission also influenced this decision. If other problems seek to address uncertainties such as the ones listed above, it only requires adjustments to the applicable models.

4.4.2 Characterize Uncertain Variables

If uncertainties are neglected in the modeling effort, not only may an individual design be biased in the overall trade space in terms of capability and cost, but the tradeoffs between design alternatives are also potentially misrepresented. Just as it is important to capture the uncertainties as accurately as possible, so too is it important to capture the relatedness of the tradeable option uncertainties to realize appropriate trends. In this spirit, an effort was made to create energy density distributions representative of the technical capabilities to date. The relativeness for energy density, performance, and cost factor uncertainties are also based on an "assessed" Technology Readiness Level (TRL) for the subsystem. At a high level these relationships are captured in Table 6 and Table 7. It is important to note that while effort was made for accuracy, this case application is for illustrative purposes only.

Energy Source	Energy Density	TRL	Uncertainty
Lithium Ion	Low	High	Low
Fuel Cell	High	Low	High

Table 6. Energy Source Subsystem: Comparative Uncertainty Relationships

MWC LIO	Performance	TRL	Uncertainty
Anchoring	Low	High	Low
Hovering	Medium	Low	High
Both	High	Medium	Medium

Table 7. MWC LIO Subsystem: Comparative Uncertainty Relationships

4.4.2.1 Probabilistic Modeling of Variables

The uncertain variables in this case application are modeled using the Beta-PERT (Program Evaluation and Review Technique) distribution [32]. The Beta-PERT distribution is typically used for modeling expert data [32]. Rather than trying to capture uncertainties in terms of means and variances, the inputs to create the Beta-PERT distribution are a minimum value, maximum value, and most likely value [32]. Lambda also controls the peak of the distribution with a value of 4 approximating a normal distribution [32]. The min, max, and most likely values are used to generate the shape parameters for the Beta Distribution ($\beta(\alpha 1, \alpha 2)$) [32]. The Beta-PERT distribution produces a smooth shape similar to the normal distribution and can represent skew [32]. A variable range and most likely estimate (mode) are more easily communicated and understood amongst multiple stakeholders rather than means and variances.

The Beta-PERT distribution was also used in this case for convenience. As mentioned in the previous chapter, the initial uncertain parameter assumptions in the deterministic model were means, and these means were simply calculated using Equation 4. This approach assured that when the centroids (means) of the Monte Carlo point clouds were used in the follow-on analysis the effect of uncertainty was isolated. If the initial model assumptions were something other than expectations, as defined by the uncertain parameter distributions, the effect of uncertainty wouldn't be clear when making comparisons. Equations 5 and 6 show the Beta distribution shape parameter calculations and Equation 7 provides an example of how the uncertain parameter distributions were sampled for the MCS.

Equation 4: Mean (μ) of Beta-PERT Distribution

$$\mu = \frac{min + (\lambda \times mode) + max}{(\lambda + 2)}$$

Equation 5: Shape Parameter 1 of Beta Distribution

$$\alpha 1 = \frac{(\mu - min)(2 \times mode - min - max)}{(mode - \mu)(max - min)}$$

Equation 6: Shape Parameter 2 of Beta Distribution

$$\alpha 2 = \frac{\alpha 1 \times (max - \mu)}{(\mu - min)}$$

Equation 7: Example of Random Sample

$$Sample = [rand\beta(\alpha 1, \alpha 2) \times (max - min)] + min$$

The PDFs for the Energy Source subsystem options are shown in Figure 4-11 and the PDFs for the MWC LIO subsystem options are shown in Figure 4-12.

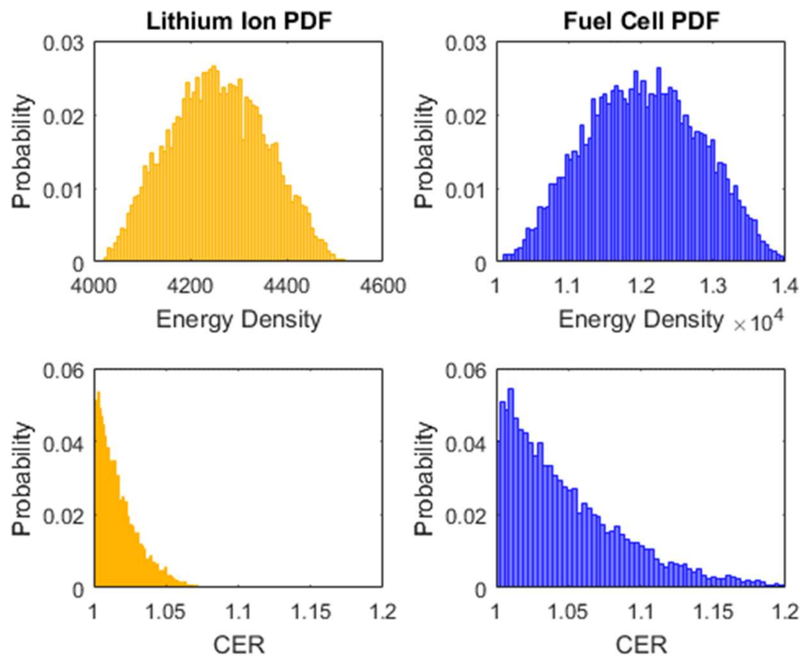

Figure 4-11:Energy Source Subsystem PDFs

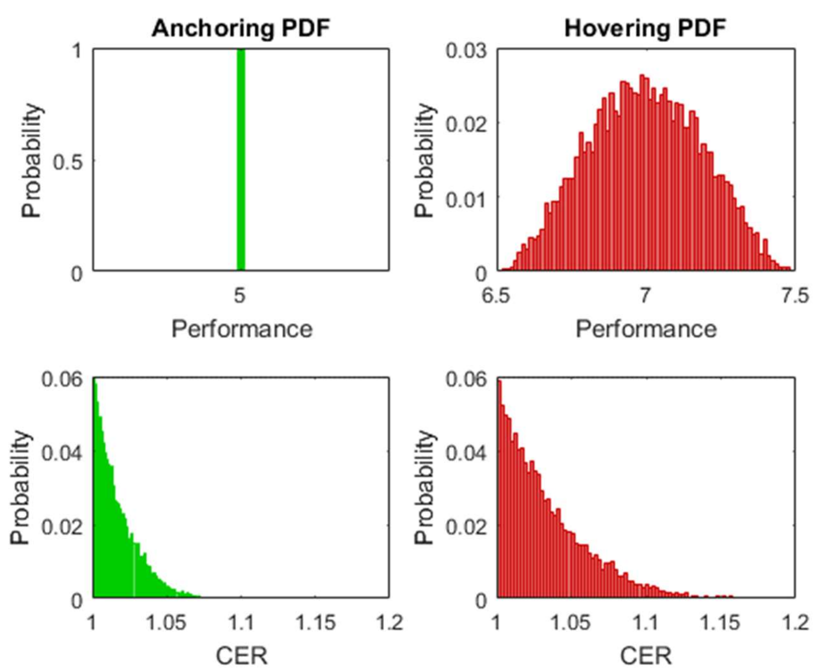

Figure 4-12: MWC LIO Subsystem PDFs

4.4.3 Create Framework for Efficient Sampling and Simulation (Optional)

This step is highly subjective to the initial model setup and where the identified sources of uncertainty interact in that process. It is necessary to identify where an uncertain parameter generates in the model structure and how uncertainties flow from one sub-model to another. Based on the mini-submersible model presented in Figure 4-7 and the sources of uncertainty identified above, it was more efficient to create "uncertainty" versions of the Range, Cost, and OMOP sub-models rather than rerun all portions of the model in its entirety. It should be noted here that each sub-model was created as a separate MATLAB function, which was called into the main file as needed. This made the uncertainty analysis a much smoother process (albeit after much trial and error). The deterministic design combinations and their outputs were loaded into a new MATLAB file and only the sub-models identified above needed to be reperformed.

The Power sub-model displayed in the upper left corner of Figure 4-7 may have caused confusion regarding the previous discussion due to the inclusion of energy density uncertainty. For clarity, the Power sub-model determined how much energy a design combination *needed*, whereas the Range sub-model determined how much energy a design combination had *available* and subsequently calculated the achievable range.

Had system infrastructure uncertainties for the energy sources, such as weight or volume, been chosen for explicit modeling these uncertainties would have generated much earlier in the model structure and would need to be propagated further. Briefly mentioned in the previous chapter, it was decided to collect these uncertainties in a higher-level energy density metric. While the prior would not be impossible, it would have substantially increased the computational complexity of the problem.

4.4.4 Run Monte Carlo Simulation & Collect Data

The approach in this case assumes no correlation between uncertain variables. Ten-thousand simulations were used for the assessment of 95 design alternatives. The 95 designs selected for further analysis are shown in Figure 4-13.

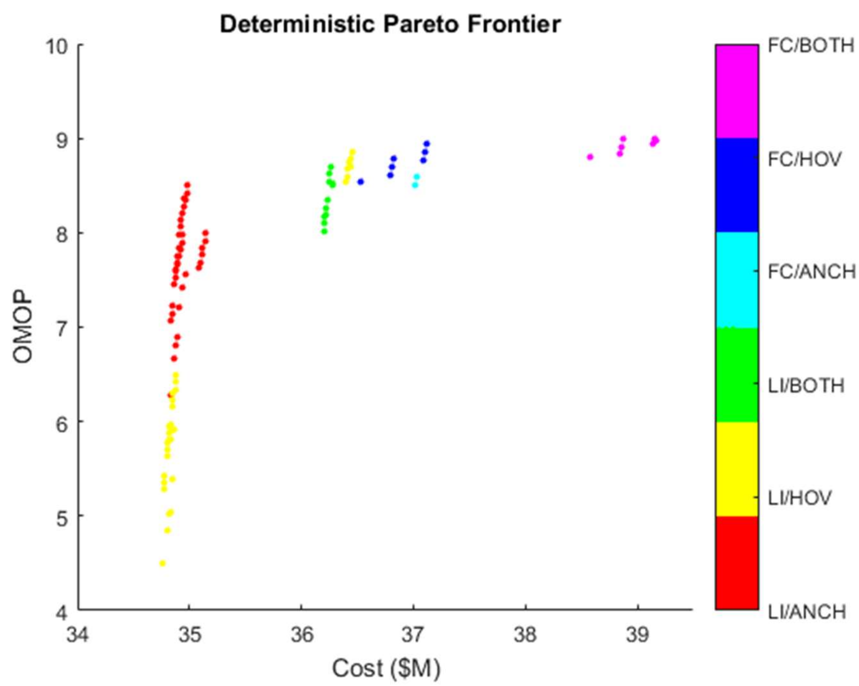

Figure 4-13: Designs Selected for Uncertainty Analysis Expressed as Energy Source & MWC LIO Combinations

The MCS supports the idea of unique uncertainty profiles for each of the 6 Energy Source and MWC LIO subsystem combinations. The raw outputs from the MCS for the 95 Pareto Frontier designs are shown in Figure 4-14.

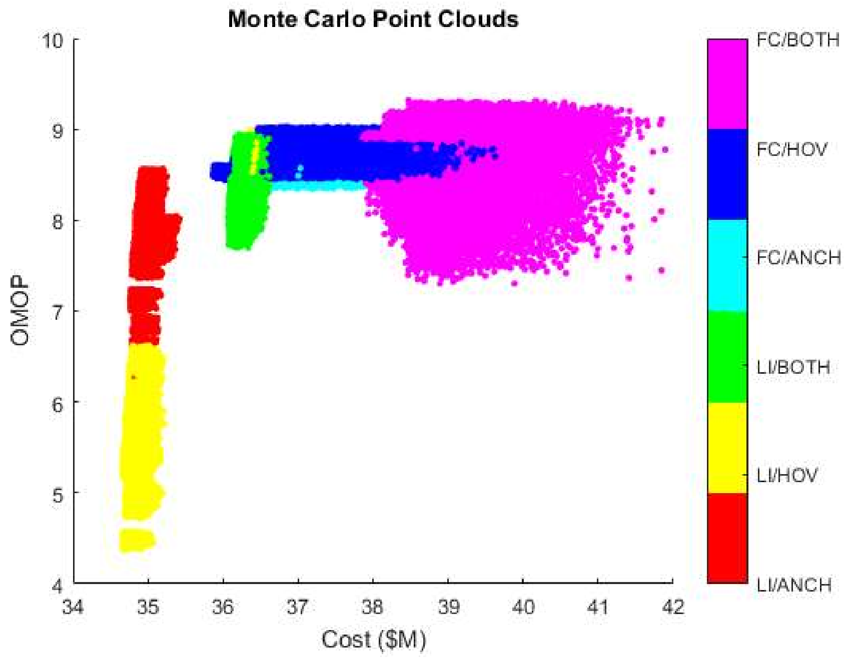

Figure 4-14: Pareto Frontier Designs: Monte Carlo Point Clouds

Figure 4-14 captures the general idea of how uncertainties can affect different design alternatives. However, it is difficult to assess if the uncertainties have an appreciable effect on the Pareto Frontier. This is especially important regarding how different design combinations relate when accounting for uncertainty, specifically in terms cost and performance. A useful metric, which assists in assessing this, is the centroid of the Monte Carlo point cloud.

Figure 4-15 displays the shift of the Pareto Frontier from the deterministic points, shown in Figure 4-13, to the centroids of the Monte Carlo point clouds, shown in Figure 4-14.

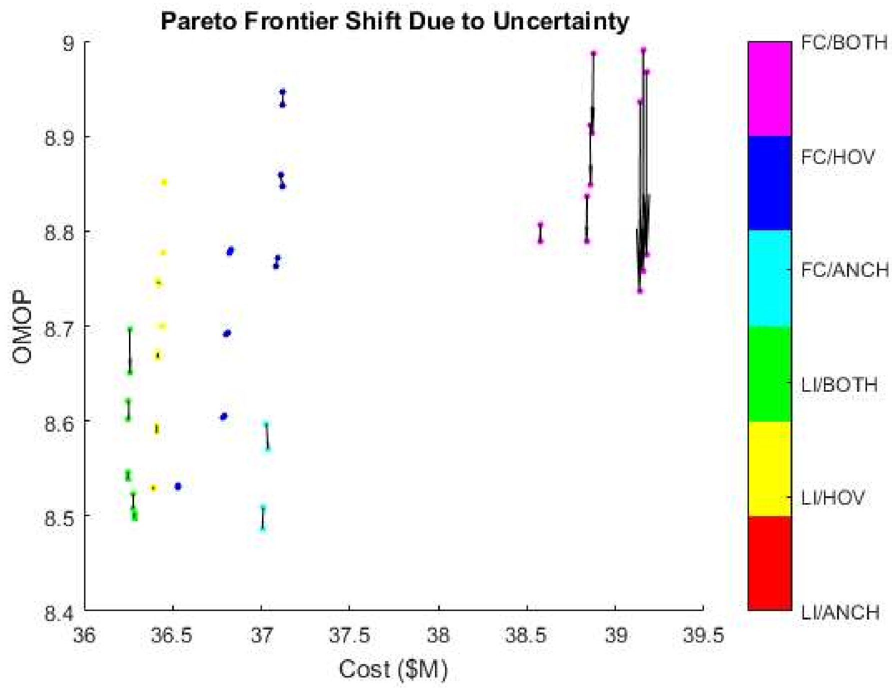

Figure 4-15: Pareto Frontier Shift Due to Uncertainty

It is important to note the scale of Figure 4-15 as this is a zoomed in perspective. While the majority of the points exhibit minor fluctuations, which can be attributed to the law of large numbers approximation, a handful of the points are worth noting. The highest performing FC/Both design combinations are quite sensitive in terms of their expected performance. The shift moves them from a Pareto dominant position to a position dominated by multiple FC/Hovering design combinations. The same is true for one of the LI/Both designs. Although the shift is not as pronounced as the FC/Both designs, it is non-negligible since the shift effects its relative position in terms of Pareto dominance to nearby LI/Hovering and FC/Hovering designs.

Figure 4-16 displays the adjusted Pareto Frontier in terms of the Monte Carlo point cloud centroids.

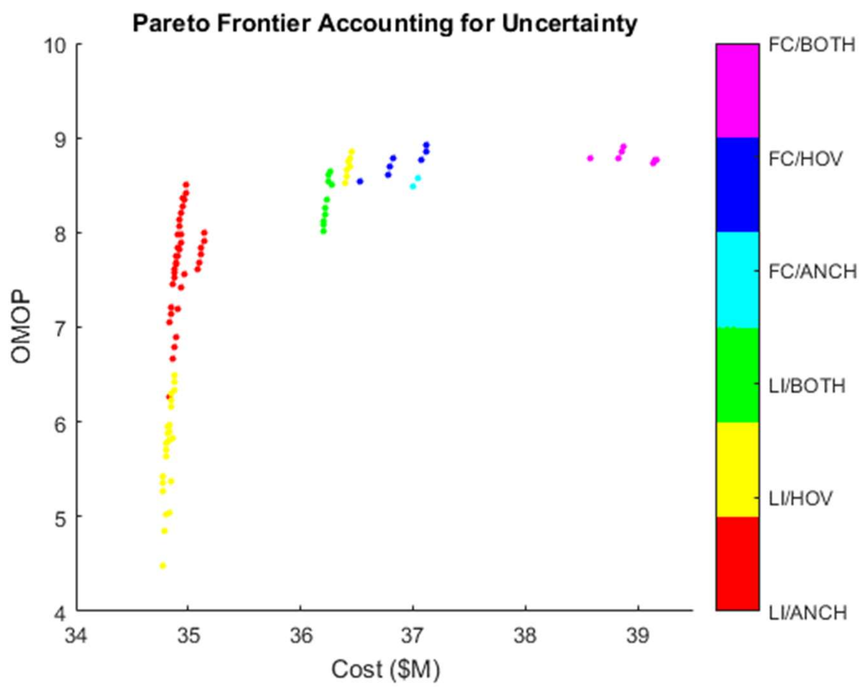

Figure 4-16: Pareto Frontier Designs: Depicted by Monte Carlo Point Cloud Centroids

The design combinations shown in Figure 4-16 that are less than $36M all exhibited compact uncertainty profiles. These design combinations were scaled out of Figure 4-15 as they were not noteworthy in this discussion.

For clarity, the remainder of this chapter highlights 1 design from each possible Energy Source and MWC LIO subsystem combination. The plots associated with all 95 designs initially selected for uncertainty analysis are found in Appendix B.

4.4.5 Generate Sample Statistics for Data

The sample statistics for the MCS were generated using MATLAB. The simulation data for each design combination was used to calculate metrics to assist in the follow-on analysis. The metrics used are the centroids of the Monte Carlo point clouds, the magnitude and direction of the shift from the deterministic design point to the Monte Carlo point cloud centroid, the areas of the Monte Carlo point clouds when bounded by a perimeter, previously defined as AoU, and the ranges of the Monte Carlo point clouds in terms of cost and OMOP. Table 8 shows the sample statistics for the 6 design combinations discussed in the rest of this chapter.

	Centroid			Range		Minimum		Maximum	
ES/MWC	**Cost**	**OMOP**	**AoU**	**Cost**	**OMOP**	**Cost**	**OMOP**	**Cost**	**OMOP**
LI/ANCH	35.0	8.50	0.04	0.35	0.13	34.9	8.44	35.3	8.57
LI/HOV	36.5	8.85	0.10	0.45	0.28	36.3	8.72	36.8	8.99
LI/BOTH	36.3	8.65	0.23	0.45	0.61	36.1	8.21	36.6	8.82
FC/ANCH	37.0	8.57	0.43	3.07	0.17	36.4	8.42	39.5	8.60
FC/HOV	37.1	8.93	0.71	3.00	0.30	36.5	8.73	39.5	9.03
FC/BOTH	38.9	8.90	4.21	3.39	1.50	38.2	7.71	41.5	9.21

Table 8. Sample Statistics Example

4.4.6 Plot Results

Plotting the results in the following manner aids in communicating how uncertainty influences the overall trade space. As discussed in the previous section, the point clouds from the MCS support the idea that unique design combinations exhibit unique uncertainty profiles. This insight is important for reducing computational complexity. It suggests that designs not selected for further analysis (i.e. dominated designs) will respond similarly to uncertainty and remain dominated. Figure 4-17 displays this idea.

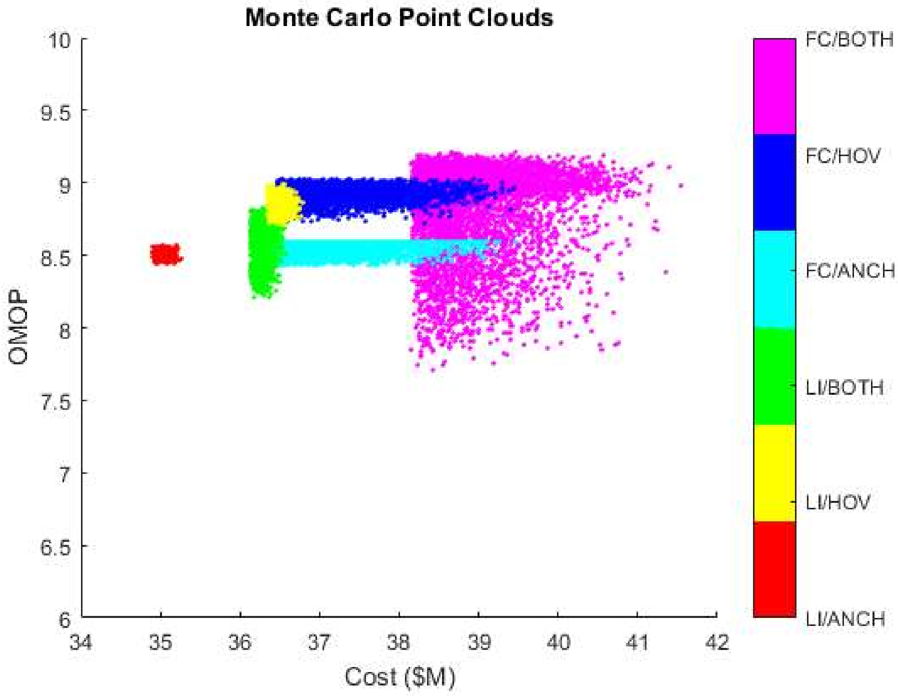

Figure 4-17: Uncertainty Profiles for 6 Pareto Frontier Designs

The MCS provides an initial visual assessment of how the subsystem level uncertainty distributions influence the design alternatives at the system level. The LI/Anchoring and LI/Hovering options appear to offer minimal cost risk with stable performance. The FC/Anchoring and FC/Hovering options appear to offer stable performance, but substantial cost risk. The LI/Both option presents minimal cost risk with some performance risk while the FC/Both option appears high risk in terms of both cost and performance.

Using the simulation data and the MATLAB boundary function a perimeter was placed around the Monte Carlo point clouds. The enclosed area was calculated and used as an AoU. An example of this is shown in Figure 4-18.

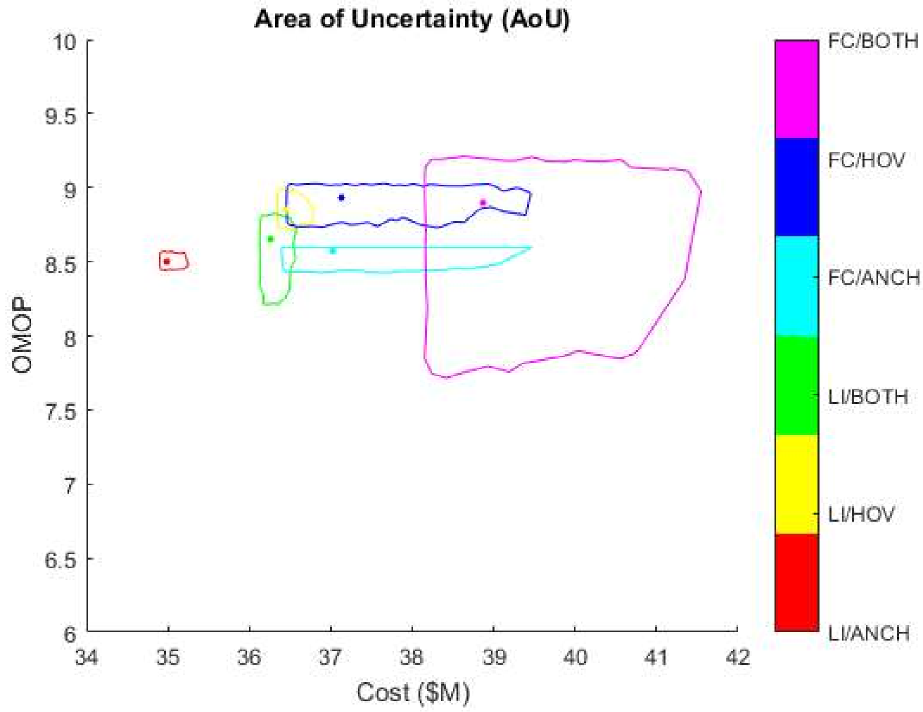

Figure 4-18: Area of Uncertainty for 6 Pareto Frontier Designs

There are several benefits to the AoU plot. First, in Figure 4-17, it was difficult to observe the entirety of the point clouds for certain design combinations due to overlap with other designs. Keeping the area inside the perimeter transparent allows us to see the relative shapes of the possible outcomes overlaid. Next, by plotting the centroid of the point cloud inside the perimeter, the essence of the density of outcomes is not lost from the previous point cloud plot, and possibly enhanced for large simulation runs. Last, even though every space inside the perimeter was not occupied during the simulation, this plot captures the realm of the possible. In other words, the AoU provides a reasonable approximation of where outcomes would occur if additional simulations are conducted. The calculated AoU is used later in this section as a measure of design risk, albeit with some limitations.

Displayed in Figure 4-18, and previously discussed, the centroids of the Monte Carlo point clouds are also calculated and used to display how multiple uncertain parameters influence the trade space. Figure 4-19 shows the Pareto shift due to uncertainty.

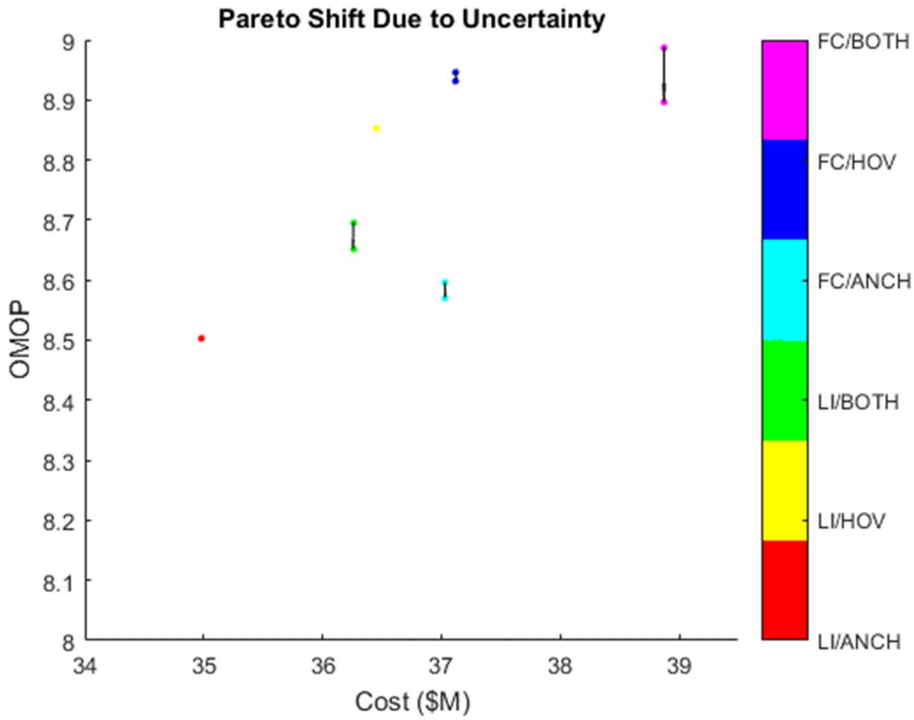

Figure 4-19: Pareto Shift Due to Uncertainty

As mentioned earlier, identifying the Pareto Frontier shift in this manner shows how individual designs are influenced by the uncertain parameters, but also how the relationships between design alternatives change. Although these designs only exhibit small shifts due to uncertainty, this plot provides valuable insight if the deterministic model assumptions do not reflect the mean value of the uncertain parameter distributions. This topic is discussed later in this chapter.

The previous plots are helpful as qualitative assessments for the implications of uncertainty on the trade space, but do not provide a simple, visual, quantitative assessment for a decision-maker. Using the centroids of the Monte Carlo point clouds as the reference point, the simulated outcomes are binned according to their cost and performance realizations. These results are displayed in Figure 4-20.

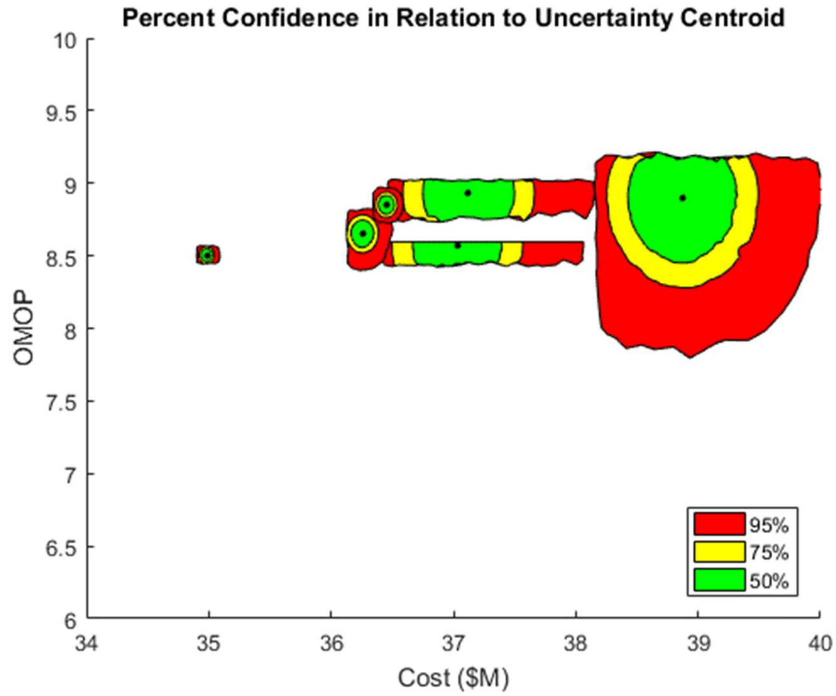

Figure 4-20: Measure of Confidence in Relation to Uncertainty Centroid

Figure 4-20 is constructed using a combination of the pointCloud, findNearestNeighbors, and boundary functions in MATLAB. This plot cleanly visualizes the implications of uncertainty on the trade space and quantifies it in terms of a measure of confidence in the cost versus performance construct.

The final plot in this section defines a new Pareto Frontier bringing uncertainty to the center of the discussion [25]. The centroid of the Monte Carlo point cloud is used to create a OMOP per cost metric and this is plotted against AoU. This creates a new decision framework for assessing designs. Figure 4-21 displays the new Pareto Frontier in this regard.

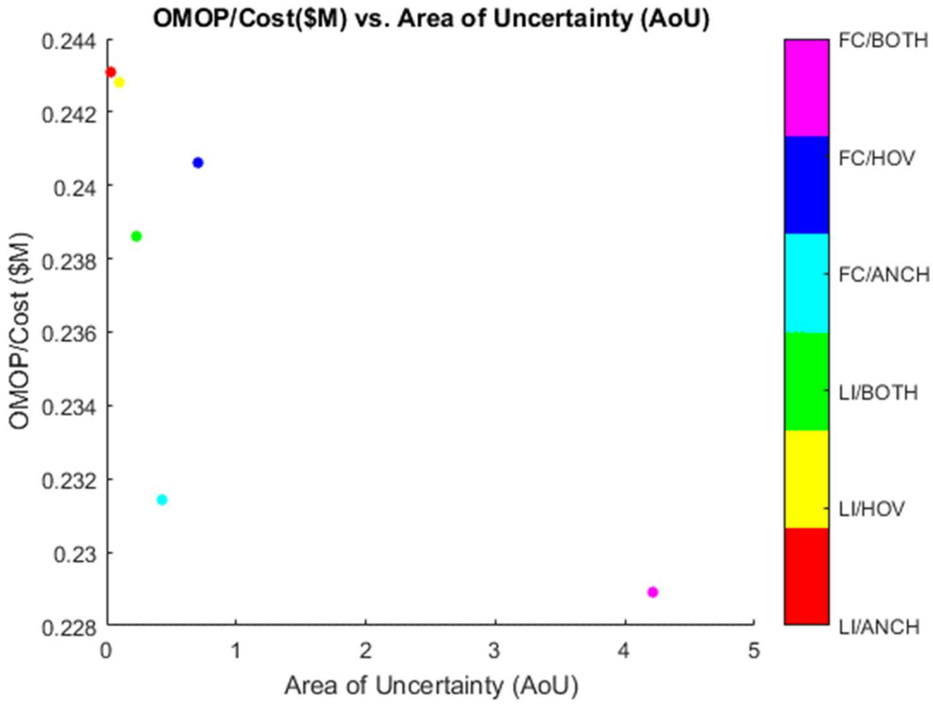

Figure 4-21: Pareto Frontier: OMOP per Cost ($M) vs. Area of Uncertainty

Assuming a decision-maker is attempting to maximize OMOP, minimize cost, and minimize uncertainty, Figure 4-21 captures the designs that best fulfill this goal in the upper left quadrant. The AoU metric in its current form truly represents uncertainty. The limitation for this metric exists in its formulation. Referring back to Figure 4-18, it is apparent that the AoU needs to be further refined into Risk and Opportunity [4]. Some realizations result in positive outcomes while others result in negative outcomes. Using the centroid as the point of demarcation, the AoU can be dissected into Performance Opportunity, Performance Risk, Cost Opportunity, and Cost Risk. Although not captured in Figure 4-21, the majority of the AoU for the designs in this case are driven by performance and cost risk due to the skew of the input uncertainty distributions. Further refinement of the AoU metric is an area for future work.

Observation: As mentioned earlier in this chapter, the approach described above uses the mean values from the individual uncertainty distributions as the baseline for the uncertain parameters in the deterministic model. Using mean values avoids biasing the follow-on analysis by isolating the effect of actual parameter uncertainty from modeling error. Modeling error in this case defined as setting a value other than the mean value as the baseline for the uncertain parameters in the deterministic model. The following analysis provides an example of the above discussion. Revisiting the assumption that multiple stakeholders find it easier to communicate in terms of most likely values and ranges instead of means and variances, if the most likely values (modes) were used as the baseline for the deterministic model instead of means, the original trade space would be biased. This bias is important to correct since the goal is to understand the underlying tradeoffs between designs. Assuming everything else remains constant, including the uncertainty distributions described earlier, if the centroids of the Monte Carlo point clouds are calculated and treated as a measure of design expectation when accounting for uncertainty the Pareto Frontier will shift. This shift is displayed in Figure 4-22 and is mostly indicative of a mode to mean correction.

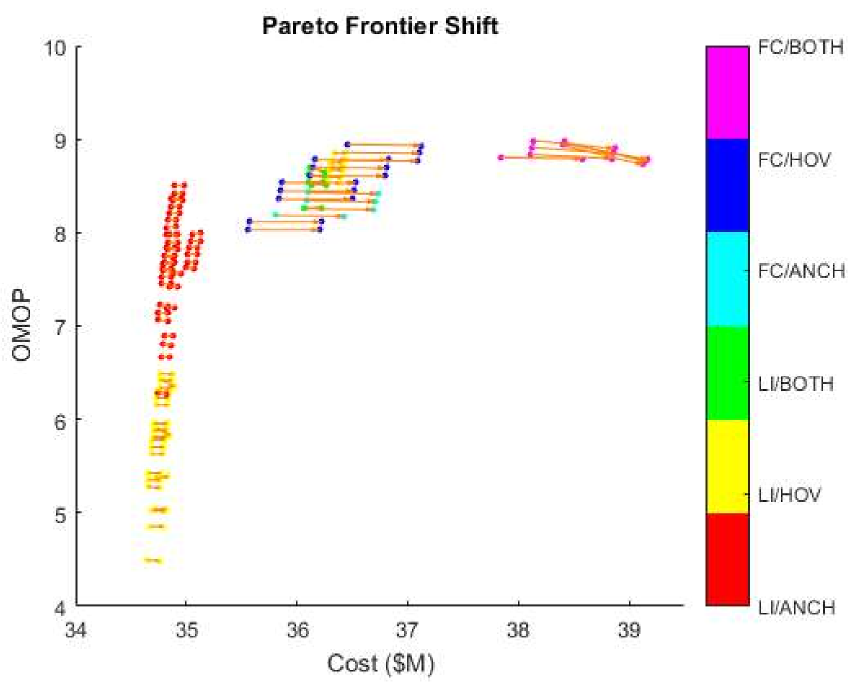

Figure 4-22: Pareto Frontier Shift: Mode to Mean

By comparing Figure 4-22 to the previously shown Figure 4-15, we can assess how much of the shift is correcting from modal values to mean values and how much is due to uncertainty.

Using the point cloud centroids in the presented approach corrects the Pareto Frontier if there are errors in the uncertain parameter assumptions in the deterministic model. While fairly benign at the upper and lower ends of the cost spectrum in terms of dominant designs, an initial error in this case has clear implications on the knee in the curve. Figure 4-23 shows the LI/Both and LI/Hovering combinations breaking out of the cluster when the Pareto Frontier is corrected.

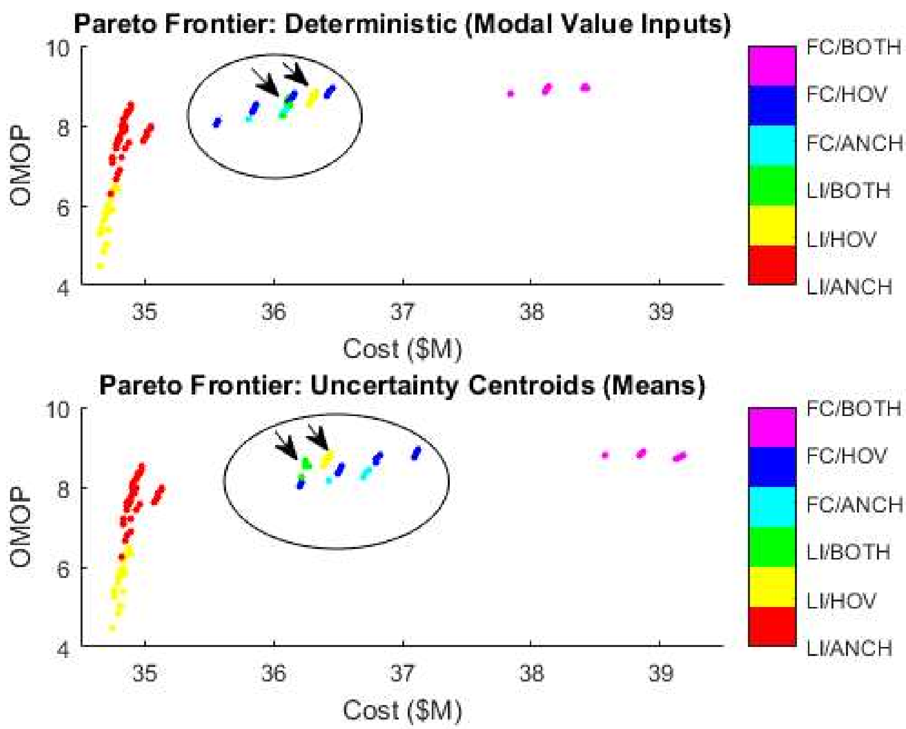

Figure 4-23: Mode to Mean Implications on Dominant Designs

FC/Hovering designs originally considered Pareto Optimal in the deterministic analysis are now less appealing in terms of cost and performance. This type of Pareto Frontier shift has clear implications on decision-making. This observation is useful when dealing with skewed distributions and obviously not applicable if all uncertainties are modeled as symmetric distributions, i.e. the mode equals the mean.

4.4.7 Evaluate Results

The initial Pareto frontier presents multiple design combinations that increase in cost with gains in performance. However, the uncertainties associated with these design combinations are left to intuition at best. Assessment of the Pareto frontier with uncertainty explicitly modeled provides a richer understanding of the design tradeoffs. A summary of the tradeoffs between the 6 designs investigated in this section are presented in Table 9.

Design Variables		**<Both>**	**Attributes**				**AoU Range**
ES	**MWC**	**LCPs**	**Range**	**OMOP**	**Cost**	**AoU**	**Cost:OMOP**
LI	ANCH	4	257	8.5	35.0	0.04	2.7 : 1
LI	HOV	4	256	8.9	36.5	0.10	1.6 : 1
LI	BOTH	2	215	8.7	36.3	0.23	0.7 : 1
FC	ANCH	4	306	8.6	37.0	0.43	18 : 1
FC	HOV	4	326	8.9	37.1	0.71	9.9 : 1
FC	BOTH	3	233	8.9	38.9	4.21	2.3 : 1

Table 9. Design Tradeoff Summary

The goal of the final evaluation is to identify the tradeoffs between design alternatives and identify if any designs rely on a single performance attribute for a large portion of their OMOP. The Cost to OMOP ratio represents the statistical range of the simulation and expresses the dominant metric driving the AoU. The design variables and/or performance attributes not represented in Table 9, namely Crew Size, Cargo Volume, Loiter Time, and LOA, were not differentiable across the different design combinations. The performance attributes remaining that drive OMOP are the LCPs, Range, and Percent of Missions Accessible. The LI/Anchoring design and the LI/Hovering design are nearly identical in terms of Range and LCPs. The only difference between the LI/Anchoring design and the LI/Hovering design is the MWC LIO subsystem. Therefore, both the cost and risk of the additional performance is clearly identified. The question here is simple: Is an additional 0.4 in OMOP worth an additional $1.5M in cost and twice the risk (risk here is being interpreted as AoU). Similar assessments can be conducted for the other design alternatives as well.

The major takeaway from the analysis in this case study is that the FC option is not a worthwhile investment for the manned, mini-submersible design. The incorporation of the FC Energy Source provides minimal performance gain over LI designs and exposes the project to extensive cost risks. This conclusion stems from a combination of the cost uncertainty associated with the FC subsystem and the fact that stakeholders expressed little interest in longer missions due to habitability concerns for the crew. This concern is reflected in the Range MOP where utility diminishes as range increases.

There are also other limitations apparent in this case study. The modeling approach is simplified and not robust in the sense that two of the FC designs, FC/Anchoring and FC/Hovering, actually exceed the objective range desired by the stakeholders. This presents a potential for repurposing space to add capability in a different capacity to achieve a higher OMOP. The model, in its current form, does not have the ability to address this issue.

4.5 Closing Remarks

The purpose of the case study in this research was to apply the approach presented and gain insight on different ways to capture and present information. The uncertainty application on the mini-submersible model demonstrates: the identification and characterization of multiple sources of uncertainty; the modification of sub-models to reduce computational time while explicitly modeling uncertainty; and the evaluation of how multiple subsystem uncertainties propagate to the system level in terms of cost versus performance for early stage designs. Ultimately, the goal was to discover how the cumulative effect of uncertainty altered the mini-submersible trade space and use this information to assist in decision-making. Observing the relative effects of uncertainty on OMOP, which in this case represented value to stakeholders, and cost enhanced the overall understanding of the conceptual design. This case study provides evidence suggesting that the most informed decision accounts for uncertainty, regardless of decision-maker risk tolerance.

Chapter 5 Conclusions and Recommendations

This research described the challenges facing the DoD in terms of budgetary and technological pressures. Multiple techniques were introduced, which help address these challenges. An approach was investigated and presented for determining the performance at risk and cost at risk for various designs in an early concept trade space. This research incorporated previous work in TSE and leveraged an approach, initially proposed by Walton [21] to insert an uncertainty analysis stage into the conceptual design process. This provided a framework to explicitly model endogenous uncertainties into the design selection process of a manned, mini-submersible.

The application of uncertainty, via Monte Carlo simulation, to the mini-submersible design problem provided several insights regarding the potential value of the analysis. First, incorporating uncertainty into early development models can inform initial requirements. For example, the fixed footprint available for the mini-submersible caused OMOP to drop off for certain designs when energy density realizations were lower than anticipated. A quantitative assessment regarding the potential to realize such an energy density and the impact on performance given the initial requirement could be relayed to the requirements community for consideration on requirement revision. This type of insight enables cooperation between the two communities in an effort "to ensure that requirements are technically achievable and affordable so that… leadership can make informed decisions about the costs associated with varying levels of performance." [9] Assuming the requirements community is unable to relax the requirement, this information is still valuable to the acquisition community. If high performance is required, but the realization potential of an undesirable scenario is also high, this could lead the acquisition community to pursue one technology in lieu of another, despite an increased risk. If a decision such as this is pursued this approach provides quantitative evidence as decision rationale. This analysis would also identify where contingency plans are necessary. Second, incorporating uncertainty into early development models can inform the acquisition community on R&D investments. Third, while TSE can answer questions such as how much does more performance cost, the incorporation of uncertainty into early development models can answer questions such as how much *could* more performance cost, if an undesirable scenario is realized. This type of insight is vital in a budget constrained program. Last, incorporating uncertainty into early development models produces risk profiles for different designs and enables the identification of robust designs in the face of uncertainty. The profiles are driven by a combination of the problem constraints, the value function, and the uncertain parameter distributions. As mentioned in chapter four, while effort was made to make the presented models technically sound, these conclusions should be taken as suggestive and not definitive.

The DoD is facing a difficult challenge and in response an increased focus is being placed on good decision-making during the MSA phase because it is a high leverage period in the DoD Acquisition Life Cycle. This thesis recommends incorporating uncertainty analysis during this phase as it requires the explicit identification and assessment of acquisition program risks at the outset of programs. In early stage design, the feasible technology options are in various stages of development. Although a specific outcome will eventually be realized, the decision framework needs to capture the distribution of possible future outcomes as these distributions are critical in accurately assessing the design tradeoffs. Additionally, the models developed, both sub-models and uncertainty models, in the MSA phase can be refined to support other phases in the DoD Acquisition Life Cycle. As an example, these models can be reused in the TMRR phase as a risk monitoring tool by updating the uncertainty distributions as development progresses, and as a framework for the systems engineering trade-off analyses. The TMRR trades are specifically meant for cost performance trade-offs to determine program affordability. The goal of the techniques discussed, including uncertainty analysis, are to provide decision-makers with as much information as possible as early as possible. The synergy of MBE, TSE, and uncertainty analysis along with continued increases in computational power present a viable means to help programs visualize risks and make the right decisions, earlier.

Appendix A: Sub-Model Flow Charts

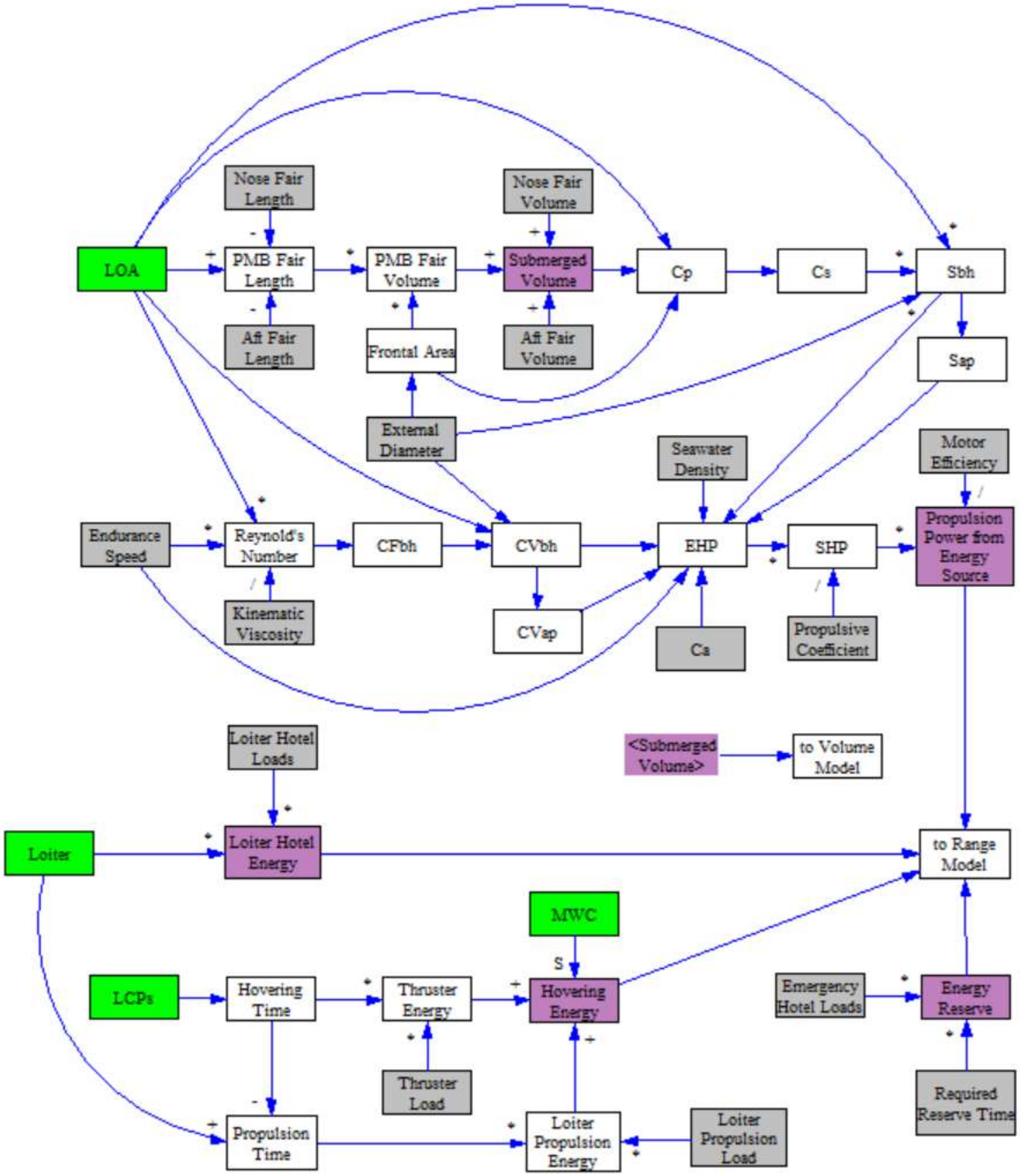

Figure A-1: Power Model

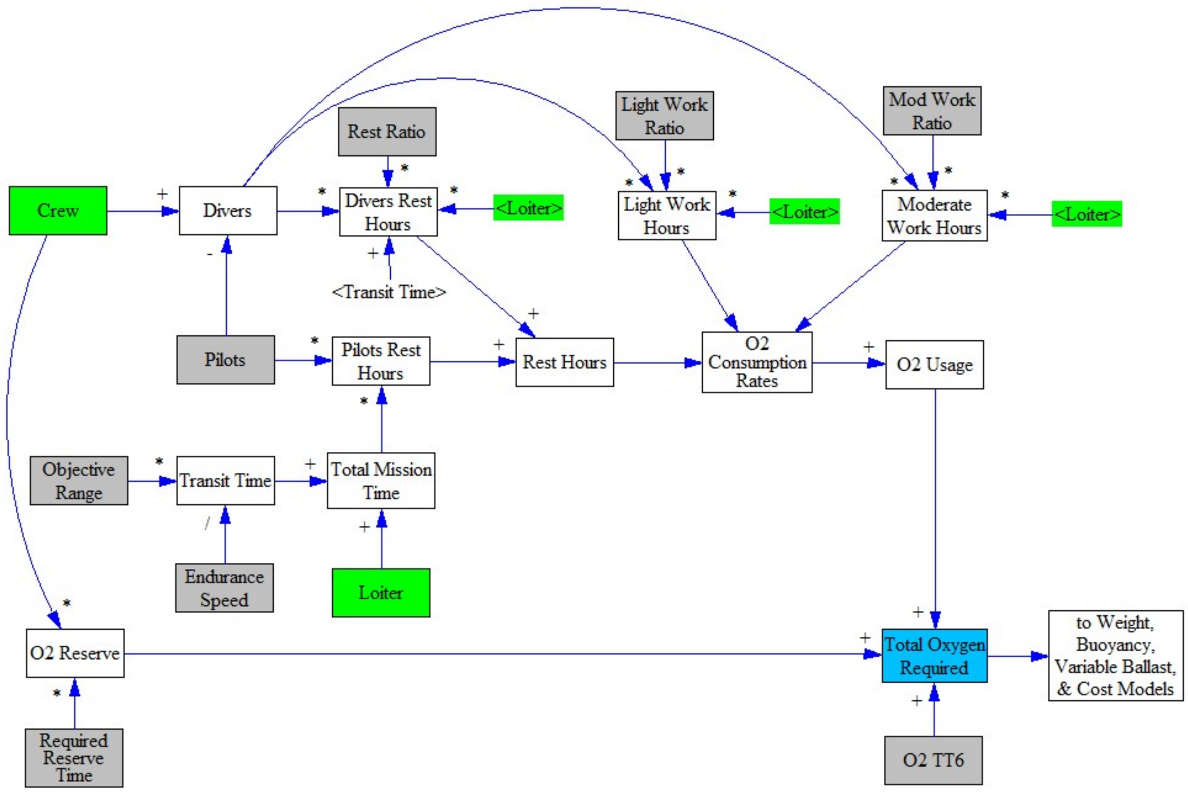

Figure A-2 Oxygen Model

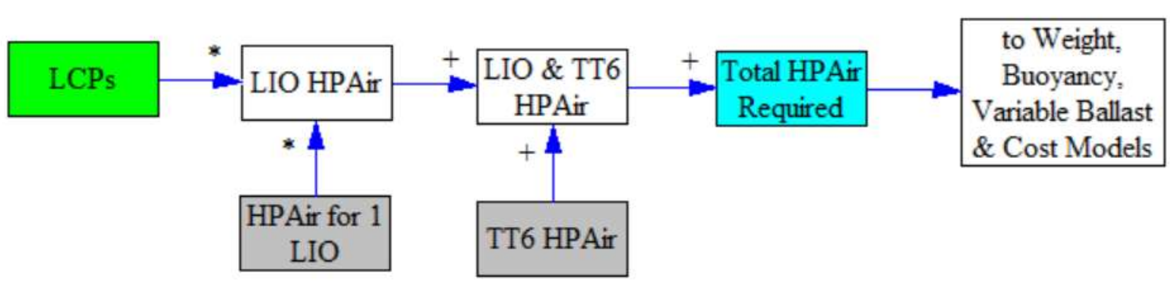

Figure A-3: High-Pressure Air Model

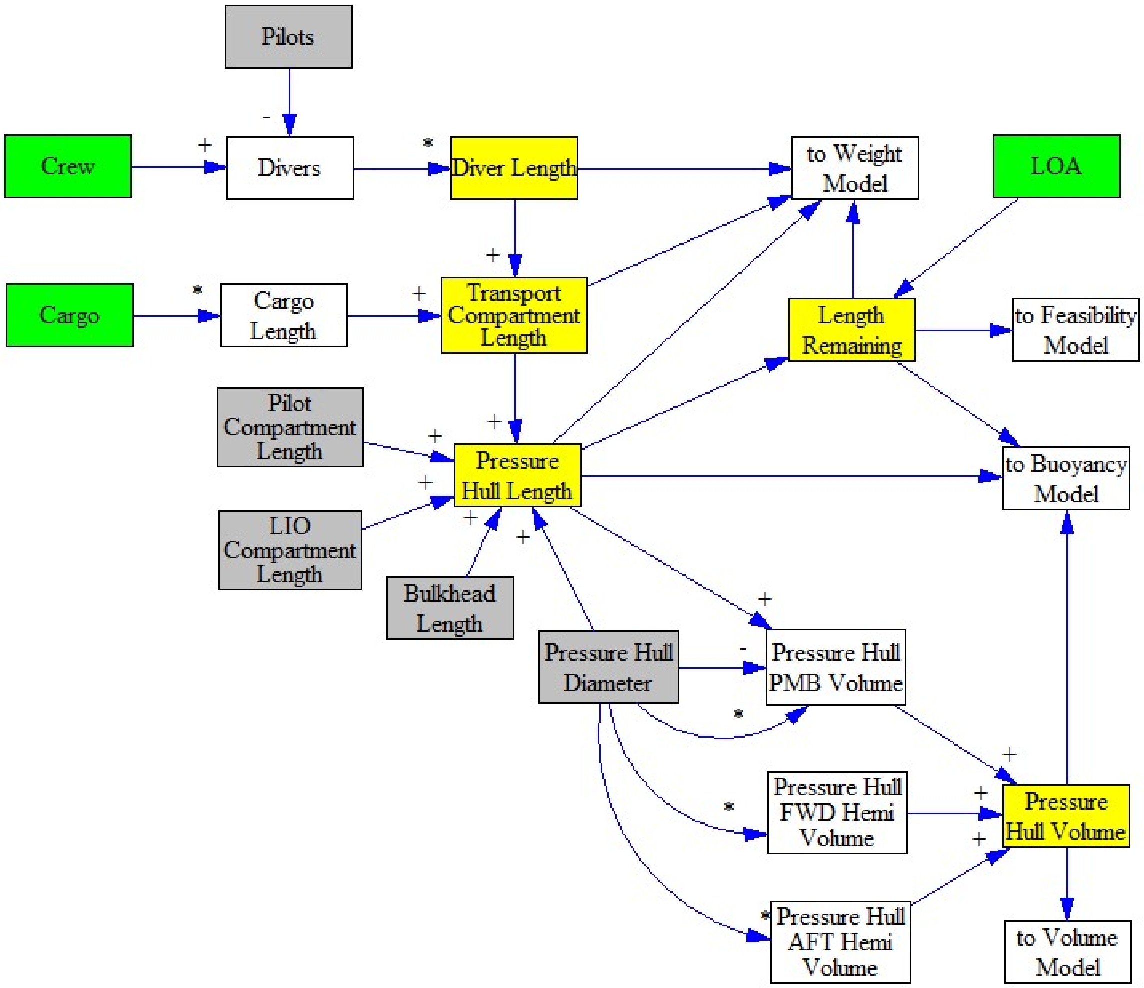

Figure A-4: Structure Model

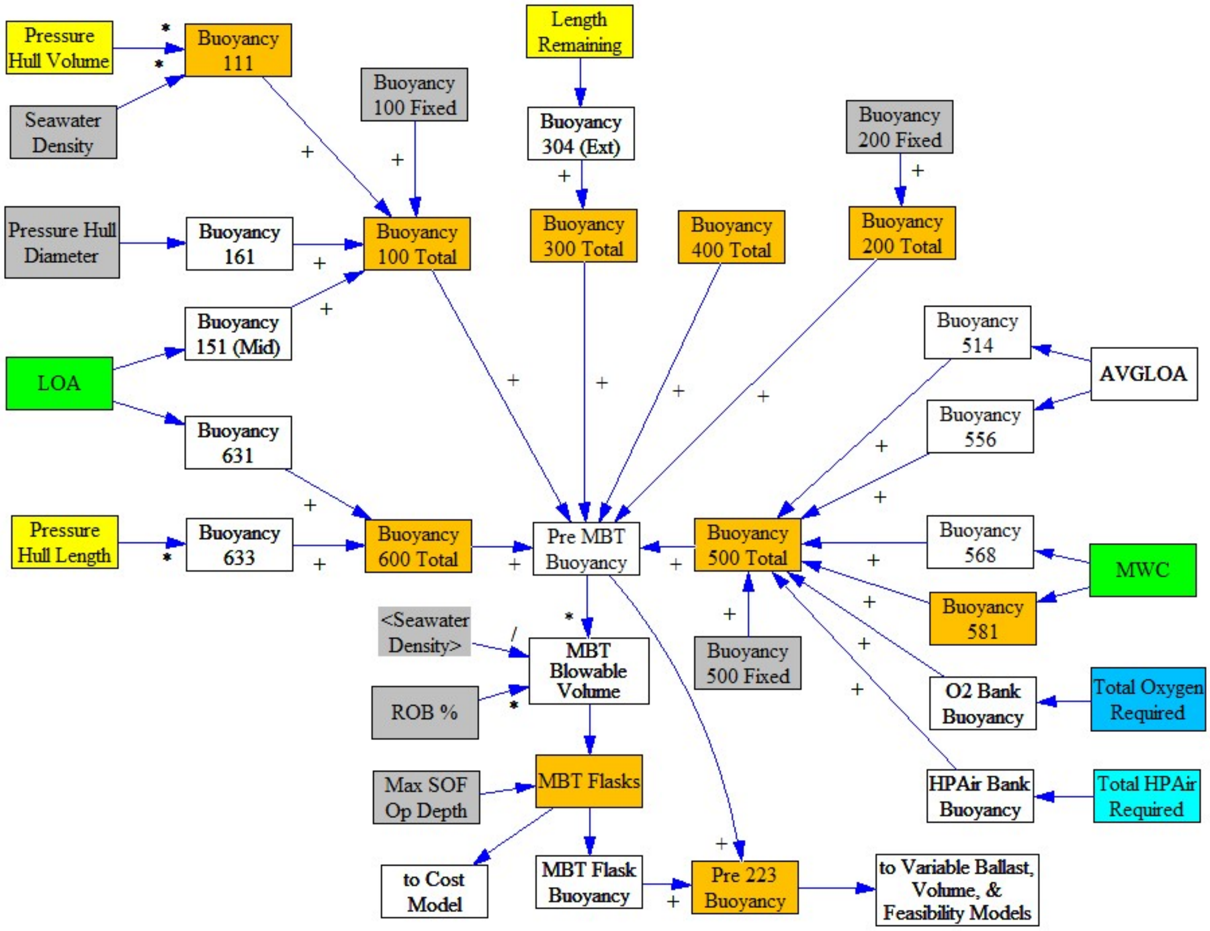

Figure A-5: Buoyancy Model

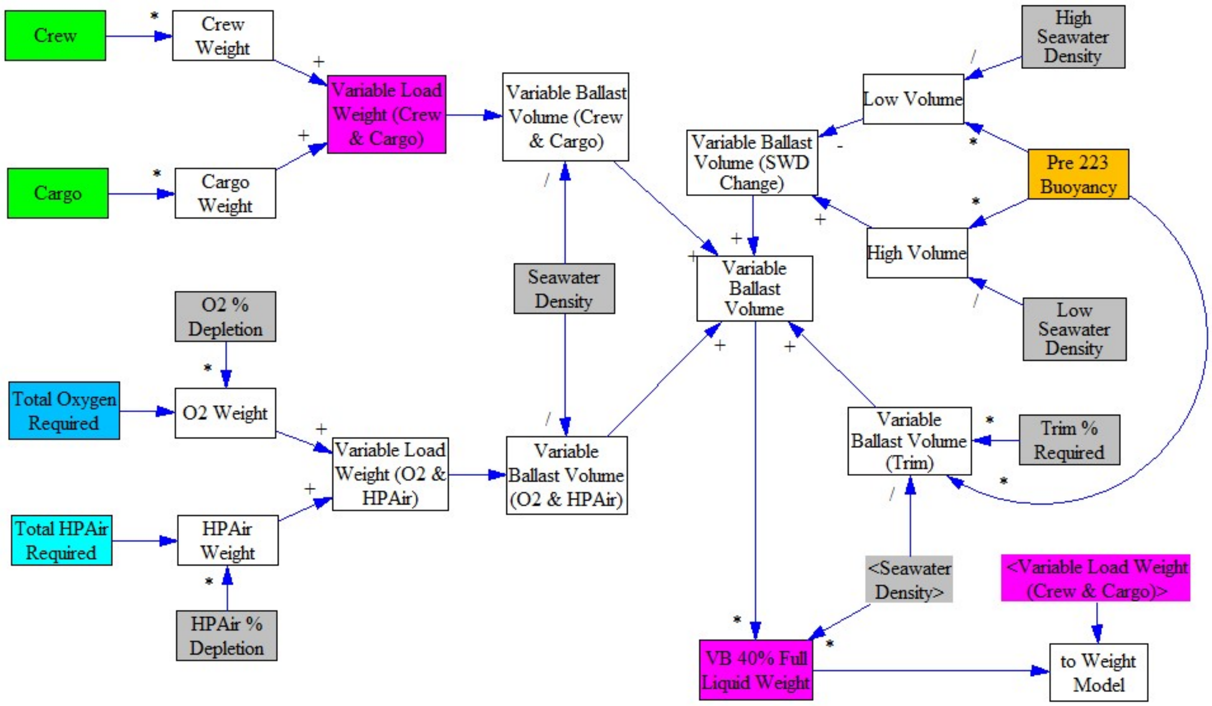

Figure A-6: Variable Ballast Model

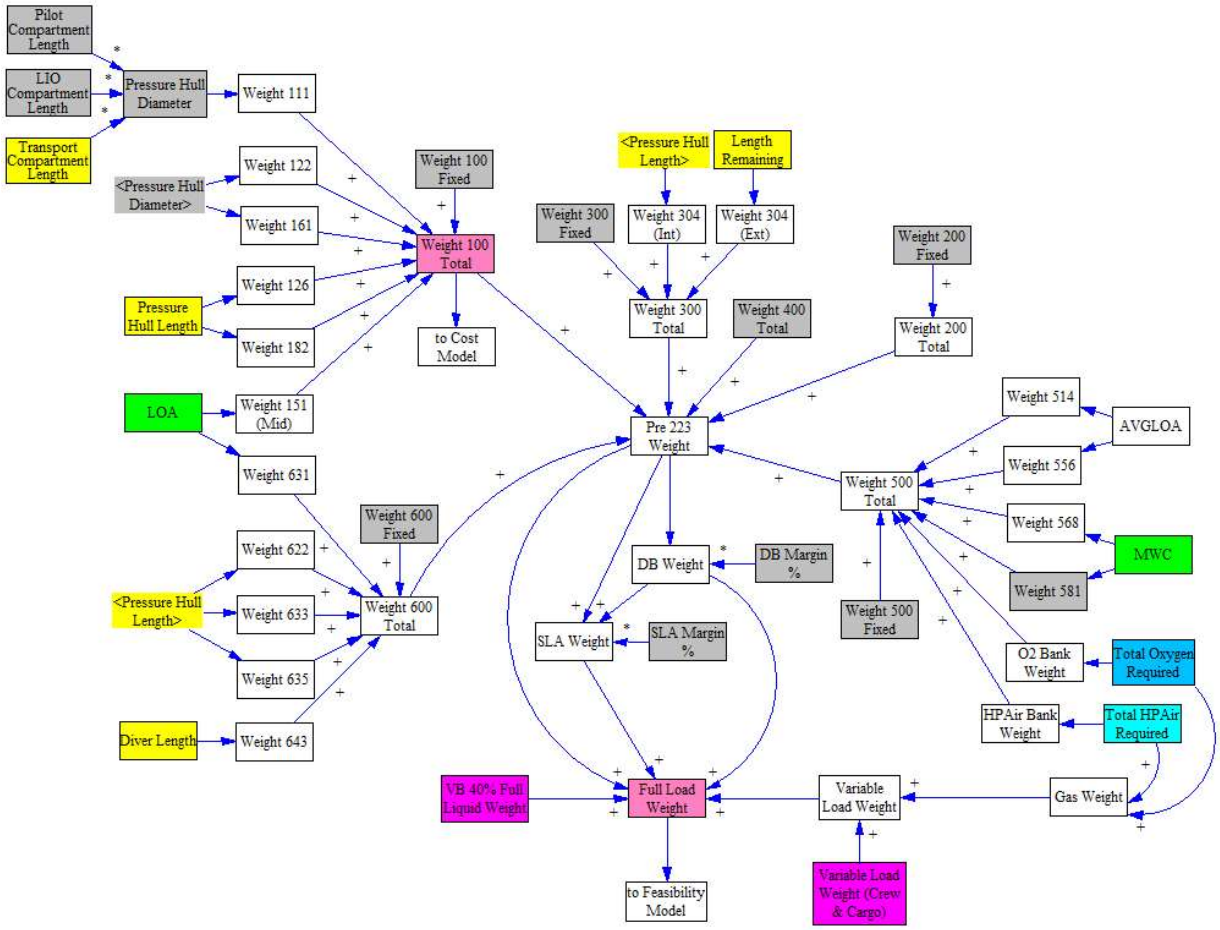

Figure A-7: Weight Model

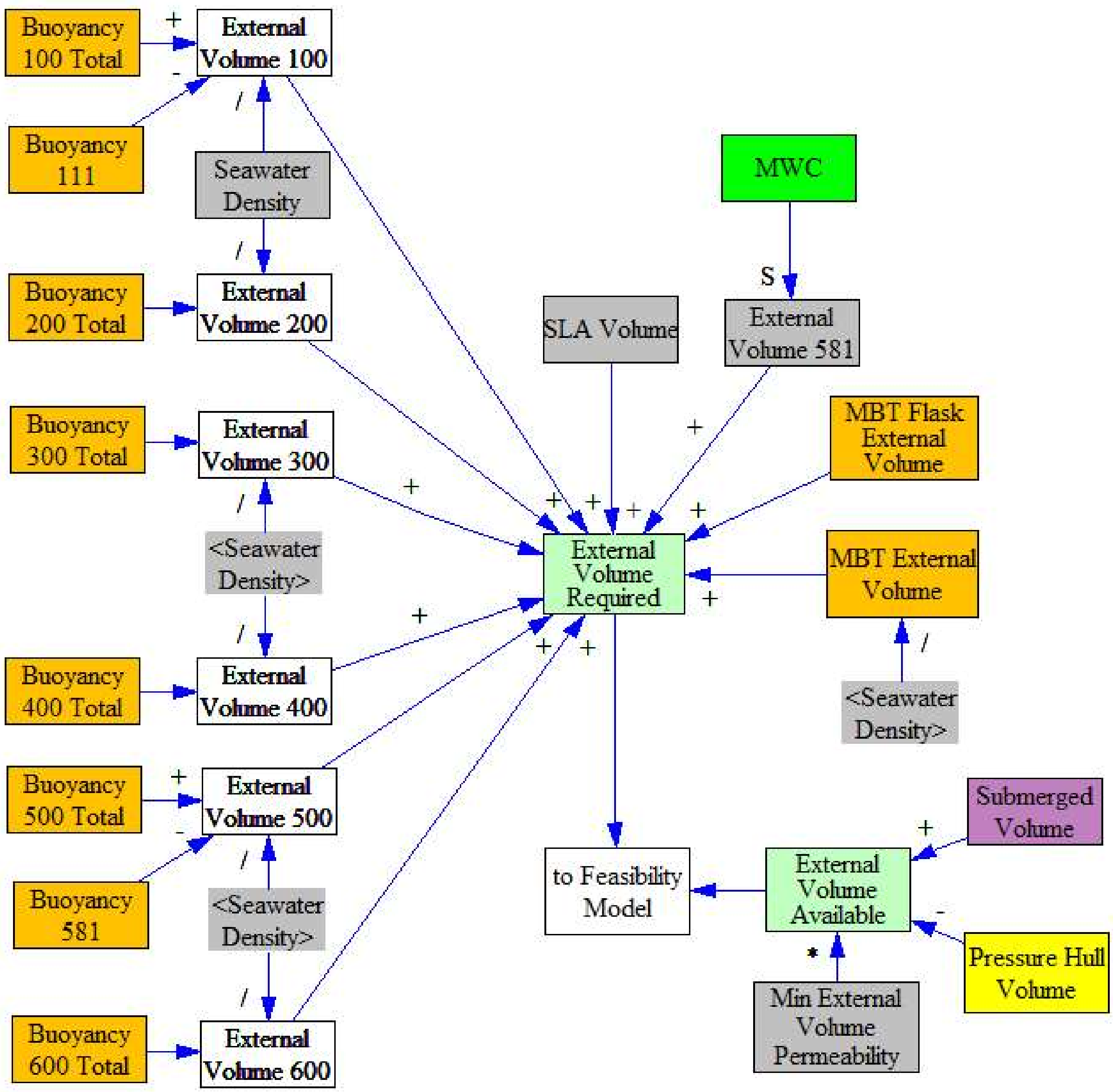

Figure A-8: Volume Model

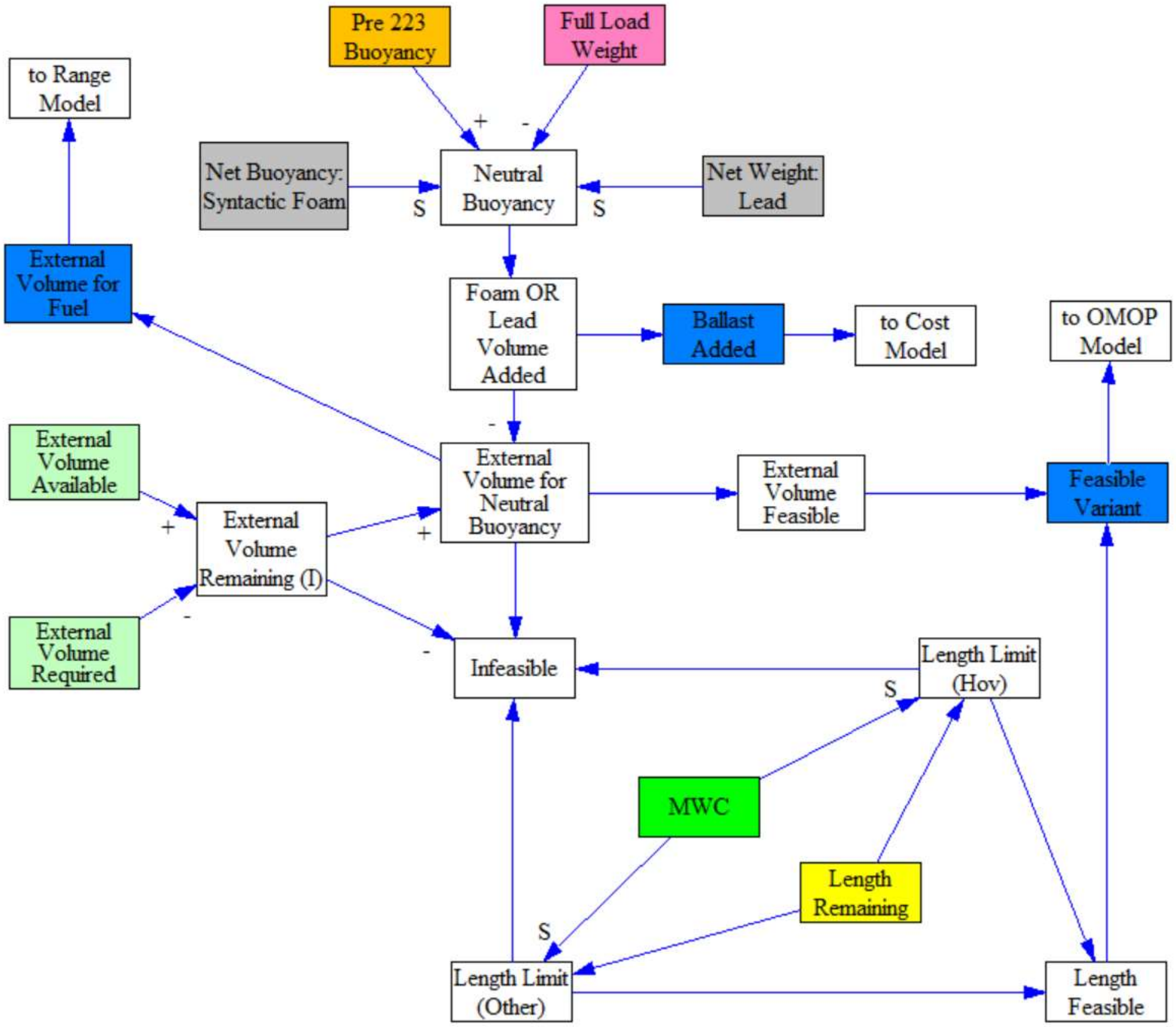

Figure A-9: Feasibility Model

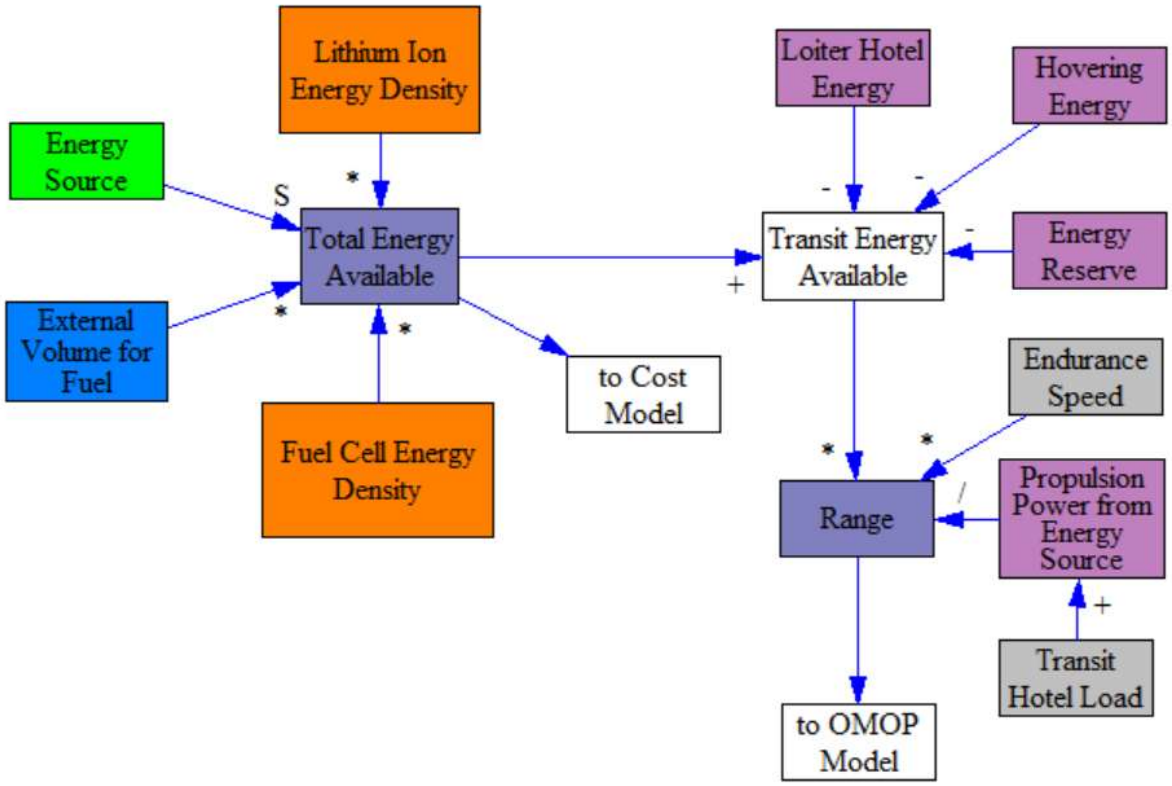

Figure A-10: Range Model

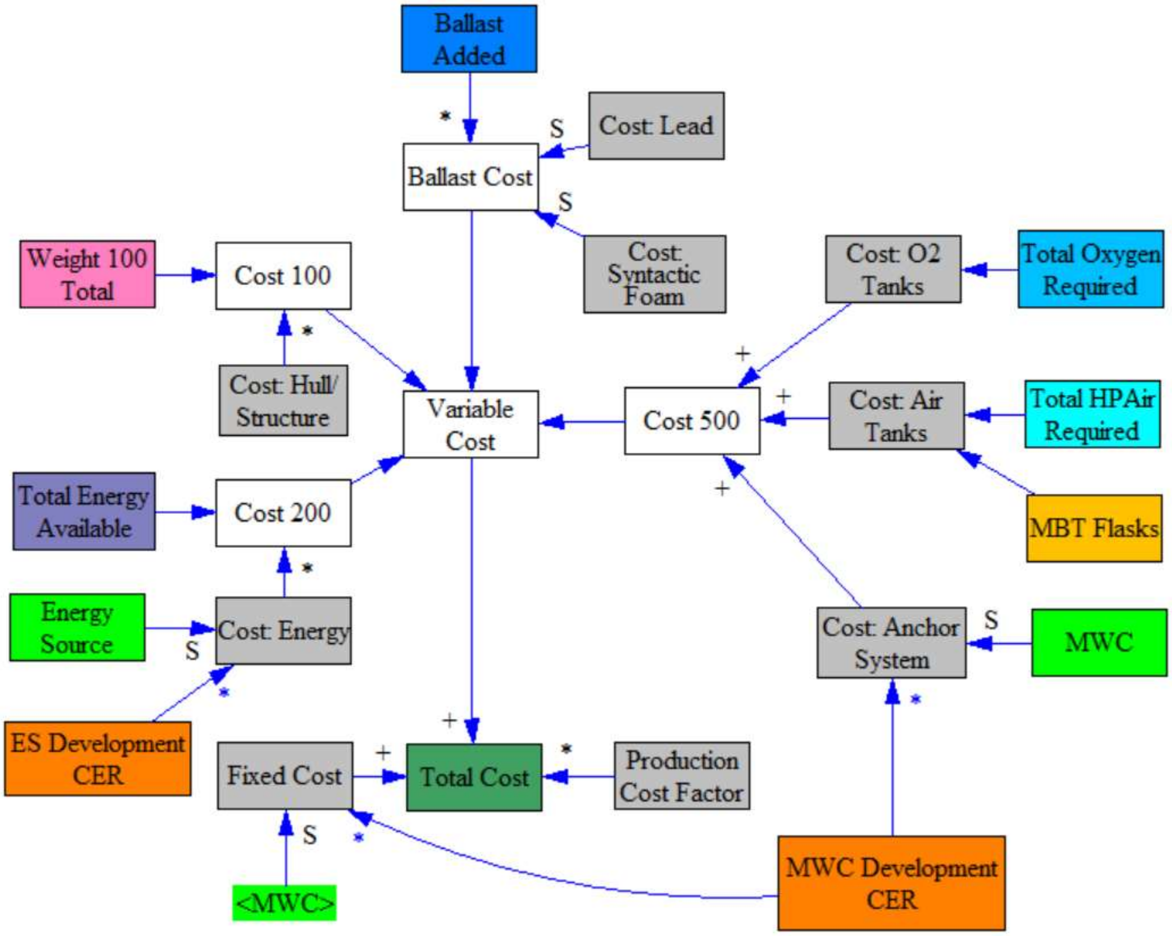

Figure A-11: Cost Model

Appendix B: Pareto Frontier Figures

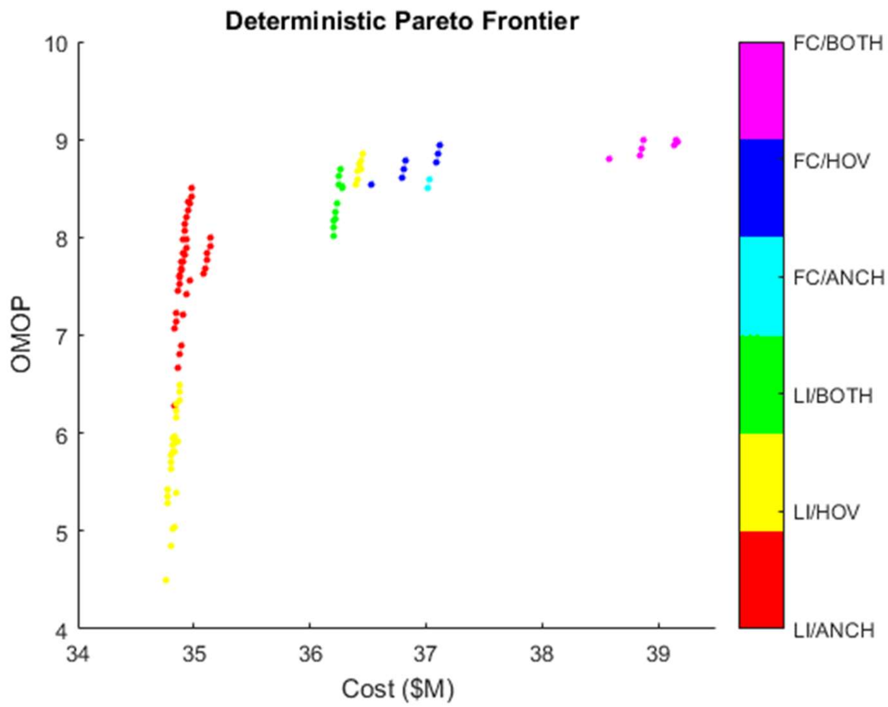

Figure B-1: Pareto Frontier: Deterministic

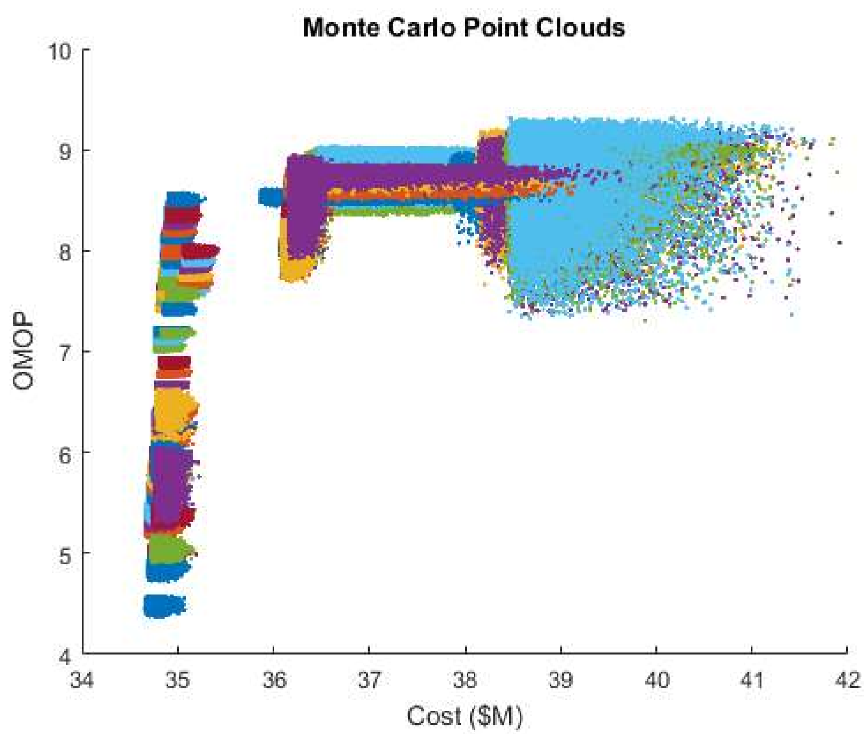

Figure B-2: Pareto Frontier: Monte Carlo Point Clouds

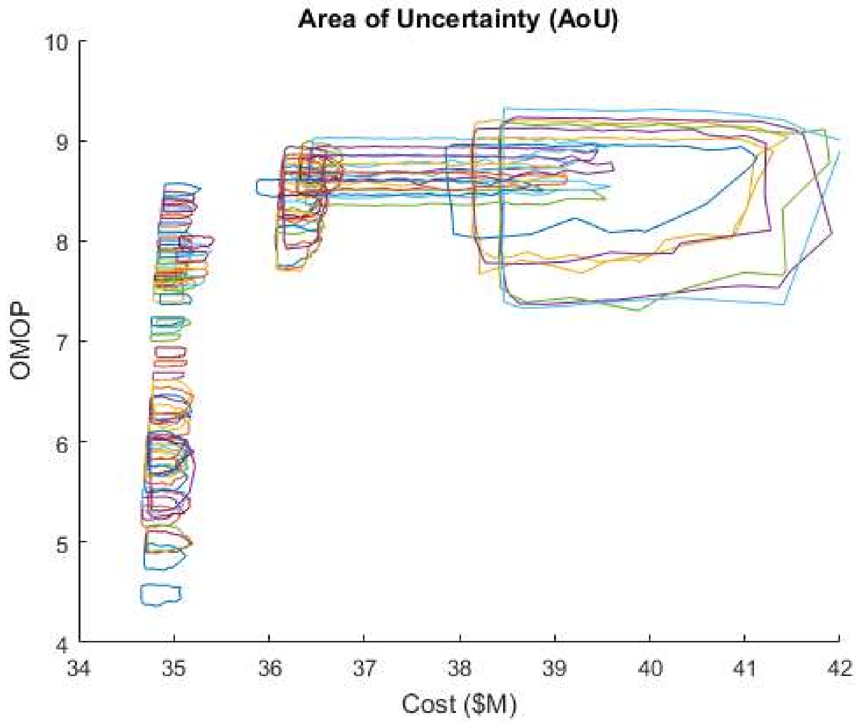

Figure B-3: Pareto Frontier: Area of Uncertainty Boundary

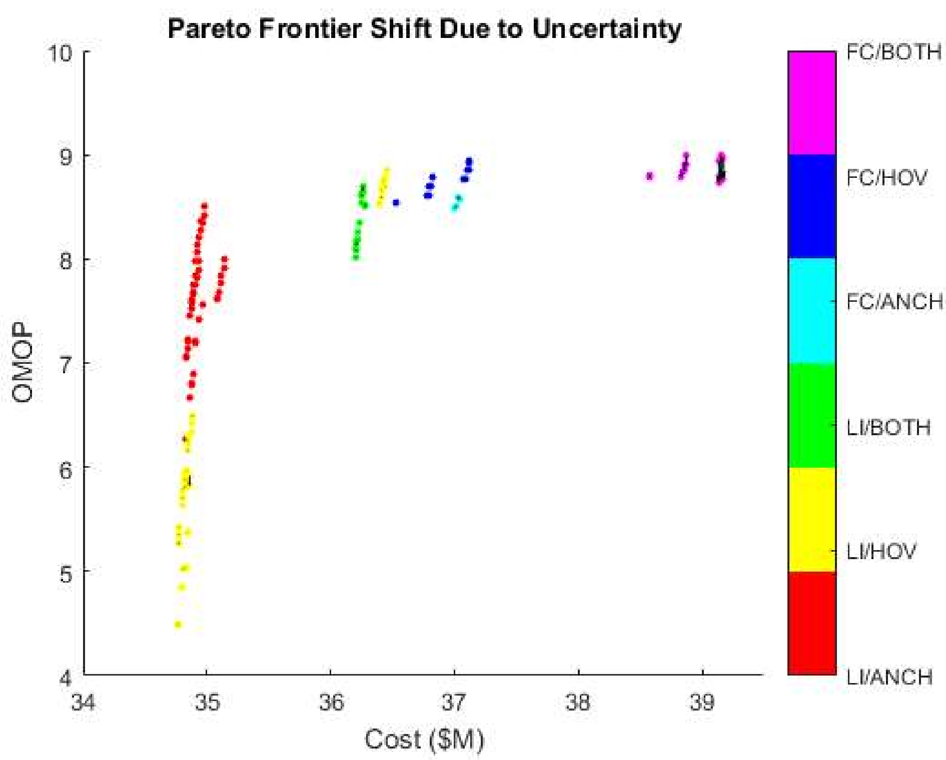

Figure B-4: Pareto Frontier: Shift Due to Uncertainty

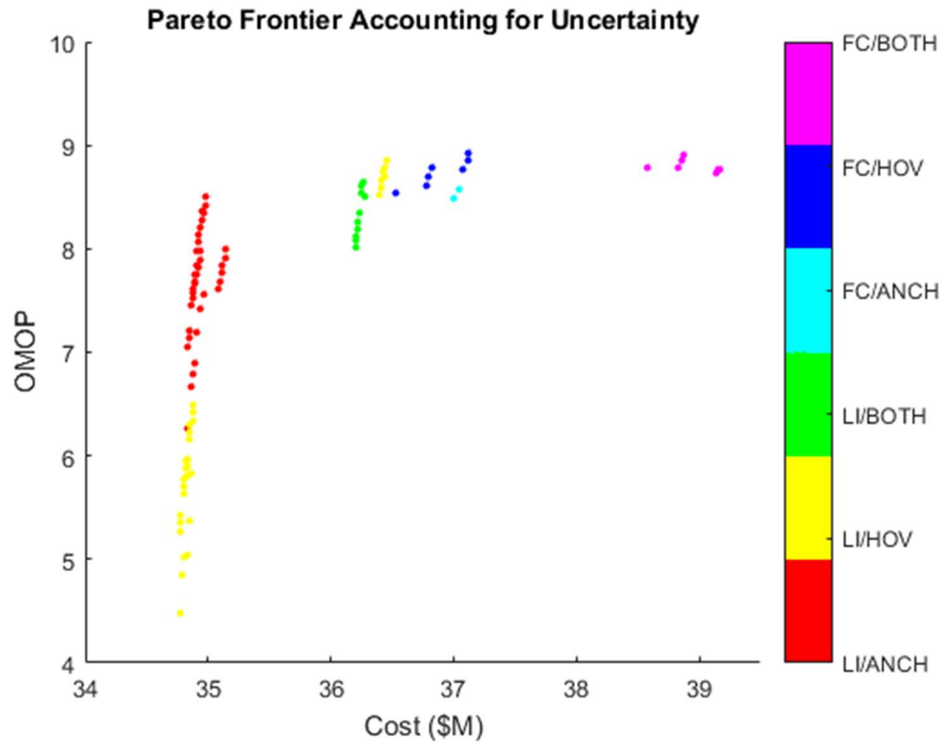

Figure B-5: Pareto Frontier: Accounting for Uncertainty (Energy Source & MWC LIO Combinations)

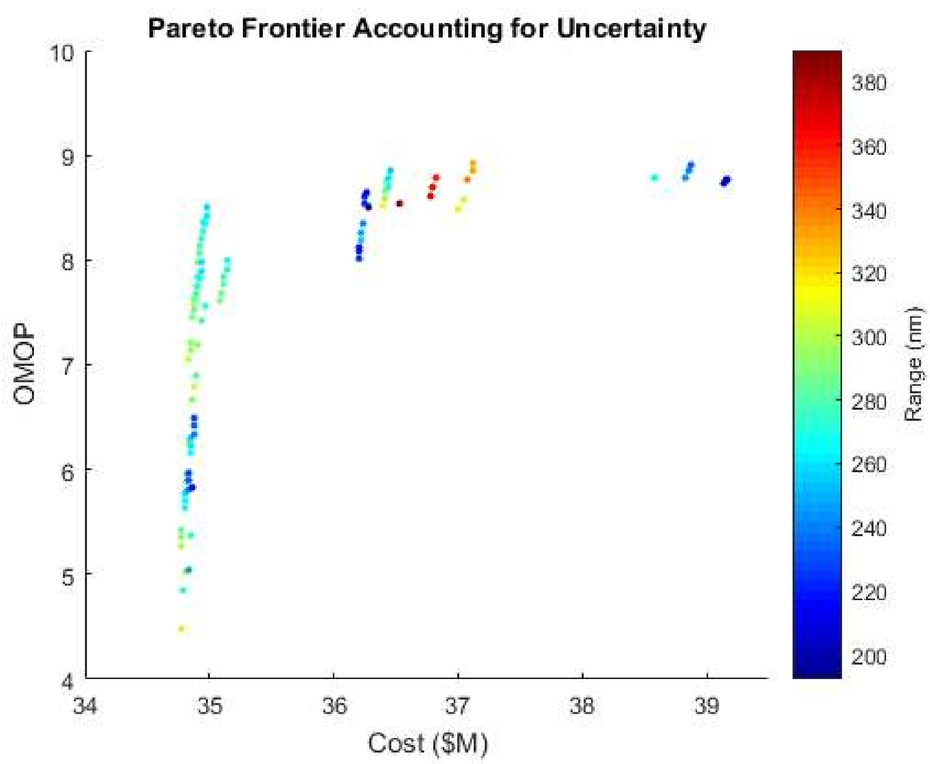

Figure B-6: Pareto Frontier: Accounting for Uncertainty (Range)

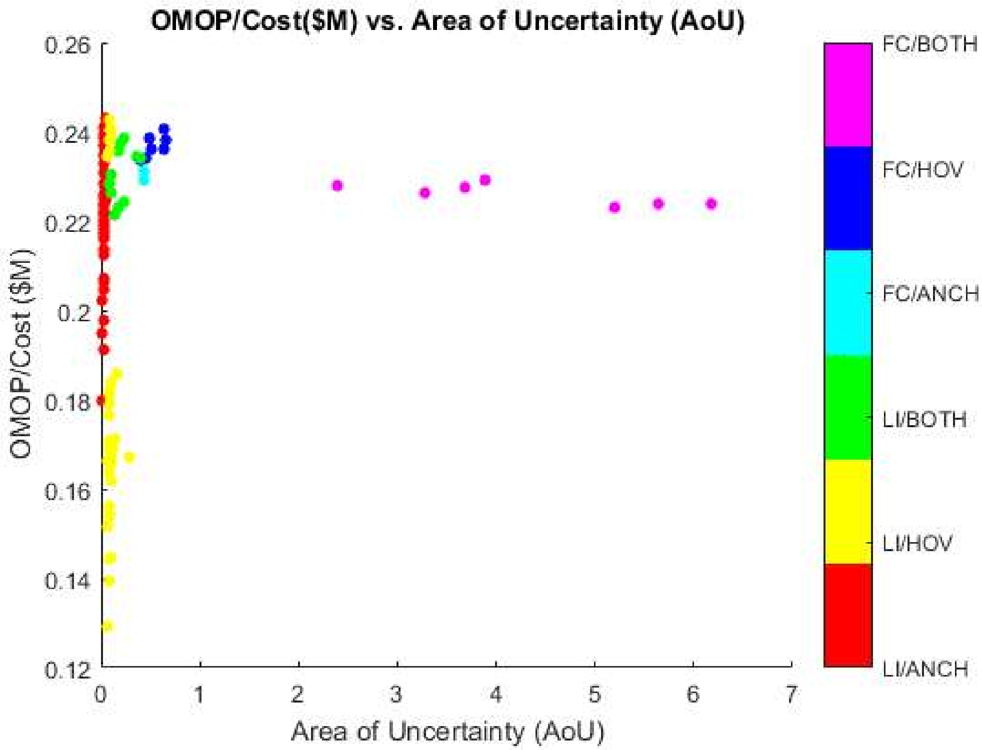

Figure B-7: Pareto Frontier: OMOP/Cost($M) vs. Area of Uncertainty (AoU)

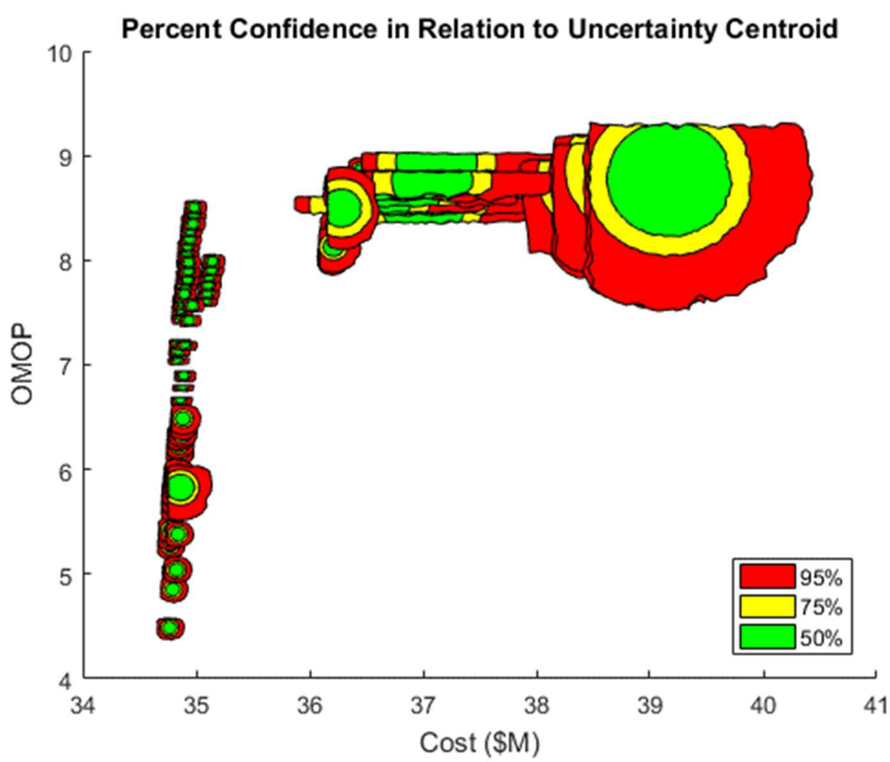

Figure B-8: Pareto Frontier: Percent Confidence in Relation to Uncertainty Centroid

Appendix C: MBE Framework

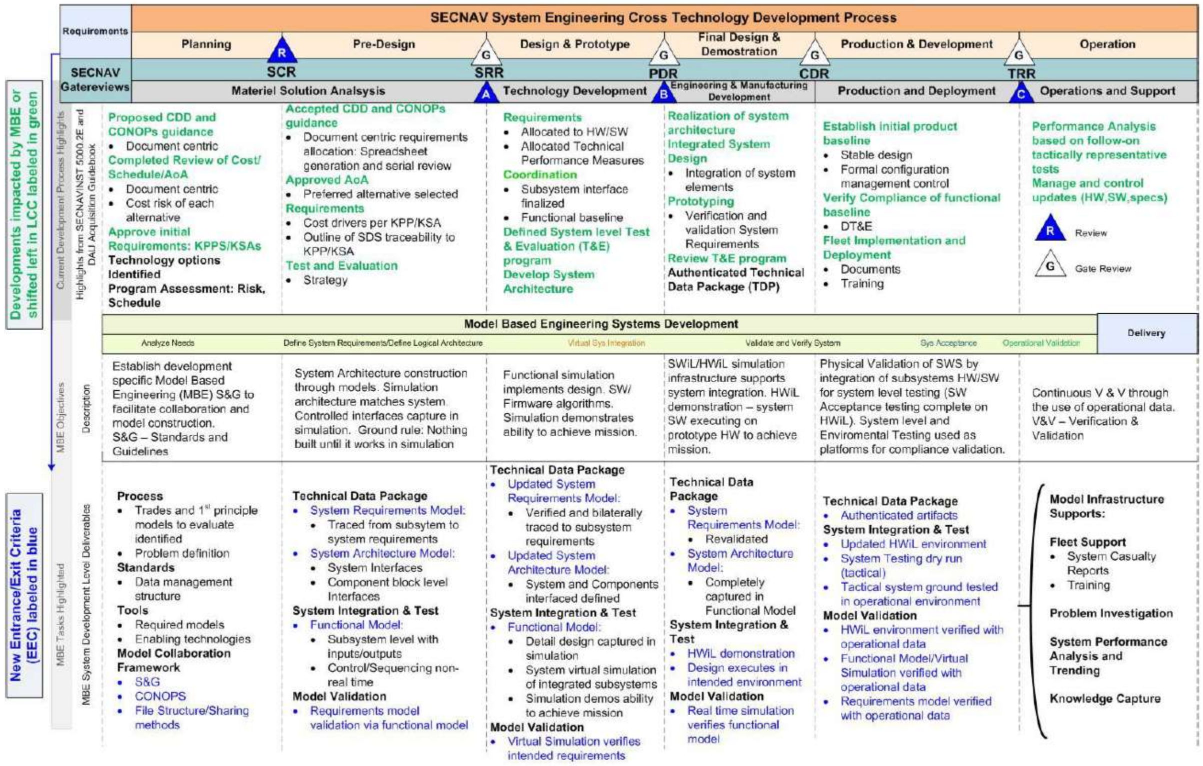

Figure C-1: MBE Acquisition Framework [5]

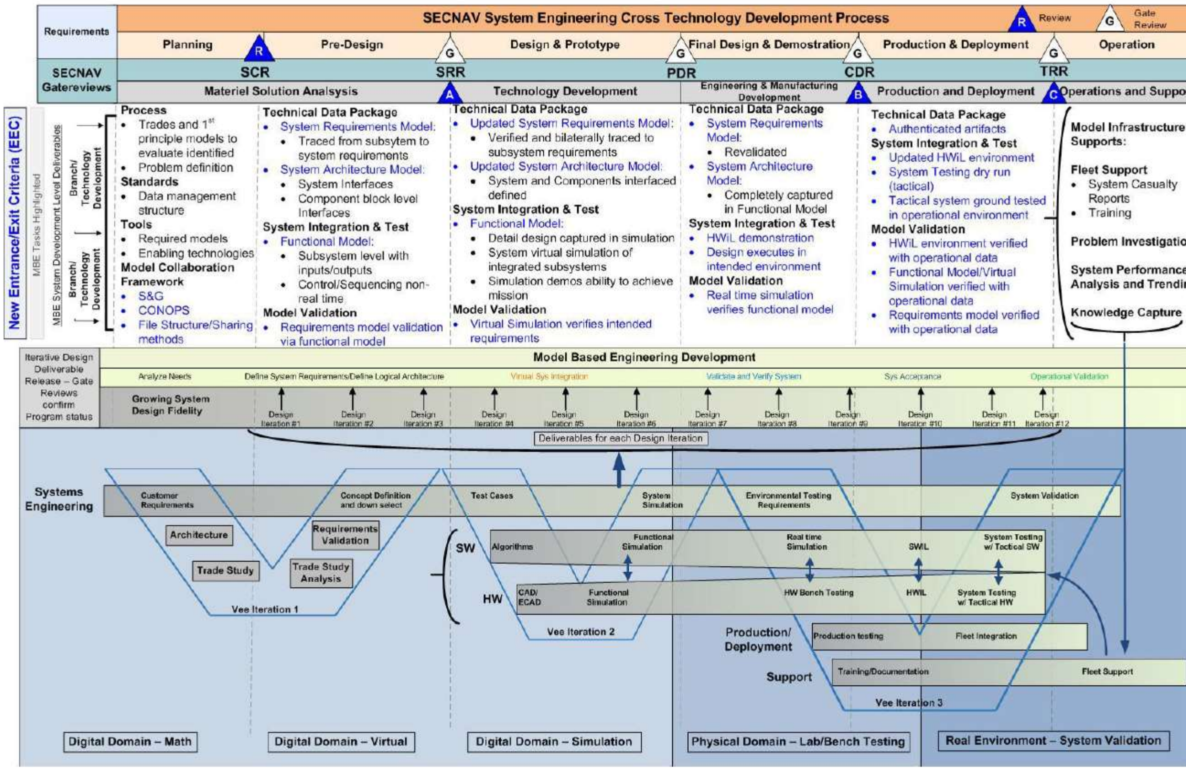

Figure C-2: MBE Integration into DoD Acquisition Life Cycle [5]

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