# Tools for Multi-Objective and Multi-Disciplinary Optimization in Naval Ship Design

Daniel Demko

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## in

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Dr. Alan J. Brown, Chairman Dr. Wayne Neu Dr. Owen Hughes

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## ABSTRACT

This thesis focuses on practical and quantitative methods for measuring effectiveness in naval ship design. An Overall Measure of Effectiveness (OMOE) model or function is an essential prerequisite for optimization and design trade-off. This effectiveness can be limited to individual ship missions or extend to missions within a task group or larger context. A method is presented that uses the Analytic Hierarchy Process combined with Multi-Attribute Value Theory to build an Overall Measure of Effectiveness and Overall Measure of Risk function to properly rank and approximately measure the relative mission effectiveness and risk of design alternatives, using trained expert opinion to replace complex analysis tools. A validation of this method is achieved through experimentation comparing ships ranked by the method with direct ranking of the ships through war gaming scenarios.

The second part of this thesis presents a mathematical ship synthesis model to be used in early concept development stages of the ship design process. Tools to simplify and introduce greater accuracy are described and developed. Response Surface Models and Design of Experiments simplify and speed up the process. Finite element codes such as MAESTRO improve the accuracy of the ship synthesis models which in turn lower costs later in the design process. A case study of an Advanced Logistics Delivery Ship (ALDV) is performed to asses the use of RSM and DOE methods to minimize computation time when using high-fidelity codes early in the naval ship design process.

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### CHAPTER 1 INTRODUCTION

### **1.1 Motivation and Background**

Naval ship concept design is traditionally an "ad hoc" process. Selection of design concepts for assessment is guided primarily by experience, design lanes, rules-of-thumb, and imagination. Communication and coordination between design disciplines (hull form, structures, resistance, etc.) require significant designer involvement and effort. Concept studies continue until resources or time runs out. Critical elements missing from this process are:

- 1. A consistent format and methodology for multi-objective decisions based on dissimilar objective attributes, specifically effectiveness, cost and risk. Mission effectiveness, cost and risk cannot logically be combined as in commercial decisions, where discounted cost can usually serve as a suitable single objective. Multiple objectives must be presented separately, but simultaneously, in a manageable format for trade-off and decision-making.
- 2. Practical and quantitative methods for measuring effectiveness. An Overall Measure of Effectiveness (OMOE) model or function is an essential prerequisite for optimization and design trade-off. This effectiveness can be limited to individual ship missions or extend to missions within a task group or larger context.
- 3. Practical and quantitative methods for measuring risk. Overall risk includes schedule, production, technology performance, and cost factors.
- 4. An accepted cost model sensitive to important producibility characteristics, but with a level of detail appropriate for concept exploration.
- 5. An efficient and robust method to search the design space for optimal concepts.
- 6. An effective framework for transitioning and refining concept development in a multidisciplinary design optimization (MDO).
- 7. A means of using the results of first-principle analysis codes at earlier stages of design.

This thesis focuses on the second and last of these critical elements.

There are a number of inputs which must be integrated when determining overall mission effectiveness in a naval ship: 1) defense policy and goals; 2) threat; 3) existing force structure; 4) mission need; 5) mission scenarios; 6) modeling and simulation or war gaming results; and 7) expert opinion. Ideally, all knowledge about the problem could be included in a master wargaming model to predict resulting measures of effectiveness for a matrix of ship performance inputs in a series of probabilistic scenarios. Regression analysis could be applied to the results to define a mathematical relationship between input ship measures of performance (MOPs) and output effectiveness. The accuracy of such a simulation depends on modeling the detailed interactions of a complex human and physical system and its response to a broad range of quantitative and qualitative variables and conditions including ship MOPs. Many of the inputs and responses are probabilistic so a statistically significant number of full simulations must be made for each set of discrete input variables. This extensive modeling capability does not yet exist for practical applications.

An alternative to modeling and simulation is to use expert opinion directly to integrate these diverse inputs, and assess the value or utility of ship MOPs in an OMOE function. Two methods for structuring these problems dominate the literature: Multi-Attribute Utility Theory and the Analytical Hierarchy Process. In the past, supporters of these theories have been critical of each other, but recently there have been efforts to identify similarities and blend the best of both for application in Multi-Attribute Value (MAV) functions. Brown [1] has adapted this combined approach to the ship concept design problem, but the use of this approach has never been validated.

As with effectiveness and risk, the multi-objective optimization requires a cost model that can generate lifecycle or total ownership cost for a specified design without direct user interaction. Cost models by their nature involve significant proprietary and sensitive data. Even within the Navy, organizations like NAVSEA 017 have resisted providing their models to the engineers. A practical and accepted cost model is required. This model must be sensitive to important producibility characteristics, but with a level of detail appropriate for concept exploration.

Once concept exploration has narrowed the design space, technologies have been selected, and major discrete design alternatives (e.g., type of propulsion, hull form, etc.) have been chosen from the full spectrum of design choices, optimization must continue as additional ship, system and subsystem details are added and more complete analysis is performed. This is a fully multidisciplinary problem that typically must employ an array of higher fidelity, discipline-specific computer codes to continue the optimization process while addressing the uncertainties inherent in the design. Higher fidelity codes are also required in concept exploration when significant departures are made from traditional design lanes to explore new technologies and new paradigms (high speed ships, automation, new materials).

The optimization quickly becomes computationally unmanageable when higher fidelity codes are used. Computational and optimization methods are required to minimize this computational burden.

### 1.1.1 Multi-Objective Optimization of Naval Ships

In this thesis, a multiple-objective genetic design optimization approach developed by Brown [2,3] is used to search the design space and perform trade-offs. This approach considers various combinations of hull form, hull materials, propulsion systems, combat systems and manning within the design space using mission effectiveness, risk and acquisition cost as objective attributes. A ship synthesis model is used to balance these parameters in total ship designs, to assess feasibility and to calculate cost, risk and effectiveness. The final design combinations are ranked by cost, risk and effectiveness, and presented as a series of non-dominated frontiers. A non-dominated frontier (NDF) represents ship designs in the design space that have the highest effectiveness for a given cost and risk compared to other designs in the design space. A nondominated solution, for a given problem and constraints, is a feasible solution for which no other feasible solution exists that is better in one attribute and at least as good in all others. Concepts for further study and development are chosen from this frontier. The "best" design is determined by the customer's preferences for effectiveness, cost and risk. Preferred designs must always be on the non-dominated frontier. This preference may be affected by the shape of the frontier and cannot be rationally determined a priori. Using a graphic similar to Figure 2, the full range of cost-risk-effectiveness possibilities can be presented to decision-makers, trade-off decisions can be made and specific concepts can be chosen for further analysis. "Knees in the curve" can be seen graphically as significant changes in the slope of the frontier.

Genetic algorithms (GAs) are used in this approach because they are able to explore a design space that is very non-linear, discontinuous, and bounded by a variety of constraints and thresholds. These attributes prevent application of mature gradient-based optimization techniques including Lagrange multipliers, steepest ascent methods, linear programming, non-linear programming and dynamic programming. GAs are also ideally-suited for multi-objective optimization since they develop a population of designs vice a single optimum. This population can be forced to spread-out over the non-dominated frontier.

The multi-objective optimization is implemented in Model Center (MC). Model Center is a computer-based design integration environment that includes tools for linking design model

components, visualizing the design space, performing trade studies and optimization, developing parametric models of the design space, and archiving results from multiple studies. By automating and simplifying these tasks, Model Center makes the design process more efficient, saves engineering time, and reduces the error in the design process [4].



Figure 1 – Two Objective Attribute Space



Figure 2 - Non-Dominated Frontiers

### 1.1.2 Overall Measure of Effectiveness

To perform the ship design optimization, quantitative objective functions are developed for each objective attribute. Effectiveness and risk are quantified using overall measures of effectiveness and risk.

The process for developing an OMOE objective function is shown in Figure 3. Important terminology used in describing this process includes:

- Overall Measure of Effectiveness (OMOE) Single overall figure of merit index (0-1.0) describing ship effectiveness over all assigned missions or mission types
- Mission or Mission Type Measures of Effectiveness (MOEs) Figure of merit index (0-1.0) for specific mission scenarios or mission types
- Measures of Performance (MOPs) Specific ship or system performance metric independent of mission (speed, range, number of missiles)
- Value of Performance (VOP) Figure of merit index (0-1.0) specifying the value of a specific MOP to a specific mission area for a specific mission type.

The process begins with the Mission Need Statement and mission description. Required operational capabilities (ROCs) are identified to perform the ship's mission(s) and measures of performance (MOPs) are specified for those capabilities that vary in the designs as a function of the ship design variables (DVs). Each MOP is assigned a threshold and goal value. Capability requirements and constraints applicable to all designs are also specified. An Overall Measure of Effectiveness (OMOE) hierarchy is developed from the MOPs using the Analytical Hierarchy Process (AHP) to calculate MOP weights and Multi-Attribute Value Theory (MAVT) to develop individual MOP value functions.

Figure 4 shows the simple OMOE Hierarchy used for the OMOE validation presented in this thesis. This OMOE represents the overall effectiveness of a notional destroyer to perform a specific mission as implemented in the HARPOON war game as described in Chapter 3. There are three MOP categories shown in this hierarchy: weapons, mobility and survivability. The MOP (metric) for weapons is number of VLS cells. Three cell capacities are considered under this MOP. Under mobility there are 2 MOPs: maximum speed and fuel capacity. Three speeds and three fuel capacities are considered under these MOPs in the study. Under survivability there are 2 MOPs: maximum sustainable damage and detection signature. Three hit limits and three detection signatures are considered under these MOPs. Each alternative under each MOP is

assigned a value of performance (0-1.0) using pairwise comparison as part of the AHP. This OMOE will be discussed in detail in Chapter 3.



Figure 3 - OMOE and OMOR Development Process



Figure 4 – HARPOON OMOE Hierarchy

In the AHP, pairwise comparison questionnaires are used to solicit expert and customer opinion, required to calculate AHP weights and value of performance (VOP). Value of Performance (VOP) functions (generally S-curves) are developed for each MOP and VOP values are calculated using these functions in the ship synthesis model. A particular VOP has a value of zero corresponding to the MOP threshold, and a value of 1.0 corresponding to the MOP goal. MOP weights and value functions are finally assembled in a single OMOE function:

$$OMOE = g[VOP_i(MOP_i)] = \Sigma w_i VOP_i(MOP_i)$$
(1)

#### Node 0

#### Compare the relative IMPORTANCE with respect to: GOAL

1 =	1 = EQUAL 3 = MODERATE 5 = STRONG 7 = VERY STRONG 9 = EXTREME																		
1	Weapons	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Mobility
2	Weapons	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Survive
3	Mobility	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Survive
Abbreviation			D	Definition															
	Goal				M	Maximize DDG Overall Effectiveness													
	Weapons Missile Vertical Launching System (VLS)																		
	Mobility Ship Movement																		
Survive Surviva					bility	7													

Figure 5 - Sample AHP Pairwise Comparison Questionnaire

#### 1.1.3 Cost

As with effectiveness and risk, the multi-objective optimization requires a cost model that can generate lifecycle or total ownership cost for a specified design without direct user interaction. Cost models by their nature involve significant proprietary and sensitive data. Even within the Navy, organizations like NAVSEA 017 have resisted providing their models to the engineers.

A Virginia Tech naval combatant cost model adapted and expanded by Dr. Brown from a late-80's ASSET cost model (the ASSET cost module has since been removed) is the baseline cost model used in this thesis. This is a weight-based model supplemented with producibility and complexity adjustment factors.

#### 1.1.4 Multi-Disciplinary Optimization

In early stage design, the design space (i.e., the number of possible combinations of the various design variables either continuous or discrete) is typically very large. Evaluating the performance of designs for even a small portion of this large design space can become prohibitive if the analyses are computationally expensive. Because of this, high-fidelity codes are typically not used in the early stages of the design process. As a result, major decisions regarding the basic elements of the design are already made before high-fidelity codes begin to be used. An important objective of this thesis is to identify methodologies that will enable high-fidelity codes to be used earlier in the design process. In this thesis, Response Surface Modeling and Design of Experiments techniques are used to generate a response surface approximation for ship bare hull structural weight.

### 1.2 Objectives

The primary objectives of this thesis are

- Validate the AHP/MAVT method for deriving a naval ship OMOE function.
- Assess the use of RSM and DOE methods for minimizing computational time when using high fidelity codes early in the naval ship design process. This is accomplished using a structural optimization case study.
- Integrate these techniques in a ship design case study.

### 1.3 Thesis Outline

Chapter 1 provides an introduction and motivation for the use of multi-objective and multidisciplinary optimization of naval ships, the Overall Measure of Effectiveness of a ship design, and the ship cost model. The objectives of this thesis are described in Chapter 1.

Chapter 2 lays the foundation and background of the Analytical Hierarchy Process and Additive Utility Models. It describes the theory behind each and provides examples of them in use in other industries.

Chapter 3 validates the OMOE and use of the Analytical Hierarchy Process through experimentation. The experiment is conducted using a naval war gaming program called HARPOON and expert decision makers.

Chapter 4 discusses Model Center tools for trade studies, design space visualization, optimization of naval ship designs, and structural design optimization using Response Surface Models and MAESTRO.

Chapter 5 applies the tools addressed in the previous chapters to a high speed naval surface combatant design case study.

Chapter 6 is a summary and conclusion.

### **CHAPTER 2** AHP AND ADDITIVE UTILITY MODELS

### 2.1 Utility Theory

When making decisions, the various objective attributes, parameters and criteria may be very different and may have different metrics. Frequently scales or units can not easily be converted to make comparisons. Utility theory, based on the foundation of decision making, is an attempt to infer subjective value, or utility, from choices. Utility theory provides a way to establish a common scale of measuring values for very different attributes or criteria. This metric may also be used with non-linear relationships using a nonlinear utility function. Utility is defined as a measure of the desirability of an outcome, usually a function of cost, benefit, or risk. A utility function transforms an outcome into a numerical value and measures the worth of an outcome. The utility of an outcome may be negative or positive. This utility function may be a simple table, a linear function, or a more complex function.

Utility theory originated in the 18<sup>th</sup> century, but wasn't significantly developed until the 20<sup>th</sup> century. The earliest accounts of utility theory date to Daniel Bernoulli's essay on the solution of the St. Petersburg paradox. Bernoulli used a utility function to explain the probability of winning money by flipping a coin. The money paid out doubled every time tails were flipped until heads was flipped. Bernoulli hypothesized that the "utility" (subjective value) of an outcome (a prize in a lottery) was not directly proportional to the money value of the prize. Rather, he proposed there was a negatively accelerating diminishing utility function, such that the "amount" of utility was proportional to the logarithm of the objective dollar value. It wasn't until 1947 that utility theory was formally developed by von Neumann and Morgenstern in their book, *Theory of Games and Economic Behavior*. One of their goals in this book was to promote the development of methods to measure utilities on numerical scales. [5,6]

In order to build a utility function, several normative axioms are used. The axioms are rational and reasonable, but do not always reflect the choices of a decision maker. When utility theory is used you assume that rational people make choices based upon these axioms. The common metric used by utility functions is called the ordered metric. The upper and lower limits of the ordered metric scale are two arbitrary points defined by the worst and best outcomes  $(U(X_{worst}) = 0 \text{ and } U(X_{best}) = 1)$ . [7]

Utility functions may be developed using questionnaires completed by the experts or decision makers. Utility functions are difficult to build. Unless the expert has a background in statistics it is often difficult to grasp the concepts of the lottery method required to objectively answer the questionnaire. Even a simple utility function requires significant effort to develop.

Utility functions compare only two attributes or parameters at a time. Multiple-attribute decisions require more than one utility function. These must be combined in some overall function. Additive utility functions use a weighted sum of individual utility functions. The sums can then be compared for each alternative since utility functions are ordered metrics. The weighting of the attributes (utility functions) is left up to the expert. This assumes that the individual comparisons are independent which is an ideal assumption, and is rarely entirely valid.

### 2.2 Multi-Attribute Utility Theory

Multi-attribute utility theory (MAUT) is an extension of utility theory. It is a basis for finding utility between alternatives that are characterized by multiple attributes. It is based on the axiom that the utility function  $U = U(g_1, g_2,...)$  is being maximized. The utility function is an equation of all the estimated values of the attributes,  $g_i$ . Multi-attribute utility theory has been widely used in situations where the decision making depends on multiple factors and the utility function of decision alternatives is based on multiple attributes. The multi-attribute utility functions are used more often than general single attribute utility functions in complex environments where a decision maker needs to evaluate the alternatives with different attributes.

MAUT allows for some interaction of attributes by decreasing the calculations within attributes. A two attribute MAU function is defined as:

$$U(X_1, X_2) = k_1 U(X_1) + k_2 U(X_2) + K k_1 k_2 U(X_1) U(X_2)$$
(2)

K is a normalizing factor equal to  $(1 - k_1 - k_2)/k_1k_2$ , where  $k_i$  is the weight an attribute has relative to the objective ( $\Sigma k_i = 1$ ), and U is the utility (scale of 0 to 1) [7]. Equation (2) calculates the total utility of an alternative which is equal to the sum of the utility of each individual attribute of the alternative times their respective weights plus any interaction of the attributes. When there is no interaction between attributes this equation becomes:

$$U(X) = \Sigma k_i U(X_i)$$
(3)

### 2.3 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was developed by Dr. Thomas Saaty in the late 1970's [8,9,10]. It is a type of decision theory. Decision theories were developed because the human mind has a limited capability to retain large amounts of information and therefore cannot always make decisions based on a thorough resolution of all the issues. Also since most complex decisions are based on a number of interacting factors having varying degrees of importance, decision theories provide a way of organizing them into a more manageable process without losing their influence on the decision. Most statistical techniques developed in the past to help make decisions fail in real-world application because of their inability to derive weights of factors based on importance. The AHP helps overcome this inability. The primary goal of the AHP is to select an alternative that best satisfies a given set of criteria out of a set of alternatives. According to Saaty, the purpose of the AHP is to evaluate and prioritize the influence alternatives have on satisfying the objective of the problem. The power of the AHP is that it can be applied in any type of decision problem. It can be considered an extension of our information processing capacity and our thought processes [8].

The advantage AHP has over other decision theories is that it better represents the way experts make decisions. It allows for relative judgments and uses the human tendency to organize attributes (criterion influencing the objective) and complex goals into a hierarchy structure (Figure 6). The hierarchy structure allows the decision maker to consider intangible attributes as well as tangible attributes by rank. This hierarchy also allows for attributes of the same class to be placed in weighted parent clusters and weighted within the parent cluster. Parent clusters are criteria that cannot be represented by a single attribute. There can be any number of parent clusters used to organize the problem, but only the final children define the alternatives. AHP is also effective when the scales of attributes conflict or if they are difficult to compare. AHP is particularly superior over other methods when a model is very unstructured.

AHP scales the weights of attributes at each level of the hierarchy with respect to a goal using the decision maker's (experts') experience and knowledge in a matrix of pairwise comparisons of the attributes. The usual application of AHP is to select the best alternative from a discrete set of alternatives. The application described in this thesis is unique because AHP is used to calculate the weights in an additive utility function that can be used as an objective function for an unlimited number of alternatives that may not be defined apriori. This method

also requires that value or utility functions be developed for each attribute to combine with the weights in the additive function.



Figure 6 – Decision Hierarchy

The process begins by defining the goal and requirements of the problem. Then alternatives are identified that satisfy the requirements. Next the relative importance of each requirement to achieve the goal is assessed. Finally, the best alternative or set of alternatives is determined.

The pairwise comparison uses a 9 point ratio scale to convert relative magnitudes into ordered metrics. The 9 point scale uses an intensity scale, shown in Table 1, to compare alternatives. This scale assumes that the decision maker has knowledge about the relative importance of the attributes being compared, and that they can express the relative importance to the nearest integer with 9 being the highest and 1 being of equal importance. Zero is not included in the comparison so that reciprocals can be used in the comparison matrix.

Intensity of _Importance	Definition	Explanation			
1	Equal importance	Two activities contribute equally to the objective			
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another			
5	Essential or strong importance	Experience and judgment strongly favor one activity over another			
7	Demonstrated importance	An activity is strongly favored and its dominance demonstrated in practice			
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation			
2,4,6,8	Intermediate values	When compromise is needed			

Table 1 – Intensity scale of pairwise comparisons [9]

Pairwise comparison is performed separately for branches (attributes) below each parent in the hierarchy. The objective is to produce a set of weights (w<sub>i</sub>) for the branches below a parent, normalized so that the sum of these weights equals one. These weights are derived from the pairwise comparison preference matrix, but pairwise comparison may not be consistent (ie: w<sub>13</sub>  $\neq$ w<sub>12</sub> w<sub>23)</sub>. If A is preferred 4 times as much as B, and B is preferred twice as much as C, then A must be preferred 8 times as much as C to be consistent. When making judgments people are naturally inconsistent. This is often a result of thought and feeling. The AHP admits and measures inconsistencies of the decision maker that may reflect the quality of the decision maker's knowledge, the content of the judgments, and stability of the solution. This is accomplished by finding the best-fit eigenvector and eigenvalues. Multiple experts can also be used in AHP which may add more inconsistency. A level in the hierarchy can be added if the experts deserve different weights due to their expertise [8].

To understand how AHP resolves inconsistency, it is useful to work backwards from a typical set of resulting weights (ex:  $w_1$ ,  $w_2$ ,  $w_3$ ), noting how they were derived and the necessary requirements for their consistency. Consider a parent with three subordinate branches. Assume that a ratio scale is used for pairwise comparison. Given a final set of weights, ( $w_1$ ,  $w_2$ ,  $w_3$ ), produced from a preference matrix W, Equation (4) shows how the elements in this matrix must be represented if it is a consistent preference matrix ( $w_{ij} = w_{ij}/w_j$ ). Its elements must follow the rules:  $w_{ij} = w_{ji}^{-1}$  and  $w_{ij} = w_{ik} w_{kj}$  for any values of *i*, *j*, and *k*.

$$W = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \frac{w_1}{w_3} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \frac{w_2}{w_3} \\ \frac{w_3}{w_1} & \frac{w_3}{w_2} & \frac{w_3}{w_3} \end{bmatrix}$$
(4)

Since each row of W is a multiple of the first row, W has a rank of 1 and there is only one non-zero eigenvalue, q. Equation (4) takes the form:

$$W \cdot w = q \cdot w \tag{5}$$

where w is the eigenvector of W corresponding to the maximum eigenvalue, q, and the elements in w are the attribute weights.

To obtain this result which is characteristic of a consistent preference matrix, Saaty [11] assumes that we start with a potentially inconsistent pairwise comparison matrix, A, where the  $a_{ij}$  judgment values are only estimates of the consistent matrix, W, and the eigenvector, x, corresponding to the maximum eigenvalue ( $\lambda_{max}$ ) of the inconsistent matrix A, is only close to w. Equation (6) represents the eigenvalue problem in the inconsistent case.

$$A \cdot x = \lambda_{\max} \cdot x \tag{6}$$

He shows that for moderate inconsistency  $\lambda_{max}$  will be close to n (number of attributes) and all other  $\lambda$ 's will be close to zero. He also shows that the elements in x represent the best approximation to the attribute weights for the inconsistent preference matrix. The closer  $\lambda_{max}$  is to n, the more consistent the judgments are shown to be. Small perturbations in A only cause small perturbations in the eigenvalues. Inconsistency is measured as  $(\lambda_{max} - n)/n$ . The inconsistent case is generally considered valid when this inconsistency is less than 10%. [10]

Normalizing, the resulting weight of the  $i^{th}$  attribute is given by Equation (7).

$$w_i = x_i / \sum_{i=1}^n x_i \tag{7}$$

An example of the AHP estimates the relative distances of 6 cities to Philadelphia [8] using experience from air travel. The decision maker uses pairwise comparisons between cities determining how many times further one city is from Philadelphia than the other city is from Philadelphia. Table 2 shows the comparison matrix completed by the decision maker. Figure 7 shows this in the hierarchy form. Figure 8 shows the AHP analysis for this example.

City	Cairo	_Tokyo_	_Chicago_	San Francisco	London	Montreal
Cairo	1	1/3	8	3	3	7
Tokyo	3	1	9	3	3	9
Chicago	1/8	1/9	1	1/6	1/5	2
San Francisco	1/3	1/3	6	1	1/3	6
London	1/3	1/3	5	3	1	6
Montreal	1/7	1/9	1/2	1/6	1/6	1

Table 2 – Comparison of distances of cities from Philadelphia (w<sub>ij</sub>)



Figure 7 – Hierarchy of Distance Example

3 1 9 3 3 9 6.454  $\frac{1}{8}$   $\frac{1}{9}$ 0.133 + 1.577i $\lambda_{\max} \coloneqq \lambda_1$   $\lambda_{\max} = 6.454$ 0.133 - 1.577i -0.23 + 0.665i  $\frac{1}{3}$  6 1  $\frac{1}{3}$  6  $\frac{1}{3}$ A :=  $\lambda := eigenvals(A)$  $\frac{1}{3}$  $\frac{1}{3}$ umax - n 5316 inconsist X := eigenvecs(A) inconsist = 0.0760.505 0.156 + 0.494i 0.156 - 0.494i -0.208 + 0.412i -0.208 - 0.412i -0.422 0.767 0.754 0.754 0.812 0.812 0.88  $0.064 - 8.726 \times 10^{-3} - 0.044i - 8.726 \times 10^{-3} + 0.044i - 0.054 + 0.033i - 0.054 - 0.033i 0.041$ X = -0.199 - 0.102i -0.199 + 0.102i 0.146 + 0.091i = 0.146 - 0.091i = -0.0770.224 0.317 -0.228 + 0.239i -0.228 - 0.239i -0.06 + 0.296i 0.189 -0.06 - 0.296i 0.051 0.027 - 0.034i0.027 + 0.034i-0.016 - 0.042i -0.016 + 0.042i -0.061 / 0.505 0.262` 0.767 0.397 0.064 0.224  $\mathbf{w} := \frac{\mathbf{x}}{\sum_{i=1}^{6} \mathbf{x}_{i}}$ 0.033  $\mathbf{x}_i \coloneqq \mathbf{X}_{i,1}$ w = 0.116 0.317 0.164 0.051 0.027

Figure 8 – Calculating Hierarchy Weights for Inconsistent Comparison Matrix

Using the Intensity Scale, Table 1, and referring to Table 2, the questions asked in the comparison are: given city A (row) and city B (column), how much further is city A from Philadelphia than city B. Only the comparisons above the diagonal are made (the diagonal being 1 since A compared to A is equal) and the reciprocals fill in the rest of the comparison matrix. The matrix is then reduced to its eigenvector with each eigenvalue being the weight or relative distance of each city from Philadelphia. Table 3 shows a comparison of the eigenvector results from the AHP to the actual distances.

	Table 5 – Real and Estimated Distances							
City	Distance from Philadelphia (miles)	Normalized Distance	Normalized Eigenvector					
Cairo	5729	0.278	0.262					
Tokyo	7449	0.361	0.397					
Chicago	660	0.032	0.033					
San Francisco	2732	0.132	0.116					
London	3658	0.177	0.164					
Montreal	400	0.019	0.027					

Table 3 - Real and Estimated Distances

### 2.4 Combination of AHP and MAUT

Once the relative importance weights of attributes are found using the AHP the overall measure of effectiveness can be defined using additive multi-attribute utility theory or multi-attribute value theory. Utility theory is really just a specific subset of value theory where the lottery method and a strict interval scale are used for the attribute value functions. More general multi-attribute value (MAV) functions can be used in place of utility functions to assess the relative value of alternatives or performance metrics for a particular attribute if explicit bounds or anchor points (goal and threshold) are established for the attribute values [12]. These value functions can then be developed using pairwise comparison of attribute values or the function can be shaped from inspection rather than using a lottery. A MAV function is defined as

$$V_i = \sum_j w_j x_{ij} \tag{8}$$

where:

 $V_i$  is the overall value of the i<sup>th</sup> alternative

- $w_j$  is the weight or relative importance of the j<sup>th</sup> criteria established from AHP
- $x_{ij}$  is the value (or score) of the i<sup>th</sup> alternative for the j<sup>th</sup> criteria (0-1)

The threshold represents the minimum value acceptable for a particular attribute. The goal represents a reasonable technology limit or a point beyond which further improvement has no additional value for the attribute. [12]

The following example of choosing the best car to buy shows the use of the AHP in conjunction with MAVT.

A customer wants to buy a new car based on price, power, and safety [13]. This example is restricted to 3 car options, a BMW, a Mercedes, and a Citroen. Criteria for the best possibility are chosen. The car needs to have airbags (Measure of Performance 1, MOP1) and anti-lock brakes (MOP2), be less than \$33,000 (MOP3), have a cylinder capacity greater than 2500 (MOP4), and have a nominal power greater than 130 (MOP5). Figure 1 shows the hierarchy tree and Table 4 gives the specifics of the three car alternatives.



Figure 9 – Car Example Hierarchy

ruble i cui speenies							
	BMW	Mercedes	Citroen				
Airbag	Yes	Yes	Yes				
Anti-lock Brakes	Yes	Yes	No				
Price	\$38,500	\$46,500	\$26,500				
Cylinder Capacity	2495	2685	1749				
Nominal Power	141	125	117				

Table 4 – Car Specifics

From the pairwise comparison completed by the customer the relative importance of safety, price, and power is 0.3, 0.4, and 0.3 respectively. In the safety cluster airbags and anti-lock brakes share equal relative importance (0.5 each). In the power cluster cylinder capacity has a relative importance of 0.4 and nominal power is 0.6. To keep this example simple the value of attribute performance (VOP) will simply be 1 if it is satisfied and 0 if it is not satisfied by the alternative. Table 5 shows the calculation of the overall measure of effectiveness (OMOE) for each alternative. It can be seen that by the criteria set by the customer the Citroen is the best alternative. The OMOE function for this analysis is:

OMOE = .3(.5\*VOP1(MOP1)+.5\*VOP2(MOP2))+.4\*VOP3(MOP3)+.3\*(.4\*VOP4(MOP4)+.6\*VOP5(MOP5))

Table 5 – Car Example VOPs and OMOE

1			
	BMW	Mercedes	Citroen
Airbag VOP	1	1	1
Anti-lock Brakes VOP	1	1	0
Cylinder Capacity VOP	0	1	0
Nominal Power VOP	1	0	0
Safety VOP (0.5*Airbag + 0.5*Anti-lock Brakes)	1	1	0.5
Price VOP	0	0	1
Power VOP (0.4*Cylinder Capacity + 0.6*Nominal Power)	0.6	0.4	0
OMOE Goal – Buy the Car (0.3*Safety + 0.4*Price + 0.3*Power)	0.48	0.42	0.55

### 2.5 Validation of AHP in other Applications

Validations of the AHP in other applications were researched to determine if there has been a validation or use of AHP similar to our OMOE application. Sections 2.5.1 to 2.5.5 describe examples that find weights of given alternatives with respect to a goal, which is similar to our application of finding weights to build an OMOE function. Each of the following examples are summaries from Rozann Saaty's *Validation Examples for the Analytical Hierarchy Process and the Analytical Network Process* [14].

### 2.5.1 Estimating Relative Areas using AHP

A simple AHP validation exercise is to estimate the relative areas of geometric shapes shown in Figure 10. The decision maker does not need any prior knowledge of the shapes. The job of the decision maker is to compare two of the shapes at a time (10 comparisons) estimating how many times larger the area of one shape is compared to the smaller shape using the fundamental scale of AHP. Figure 11 shows the hierarchy in Super Decisions, an AHP program. A comparison matrix completed by an arbitrary decision maker is shown in Figure 12.



Figure 11 – Relative Area Hierarchy in Super Decisions

🗿 Comparisons for "Alternatives - the Areas" wrt "Goal Node" 📃 🗆 🔀									
File Computations Misc. Help									
Graphic Verbal Matrix Questionnaire									
A: Circle is 9.0 time	A: Circle is 9.0 times more bigger than B: Triangle								
Inconsistency	B: Triangle	C: Square	D: Diamond	E: Rectangle					
A: Circle	<b>- 9</b> .0	2.0	<b>-</b> 2.5	6.0					
B: Triangle		<b>1</b> 5.0	<b>1</b> 3.0	1 2.0					
C: Square			<b>=</b> 1.5	<b>a</b> 3.0					
D: Diamond				2.0					

Figure 12 - Relative Area Comparison Matrix from Super Decisions

The results of this comparison are calculated by Super Decisions and are show below in Figure 13. Table 6 shows the comparison of the actual relative values vs. the ones found using the AHP.



Figure 13 – Relative Area Results from Super Decisions

Figure	<b>AHP Relative Area</b>	<b>Actual Relative Area</b>
А	0.46	0.47
В	0.05	0.05
С	0.24	0.24
D	0.16	0.14
Е	0.08	0.09

Table 6 – Relative Area AHP vs. Actual

The results show that the order and weights of the figures derived from the Analytical Hierarchy Process are very close to the actual.

#### 2.5.2 Estimating Relative Drink Consumption with AHP

This example shows that the relative scale works well on homogeneous elements of a real life problem. A matrix of paired comparison judgments is used to estimate relative beverage consumption in the United States. This exercise was done by a group of about 30 people who arrived at a consensus for each judgment. The types of beverages are listed on the left and at the top. The judgment is an estimate of how consumption of the drink on the left dominates that of the drink at the top. For example, when the judgment for coffee (row label) versus wine (column label) was made, it was thought that coffee is consumed extremely more and a 9 is entered in the first row and second column position. The value 1/9 is automatically entered in the second row and first column position. If the consumption of a drink on the left does not dominate that of a drink at the top, the reciprocal value is entered. For example in comparing coffee and water in the first row and eighth column position, water is consumed slightly more than coffee and a 1/2 is entered. Correspondingly, a value of 2 is entered in the eighth row and first column position. The bottom of Table 7 shows that the derived values obtained by computing the principal eigenvector of the matrix and normalizing it and the actual values obtained from the pages of the Statistical Abstract of the United States are similar.

Coffee         1         9         3         1         1/2         1         1           Wine         1/9         1         1/3         1/9         1/9         1/9         1           Tea         1/3         3         1         1/4         1/5         1/4         1           Beer         1         9         4         1         1/2         1         1           Sodas         2         9         5         2         1         2         1           Milk         1         9         4         1         1/2         1         1	Drink Consumption in the U.S.	Coffee	Wine	Tea	Bee r	Sodas	Milk	Water
Wine         1/9         1         1/3         1/9         1/9         1         1           Tea         1/3         3         1         1/4         1/5         1/4         1           Beer         1         9         4         1         1/2         1           Sodas         2         9         5         2         1         2           Milk         1         9         4         1         1/2         1         1	Coffee	1	9	3	1	1/2	1	1/2
Tea         1/3         3         1         1/4         1/5         1/4         1           Beer         1         9         4         1         1/2         1           Sodas         2         9         5         2         1         2           Milk         1         9         4         1         1/2         1         1	Wine	1/9	1	1/3	1/9	1/9	1/9	1/9
Beer         1         9         4         1         1/2         1           Sodas         2         9         5         2         1         2           Milk         1         9         4         1         1/2         1         1	Tea	1/3	3	1	1/4	1/5	1/4	1/5
Sodas         2         9         5         2         1         2           Milk         1         9         4         1         1/2         1         1	Beer	1	9	4	1	1/2	1	1
Milk 1 9 4 1 1/2 1 1	Sodas	2	9	5	2	1	2	1
	Milk	1	9	4	1	1/2	1	1/2
Water 2 9 5 1 1 2	Water	2	9	5	1	1	2	1

Table 7	– AHP Drink Consumption Example [14	·]
	Which Drink is Consumed More in the U.S.?	

An Example of Estimation Using Judgments

The derived scale based on the judgments in the matrix with consistency .022 is: Coffee Wine Теа Beer Sodas Milk Water 129 .177 019 042 .116 190 327 The actual consumption for the year 1998 (from Statistical Abstract of the United States, published in 2001) is: 010 .120 .180 .040 .180 .140 .330

### 2.5.3 Airline Market Share Model with AHP

Another example of validation of the AHP is with the US Airline Market Share in 2000. The model was built using Super Decisions and the weighted results were compared to actual market results of the airlines in 2000. The hierarchy structure is shown in Figure 14. The models results are compared to the actual market in Table 8. To do a successful market estimation, the modeler must be very knowledgeable about that particular market, because making successful judgments depends on accumulated knowledge. Over the past several years, students have done dozens of market share models with remarkably good results. Students who know the business intimately without access to numerical information until after the exercise has been completed work this example and the following one in the classroom.

10010 0 11111		
Airline	<b>Model Results</b>	Actual Market (2000)
American	23.9	24
United	18.7	19.7
Delta	18.0	18.0
Northwest	11.4	12.4
Continental	9.3	10.0
US Airways	7.5	7.1
Southwest	5.9	6.4
American West	4.4	2.9

Table 8 - Airline Model Results vs. Actual Market Share



Figure 14 – Airline Model

### 2.5.4 Superstore Market Share Model with AHP

Another example of validation of the AHP is with the relative market share of the superstores, KMart, Target, and Walmart. The model was built using Super Decisions and the weighted results were compared to actual market results of the airlines in 2000. The hierarchy structure is shown in Figure 15. The first level is the 3 superstores. Each superstore is evaluated based on its advertising, location, customer groups, merchandise, and characteristics of the store. The model results are compared to the actual market share in Table 9.

Competitor	ANP Results	Actual Market Share
Walmart	59.8	54.8
Kmart	24.8	25.9
Target	15.4	19.2

Table 9 – Superstore Model Results vs. Actual Market Share



Figure 15 – Superstore Model Hierarchy

### 2.5.5 Predicting the winner of the 2003 World Series using AHP

This model was used to predict the winner of the 2003 Baseball World Series. At the beginning of the 2003 baseball playoffs Dan Rowlands [15] built an AHP model to predict the winners of each round of the playoffs. He collected data for each team in the playoffs based on the regular season statistics. These include starting pitching, defense, base running, hitting, hitting under pressure, home field advantage as well as a few others. Based upon his expertise of the game the criteria was weighted based upon: good pitching beating good hitting, and defense and base running win in the playoffs. Rowland also factored for the will to win, history of greatness, and overachievers.

A partial hierarchy is shown in Figure 16. Since this model is large it will only be highlighted. The results of the model are shown in Figure 17. These results can then be used to figure out head to head series between two teams, for example New York (0.21) would win over Minnesota (0.11). From looking at the results it is figured that the Yankees would be in the final round while Oakland and Florida should also make it far.



Figure 16 – Baseball Playoffs Model Hierarchy

🔁 New synthesis for: Super Decisions Main Window: 2003Wor 💻 🔲 🗙					×
Here are the overall synthesized priorities for the alternatives. You synthesized from the network Super Decisions Main Window: 2003WorldSeries.mod: formulaic					
Name	Graphic	Ideals	Normals	Raw	
Atlanta		0.377268	0.077751	0.158024	
Boston		0.362682	0.074745	0.151915	
Chicago		0.428785	0.088368	0.179603	
Florida		0.742149	0.152948	0.310860	
Minnesota		0.542684	0.111841	0.227311	
New York		1.000000	0.206089	0.418864	
Oakland		0.819048	0.168796	0.343070	
San Francis~		0.579667	0.119463	0.242802	

Figure 17 – Baseball Playoffs Model Results [14]

The following are the actual outcomes of the playoffs:

### **Divisional Playoffs**

New York (0.21) over Minnesota (0.11)

Boston (0.07) over Oakland (0.17)

Chicago (0.09) over Atlanta (0.08)

Florida (0.15) over San Francisco (0.12)

### League Championship Series

New York (0.21) over Boston (0.07)

Florida (0.15) over Chicago (0.09)

### **World Series**

```
Florida (0.15) over New York (0.21)
```

The model successfully predicted 5 of the 7 playoff series. The series of Boston vs. Oakland went to 5 games and the World Series went to 6 games. Although the World Series wasn't predicted correctly this is still very accurate.

### 2.6 Why are these validations not sufficient for our application?

These examples provide confidence in the AHP, but they do not prove that the AHP will be effective in an OMOE ship design application. For our application, we will use the AHP to calculate value function weights of attributes (MOPs), and also to define the value functions. The hierarchies of these examples are very similar to the OMOE hierarchy with attributes and attribute weights that correspond to MOPs and MOP weights. In the typical implementation of the AHP only discrete variables and discrete numbers of alternatives are used, but when using a continuous value function many alternatives may be considered that are not known a priori.

In the previous examples the lowest level of the hierarchy has different characteristics all relating to the same group. For instance in the superstore example white collar, blue collar, families, and teenagers all relate to the customer groups. In the application using OMOE the lowest level of the hierarchy applies to different values of a given characteristic or MOP. For example 18 cells, 36 cells, and 54 cells are different weapon package values relating to the Vertical Launching System weapons characteristic of a ship design. By defining goals and thresholds it is possible to implement a zero to one value index for these MOPs and build value functions without needing to specify the designs that achieve a given level of performance in advance. In order to better validate this method, an experiment was devised that includes both weights and values functions in an OMOE function applied to a simple naval ship problem in a manner similar to how it would be used in naval ship design. This experiment is described in Chapter 3.

### CHAPTER 3 OMOE EXPERIMENT

AHP and MAVT can be used to build an OMOE and OMOR function to properly rank and approximately measure the relative mission effectiveness and risk of design alternatives, using trained expert opinion to replace complex analysis tools. An experiment is performed to prove this hypothesis.

The experiment compares the ranking of 16 ships using two methods. The first method uses an OMOE and expert opinion to rank the ships, (experiment) and the second method uses the results of combat (war game) simulation to rank the ships (control). In the first method, experts are taught the relative importance of ship characteristics to achieve a specified ship mission using HARPOON, a ship and air combat simulator described in Section 3.1. The experts then answer an AHP pairwise comparison questionnaire to determine the weights and values (VOPs) of each MOP in the OMOE hierarchy with respect to the ship's HARPOON mission. This data is used to build an OMOE function for this mission. The OMOE function is used to rank 16 ships with different designs based on mission effectiveness. Next, the second method is used to rank the 16 ships using HARPOON to directly assess their mission effectiveness. A successful experiment should provide the same ranking with similar relative effectiveness. The detailed steps followed in this experiment were as follows:

- 1. Choose a naval ship class and mission types to be studied. The mission types must be realistic, not too complex, and within the capabilities of HARPOON.
- 2. Determine the required operational capabilities (ROCs) needed perform the mission. MOPs (ship measures of performance) are specified for each of the ROCs. Again, these must be simple enough for the experts to assess their value with a reasonable amount of training and experience (20 hours each).
- 3. Determine goal, threshold and baseline design characteristics for each measure of performance (MOP).
- 4. Create an OMOE hierarchy for the MOPs using the AHP.
- 5. Prepare a HARPOON naval war game/battle scenario with conditions of victory to reflect the ship's mission. These are the goal or success metrics for the mission.
- 6. Train the experts and provide battle experience using HARPOON in the specified scenario. Ten experts individually complete a HARPOON tutorial and then play this scenario in a series of 12 war games over 20 hours. Each time, the ships used in the scenario have different design characteristics consistent with the ROCs and MOPs they will be asked to compare. The designs are all variants of the baseline design with a single design characteristic changed to the goal or threshold value for one of the MOPs.

- 7. Assemble the expert opinion by having the experts complete a questionnaire for the OMOE hierarchy, making pairwise comparisons of the MOPs based on their experience playing the battle scenarios.
- 8. Use the questionnaire results to calculate the AHP eigenvalue weights and VOPs, and develop an OMOE function for the specified mission and design characteristics.
- 9. Use a Design of Experiments (DOE) method to define 16 different ships with various combinations of goal and threshold design characteristics spanning the design space.
- 10. Calculate an OMOE value for each of these ship designs using the OMOE function.
- 11. Rank the ships based on their OMOE value from most effective to least effective.
- 12. Select a single expert to "play" the scenario 10 times using the same 16 designs. Record the results for each design.
- 13. Rank the 16 designs from best to worst based on these results.
- 14. Compare the OMOE ranking to the direct ranking.

### **3.1 HARPOON Description**

HARPOON III is an unclassified air and naval warfare simulator. Although originally marketed as a computer game, HARPOON has developed over time into a remarkably realistic, flexible, and capable warfare modeling tool. Contributions and improvements from an active user's group, many with extensive naval experience, have consistently improved its realism, databases and usability. Most elements of a modern naval task force and likely battle scenarios can be modeled and exercised. HARPOON has been used extensively by various military activities around the world as a training and what-if simulation tool. [16] HARPOON includes databases for over 400 classes of ships from dozens of countries. It also uses databases of the weapon systems, munitions, propulsion systems, and fuels. The HARPOON II Admiral's Edition includes 120 programmed scenarios, most of which are modeled after real battles. HARPOON was chosen for this experiment because of its flexibility to change ship characteristics and battle scenarios, its battle realism, and its extensive databases.

When playing HARPOON, the gamer has control of "battle pieces". Battle pieces can be individual ships (the focus of this study), squadrons of ships that act as a single entity to carry out a mission, individual submarines, individual aircraft, aircraft squadrons, or land base facilities. Figure 18, Figure 19 and Figure 20 are examples of the HARPOON simulation environment. Having control over a battle piece allows the user to navigate, search for aircraft, land bases, surface ships, and submarines, and engage enemies with a range of weapons. The
objective (victory conditions) varies for each scenario and is stated at the beginning. An objective can have any number of victory conditions for destroying certain types and numbers of enemy ships or protecting friendly ships. Winning a scenario occurs when all victory conditions are met. Then end of a scenario occurs when a game is won or a set time period runs out (varies for each scenario).

In preparation for the experiment it was important to learn the capabilities and limitations of HARPOON. From HARPOON's tutorial and practice gaming, the following capabilities were identified and exercised:

- Control the navigation, speed, and mission of individual ships, aircraft, submarines, and squadrons.
- Use radar and sonar.
- Vary the speed, fuel capacity, armor thickness, sustainable damage, detection signatures, gun mounts, sensors, communication, air facilities, and weapons capacity of a ship.
- Change weather conditions, victory conditions and time duration of a scenario.
- Change difficulty settings and levels of computer help in navigation and aircraft control.

With limited time and resources only a subset of HARPOON's capabilities were used. The following sections describe the HARPOON features chosen for this experiment and the process for choosing them.



Figure 18 – HARPOON Screenshot 1



Figure 19 – HARPOON Screenshot 2



Figure 20 – HARPOON Screenshot 3

## **3.2** Preparing the Experiment (Steps 1-5)

## 3.2.1 HARPOON Ships and Mission Types

First the baseline ship class for this study was determined. This selection was limited to the classes included in HARPOON's database. Since this is a surface ship study, submarines were excluded. Ships carrying aircraft were also excluded to simplify the simulations and focus on the

characteristics of the ship. Four classes from HARPOON were considered that fit this study: CG47 Ticonderoga, DD 963 Spruance, DDG 51 Arleigh Burke, and FFG 7 Perry. Appendix A provides a brief description of these ships in HARPOON. From these, DDG 51 was selected because it is most representative of a modern surface combatant without the added capability and complexity of a cruiser.

According to the Military Analysis Network (FAS.org) [17] the Arleigh Burke Destroyers were designed to be used in high threat areas to conduct anti-air warfare (AAW), anti-submarine warfare (ASW), anti-surface warfare (ASUW), and strike warfare (STK). The first three warfighting capabilities were chosen to be included in the mission for this study.

#### 3.2.2 HARPOON Mission Scenarios

HARPOON includes 120 programmed scenarios, most of which are modeled after real battles. Each scenario was studied to see who the players were (which countries), what "battle pieces" were used, and what type of opposition will be encountered (air, surface, and submarine threats). For this experiment only one scenario is needed, but it needs to use individual surface ships and span the three multi-mission warfighting areas listed in Section 3.2.1. The mission scenario must include encounters with air threats (AAW), submarine threats (ASW), and surface ship threats (ASUW). The 120 scenarios were narrowed down to 12 scenarios based on having at least one individual surface combatant as a "battle piece". These were then further filtered down to 6 since some used coast guard cutters, not applicable to this study. The scenarios can be altered to add/delete/change "battle pieces", change victory conditions, and change the time period allowed. Since these scenarios are proven as challenging and error free it is desired keep changes to a minimum. Descriptions of the 6 remaining scenarios are as follows:

#### **Airplane Gambit**

Good guys: US- 1 nuclear sub, 2 frigates Enemies: Soviets Mission: Protect Azores from surface, air, and submarine attacks. Type of Threats Encountered: surface, air, submarine

#### **Car Carrier Convoys**

Good guys: US- 6 merchant ships, 3 destroyers, 2 frigates Enemies: Soviets Mission: Escort merchant vessels to Hiroshima with minimal losses. Type of Treats Encountered: submarine

#### Sanctions

Good guys: US-2 frigates, 2 destroyers, 1 cruiser Enemies: North Korea, China Mission: Blockade North Korean transport vessels and defend against Chinese naval units. Type of Threats Encountered: surface, air, submarine

#### **Yellow Surprise**

Good guys: UK- 2 nuclear subs, 1 frigate, 5 surface vessels Enemies: China Mission: Defend shipping and shore based facilities and attack Chinese coastal targets. Type of Threats Encountered: surface, air, submarine

#### The Eyes of Inchon

Good guys: US- 3 squadrons, 2 nuclear subs, 1 frigate Enemies: North Korea Mission: Show a strong naval force to discourage North Koreans from engaging in war. Type of Threats Encountered: surface, air, submarine

#### **The Great Satan**

Good guys: US-1 squadron, 1 nuclear sub, 1 cruiser Enemies: Iran Mission: Protect the straight of Hormuz from being closed. Type of Threats Encountered: surface, air, submarine

The Sanctions Scenario was chosen because it uses 5 combat surface vessels, and because it encounters air, surface, and submarine threats. The scenario was modified to better fit the needs of this experiment by using 5 DDG51 destroyers, all with the same characteristics (example: 5 Damage Threshold ships) in place of 2 frigates, 2 destroyers and 1 cruiser. In the Sanctions scenario the main surface threat is small patrol boats. To make the scenario more challenging and better exercise the DDG required capabilities, two enemy destroyers were added as additional threats. In the experiment, this scenario is run 10 times with everything the same except for the DDG design characteristics which are varied to span the design space as discussed in Section 3.2.3.

The length of the scenario is limited to 3 hours. There are two victory conditions in Sanctions: 1) sink 5 patrol boats; 2) no US ships sunk. These are modified to three victory conditions based on the mission specified in Section 3.2.1: 1) sink 2 enemy destroyers, 2) sink 7 patrol boats, 3) no losses of US destroyers. To accomplish victory condition 3 anti-air and anti-surface operations are required. To win a scenario all three of these conditions must be met. Each victory condition is easy to accomplish on its own, but completing all 3 simultaneously is

difficult. This was done to push the experts to the limit to see which characteristics are most effective and in what combination.

### 3.2.3 ROCs, MOPs and Design Characteristics

To support the missions described in Section 3.2.1, the capabilities listed in Table 10 are required. The ship's ability to perform these functional capabilities is measured by an explicit Measure of Performance (MOP).

ROC	Description	MOP
MOB 1	Steam to design capacity in most fuel efficient manner	MOP2 – Speed
		MOP3 – Fuel Capacity
MOB 3	Prevent and control damage	MOP4 – Sustainable Damage
		MOP5 – Detection Signature
MOB 5	Maneuver in formation	Required for all designs
MOB 7	Perform seamanship, airmanship and navigation tasks (navigate,	Required for all designs
	anchor, mooring, scuttle, life boat/raft capacity, tow/be-towed)	
MOB 10	Replenish at sea	Required for all designs
MOB 12	Maintain health and well being of crew	Required for all designs
MOB 13	Operate and sustain self as a forward deployed unit for an extended	MOP1 – Weapons Capacity
	period of time during peace and war without shore-based support	MOP2 – Fuel Capacity
MOB 16	Operate in day and night environments	Required for all designs
MOB 17	Operate in heavy weather	Required for all designs
MOB 18	Operate in full compliance of existing US and international	Required for all designs
	pollution control laws and regulations	
AAW 1.2	Provide unit self defense	MOP1 – Weapons Capacity
AAW 5	Provide passive and softkill anti-air defense	Required for all designs
AAW 6	Detect, identify and track air targets	Required for all designs
ASU 1	Engage surface threats with anti-surface armaments	MOP1 – Weapons Capacity
ASU 4.1	Detect and track a surface target with radar	Required for all designs
ASU 6	Disengage, evade and avoid surface attack	MOP2 – Speed
ASW 1	Engage submarines	MOP1 – Weapons Capacity
ASW 4	Conduct airborne ASW/recon (LAMPS)	Required for all designs
CCC 3	Provide own unit CCC	Required for all designs
CCC 4	Maintain data link capability	Required for all designs
SEW 2	Conduct sensor and ECM operations	Required for all designs
SEW 3	Conduct sensor and ECCM operations	Required for all designs
INT 1	Support/conduct intelligence collection	Required for all designs
INT 2	Provide intelligence	Required for all designs
INT 3	Conduct surveillance and reconnaissance	Required for all designs
NCO 3	Provide upkeep and maintenance of own unit	Required for all designs
NCO 19	Conduct maritime law enforcement operations	Required for all designs
LOG 1	Conduct underway replenishment	Required for all designs
LOG 2	Transfer/receive cargo and personnel	Required for all designs

Table 10 - Required Operational Capabilities and MOPs

In HARPOON the characteristics and performance of ships in its database can be altered or entirely new ships can be created. There are 10 ship characteristics that can be changed in this game; armor thickness, sustainable damage (HARPOON calls this damage points), detection signatures of the ship, gun mounts, propulsion systems, sensors, communication, fuel capacity, air facilities, and weapons capacity.

The armor thickness of the ship provides its ability to sustain damage without sinking or becoming inoperable. Armor thicknesses can be specified for four regions of the ship, general (main decks and belts), engineering (steering and propulsion spaces), bridge (command and control), and sensors (waveguides and antennas). Armor thickness is specified as either none, light (< 2" steel), medium (3"-5" steel), heavy (6"-11"), or special (>12"). If the ship takes a hit in a region of importance, for example steering, and does not have sufficient armor the ship will lose all mobility.

The amount of damage sustained is the amount of hits a ship can take before being sunk. HARPOON uses a metric called damage points specifying the amount of damage a ship can absorb before being destroyed. For example, typical damage points for a destroyer are about 200 while damage points for a patrol boat are about 30. This means that a destroyer can absorb about 7 times as many hits as a patrol boat can before being sunk.

The detection signatures of the ship refer to the cross sectional area seen by enemy sensors. It is broken down into the area seen by passive/ active sonar, visual, infra-red, and radar from the bow (straight on), side, stern. The areas can be increased or decreased to make the ship look larger or smaller to enemy sensors.

Gun mounts refer to the different guns, missile launchers, and decoy systems a ship has. There are over 800 different weapons and weapons packages available in HARPOON. Each mount's location and range of motion is specified.

The propulsion systems specified for a ship determine its speed. Different power plants can be used to change the speed or the characteristics of the power plants themselves can be altered to achieve desired speeds.

HARPOON has different sensor equipment alternatives which have different detection capabilities and ranges. It also has communication equipment alternatives which have different ranges.

A ship's fuel capacity is specified in metric tons (MT). This determines the endurance range of the ship. HARPOON brings realism by having different speeds consume the fuel faster or

slower. Fuel can be specified for the ship's propulsion and electrical, aviation, or weapons systems power.

The air facility characteristic determines what types of aircraft the ship can accommodate. It can be specified to accommodate for helicopters or fighter planes and the numbers of each.

The weapons capacity characteristic determines the amount of ammunition carried by the ship. Weapons can be specified by gun mount or packages of magazines.

Because of the limited time and resources in this study, only 5 of these characteristics are chosen to be design variables. These are sustainable damage, detection signature, propulsion system (speed), fuel capacity, and weapons capacity. In preliminary studies using HARPOON with the selected scenario, these characteristics were shown to have the greatest impact on mission effectiveness. The other 5 characteristics are kept constant for all design variants. The air facility was not used to place more emphasis on ship characteristics. Table 10 also shows the relationship between the required operational capabilities (ROCs) and the Measures of Performance (MOPS). During the AHP process MOP (or design) alternatives are assigned a Value of Performance (0.0-1.0) which are combined with the MOP weights to calculate the OMOE using Equation (1).

#### 3.2.4 Goals, Thresholds, and Hierarchy

The 5 measures of performance (MOPs) are arranged into an overall measure of effectiveness (OMOE) hierarchy shown in Figure 4. The OMOE hierarchy is the basis for the pairwise comparison and the AHP calculation of MOP weights. There are three MOP categories shown in this hierarchy: weapons capacity, mobility and survivability. The MOP for weapons is number of VLS cells. Three cell capacities are considered under this MOP. Under mobility there are 2 MOPs: maximum speed and fuel capacity. Maximum speed is determined by the selection of a propulsion plant. Three speeds and three fuel capacities are considered under these MOPs. Under survivability there are 2 MOPs: maximum sustainable damage and detection signature. Three hit limits and three detection signatures are considered under these MOPs. Each alternative under each MOP is assigned a value of performance (0-1.0). Threshold MOP alternatives were determined in preliminary HARPOON exercises so that if a ship has a threshold value of a given characteristic the user has just enough of that characteristic to achieve the objectives in the battle scenario, the baseline value gives the user a little more than enough, and the goal value gives the

user more than enough to win the scenario. Table 11 lists the MOP alternatives. The "baseline" detection signatures are listed in Table 12 with cross sectional areas of the ship as seen from head on, the side, and the rear of the ship.



Figure 21 – Experiment OMOE Hierarchy

<b>Design Parameter</b>	Threshold	Baseline	Goal
Damage Points	195	210	225
Detection Signature	$+5 \text{ m}^2$	Baseline	$-5 \text{ m}^2$
Fuel Range	400 Mtons	800 Mtons	1800 Mtons
VLS	18 cells	36 cells	54 cells
Max Speed	27 knots	31 knots	35 knots

Table 11 – Summary of MOP Alternatives

-1 and $-12 - 12$ as the Detection signature	Table 12	– Baseline	Detection	Signatures
--	----------	------------	-----------	------------

	Front	Side	Back
Passive Sonar	95 m <sup>2</sup>	95 m <sup>2</sup>	95 m <sup>2</sup>
Active Sonar	$25 \text{ m}^2$	$40 \text{ m}^2$	$25 \text{ m}^2$
Visual	$240 \text{ m}^2$	$285 \text{ m}^2$	$240 \text{ m}^2$
Thermal	$140 \text{ m}^2$	$215 \text{ m}^2$	$170 \text{ m}^2$
Radar	$210 \text{ m}^2$	$255 \text{ m}^2$	$210 \text{ m}^2$

Ten different DDG 51 variants were developed for training the experts in the value of individual MOPs. Each variant has the baseline value for 4 MOP (design) characteristics and either a threshold or goal value for the 5<sup>th</sup> characteristic. The ship is named after the 5<sup>th</sup>

characteristic and its value. For example damage threshold has a threshold sustainable damage of 195 DP, a baseline signature (described below), a baseline speed of 31 knots, a baseline fuel capacity of 800 MT, and a baseline weapons capacity of 36 VLS cells. Table 13 lists the design variants.

			0		
Shin Variant	MOP1	MOP2	MOP3	MOP4	MOP5
	Damage	Signature	Speed	Fuel	
Damage Threshold	Threshold	Baseline	Baseline	Baseline	Baseline
Damage Goal	Goal	Baseline	Baseline	Baseline	Baseline
Signature Threshold	Baseline	Threshold	Baseline	Baseline	Baseline
Signature Goal	Baseline	Goal	Baseline	Baseline	Baseline
Speed Threshold	Baseline	Baseline	Threshold	Baseline	Baseline
Speed Goal	Baseline	Baseline	Goal	Baseline	Baseline
Fuel Threshold	Baseline	Baseline	Baseline	Threshold	Baseline
Fuel Goal	Baseline	Baseline	Baseline	Goal	Baseline
VLS Threshold	Baseline	Baseline	Baseline	Baseline	Threshold
VLS Goal	Baseline	Baseline	Baseline	Baseline	Goal

Table 13 – Ship Design Matrix

## **3.3** Performing the Experiments (Step 6-7)

#### 3.3.1 Experts

Experts are trained using a HARPOON tutorial (Section 3.3.2), and by playing the Sanctions Scenario with the 10 design variants listed in the design matrix (Table 13). Once trained, they complete the pairwise comparisons questionnaire (Section 3.3.4). Seven experts were chosen from ocean and aerospace engineering undergraduate students. These students did not have any prior knowledge of ship characteristics, military experience or experience with HARPOON. All their decisions were made from playing HARPOON in this study. Due to time constraints, the training was designed to take to about 20 hours to complete the 10 simulations.

#### 3.3.2 HARPOON Tutorial

The first step in the expert's training is to complete the HARPOON Tutorial provided with HARPOON. The tutorial consists of eight lessons; Orientation, Course and Speed, Using Sensors, Using Weapons, Submarine Operations, Air Operations, Using the Mission Editor, and Using the Formation Editor. Since this study doesn't use submarines or aircraft the experts were instructed to skip Submarine Operations and Using the Formation Editor.

#### 3.3.3 Scenario Runs/ Recording of Scenario Data

After completing the tutorial, each expert was assigned a random run order to complete the 10 simulations. The first two runs were repeated at the end to access a learning curve. The mission for the scenarios was explained as navigating the five destroyers, engaging any hostile units, and managing weapon and fuel supplies to complete the three victory conditions. After each run a summary of conclusions was recorded by each expert to aid them in the final questionnaires. The summary asks whether or not each victory condition was met, the time for completion, the percent damage each ship absorbed for both sides, and general observations on the performance of the ships. A sample summary form is provided in Appendix D.

#### 3.3.4 Questionnaires

Once all runs were completed, the experts completed the pairwise comparison questionnaires. There is a questionnaire for each node of the hierarchy. The questionnaires asked the experts to compare two attributes on a relative importance scale of 1-9 with respect to completing the victory conditions. Three questionnaires, Table 14 to Table 16, are used to calculate MOP weights, and five questionnaires, Table 17 to Table 21, are used to calculate VOPs for individual MOP alternatives. Questionnaire results are provided in Appendix C – Questionnaire Data.

				Con	ıpare	the r	elativ	e IMI	PORT	ANC	CE wi	th res	pect t	o: GC	) AL	Node	0		
1 =	EQUAL 3	= M(	ODEF	RATE	5 =	- STR	.ONG	7 =	VER	Y ST	RON	G 9	=EX	TRE	ME				
1	Weapons	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Mobility
2	Weapons	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Survive
3	Mobility	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Survive
[	Abbreviatio	m			D	efinit	ion												
	Goal				M	Iaxim	ize D	DG C	Overal	ll Eff	ective	ness							
	Weapons				M	lissile	e Vert	ical L	aunc	hing	Syster	m (VI	LS)						
	Mobility				SI	hip M	lovem	ent			-								
	Survive				SI	arviv	ability	,											

Table 14 – MOP Weight Questionnaire Node 0

# Table 15 - MOP Weight Questionnaire Node 20000

	Node 20000 Compare the relative IMPORTANCE with respect to: Mobility < GOAL
1 = EQUAL $3 = MC$	DERATE 5 = STRONG 7 = VERY STRONG 9 = EXTREME
1 S	peed 9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9 Fuel
Abbreviation	Definition
Goal	Maximize DDG Overall Effectiveness
Mobility	Ship Movement
Speed	Sustained Speed (knots)
Fuel	Shin Fuel Canacity (Range)

# Table 16 - MOP Weight Questionnaire Node 30000

	Compare the relative IMPORTANCE with respect to: Survive < GOAL
1 = EQUAL  3 = MO	DERATE 5 = STRONG 7 = VERY STRONG 9 = EXTREME
1 Det	ect 9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9 Damage
Abbreviation	Definition
Goal	Maximize DDG Overall Effectiveness
Survivo	Survivability
Survive	
Dectect	Detection Signature

# Table 17 – VOP Questionnaire Node 10000

		Com	pare	e the	rela	tive	IM	POI	RTA	NC	E w	th r	espe	ect to	o: W	/eap	ons	< G	Noc OA	le 10000 L
1 = EQUAL	3 =	= MODEF	AT	Е 5	i = S	TR	ON	3 7	7 = 1	VER	Y S	TRO	ONC	39	= E	XT	REN	ИE		
	1	18 cells	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	36 cells
	2	18 cells	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	54 cells
	3	36 cells	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	54 cells
ŧ																				
Abbreviatio	n			Def	initi	on														
Goal				Max	imi	ze D	DG	Ov	eral	l Efi	fecti	ven	ess							
Weapons				Mis	sile	Vert	ical	La	uncl	ing	Sys	tem	(VI	S)						
18 cells				Thre	esho	1d (I	Low	)-	VLS	5 w/	18 1	niss	iles	in 1	mo	dule	e			
36 cells				Base	eline	e (M	iddl	le) -	- VL	S w	/ 36	mis	sile	s in 1	2 m	odul	es			
54 cells				Goa	1 (H	igh)	- V	LS	w/ .	54 m	issi	les i	n 3 :	mod	ules	8				

			41						NO	F							۲ ـ ۱۰	:1:4	Noc	le 21000
		Compare	the	rela	tive	IIVL	POR	ΠA	NC.	E WI	ith r	espe	et to	5: SJ	peed	1 < 1	/100	inty	< 6	TOAL
1 = EQUAI	L 3	= MODER	AT	Е 5	i = 5	TR	ON	3 7	/ = 1	VER	Y S	TRO	ONC	3 9	= E	XT	REN	ИE		
-	1	27 knots	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	31 knots
	2	27 knots	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	35 knots
	3	31 knots	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	35 knots
Abbreviatio	on			Def	initi	on														
Goal				Max	imi	ze D	DG	Ov	eral	l Ef	fecti	vene	ess							
Mobility				Ship	M	oven	nent													
Speed				Sust	aine	ed S	peed	l (kı	iots	)										
27 knots				Spee	ed T	hres	shol	d (L	ow)											
31 knots				Spee	ed E	asel	line	(Mi	ddle	e)										
35 knots				Snee	-d C	hoal	(Hi	oh)												

## Table 19 - VOP Questionnaire Node 22000

		Compa	re th	e re	lativ	∕e TN	/IPC	)RT	AN	CEN	vith	rest	pect	to: 1	Fuel	< N	ſobi	lity	No < G	de 22000
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I-EQUA	1	400 MT	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	800 MT
	2	400 MT	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	1800 MT
	3	800 MT	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	1800 MT
Abbreviatio	211			Det	finit	ion														
Goal	511			Ma	xim	ize I	DDC	G O	vera	11 Ef	ffect	iven	ess							
Mobility				Shi	рM	ove	mer	ıt												
Fuel				Shi	pFι	iel C	Capa	city	(Ra	inge	)									
400 MT				Fue	l Tł	iresł	ıold	(Lo	w)	-										
800 MT				Fue	el Ba	seli	ne (	Mid	ldle)	)										
1800 MT				Fue	1 G	cal (	Hio	h)												

# Table 20 - VOP Questionnaire Node 31000

																			No	de 31000
		Compar	e the	e rel	ative	e IN	IPO	RTA	ANC	Εw	ith	resp	ect t	to: D	)ete	ct <	Sur	vive	< 0	JOAL
1 = EQU	JAL	3 = MODEH	RAT	Έ	5 = 5	STR	.ON	G	7 = `	VEF	RY S	STR	ON	G 9	P = I	EXT	RE	ME		
	1	+ 5 (Bad)	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Baseline
	2	+ 5 (Bad)	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	- 5 (Good)
	3	Baseline	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	- 5 (Good)
Abbrevia	ation			Det	finiti	on														
Goal				Ma	ximi	ze I	DDC	O ť	veral	1 Ef	fect	iven	ess							
Survive				Sur	viva	bili	ty													
Detect				Def	tectio	on S	ign	atur	e											
+ 5 (Bad	)			Def	tectio	on S	ign	atur	e Th	resh	old	(m <sup>2</sup>	)							
Baseline				Def	tectio	on S	ign	atur	e Ba	seliı	ne (I	Mid	dle)							
E (Caa	<b>A</b> )			Def	ectio	on S	lion	ature	Go	al (1	m2)									

	Compare	the	relati	vel	IME	OR	דעד	NCE	wi	th re	sne	et to	· Da	ma	7 <b>0</b> <	Sur	vive	Nod $< 0$	le 32000
	compare	ine .	Clut			011					ope			ina	50 .				JOILE
1 = EQUAL 3	= MODER	AT	E 5	= S	TR	ON	3 7	/ = <b>\</b>	/ER	Y S	TRO	ONC	39	= E	XTI	REN	ЛE		
1	195 Hits	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	210 Hits
2	195 Hits	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	225 Hits
3	210 Hits	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	225 Hits
Abbreviation			Defi	nitio	on														
Goal			Maxi	imiz	ze D	DG	Ov	eral	l Ef	fecti	iven	ess							
Survive			Surv	ival	oilit	y													
Damage			Dam	age	To	lera	nce (	(Poi	nts)										
195 Hits			Thre	sho	ld E	)am	age	Tole	eran	ce(L	low)	)							
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		_	~ •	-			· •		/ 7 7	· • • •									

Table 21 - VOP Questionnaire Node 32000

## 3.4 Calculating OMOE Weights (Step 8-11)

#### 3.4.1 Questionnaire Data Interpretation

The questionnaire is based on a relative scale from 9 to 1, with 1 as the neutral point. All the data collected was normalized to have 0 as the neutral point for calculation purposes. For example an answer of strength 9 on the right side was normalized to 8, an answer of strength 9 on the left side was normalized to -8, and a neutral strength 1 was normalized to 0. This was done so that when taking averages and standard deviations, regular mathematical equations could be used. Once the average was found it was converted back to the 9 to 1 strength scale. Appendix C – Questionnaire Data provides the data ranges and standard deviations of the questionnaire data.

#### 3.4.2 OMOE Generator and Expert Choice

The hierarchy structure of this experiment was built in EXPERT CHOICE (EC). EXPERT CHOICE is a decision making program based on the principles of the Analytic Hierarchy Process. It allows the user to structure a decision into objectives and alternatives using a hierarchy tree (like the one in Section 3.2.4). EC uses pairwise comparison to rank the alternatives of an objective by weight. EC also has the capability to perform sensitivity analysis.

The 8 sets of VOP questionnaire data collected (one for each expert and an average) were entered into the questionnaire section of EC. This VOP data is shown in Table 22 and Table 23. MOP weights were calculated for each expert using the AHP. These MOP weights are listed in

Table 24. The questionnaire average was found by using the average questionnaire answers as an 8<sup>th</sup> set of inputs to calculate weights in EC.

	N1	N2	N3	N10001	N10002	N10003	N20000	N30000	N21001	N21002	N21003
Expert1	-2	-4	-3	7	9	5	7	-5	4	9	4
Expert2	-5	-7	3	7	9	3	1	-5	3	5	1
Expert3	-7	-6	-2	7	9	7	4	3	3	5	2
Expert4	-8	1	5	4	9	4	1	4	1	3	1
Expert5	-5	-7	-3	5	7	5	-5	-3	3	5	3
Expert6	-7	-3	3	5	9	5	1	-5	5	9	5
Expert7	-6	3	2	3	7	5	3	-3	2	4	3
Ave.	-6	-4	2	5	8	5	2	-3	3	6	3

Table 22 – VOPs from Questionnaires Part 1

Table 23 – VOPs from Questionnaires Part 2

	N22001	N22002	N22003	N31001	N31002	N31003	N32001	N32002	N32003
Expert1	9	9	9	5	9	3	7	5	2
Expert2	1	1	1	7	9	5	7	7	1
Expert3	3	7	4	1	3	1	1	3	1
Expert4	1	1	1	2	6	2	5	8	5
Expert5	3	5	3	5	7	5	3	5	3
Expert6	5	9	5	3	6	3	1	4	1
Expert7	4	7	4	6	9	6	4	7	5
Ave.	4	6	4	4	7	4	4	6	3

### Table 24 – MOP WEIGHTS from Questionnaires

	Weapons	Fuel	Damage	Detection	Speed	Consistency
Expert 1	.558	.280	.021	.100	.041	0.14
Expert 2	.739	.045	.029	.141	.046	0.15
Expert 3	.760	.115	.072	.024	.029	0.13
Expert 4	.500	.036	.341	.086	.037	0.05
Expert 5	.731	.031	.021	.060	.157	0.10
Expert 6	.669	.044	.041	.202	.044	0.05
Expert 7	.360	.093	.129	.388	.030	0.33
Mean Weights	.617	.092	.093	.143	.055	
(Excluding Ques. Ave.)						
Standard Deviation	.108	.113	.042	.082	.139	
Questionnaire Ave.	.701	.071	.048	.145	.035	0.06

## 3.5 Validation (Step 12-14)

To validate the OMOE method and prove the hypothesis, 16 ships are ranked based on the OMOE functions developed from expert opinion, and compared to the ranking of the same 16 ships using HARPOON directly. A design of experiments (DOE) was used to choose 16 representative ship designs from the 243 possible in the design space. The 16 designs are ranked

by effectiveness (OMOE) from the OMOE functions developed using the questionnaire average method and the mean OMOE method.

#### **3.5.1** Design of Experiment (DOE)

With 5 ship characteristics and 3 possible values for each, there are 243 possible combinations of ship designs ( $3^5$ ). Because of time and resource constraints, this was too many to assess directly in the simulation. It was manageable for only 20 or less ship designs to be evaluated. A design of experiments (DOE) was used to choose the designs. To ensure a sufficient representation of the design space, a  $\frac{1}{2}$  fraction factorial DOE method was used to select the combinations of characteristics to use for the representative designs.

A factorial experiment is useful when several characteristics are of interest in a design. A full factorial experiment is a complete replication of the entire design space, all possible design combinations at all levels of the characteristics. The baseline level of each characteristic was omitted (ie. only threshold and goal characteristics were considered) to reduce the number of designs and limit the experiment time. This results in a  $2^5$  (32 designs) full factorial experiment. In a  $2^5$  experiment there are 31 degrees of freedom, 5 of which correspond to main effects, 10 correspond to two-factor interactions and 16 correspond to higher order interactions (three-factor interactions or more). A main effect is a change in response due to a change in level of a factor. Factor interactions occur when the change in response between two levels of one factor is not the same at all levels of the other factors. For example there is a response difference of 2 between the high and low levels of factor A while factor B is at its low level and a response difference of 3 between the high and low levels of factor A while factor B is at its high level). The higher order interactions are of no value in this experiment. Therefore a  $\frac{1}{2}$  fraction factorial experiment can be used. [18]

A  $\frac{1}{2}$  fraction factorial experiment uses half the designs from a full factorial experiment,  $2^{5-1}$  (16 designs). Construction of a  $2^{5-1}$  experiment starts from the full factorial experiment with the last (fifth) characteristic column removed. This is called the basic experiment, shown in Table 25. If a characteristic has a threshold value it receives a "-1". If a characteristic has a goal value it receives a "1". The value of the fifth characteristic is found by taking the product of the first 4 characteristics. If the product is positive, the  $5^{th}$  characteristic is given the goal value "1". If the product is negative, the  $5^{th}$  characteristic is given the threshold value "-1". All combinations with the fifth characteristic are not considered. This is a proven method in statistical design of

experiments to provide a full representation of the design space. Table 26 lists the characteristics and their values for the final 16 ship designs. A "-1" indicates that the design has a threshold value for the characteristic and a "1" indicates a goal value.

	1 4010 20		51511 01 2	
Ship #	Weapons	Fuel	Damage	Detection
1	-1	-1	-1	-1
2	1	-1	-1	-1
3	-1	1	-1	-1
4	1	1	-1	-1
5	-1	-1	1	-1
6	1	-1	1	-1
7	-1	1	1	-1
8	1	1	1	-1
9	-1	-1	-1	1
10	1	-1	-1	1
11	-1	1	-1	1
12	1	1	-1	1
13	-1	-1	1	1
14	1	-1	1	1
15	-1	1	1	1
16	1	1	1	1

Table 25 – Basic Design of  $2^{5-1}$ 

Table 26 _	Shin	Decion	Characteristic	Values	for $\frac{1}{2}$	Fract	ion	Factorial	Decion
1a01020 –	SIIIP	DUSIGI		values	101 /2	2 1 1 4 0	IUII .	racional	DUSIGI

_Ship #_	Weapons	Fuel	Damage	Detection	Speed
1	-1	-1	-1	-1	1
2	1	-1	-1	-1	-1
3	-1	1	-1	-1	-1
4	1	1	-1	-1	1
5	-1	-1	1	-1	-1
6	1	-1	1	-1	1
7	-1	1	1	-1	1
8	1	1	1	-1	-1
9	-1	-1	-1	1	-1
10	1	-1	-1	1	1
11	-1	1	-1	1	1
12	1	1	-1	1	-1
13	-1	-1	1	1	1
14	1	-1	1	1	-1
15	-1	1	1	1	-1
16	1	1	1	1	1

#### 3.5.2 OMOE Calculation for Representative Ships Based on Expert Opinion

OMOEs are calculated for each of the 16 ships using weights calculated individually for each expert, mean weights calculated from the individual expert weights, and weights calculated using the average preferences from the questionnaires, Table 24. OMOEs are then calculated using Equation 1. When calculating OMOEs, goal characteristics are given a value of performance

(VOP) of 1.0, and threshold characteristics are given a VOP of zero. A ship having all threshold values has an OMOE of 0.0, and a ship having all goal values has an OMOE of 1.0. Ships having combinations of goal and threshold characteristics have an OMOE between 0.0 and 1.0. For example, the Questionnaire Average OMOE for Ship Design 1 is:

$$(0 * 0.701) + (0 * 0.071) + (0 * 0.048) + (0 * 0.145) + (1 * 0.035) = 0.035$$

Next, the 16 ship designs are ranked based on their OMOE. In all there are 9 sets of ranks, 1 for each expert, 1 for the average of the questionnaires, and 1 for the mean weights from Expert Choice. OMOEs for each design calculated using the average of the questionnaires and using the mean weights are listed in Table 27 with their resulting ranks.

Ship #	OMOE from Questionnaire Average	Average Rank	OMOE from Mean Weights	Mean Rank
1	0.035	16	0.055	16
2	0.701	8	0.617	8
3	0.071	14	0.092	15
4	0.807	6	0.764	7
5	0.048	15	0.093	14
6	0.784	7	0.765	6
7	0.154	12	0.240	12
8	0.820	5	0.802	5
9	0.145	13	0.143	13
10	0.881	4	0.815	4
11	0.251	10	0.290	11
12	0.917	2	0.852	3
13	0.228	11	0.291	10
14	0.894	3	0.853	2
15	0.264	9	0.328	9
16	1.000	1	1.000	1

Table 27 – Ship Design Ranking by OMOE and Expert Opinion

#### 3.5.3 Ship Ranking from HARPOON

Next, the 16 ships are ranked directly using HARPOON and the Sanctions Scenario. The ships are ranked based on several metrics. A ship design receives 1 point for each victory condition completed. If a victory condition is only partially completed a fraction of a point is given. The point fractions for partial completions are summarized later in this section. Since there are 10 possible patrol boats to sink, for the patrol boat victory condition extra points are given if more than 7 (required to satisfy the victory condition) patrol boats are sunk. The total score for each ship design equals the sum of the points for the 3 victory conditions. Table 28

shows the HARPOON results for each ship design. Victory Condition 1 is to completely destroy 2 enemy destroyers, Victory Condition 2 is to destroy 7 patrol boats, and Victory Condition 3 is to prevent the loss of any US ships. For the first victory condition, 1 point is given if both enemy DDGs are destroyed, <sup>1</sup>/<sub>2</sub> point for one, and 0 points for zero enemy DDGs. In the second victory condition the number of patrol boats destroyed is divided by the required number (7) to calculate the points given. For the third victory condition 1 point is given if all US ships remained in tact and undamaged. For every ship sunken, 0.2 points are subtracted from 1. If a ship is damaged but not sunk, the percent damage is multiplied times 0.2 and subtracted from the total. The highest possible score is 3.43 points.

Ship #	Victory Condition 1	Victory Condition 2	Victory Condition 3	Total
1	0.00	0.43	0.40	0.83
2	1.00	0.86	0.72	2.58
3	0.50	1.00	0.67	2.17
4	0.50	1.43	0.81	2.74
5	0.50	1.00	0.80	2.30
6	1.00	0.86	0.75	2.61
7	0.50	1.14	0.80	2.44
8	1.00	1.00	0.76	2.76
9	0.00	0.86	0.68	1.54
10	1.00	1.14	0.69	2.83
11	1.00	1.14	0.40	2.54
12	1.00	1.14	0.75	2.89
13	0.50	1.43	0.55	2.47
14	1.00	1.00	0.82	2.82
15	0.50	1.29	0.76	2.54
16	1.00	1.43	0.73	3.16

Table 28 – HARPOON Direct Comparison Results

#### **3.5.4 OMOE Results and Conclusions**

Finally, the results from Table 28 are ranked by total points from highest to lowest, and compared to the predicted rankings from the Analytical Hierarchy Process and Overall Measure of Effectiveness calculations, Table 27. Table 29 shows the ship rankings using the different methods and the difference compared to the actual simulation rank. Figure 22 and Figure 23 graphically show the difference between the simulation rank and the rankings from the other methods. A horizontal line means there is no difference in rank for that ship.

Table 29, Figure 22, and Figure 23 show that the OMOE calculation method using the questionnaire averages most closely matches the direct simulation results. The OMOE mean rank method also provides a good match. Neither method provides a perfect match. In

conclusion, the questionnaire average OMOE function provides a reasonable prediction of direct simulation results, proving the hypothesis that it is an acceptable tool for ranking design alternatives in concept exploration ship optimization.

Ship #	Simulation Rank	OMOE Mean Rank	Sim Mean Difference	Questionnaire Average Rank	Sim. – Ave. Difference
16	1	1	0	1	0
12	2	3	1	2	0
10	3	4	1	4	1
14	4	2	2	3	1
8	5	5	0	5	0
4	6	7	1	6	0
6	7	6	1	7	0
2	8	8	0	8	0
15	9	9	0	9	0
11	10	11	1	10	0
13	11	10	1	11	0
7	12	12	0	12	0
5	13	14	1	15	2
3	14	15	1	14	0
9	15	13	2	13	2
1	16	16	0	16	0
		Total Diff.	12	Total Diff.	6

Table 29 - Rank and Rank Differences

#### **Design Rank Comparison**



Figure 22 – Simulation Rank vs. OMOE Mean Rank



Figure 23 – Simulation Rank vs. Questionnaire Average Rank

## CHAPTER 4 TOOLS FOR SHIP MULTI-DISCIPLINARY OPTIMIZATION

This chapter describes the methods, software, and software features used to search design space for non-dominated designs in concept exploration for a naval surface combatant. In early stage design, the design space (i.e., the possible combinations of the various design variables, both continuous and discrete) is typically very large. This is a fully multidisciplinary problem that typically must employ an array of higher fidelity, discipline-specific computer codes to perform the necessary assessment and analysis required for the optimization. Multidisciplinary in a ship design context means different disciplines such as hull form, structures, hydrodynamics, weights, stability, power, propulsion, etc. are required for analyses. Evaluating the performance of designs for even a small portion of this large design space can become prohibitive if these analyses are computationally expensive. Because of this, high-fidelity codes are typically not used in the early stages of the design process. As a result, major decisions regarding the basic elements of the design are already made before high-fidelity codes begin to be used. An important objective of this thesis is to identify methodologies that will enable high-fidelity codes to be used earlier in the design process. Response Surface Modeling and Design of Experiments techniques are used to generate a response surface approximation for the results or response of more complex and computer-intensive engineering models.

## 4.1 Ship Synthesis Model

#### 4.1.1 Overview

As shown in Figure 24, the ship synthesis model is used to balance and assess designs selected by the multi-objective genetic optimizer (MOGO) in our Concept Exploration process. A flow chart for the synthesis model used in the case study for this thesis, and its interface with the MOGO in Model Center (MC) is shown in Figure 25. The case study is for an Advanced Logistics Delivery Ship (ALDV) described in Chapter 5. The synthesis model assesses the balance of the ship in terms of weight, displacement, volume, area and power. Values of Performance (VOPs), an Overall Measure of Effectiveness (OMOE), Overall Measure of Risk (OMOR), and life cycle cost are also calculated by the synthesis model. These characteristics determine a ship's feasibility and superiority or dominance relative to other ships in the design

space. Modules in the baseline synthesis model were developed using simple parametric equations written in FORTRAN, and are integrated and executed in Model Center. This thesis investigates an improvement to this model using a response surface model to calculate structural weight in the ALDV case study. The structural weight RSM uses MAESTRO (described in Section 4.5) to assess adequacy and calculate the bare hull structural weight of adequate designs.



Figure 24 – Concept Exploration Process

## 4.1.2 Ship Synthesis Modules (for ALDV)

- Input Module Inputs, decodes and processes the design variable vector and other design parameters that are constant for all designs. Provides this input to the other modules.
- ALDV Hull Form Module Calculates hull form principal characteristics and supplies them to other modules. It scales the "parent" (baseline) characteristics to match the specified displacement and hull form type. It calculates the scaling factor, scales the parent hull characteristics to the daughter hull, adds appendage volumes, and calculates daughter hull characteristics including lengths, areas, and volumes.
- Combat Systems Module Retrieves combat systems data from the Combat Systems Data Base as specified by the combat system design variables. Calculates payload SWBS weights, VCGs, areas and electric power requirements and assesses performance for the total combat system.
- Propulsion Module Retrieves propulsion system data from the Propulsion System Data Base as specified by the propulsion system design variable. Database generated by modeling similar power plants in ASSET using single baseline design.



Figure 25 – Ship Synthesis Model

- Space Available Module Calculates available volume and area, minimum depth required at amidships, cubic number, CN, and the height and volume of the machinery box.
- Electric Power Module Calculates maximum functional electric load with margins (KW<sub>MFLM</sub>), required generator power (KW<sub>GREQ</sub>), required average 24-hour electric power (KW<sub>24AVG</sub>), and required auxiliary machinery room volume (V<sub>AUX</sub>). It estimates system power requirements using known values and parametric equations, sums and applies margins, assumes one ship service generator is unavailable, uses a power factor of 0.9, and uses the electric load analysis method from DDS 310-1.
- Resistance Module Calculates hull resistance, sustained speed, and required shaft horsepower at endurance speed and sprint speed. The resistance is calculated using the Holtrop-Mennen regression-based method. It takes the input data of the individual side and center hulls and calculates the resistance for each. It adds the individual hull resistances with a 10% addition for hull interference. The module then calculates the effective bare hull power, appendage drag, and air drag. The propulsive coefficient is approximated. The sustained speed is calculated based on total BHP available with a 25% margin.

- Weight and Stability Module Calculates single digit SWBS weights, total weight, fuel weight, and GM/B ratio using parametric equations and known weights. The module uses a combination of known weights and parametric equations to calculate the SWBS weights. KG is calculated from single digit weights and VCGs, estimated using parametric equations. The KM is calculated using geosim scaling of the parent hull KM.
- Tankage Module Calculates tankage volume requirements based on required sprint and endurance range, and parametric equations. It uses a number of input variables including fluid specific volumes, ballast type, transmission efficiency, fuel weight, fuel consumption at sprint and endurance speeds, average generator engine fuel consumption, average electric load, sprint and endurance speed, total propulsion engine BHP, potable water weight, and lube oil weight. It uses parametric equations for various tank volumes and design data sheet DDS-200-1 for endurance fuel calculations. It outputs total required tankage volume, fuel tank volume, sprint range and endurance range.
- Space Required Module Calculates deckhouse arrangeable area required and available, and total ship area required and available using parametric equations. Inputs include number and type of personnel, cubic number, known area requirements, hull and deckhouse volumes, large object volumes, average deck height, beam, and stores duration.
- Feasibility Module Assesses the overall design feasibility of the ASC. It compares available to required characteristics including total arrangeable ship area, deckhouse area, sustained speed, electrical plant power, minimum and maximum GM/B ratios, endurance range, sprint range, and transom beam.
- Risk Module Calculates a quantitative Overall Measure of Risk (OMOR) for a specific design taking into account performance risk, cost risk, and schedule risk.
- Cost Module Calculates cost using the Naval Surface Warfare Center Carderock Small Fast Ship Cost Calculator. This calculator uses parametric equations for construction costs based on single digit (SWBS) weights, hull type, hull and deckhouse material, propulsion power type, propulsor type, and propulsion power. Fuel and personnel costs are added to calculate life cycle cost. It normalizes costs to the base year (2003) to find discounted life cycle cost. Other life cycle costs are assumed to be the same for all designs. It assumes a service life of 30 years with 3000 steaming hours underway per year. All recurring costs are excluded. The calculator assumes historical costs of modern surface combatants.
- Effectiveness Module Calculates Values of Performance (VOPs) for sprint range, endurance range, provisions duration, sustained speed, draft, personnel, and RCS using their VOP functions. Inputs combat system VOPs from the combat system module. Calculates the OMOE using these VOPs and their associated weights. [19,20]

The weight module uses fuel as a slack variable: fuel weight = total weight – weight of everything else. Ship balancing of weight is therefore obtained without iteration. A design is

considered feasible if feasibility requirements assessed in the feasibility module and performance thresholds are satisfied simultaneously. If a design is feasible, the synthesis model continues to calculate cost, effectiveness and risk. These characteristics are the objective attributes for a Multi-Objective Genetic Optimization (MOGO) that is used to search the design space and identify non-dominated designs as described in section 1.1.1.

The MOGO is run in Model Center using a Darwin optimization plug-in (described in section 4.3), Figure 24 and Figure 25. The three objective attributes for the ALDV optimization are average follow ship acquisition cost, risk (technology performance, cost, and schedule risk), and overall effectiveness (OMOE). In the first design generation, the optimizer defines 200 balanced ships at random using the MC ship synthesis model to balance each design and quantify feasibility, cost, effectiveness, and risk. Each of the designs in this generation is ranked according to its fitness or dominance in the three objectives compared to the other designs in the population. When infeasibility or niching (bunching-up) in the design space occurs, penalties are assigned to the corresponding design. The second design generation of the optimization process is randomly selected from the first design generation, with higher probabilities of selection assigned to higher-fitness designs. Twenty-five percent of this second design generation is selected for crossover or swapping of design variable values. An even smaller percentage of randomly selected design variable values are then mutated or replaced with a new value at random. This process is repeated up to 300 times, and as each generation of ship designs is selected, the ship designs spread out and converge on the non-dominated frontier. Each ship design on the non-dominated frontier provides the highest effectiveness for a given cost and risk relative to other ship designs in the design space. The "best" design is determined by the customer's preference in terms of effectiveness, cost, and risk. [19,20]

#### 4.1.3 Interchanging Modules

Since the synthesis model is separated into different modules it is possible to replace certain modules or equations within a module with discipline-specific codes and Response Surface Models (RSM), described in Section 4.6. In this thesis a response surface model is used as a surrogate approximation for a computationally intensive mathematical analysis (MAESTRO). It is created using a set of data with inputs and their responses supplied from using a DOE. This moves the ship synthesis model from simple parametric equations (rough estimates) to more realistic estimates. Examples of discipline specific codes include MAESTRO for estimating

minimum adequate structural weight and SWAN for estimating sea keeping performance. Model Center has the ability to incorporate wrapped codes, integrating input and output variables of the codes with other modules. In the ALDV case study MAESTRO is run in Model Center prior to the optimization. Data is collected using a DOE to build a RSM which is added to the synthesis model to replace the simple parametric structural weight equation. This greatly reduces run time in the ship synthesis model assessment and analysis.



Figure 26 – Model Center Environment

## 4.2 Model Center Overview

The multi-objective optimization, design of experiments and response surface modeling are implemented in Model Center (MC). Model Center is a computer-based design integration environment that includes tools for linking design model components, wrapping analysis programs and running them in an automated fashion, visualizing the design space, performing trade studies and optimization, developing parametric models of the design space, and archiving results from multiple studies. By automating and simplifying these tasks, Model Center makes the design process more efficient, saves engineering time, and reduces error in the design process. Figure 26 is an example of the Model Center environment.

## 4.3 Darwin Optimizer

Darwin is a genetic algorithm-based trade study tool designed specifically for solving "real world" engineering optimization problems. Genetic Algorithms (GAs) are probability-based algorithms that utilize processes analogous to natural selection to search for the best designs. Darwin is capable of solving design problems with both discrete and continuously valued design variables, and any number of constraints. Darwin is also able to perform Multi-Objective Genetic Optimization as described in Section 4.1.2. The algorithm is well suited for discontinuous, noisy, and/or multi-modal design spaces.

er neip							
bjective Definition							
Objective			Value			ļ.	Goal
ASC.Cost.LCC						0.0000000	minimize 🗸
ASC.Risk.OMOR						0.0000000	minimize 🔽
ASC.Effectiveness.OMOE						0.0000000	ma×imize 🔽
Constraint		Value	Lo	wer Bound	aqU	er Bound	
ASC.Feasibility.ERRORTA			0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORDA			0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORVs			0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORKW			0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORGMMIN			0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORGMMA)	e		0.0000000		0.0		1.0E+30
ASC.Feasibility.ERRORD10			0.0000000		0.0		1.0E+30
esign Variables							
l <b>esign Variables</b> Variable	Туре	Value	Start Value	Lower E	3ound Upp	er Bound E	Edit
l <b>esign Variables</b> Variable ASC.Input.Disp_in	Type	Value	Start Value 2800.0	Lower E	3ound Upp 2000.0	er Bound E 4000.0	Edit
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Variable ASC.Input.Disp_in ASC.Input.VD_in ASC.Input.CHMAT_in ASC.Input.CDHMAT_in ASC.Input.NCPS_in ASC.Input.NCPS_in ASC.Input.NDEGAUS_in	Type continuous continuous discrete discrete discrete discrete discrete	Value	Start Value 2800.0 1800.0 2 1 0 4 0	Lower E 2800.0 1800.0 2 2 1 2 0 4 0 0 0	3ound Upp 2000.0 1000.0	er Bound E 4000.0 4000.0 0 0 0 0 0 0 0 0 0 0 0 0 0	Edit
Variables ASC.Input.Disp_in ASC.Input.VD_in ASC.Input.CHMAT_in ASC.Input.CDHMAT_in ASC.Input.NCPS_in ASC.Input.NCPS_in ASC.Input.NDEGAUS_in ASC.Input.CAUTO_in	Type continuous discrete discrete discrete discrete discrete continuous	Value	Start Value 2800.0 1800.0 2 1 0 4 0 0.5	Lower E 2800.0 1800.0 2 1 1 0 4 0 0 0 0 0 0 0 0 5 0.5	3ound Upp 2000.0 1000.0 0.5	er Bound E 4000.0 4000.0 0 0 0 0 0 0 0 0 0 0 0 0 0	cdit
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Variable ASC.Input.Disp_in ASC.Input.Disp_in ASC.Input.CHMAT_in ASC.Input.CDHMAT_in ASC.Input.NCPS_in ASC.Input.NCPS_in ASC.Input.NDEGAUS_in ASC.Input.MDEGAUS_in ASC.Input.MCM_in Single Analysis	Type continuous discrete discrete discrete discrete discrete continuous discrete	Value	Start Value 2800.0 1800.0 2 1 0 4 0 0.5 2	Lower E 2800.0 1800.0 2 2 1 2 0 4 0 0 0 0 0 0 0 0 5 2 1	3ound Upp 2000.0 1000.0 0.5	er Bound [ 4000.0 4000.0 0 1.0 Create Super-	Edit
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Variable Variable ASC.Input.Disp_in ASC.Input.CDIn ASC.Input.CDIMAT_in ASC.Input.CDHMAT_in ASC.Input.NCPS_in ASC.Input.NCPS_in ASC.Input.NDEGAUS_in ASC.Input.MCM_in Single Analysis Objective(s):	Type continuous discrete discrete discrete discrete discrete continuous discrete	Value	Start Value 2800.0 1800.0 2 1 0 4 0 0.5 2 2	Lower E 2800.0 1800.0 2 1 0 0 0 0 0 0 0 0 0 0 0 0 0	3ound Upp 2000.0 1000.0 0.5	er Bound E 4000.0 4000.0 1.0 Create Super- Elapsed Time:	Edit

Figure 27 – Darwin Graphical User Interface

Darwin features an intuitive graphical user interface, shown in Figure 27, which allows the user to quickly define the optimization problem by dragging and dropping variables from Model Center's component tree, view optimization results in real time, and configure optimizer parameters (shown in Figure 28). [4]

불 Optimization Parameter	rs		X					
Optimization Output								
	Automatically Select	Optimization Parameters						
General								
Population Size	54 🕏	🗹 Us	e Memory?					
Selection Scheme	Multiple Elitist	~						
Preserved Designs	16 💭							
Seed Value	0	(Random = 0)						
Convergence	Convergence							
Maximum Generation	ns 100 荣							
Convergence Metho	d Generations w	//o Improvement 🛛 💌	20 🚭					
Minimum % Change	Minimum % Change of Pareto Population Required for Improvement							
Genetic Operators	Genetic Operators							
c	liscrete	continuous						
Crossover Probablil	ty 1 🕏	Crossover Probability	1 🕏					
Mutation Probabili	ty 0.05 🕏	Mutation Probability						
Constraint Tolerar	Constraint Tolerance							
Max Constraint Viol	ation 0.05 🚭		0.1 🖨					
Percent Penalty	0.5 荣							
Cancel	Set Defaults	[	ок					

Figure 28 – Darwin Optimization Parameters Window

## 4.4 Design of Experiments Tool

The Design of Experiments (DOE) Tool in Model Center simplifies and structures the purposeful changing of inputs to a model to efficiently and effectively observe the corresponding changes in outputs (response variables). This is necessary to the building of a Response Surface

Model of the parent (more complex) model as will be discussed in Section 4.6. A set of valid values for each input variable constitutes a design point. The tool is used to efficiently select design points, and collect the responses of the model to these design points. Tools are provided to graphically set up and conduct this experiment. Figure 29and Figure 30 show the DOE tool's graphical user interface. [4]



Figure 29 - DOE Graphical User Interface in Model Center

To perform a DOE, a set of input and response variables are selected with upper and lower boundary values for the input variables. An experiment design is a pre-defined set of design points selected using a DOE algorithm. Some DOE algorithms are selected to test a design for robustness (extent to which designs in the design space are feasible), other DOE algorithms are selected to quantify design variable's effect on each other, and other DOE algorithms are selected to screen a large number of design variables to isolate the most important ones. The following DOE algorithms are available in the Model Center DOE tool:

- Half Fractional Factorial
- Eighth Fractional Factorial
- Sixteenth Fractional Factorial

- Foldover
- Plackett-Burman
- Parameter Scan
- Full Factorial
- Latin-Hypercube
- Central Composite
- Face Centered Central Composite
- Box-Behnken

The half fractional factorial, eight fractional factorial, sixteenth fractional factorial, foldover, and Plackett-Burman designs are all screening experiments. Screening experiments are used as a pre-process to identify which variables are most active. These are most useful when many variables are present and therefore many design points.

The parameter scan and full factorial designs sample the whole design space. The parameter scan only allows two levels (high and low) of each variable to be tested while the full factorial allows two or more levels of each variable to be tested.

Phoenix Integration suggests the Latin-Hypercube design for our application since it takes a random sample of the design space. The Latin-Hypercube is similar to full factorial except that the internal space is divided into segments to achieve a more thorough investigation of the design space. The Latin-Hypercube allows the user to specify how many designs to sample within the design space. The specified number of designs determines how many segments a variable is broken into and how many random combinations of variables and segments are chosen.

When the DOE tool is run, it repeatedly sets the values for the design variables and then calculates each of the response variables. At each iteration, it stores the values in a Data Explorer, shown in Figure 31. The Data Explorer displays the inputs and outputs for each design point in a table which can be exported to Excel if desired. It also has the capability to generate graphs of responses vs. desired inputs, carpet and surface plots to display a response vs. two variables, or a main effects plot. The Main Effects Plot displays the sensitivity of the input variable to the response. A main effect is the difference between the average output of an input variable's upper and lower values. The input variable with the largest main effect has the greatest influence on the response variable.

Desir	in Variables				
C Colig	i i valiables				
+2	Name	Valu	es		
	Model.MaestroWrapper.Depth	Low	9.5	High: 11.5	*
	Model.MaestroWrapper.Beam	Low	9	High: 11	*
	Model.MaestroWrapper.Length	Low	133.5	High: 178.5	*
	Model.MaestroWrapper.HullSep	Low	10	High: 14	*
	Model.MaestroWrapper.Ub	Low	.6	High: .65	4
	Design: Latin-Hypercube	~	Num leve	els: 100 🛋 100 ru	ins
Resp	Design: Latin-Hypercube	~	Num leve	els: 100 🔹 100 ru	ins
Resp 2014	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight	V	Num leve	els: 100 🛫 100 ru	uns
Resp 2014	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight	~	Num leve	els: 100 🖍 100 ru	uns
Resp ==== #==	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight	~	Num leve	els: 100 🔹 100 ru	ıns
Resp #* *	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight	~	Num leve	els: 100 🔹 100 ru	ins
Resp #* ** **	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight	<b>V</b>	Num leve	els: 100 🔹 100 ru	uns
Resp #* ** **	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight		Num leve	els: 100 🗶 100 ru	INS
Resp #* ?* ?*	Design: Latin-Hypercube onses Model.MaestroWrapper.Weight		Num leve	els: 100 🔹 100 ru	Ins

Figure 30 – DOE Graphical User Interface

🗖 Data Explorer : 4/6/2005, 15:10:52										
Data Edit Page										
1 - Table Legend: input v	alid output	invalid (	output	modified value	Je					
\$17.00 \$17.75										
1.34e+007 1.34e+007	1	2	3	4	_ ^					
51/2 51/2 design variable (Model.MaestroWrapper.Depth)	9.77545	10.5343	10.1875	10.1272	9.5					
1.40235e+041 1.40235e+ design variable (Model.MaestroWrapper.Beam)	9.2768	10.2249	10.9017	9.87644	9.5					
\$17.00 \$17.75 design variable (Model.MaestroWrapper.Length)	138.898	172.55	138.448	143.886	13					
51/2 51/2 design variable (Model.MaestroWrapper.HullSep	11.2647	11.9072	13.42	13.6978	10.					
15.23 15.23 design variable (Model.MaestroWrapper.Cb)	0.64024	0.62357	0.60376	0.61334	0.E					
2 - Weight response (Model.MaestroWrapper.Weight)	1.6022e+006	2.1204e+006	1.8443e+006	1.8088e+006	1.E					
Model.MaestroWrapper.modnum	2	2	2	2	2					
Model.MaestroWrapper.subnum	3	3	3	3	3					
Model.MaestroWrapper.cycles	1	1	1	1	1					
Model.MaestroWrapper.Depth	9.77545	10.5343	10.1875	10.1272	9.5					
Model.MaestroWrapper.Beam	9.2768	10.2249	10.9017	9.87644	9.5					
Model.MaestroWrapper.Length	138.898	172.55	138.448	143.886	13					
Model.MaestroWrapper.HullSep	11.2647	11.9072	13.42	13.6978	10.					
Model.MaestroWrapper.Cb	0.64024	0.62357	0.60376	0.61334	0.E =					
Model.MaestroWrapper.Weight	1.6022e+006	2.1204e+006	1.8443e+006	1.8088e+006	1.E					
Add Page/Chart					>					
For Help, press F1										

Figure 31 – Model Center's Data Explorer

## 4.5 MAESTRO [22]

The baseline ALDV ship synthesis model uses a very simple equation to estimate structural weight, sensitive only to displacement. To provide a more precise and robust estimate of structural weight sensitive to additional important global design variables, a response surface model for sufficient structural weight was developed using MAESTRO. A structural weight minimization was performed for each set of data collected to develop the RSM, a disciplinary optimization within a global ship optimization.

MAESTRO is a finite element analysis program for rationally-based analysis, evaluation, and structural optimization of ships. MAESTRO produces an optimum design based on any designer-specified measure of merit such as weight, cost, or any combination of these. The primary purpose of MAESTRO is for design, but it can be used to analyze an existing structure (or proposed design) using just the analysis and evaluation portions of the program and not the optimization portion. The program's underlying theory and a detailed description of its principal features are given in Hughes' *Ship Structural Design* [21], which constitutes the Theoretical Manual for the program.

The MAESTRO method of design is referred to as "rationally-based" because it includes, in each design cycle, all of the following:

- For the complete structure, a rapid, "design-oriented" finite element analysis which uses elements that are suited for preliminary design, as distinct from general purpose finite element programs which are more suited for analysis of details.
- An explicit evaluation of all limit states (ultimate strength and serviceability), at both levels (member level and "module", or multi-member level), for all load cases, thus establishing which limit states are currently critical (in the current design cycle) for each member, and by how much.
- Formulation of the linearized limit state equations, which utilize partial safety factors in order to achieve a consistent degree of structural reliability.
- Multi-objective optimization based on any combination of individual measures of merit (linear or nonlinear) such as structural weight, material cost, fabrication cost, and any other desired performance factors that are functions of the member size variables (plate thicknesses, web heights, flange breadths, etc.). Besides the limit state equations, the optimization can accommodate any number of designer-specified constraints, such as those relating to fabrication aspects or operational requirements.

The MAESTRO Optimization module uses sequential linear programming to redesign the structure. This optimization eliminates any structural inadequacies while achieving an optimum

design based on user specified objectives (goals), which may be weight or cost or both of these, in a weighted non-dimensional combination. In its optimization mode MAESTRO iterates the structure through design cycles in which it revises scantlings, reruns the finite element analysis, and reevaluates the structural adequacy of each member for all failure modes and load cases. This iterative process continues until the structure has converged to an optimum design that has no structural inadequacies. [22]

#### 4.6 Response Surface Model (RSM)

Response surface models are often used as surrogate approximations for computationally intensive mathematical analyses or simulations. For example, you may have a numerical analysis that computes the critical displacements of a structural component as a function of several geometry parameters. If this analysis has to be run repeatedly, the computational expense may become prohibitive. [4]

Model Center's RSM plug-in can be used to construct computationally efficient response surface models that approximate the output of a simulation over a selected range of the input variables. The plug-in uses data collected from a DOE study (Phoenix Integration recommends using the Latin Hypercube DOE since this most effectively samples the design space). Once the study is complete the plug-in can be launched from the Data Collector. If sufficient data is provided (RSM tool shows an error if there is insufficient data), the response surface model can be created from some or all of the input and response variables from the DOE study. The response surface can be modeled using several polynomial model options including Quadratic Stepwise Regression, Cubic Stepwise Regression, Linear, Linear plus Quadratic Interaction Terms, Full Quadratic, Linear plus Quadratic and Cubic Interaction Terms, and Full Cubic. After creating a response surface, statistical details and graphs can be viewed. An example is shown in Figure 32. The statistical details describe how well the response surface fits the data provided. However, this does not necessarily mean the response surface describes the actual response of the parent model. It is only an approximation of the actual response, and the fit is only representative of the actual response if it is based on sufficient and precise data. The efficiency of the DOE algorithm and the number of samples determine the sufficiency of the data. Since the purpose of a RSM is to reduce computational time, large sample sizes are selfdefeating. Therefore the DOE algorithm must be carefully chosen to sufficiently represent the design space.

A surface can be created using all the polynomial models and the best fit chosen. Once a response surface is chosen it can be returned to Model Center as a module or to replace a calculation in a module. This module can then be used in place of the parent disciplinary model (MAESTRO) for rapidly performing tasks such as parametric design studies or design optimization.



Figure 32 – RSM Details and Graph [4]
# CHAPTER 5 ALDV CASE STUDY

In this chapter, a case study is described based on a concept exploration ship design from Virginia Tech's 2005 senior ship design class. The ship is an Advanced Logistics Delivery Ship (ALDV). Its primary mission is to deliver logistics to marines ashore from a seabase using unmanned gliders. ALDV requires storage for the glider payloads and the aircraft. It must be high speed to travel from seabase to offshore, and it must be capable of launching the aircraft. Section 1.1 described the general multi-objective optimization and OMOE development process. The following sections describe the ALDV application of this process. The OMOE development process begins with the mission description and Mission Need Statement (Appendix E – ALDV Mission Need Statement).

## 5.1 ALDV OMOE

#### 5.1.1 ALDV Mission

ALDV will transport and deliver marine logistics support from an off-shore seabase or shuttle ship (TAO, ADCX) to a dispersed, inland, Marine Expeditionary Brigade (MEB) using unmanned gliders, part of an Advanced Logistics Delivery Support System (ALDS). ALDV will also support the V-22 Osprey by providing at least one helicopter deck and refueling capabilities. ALDV may also support humanitarian missions by delivering supplies to victims of natural disasters. [23]

### 5.1.2 Mission Scenarios

A typical mission scenario for the primary ALDV mission is provided in Table 30. This mission scenario is used to establish the design requirements of the ship (e.g., speed, endurance, cargo capacity, etc.).

Day	ALDV Mission Description			
1 - 5	Transit from CONUS to seabase			
6	Refuel and restock supplies at seabase or shuttle ship			
7	Transit from seabase to littoral zone			
8-11	Deliver supplies to inland troops via unmanned glider			
12	Return to seabase			
13	Refuel and restock supplies at seabase or shuttle ship, perform maintenance			
14	Transit from seabase to littoral zone			
	Continuously refuel and restock using seabase or shuttle ships and travel			
15 - 175	back and forth along littoral zone to deliver supplies to inland troops.			
Refuel V-22s.				
175 - 180	Return to CONUS			

 Table 30 - Military Mission Scenario [23]

Required operational capabilities (ROCs) are identified to perform the ship's missions, and measures of performance (MOPs) are specified for those capabilities that vary in the designs as a function of the ship design variables (DVs). Table 31 is a summary of ROCs with the corresponding MOPs and DVs for ALDV. Each MOP is assigned a threshold and goal value. Table 32 summarizes the MOP goals and thresholds. Capability requirements and constraints applicable to all designs are also specified.

An Overall Measure of Effectiveness (OMOE) hierarchy is developed from the MOPs using the Analytical Hierarchy Process (AHP) to calculate MOP weights and Multi-Attribute Value Theory (MAVT) to develop individual MOP value functions.

ROC	Primary MOP or Constraint	Threshold or Constraint	Goal	Related DV
MOB 1 - Steam to design capacity in most fuel efficient manner	MOP 6 – Sprint Range MOP 7 – Endurance Range MOP 9 – Sprint Speed	250 nm 2500 nm 40 knots	500 nm 3500 nm 50 knots	DV1 - Waterline Length DV 5 - Propulsion system alternative
MOB 3 - Prevent and control damage	MOP 13 – Personnel Vulnerability MOP 10 – RCS MOP 11 – Acoustic Signature MOP 12 – Magnetic Signature MOP 1 – MCM	60 3000 ft3 Mechanical LM2500+ No Degaussing	35 500 ft3 IPS ICR Degaussing	DV6 - Manning and automation factor DV2 - Deckhouse volume DV5 - Propulsion system alternative DV8 - Degaussing system
MOB 5 - Maneuver in formation	Required all designs			
MOB 7 - Perform seamanship, airmanship and navigation tasks (navigate, anchor, mooring, scuttle, life boat/raft capacity, tow/be-towed)	Required all designs			
MOB 10 - Replenish at sea	Required all designs			
MOB 12 - Maintain health and well being of crew	Required all designs			
MOB 13 - Operate and sustain self as a forward deployed unit for an extended period of time during peace and war without shore-based support	MOP 7 - Endurance Range MOP 8 - Provisions	2500 nm 20 days	3500 nm 45 days	DV1 - Waterline Length DV5 - Propulsion system alternative DV15 - Provisions duration
MOB 16 - Operate in day and night environments	Required all designs			
MOB 17 - Operate in heavy weather	Required all designs			
MOB 18 - Operate in full compliance of existing US and international pollution control laws and regulations	Required all designs			
AAW – Anti-Air Warfare Capabilities	MOP 5 – AAW	AAW = 4	AAW = 1	DV7 - AAW
ASUW – Anti-Surface Ship Attack Capabilities	MOP 3 – ASUW	ASUW = 3 LAMPS = 4	ASUW = 1 $LAMPS = 1$	DV8 - ASUW DV12 - LAMPS
ASW A Conduct airborne	MOP 4 – ASW	ASW = 2	ASW = 1	DV9 - ASW
ASW/recon (LAMPS)	MOP 2 – C4ISR	LAMPS = 4 $C4ISR = 2$	LAMPS = 1 $C4ISR = 1$	DV12 - LAMPS DV11 - C4ISR
ASW 5 – Support airborne ASW/recon	MOP 2 – C4ISR	LAMPS = 4 $C4ISR = 2$	LAMPS = 1 $C4ISR = 1$	DV12 - LAMPS DV11 - C4ISR
ASW 10 – Disengage, evade and avoid submarine attack by employing	MOP 4 – ASW	ASW = 2 LAMPS = 4	ASW = 1 $LAMPS = 1$	DV9 - ASW DV12 - LAMPS

ROC	Primary MOP or Constraint	Threshold or Constraint	Goal	Related DV
countermeasures and evasion techniques	MOP 9 – Sprint Speed MOP 6 – Sprint Range	40 knots 250 nm	50 knots 500 nm	DV5 - Propulsion System alternative
CCC 1.6 – Provide a Helicopter Direction Center (HDC)	Required all designs	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
CCC 3 - Provide own unit CCC	MOP 2 – C4ISR	C4ISR = 2	C4ISR = 1	DV11 - C4ISR
CCC 4 - Maintain data link capability	MOP 2 – C4ISR	C4ISR = 2	C4ISR = 1	DV11 - C4ISR
FSO 3 – Provide Support services to other units	Required all designs	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
NCO 3 - Provide upkeep and maintenance of own unit	Required all designs			
LOG 2 – Transfer / Receive cargo and personnel	Required all designs			
LOG 3 – Seabase Docking Capability	Required all designs			
LOG 4 – Support land based personnel with logistics support via ALDV	MOP 15 - ALDV Cargo	3 days	8 days	DV6 - ALDV Cargo
AMW 6.1 – Conduct day helicopter, short/vertical takeoff and landing	Required all designs	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
AMW 6.3 – Conduct all weather helicopter operation	Required all designs	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
AMW 6.6 – Conduct helicopter refueling	Required all designs	LAMPS = 4	LAMPS = 1	DV12 - LAMPS

Table 32 – ALDV Measures of Performance (MOPs) [23]

Primary MOP or Constraint	Threshold or Constraint	Goal	Related DV
MOP 1 - MCM	MCM = 2	MCM = 1	DV10 - MCM
MOP 2 - C4I	C4I = 2	C4I = 1	DV11 - C4I
MOD 2 ASLIW	ASUW = 3	ASUW = 1	DV8 - ASUW
MOF 5 - ASUW	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
MOD 4 ASW	ASW = 2	ASW = 1	DV9 - ASW
MOF 4 - ASW	LAMPS = 4	LAMPS = 1	DV12 - LAMPS
MOP 5 – AAW	AAW = 4	AAW = 1	DV7 - AAW
MOP 6 - Sprint Range	250 nm	500 nm	DV1 - Waterline Length
			DV5 - Propulsion System alternative
MOD 7 Endurance Pange	2500 nm	2500 nm	DV1 - Waterline Length
MOF / - Endurance Kange	2300 IIII	3300 IIII	DV5 - Propulsion System alternative
MOP 8 - Provisions	20 days	45 days	DV15 - Provision Duration
MOP 9 - Sprint Speed	40 knots	50 knots	DV5 - Propulsion system alternative
MOP 10 - RCS	3000 ft3	500 ft3	DV3 - Deckhouse volume
MOP 11 - Acoustic Signature	Mechanical Drive	IPS	DV5 - Propulsion system alternative
MOP 12 - Magnetic Signature	No degaussing	Degaussing	DV8 - Degaussing system
MOP 13 - Personnel Vulnerability	60	35	DV6 - Manning and automation factor
MOP 14 - CBR	No CPS	Full CPS	DV14 - N <sub>CPS</sub>
MOP 15 - ALDV Cargo	3 days	8 days	DV16 - ALDV Days

The ALDV OMOE hierarchy is shown in Figure 33. There are 15 ALDV MOPs. Each alternative or under each MOP or each MOP metric is assigned a value of performance (0-1.0) using pairwise comparison or value of performance function as part of the AHP.

In the AHP, pairwise comparison questionnaires are used to solicit expert and customer opinion, required to calculate AHP weights and value of performance (VOP). An example of the pairwise comparison used for ALDV is shown in Figure 34. Value of Performance (VOP) functions, generally S-curves for continuous MOPs like Figure 35 and discrete values between 0

and 1 for discrete MOPs, are developed for each MOP, and VOP values are calculated using these functions in the ship synthesis model. A particular VOP has a value of 0.0 corresponding to the MOP threshold, and a value of 1.0 corresponding to the MOP goal. The MOP weights found for ALDV are shown in Figure 36 and Table 33. MOP weights and value functions are finally assembled in a single OMOE function:



Figure 33 - ALDV OMOE Hierarchy







Figure 35 - S-shaped VOP Curve [23]



Figure 36 – MOP Weights [23]

	$\lfloor 2 \rfloor$
MOP1 MCM	0.0035
MOP2 C4SI	0.0214
MOP3 ASUW	0.002
MOP4 ASW	0.0069
MOP5 AAW	0.0108
MOP6 Sprt Range	0.021
MOP7 End Range	0.0364
MOP8 Provisions Duration	0.0132
MOP9 Sprt Speed	0.1193
MOP10 RCS	0.0409
MOP11 Acoustic Signature	0.0053
MOP12 Magnetic Signature	0.0123
MOP13 Personnel	0.0211
MOP14 CBR	0.0318
MOP15 ALDS Cargo	0.6541

## Table 33 - MOP Weights [23]

# 5.2 ALDV Structural Design and RSM

#### 5.2.1 Baseline Structural Design Example

In the concept exploration phase of the design process the ship synthesis model is used to balance and assess designs in the design space. ALDV has a trimaran hullform. A baseline hullform model was created in MAESTRO to be used as a "rubber ship" to estimate the structural weight of designs with different principle characteristics. The length, center hull beam, depth, and hull separation are varied in MAESTRO to reflect alternative designs in the ship synthesis model. Length is the ship length at the waterline, beam is the center hull beam at the waterline, depth is measured from the keel to the bottom of the cross structure at midships, and hull separation is measured from the centerline to the center of a side hull as shown in Figure 38. The scantlings of this new MAESTRO models are optimized and the structural weight is estimated. During the structural optimization and weight assessment the structure is treated as a non-floating structure. Longitudinal bending moments are applied to simulate a hogging wave case and a sagging wave case. The baseline MAESTRO model is shown in Figure 37 and its principle characteristics are shown in Figure 38.



Figure 37 – Baseline MAESTRO Structure Model



Figure 38 – Baseline Characteristics in Body Plan and Plan Views

#### 5.2.2 Wrapping MAESTRO in Model Center

The current ship synthesis weights module uses a simple parametric model to estimate structural weight. It is desired to substitute a MAESTRO response surface model. The RSM is developed in Model Center (MC) using a "wrapper" for the MAESTRO structural assessment and optimization solver. A FORTRAN structural design interface (SDI) was also written to modify the MAESTRO baseline input file to the desired global ship principle characteristics. Model Center uses this program to perform a DOE and develop a RSM.

### 5.2.2.1 Modifying the Parent Hullform

The SDI reads and modifies the input file (.dat) for input to the MAESTRO solver. Length is changed by adding or subtracting parallel mid-body in the parent hull, shown in Figure 39, and changing the starting x coordinate of all modules affected by the added mid-body. Since the parent model uses a frame spacing of 1.5 meters, any input length is rounded to the nearest 1.5 meter increment. The SDI calculates the number of sections to be added to the mid-body module  $(N_{\text{SECTIONS}} = (L_{\text{NEW}} - 178.5)/1.5)$  and the change in length (D<sub>X</sub>) to be added to all the modules following the expanded module.



Figure 39 - Parent Hull Parallel Mid-Body Module



Figure 40 – MAESTRO .dat Sample File

To modify the .dat file for beam and depth, scaling factors multiply the nodes' beam (z) and depth (y) coordinates. For depth, all nodes' (y) coordinates are multiplied by  $D_{\text{NEW}}/D_{\text{PARENT}}$ . For beam, all nodes are multiplied by B<sub>NEW</sub>/B<sub>PARENT</sub>. Changes in hull separation can also increase or decrease the overall beam. This is accomplished by changing the (z) coordinates of the outriggers where:  $Z_{\text{NEW}} = [\text{HullSep} - (B_{\text{NEW}} / B_{\text{PARENT}} * 10.27)]$ . HullSep is the desired hull separation (input) measured from the centerline to the center of an outrigger. Figure 40 is a sample of the MAESTRO .dat file showing where length, beam, and draft are modified.

### 5.2.2.2 Optimizing the New Hull Form in MAESTRO and Finding Structural Weight

Once the parent hull ship has been modified to reflect the current design's principle characteristics, scantlings are optimized for adequacy and minimum weight using MAESTRO's optimization function. Finally, the structural weight is calculated using the MAESTRO solver.

Problems encountered when implementing this method included:

- The MAESTRO Optimizer only optimizes one module at a time. •
- MAESTRO doesn't update the .dat file with the new scantlings. •
- The Optimizer converges while there are still inadequate strakes.

• As scantlings vary, the weight changes and this changes the loads on a floating structure.

The SDI runs the MAESTRO optimizer for one module then updates the .dat input file to run MAESTRO again for the next module. However, this approach increases the run time from a few minutes to a non-desirable few hours. The SDI also searches the output file from the last MAESTRO module run for the new scantlings then reads and writes them back into the .dat file in the correct places. The module optimization order starts at the middle of the ship structure and works its way to the bow and stern, alternating sides. This order is performed because the middle of the ship has the greatest bending moments and affects the modules towards the bow and stern. The parent hullform has 25 modules broken into 5 substructures of 5 modules each. The program starts by optimizing module 3 of substructure 3 then module 2 of substructure 3, then module 4 of substructure 3, then module 1 of substructure 1 and module 5 of substructure 5 are optimized. The complete order is as follows:

- 1. Module 3 of Substructure 3
- 2. Module 2 of Substructure 3
- 3. Module 4 of Substructure 3
- 4. Module 1 of Substructure 3
- 5. Module 5 of Substructure 3
- 6. Module 5 of Substructure 2
- 7. Module 1 of Substructure 4
- 8. Module 4 of Substructure 2
- 9. Module 2 of Substructure 4
- 10. Module 3 of Substructure 2
- 11. Module 3 of Substructure 4
- 12. Module 2 of Substructure 2
- 13. Module 4 of Substructure 4
- 14. Module 1 of Substructure 2
- 15. Module 5 of Substructure 4
- 16. Module 5 of Substructure 1
- 17. Module 1 of Substructure 5
- 18. Module 4 of Substructure 1
- 19. Module 2 of Substructure 5
- 20. Module 3 of Substructure 1
- 21. Module 3 of Substructure 5
- 22. Module 2 of Substructure 1
- 23. Module 4 of Substructure 5
- 24. Module 1 of Substructure 1
- 25. Module 5 of Substructure 5

The problem of MAESTRO converging while there are inadequate strakes is because MAESTRO has the option of rounding scantlings to discrete numbers. This occurs after optimization takes place. During the rounding process, some strakes that were previously adequate from optimization become inadequate after rounding. To solve this, the discrete option was not used in optimizing the scantlings. The ability to use libraries of discretized stiffeners and plate thicknesses directly in the MAESTRO optimization, and the ability to perform a global ship optimization would be very valuable.

The problem of weight changes during optimization and resulting changes in draft and trim for hydrostatic balance in MAESTRO does not support the global ship optimization where displacement is an independent design variable and is fixed for a given structural optimization. MAESTRO would have to compensate for changes in structural weight with changes in loads which it is not able to do. This global algorithm will be reconsidered and possibly changed, but a temporary solution treats the ship as a non-floating structure without self weight. Bending moment curves are calculated using the ABS guide for high speed naval craft [24]. Equations (10) and (11) are longitudinal sagging and hogging maximum bending moment equations specific to trimaran hull forms.

$$MaxM_{s} = 110.0*C_{1}*Length**2*(2*HullSep + 2*SideBeam)*(C_{B} + 0.7)$$
(10)  

$$MaxM_{h} = -190.0*C_{1}*Length**2*(2*HullSep + 2*SideBeam)*C_{B}$$
(11)  
where C<sub>1</sub> = 10.75 - ((300.0 - Length)/100.0)\*\*1.5.

These maximum bending moments are applied to the ship in accordance to Figure 41.



This approach eliminates balancing. When each module is optimized it is treated as a cut structure including the module on either side with an external bending moment applied at the cuts in accordance with Figure 41. Once the entire ship is optimized, a final run is performed to calculate the structural weight. This is purely an analysis run for self weight. Gravity is turned on to allow MAESTRO to calculate total mass.

### 5.2.2.3 Model Center MAESTRO Wrapping Script

MAESTRO is "wrapped" using Analysis Server (AS) for use in Model Center (MC). The wrapper allows the MAESTRO optimization to be executed as a single component and linked to other components in MC. The particular wrapper for MAESTRO performs the following functions:

- 1. Reads the global design variable inputs from Model Center.
- 2. Writes an input file for modifying the .dat file.
- 3. Runs the SDI FORTRAN code that modifies the .dat file.
- 4. Runs the MAESTRO optimizer for the first module.
- 5. Runs the SDI updating the .dat file with new scantlings for the first module.
- 6. Repeats Steps 4 and 5 for all the modules.
- 7. Runs MAESTRO for the final analysis to find the optimized structural weight.
- 8. Retrieves the structural weight from the MAESTRO output.
- 9. Sends the structural weight back to Model Center.

Since this wrapper calls MAESTRO so many times, run time for one ship design can take up to a few hours.

#### 5.2.2.4 Creating a Design of Experiments and Response Surface Model

The MAESTRO structural design interface component can be run in MC as a structural weight module in the ship synthesis model or a DOE can be performed to build a RSM for sufficient structural weight. Because of the long run time and efficiency of the RSM and DOE process, a RSM was created to replace the current ship synthesis model structural weight equation.

The first step in creating a RSM for structural weight is to generate a valid data set using a DOE. Each entry in the data set contains the input variables (length, beam, depth, hull separation, and block coefficient) and the output, structural weight. The DOE requires ranges for the input variables, and selection of the type of experiment. MC has a variety of experiment designs to choose from:

• Parameter Scan

- Box-Behnken
- Central Composite
- Eighth Fractional Factorial
- Face Centered Central Composite
- Foldover
- Full Factorial
- Half Fractional Factorial
- Latin-Hypercube
- Plackett-Burman
- Sixteenth Fractional Factorial

Phoenix Integration suggests the Latin-Hypercube design for this application since it takes a random sample of the design space. The Latin-Hypercube is similar to a Full Factorial design except that the design space is divided into discrete alternatives selected randomly to achieve a more thorough investigation of the design space. The Latin-Hypercube design allows the user to specify the number of alternatives to sample within the design space. Two Latin-Hypercube DOEs of 30 designs and 100 designs were performed to determine if additional designs significantly improved the response surface.

The run time for the 30 design DOE was about 2 days, and the run time for the 100 design DOE was about 1 week on our computer with a 3 GHz processor and 2 GHz of RAM. The data was collected in MC, input into the RSM tool, and response surfaces were created. The RSM tool has several different polynomial model types as described in Section 4.6. A response surface is created for every type of polynomial and compared to determine which has the best fit to the data set. The 30 design data set did not have sufficient points to create surfaces with the full cubic and linear with cubic terms models. The 100 design data set did. There are 4 statistical checks to assess how well a polynomial response surface fits the data. The smaller the standard error, S, and the closer the coefficient of variation, CoV, is to 0%, the better the fit. There is also a better fit if the ratio of the regression sum of squares to the total sum of squares, R-Sq, is closer to 100%, and if the adjusted R-Sq is closer to R-Sq. By comparing S, CoV, R-Sq. and adjusted R-Sq for all the polynomial surface models, both 30 designs and 100 designs, it was determined that the 100 design full cubic response surface had the best and sufficient fit to the data. The statistical data comparing the 30 and 100 design runs is shown in Table 34. It can be seen that the CoV and the difference between R-SQ and adjusted R-SQ is smaller for 100 designs. No runs of more than 100 designs were run since the differences between 30 and 100 designs are so small it is unlikely to get closer results. The equation of this response surface

model is then inserted in the structural bare hull weight calculation in the ship synthesis model. This equation takes the form as follows:

Depth	-1.47E+07
Beam	3.82E+06
Length	1.16E+06
HullSep	-2.33E+06
Cb	-1.04E+09
Depth*Depth	1.16E+06
Beam*Beam	6.43E+05
Length*Length	-1.80E+03
HullSep*HullSep	2.17E+05
Cb*Cb	2.35E+09
Depth*Beam	-1.27E+05
Depth*Length	2.09E+04
Depth*HullSep	-6.83E+04
Depth*Cb	5.94E+06
Beam*Length	-9.70E+03
Beam*HullSep	1.77E+05
Beam*Cb	-3.16E+07
Length*HullSep	1.89E+04
Length*Cb	-3.40E+06
HullSep*Cb	-6.90E+06
Depth*Depth*Depth	9.80E+02
Beam*Beam*Beam	-4.20E+04
Length*Length*Length	1.61E+00
HullSep*HullSep*HullSep	-4.89E+02
Cb*Cb*Cb	-1.48E+09
Depth*Depth*Beam	-5.27E+04
Depth*Depth*Length	-4.67E+01
Depth*Depth*HullSep	-1.54E+04
Depth*Depth*Cb	-7.32E+05
Depth*Beam*Beam	5.52E+04
Depth*Beam*Length	-4.72E+02
Depth*Beam*HullSep	3.55E+03
Depth*Beam*Cb	2.38E+05
Depth*Length*Length	-4.81E+01
Depth*Length*HullSep	-4.95E+02
Depth*Length*Cb	7.65E+03
Depth*HullSep*HullSep	8.48E+03
Depth*HullSep*Cb	3.64E+05
Depth*Cb*Cb	1.61E+06
Beam*Beam*Length	-1.33E+03
Beam*Beam*HullSep	5.33E+02
Beam*Beam*Cb	3.88E+05
Beam*Length*Length	3.75E+00
Beam*Length*HullSep	1.66E+02
Beam*Length*Cb	6.21E+04
Beam*HullSep*HullSep	-8.52E+03
Beam*HullSep*Cb	-8.05E+04
Beam*Cb*Cb	1.04E+07
Length*Length*HullSep	-1.28E+01
Length*Length*Cb	2.75E+03
Lengtn*HullSep*HullSep	-5.16E+02
Lengin*HullSep*Ub	2.88E+03
Lengui*UD*UD Uullean*Uullean*Ch	1.4/E+00
nunsep*nunsep*Cb	-1.94E+05
nunsep · Co··Co	0.2/E+00

where: Structural Weight =  $2.05 \times 10^8$  + (constant in column 2)\*(variable in column 1)

Table 34 – 30	and 100 Desi	gn Run Stat	istical Data

Number of Design Samples	Standard Error, S	Average Response	Coefficient of Variation, CoV	R-SQ	Adjusted R-SQ
30	$2.038 \times 10^4$	$1.790 \times 10^{6}$	1.14%	99.76%	99.22%
100	$1.959 \times 10^4$	1.791x10 <sup>6</sup>	1.09%	99.65%	99.21%

## 5.3 ALDV Ship Synthesis Model Design Space

In the ALDV case study each ship design is described using 16 design variables summarized in Table 35. The DV values for a design are selected by the MOGO from the range indicated and input into the ship synthesis model described in Section 4.1.2. The designs are balanced, assessed for feasibility, and objective attributes are calculated.

	Description	Lower Bound	Upper Bound	Discrete/Continuous
1	LWL Waterline Length	156 m	195 m	Continuous
2	VD Deckhouse Volume	100 m <sup>3</sup>	1200 m <sup>3</sup>	Continuous
3	CDHMAT Deckhouse Material	1=steel	2=aluminum	Discrete
4	BALtype Type of Fuel/Ballast Tanks	0=clean ballast	1=compensated fuel system	Discrete
5	PSYS Propulsion System	1	9	Discrete
6	Cman Manning Factor	0.5	1	Continuous
7	AAW Anti-Air Warfare System	1	4	Discrete
8	ASUW Anti-Surface Warfare System	1	3	Discrete
9	ASW Anti-Submarine Warfare System	1	2	Discrete
10	MCM Mine Counter Measures	1	2	Discrete
11	C4I Command, Control, Communication, Computer, Intelligence	1	2	Discrete
12	LAMPS LAMPS Combat System	1	4	Discrete
13	Ndegaus Degaussing	0=none	1=degaussing system	Discrete
14	Ncps Collective Protection System	0=none	2=full	Discrete
15	Ts Stores Duration	20 days	45 days	Discrete
16	TALDS Days of MEB Support	3 days	8 days	Discrete

Table 35 - ALDV Design Variables (DVs)

## 5.4 ALDV Optimization

The objective of optimization in the concept exploration phase of ship design is to identify non-dominated designs in the feasible design space. This is accomplished using a multiobjective genetic optimization in Model Center as described in Section 1.1.1. Through test runs it was discovered that the MOGO tends to locally optimize around certain discrete design variable values, particularly when the resolution for continuous variables is very fine and there are hundreds of continuous variable values being considered, and only a few values of discrete variables. This is very undesirable, so several possible solutions were tried. One solution is to have a single optimization run for each value of each discrete design variable and integrate the results. This is very computationally expensive. It was found that if the resolution of the continuous variables is kept as course as possible, and the mutation rate for discrete variables is much higher than for continuous variables, the problem is minimized. A two-part optimization process was devised. Part I is a broad multi-objective optimization created to select the discrete variable values and only roughly select continuous variable values. Part II fixes the discrete variable values based on preferred designs selected from the Part I non-dominated frontier, and optimizes the continuous variables with a much finer resolution. This also allows better use of Model Center's visualization tools which are intended primarily for exploring the relationship of continuous variables.

#### 5.4.1 MOGO Optimization Part I

The MC MOGO is configured using the Darwin optimizer interface described in Section 4.3 and shown in Figure 27. In the MOGO interface window the objectives are specified as maximizing effectiveness (OMOE) while minimizing risk (OMOR) and cost (Average Follow Ship Acquisition Cost). The input (DVs) and their ranges from Table 35 are specified, and the following feasibility constraints are applied:

- Total arrangeable area required ratio must be > 0.
- Deckhouse area required ratio must be > 0.
- Sustained speed required ratio must be > 0.
- Generator power required ratio must be > 0.
- Minimum GM/B required ratio for stability and safety must be > 0.
- Maximum GM/B required ratio to limit accelerations must be > 0.
- Depth at station 10 required ratio must be > 0.
- Endurance range required ratio must be > 0.
- Sprint range required ratio must be > 0.
- Transom width required ratio must be > 0.
- Maximum total manning required ratio must be > 0.

Next the optimization parameters, Figure 28, are specified for Part I. The population size for each generation is specified as 200. The selection scheme is selected for elitist. Elitist selection takes the worst design from the child population and replaces it with the best design from the

parent population [4]. The optimizer is set to stop after 50 generations without improvement or a maximum of 150 generations. This convergence criteria requires a minimum 0.1 % change of the population to be considered an improved generation. The mutation probability for discrete variables is increased from 0.05 to 0.2. Other genetic operator parameters are maintained at their default values.

#### 5.4.2 Part I Results

Figure 42 shows the effectiveness-cost-risk frontier generated by the genetic optimization. Each point in Figure 42 represents objective attribute values for a feasible non-dominated ship design. A 2D representation of the non-dominated frontier is shown in Figure 43. Non-dominated frontiers for different levels of risk (OMORs) are represented by different colors on the cost and OMOE plot. "Knees" in the curve are distinct irregularities at the top of steep slopes where substantial effectiveness improvement occurs for a small increase in cost. The "knees" are labeled as candidate designs for discussion. These designs are often the preferred possibilities for the customer.

The figures show that as cost and risk increase, effectiveness increases. The OMOE value is mainly driven by the ALDS mission cargo duration ( $T_{ALDS}$ ). Increasing  $T_{ALDS}$  greatly increases the OMOE. However, increasing  $T_{ALDS}$  also increases the weight and size of the ship, which leads to a higher cost.

For this case study the discrete variable values of non-dominated Design #23 are chosen to be used in Part II. This design is chosen because it is a distinct "knee" on the curve. It has an OMOR of 0.2953 and an OMOE of 0.3434 with a follow ship cost of \$572.27 million. Table 36 summarizes the design variable values for Design #23.

Design Variable Description		Trade-off Range	Design 23 Values
LWL	Waterline Length	156 m – 195 m	187 m
VD	Deckhouse Volume	$100 \text{ m}^3 - 1200 \text{ m}^3$	600 m <sup>3</sup>
CDHMAT	Deckhouse Material	1 = steel, $2 = $ aluminum	1 = steel
BALtype	Type of Ballast	0 = clean ballast, 1 = compensated fuel system	0 = clean ballast
PSYS	Propulsion System	9 Options	Option 3
Cman	Manning Coefficient	0.5 - 1.0	0.8985
AAW	Anti-Air Warfare	4 Options	Option 4
ASUW	Anti-Surface Warfare	3 Options	Option 2
ASW	Anti-Submarine Warfare	2 Options	Option 2
MCM	Mine Counter Measures	2 Options	Option 2

Table 36 - Design Variables Summary

Design Variable	Description	Trade-off Range	Design 23 Values
C4I	Control Systems	2 Options	Option 2
LAMPS	LAMPS	4 Options	Option 4
Ndegaus	Degaussing System	0 = none, 1 = degaussing system	0 = none
Ncps	Collective Protection System	0 = none, $2 = $ full	2 = full
Ts	Number of stores days	20 days – 45 days	34 days
Talds	ALDS cargo duration	2 days – 8 days	5 days



Figure 42 – 3-D Non-Dominated Frontier Part I



Figure 43 – 2-D Non-Dominated Frontier Part I

#### 5.4.3 MOGO Optimization Part II

Part II of the MOGO optimization is configured in the same manner as Part I. The main difference being the design variables used. All discrete variable values are fixed at the Design #23 values, Table 37. Risk is not used as an objective since the only continuous variable risk depends on is the manning and automation factor which is also fixed at its Design #23 value. This leaves only two continuous variables to optimize in Part II. Since ALDS mission cargo duration ( $T_{ALDS}$ ) is such an important design variable, it is converted to a continuous variable, its resolution is increased, and it is also included as an optimization variable.

To add greater flexibility and higher resolution the hull model is changed from a simple geosim to allow the lengths, beams, and drafts to change independently of each other. In Part I only the LWL is varied and all other principle characteristics are scaled based on the ratio: LWL<sub>input</sub>/LWL<sub>parent</sub>. Now LWL, CHB (beam of the center hull), D10 (depth at station 10), and HullSep (distance from the centerline to center of an outrigger) are varied independently and all other principle characteristics are calculated using separate length, beam, and depth scaling factors. Table 38 summarizes these ranges and resolutions.

Design Variable	Design 23 Values
CDHMAT	1 = steel
BALtype	0 = clean ballast
PSYS	Option 3
Cman	0.8985
AAW	Option 4
ASUW	Option 2
ASW	Option 2
MCM	Option 2
C4I	Option 2
LAMPS	Option 4
Ndegaus	0 = none
Ncps	2 = full
Ts	34 days

Table 37 – Discrete Values for Design #23

Table 38 – Design Variable Ranges Part II

Design Variable	Lower Bound	<b>Upper Bound</b>	Resolution
LWL	156 m	195 m	0.1 m
CHB	9.0 m	12.5 m	0.1 m
D10	9.5 m	13.0 m	0.1 m
HullSep	11 m	15 m	0.1 m
VD	$100 \text{ m}^3$	$1200 \text{ m}^3$	$10 \text{ m}^3$
TALDS	2 days	8 days	0.1 days

#### 5.4.4 Part II Results and Conclusions

Figure 44 shows the results of Part II in a 2-D plot since risk is not involved. The limiting factor in this case is TALDS. Effectiveness is increased mainly with increasing the number of TALDS days. The space required for increased TALDS days is limited by the size of the ship. The ship size is limited by the propulsion system. Since the propulsion system is fixed in Part II the size is limited to satisfy the sustained speed threshold.

The high end Design #13 has an OMOE of 0.4982 with the same risk as Design #23 of Part I and a cost of \$550.3 million, \$22 million less than Design #23. Another point of interest is Design #8 with an OMOE of 0.3355 and cost of \$539.7 million. This cost about \$32.4 million less than the baseline Design #23 and has only slightly less effectiveness. Other significant knees in the Part II curve occur at design points 1, 3, 5, and 12. Table 39 shows a comparison of these significant designs. From Table 39 it can be seen that TALDS, which was established in Part I to affect OMOE the most, is closely related to length and center hull beam. Plotting these designs on the Part I 2-D Non-Dominated Frontier shows they have significantly higher effectiveness for the associated cost and risk, Figure 45.

Since the ship is no longer a geosim the length, beam, depth, and hull separation can vary independently allowing for principle characteristics which maximize speed and volume required for TALDS. This greater flexibility from having more independent variables leads to the more refined optimization noted in the previous paragraph. In Table 39 the geosim values corresponding to a particular LWL are shown in parenthesis. The actual values have a significant departure from the geosim values particularly with depth. Speed and TALDS can now be optimized with less dependence. Therefore allowing the variables to be independent of a geosim proves to be significantly important to the model.





rable 57 Significant Design Comparison										
	LWL	СНВ	D10	HullSep	VD	TALDS	Vs	E	Cost	
Design	(m)	(m)	(m)	(m)	(m <sup>3</sup> )	(days)	(knts)	(nm)	(\$M)	OMOE
23 (Part I)	187.0	(11.5)	(12.1)	(13.9)	600	5.0	42.5	3236	572.3	0.3434
1	156.0	12.5 (9.6)	9.5 (10.1)	11.0 (11.6)	380	2.0	46.1	7937	487.7	0.2313
3	158.1	12.5 (9.7)	9.5 (10.2)	11.1 (11.8)	490	3.3	46.0	5143	491.8	0.2479
5	159.1	12.5 (9.8)	11.1 (10.3)	11.0 (11.8)	460	4.4	43.1	3563	524.2	0.2883
8	181.5	12.4 (11.2)	10.4 (11.8)	11.6 (13.5)	1180	4.8	44.7	3322	539.7	0.3355
12	166.5	12.4 (10.3)	11.8 (10.8)	11.2 (12.4)	740	5.4	42.1	3307	542.6	0.4179
13	163.9	12.1 (10.1)	12.6 (10.6)	12.0 (12.2)	690	6.0	41.1	2417	550.3	0.4982

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Figure 45 – Part I Non-Dominated Frontier with Part II Significant Designs

This case study shows that Response Surface Models and Design of Experiments simplify and speed up the process of a ship synthesis model. Finite element codes such as MAESTRO improve the accuracy of the ship synthesis models which in turn lower costs later in the design process. By using a more accurate structural weight equation the ship synthesis model is improved and closer represents the design later in the naval ship design process. By splitting the optimization process to pre-select discrete variables then run the optimization again to select the continuous variables yields non-dominated designs with higher effectiveness for a given cost and risk.

# CHAPTER 6 CONCLUSIONS AND FUTURE WORK

## 6.1 **OMOE Experiment Conclusions**

A method is presented that uses the Analytic Hierarchy Process combined with Multi-Attribute Value Theory to build Overall Measure of Effectiveness and Overall Measure of Risk functions to properly rank and approximately measure the relative mission effectiveness and risk of design alternatives, using expert opinion to replace complex analysis tools.

This method is validated by comparing the ranking of 16 ships using two methods. The first method uses the OMOE and expert opinion and the second method uses the results of direct combat simulation. Results show that the OMOE function created from the expert opinion questionnaire average provides a good prediction of direct simulation results, proving this method can be an acceptable tool for ranking design alternatives in concept exploration ship optimization.

#### 6.2 OMOE Experiment Future Work

Future work of this experiment can investigate if there is a need to include the experts as a level in the OMOE hierarchy. In this thesis all experts were considered to have equal experience and therefore their individual opinions were treated equal. If experts have different backgrounds and differing experience levels the AHP allows for weighting of the experts themselves by including them as a level in the hierarchy.

#### 6.3 ASC Ship Synthesis Model Conclusions

This case study shows that Response Surface Models and Design of Experiments simplify and speed up the process of a ship synthesis model. Finite element codes such as MAESTRO improve the accuracy of the ship synthesis models which in turn lower costs later in the design process. By using a more accurate structural weight equation the ship synthesis model is improved and closer represents the design later in the naval ship design process. By splitting the optimization process to pre-select discrete variables then run the optimization again to select the continuous variables yields non-dominated designs with higher effectiveness for a given cost and risk.

# 6.4 ASC Ship Synthesis Model Future Work

This ship synthesis model is created to evolve with evolving technology and learned experience. As newer and more accurate software becomes available for ship disciplines they can be wrapped and substituted into this model. The MAESTRO model itself can be expanded to include a library of parent ship hull forms. As indicated in Chapter 5 many problems used temporary solutions that can be further researched and developed.

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# **APPENDIX A – DETAILED SHIP CLASS CHARACTERISTICS**

#### [16]

#### CG 47 Ticonderoga

These cruisers, when launched, ushered in a new age in coordinated air defense. The Aegis system is a set of fully integrated sensors and weapons systems, all working together to automatically detect, track, and engage large swarms of aircraft and missiles.

While having the capability for just about any surface warfare task, the Ticonderoga's were designed for one principle task; air defense. With large magazines for SM-2 missiles, plus the high sustained engagement rate of the Aegis system, these cruisers are generally the air defense backbone of every US carrier group. Ticonderogas cannot carry the longer range SM-2ER (extended range) version of the standard missiles, which means they should stay near the center of a formation (5 nm or so) where their air defense umbrella can be extended over all high value units. Like all US cruisers, these ships could use more point defense.

The first two ships of the class, the Ticonderoga and the Yorktown (the "baseline 0" ships), are not fitted to carry the LAMPS III Seahawk and so carrying the SH-Z Seasprite instead. They are otherwise the same as the follow-on Ticonderoga baseline 1.

Ship Type: CG -- Surface Combatant Max Speed: 35 knots General Armor: Light Engineering Armor: Medium Bridge Armor: Light Sensor Armor: Light Displacement: 7015 tons Damage Points: 216 Length: 172.8 m Crew: 358 Maximum Sea State: 5 **Detection Signatures** side bow stern Passive Sonar 97 98 100 Active Sonar 25 40 25 Visual 238 297 237 Infra-red 138 227 168 Radar 208 267 208 Air Facilities: Hangar X 2 Medium Aircraft Pad with Haul-Down X 1 Medium Helo Propulsion: LM 2500 COGAG Sensors: AN/SPS-55 360 (000 - 000) AN/SPY-1A 360 (000 - 000) AN/SPS-49(V)7 360 (000 - 000) AN/SPQ-9A 360 (000 - 000) AN/SPG-62 (Mk-99) BOW (225 - 135) AN/SPG-62 (Mk-99) STRN (045 - 315) AN/SLQ-32(V)3 (ESM BAND 1) 360 (000 - 000) AN/SLQ-32(V)3 (ECM) 360 (000 - 000) AN/SLQ-25 Nixie 360 (000 - 000) Decca (Series) 360 (000 - 000) LN-66 360 (000 - 000) AN/SOS-53 BOW (225 - 135) AN/SSQ-72 360 (000 - 000) LowLight TV 360 (000 - 000)

Mounts:

127mm/54 Mk45 c20 BOW (225 - 135) 127mm/54 Mk45 c20 STRN (045 - 315) Mk36 SRBOC c6 PF (270 - 360) Mk36 SRBOC c6 SF (000 - 090) Mk141 c4 PS (180 - 360) Mk141 c4 SS (000 - 180) 12.7mm MG c100 PEA (180 - 315) 12.7mm MG c100 PEF (225 - 045) 12.7mm MG c100 SEA (045 - 180) 12.7mm MG c100 SEF (000 - 135) Mk26 Mod 2 c64 Mk15 Block 0 CIWS c3 PS (180 - 360) Mk15 Block 0 CIWS c3 SS (000 - 180) Mk26 Mod 0 c24 BOW (225 - 135) Mk50 Mod 2 Decoy Launcher c1 PMA + Mk50 Mod 2 Decoy Launcher c1 SMA + 25mm/87 Mk38 Bushmaster c15 PEA (180 - 315) 25mm/87 Mk38 Bushmaster c15 SEA (045 - 180) 324mm Mk32 SVTT Triple c3 PS (225 - 315) 324mm Mk32 SVTT Triple c3 S (045 - 135) Communications: Link 11 AN/WSC-3 Link 14 Link 4A VHF (Sec) UHF (Sec) U/W Telephone SATCOM AN/WSC-3A LAMPS III Ship Datalink Standard Command DL (Aegis) Fuel Storage: Gas Fuel X 2000 Diesel Fuel X 2000 Aviation Fuel X 20 Magazines: Mk-46 NEARTIP c6 Mk-50 ALWT c6 20mm Mk-15 Mod 0 CIWS Burst c20 20mm Mk-15 Mod 0 CIWS Burst c20 127mm/54 Mk-42/Mk-45 c400 Mk36 SRBOC Magazine c96 SLQ-49 Magazine c8 Ticonderoga I/II c30 Ship Flags: Refuel Astern In x 2 Refuel from Port x 2 Refuel from Starboard x 2 Replenish from Port x 2 Replenish from Starboard x 2 Helo in-flight refuel capable

#### DD 963 Spruance (VLS)

The original Spruance design was criticized as being under armed in comparison with similar Soviet vessels. With only two 127 mm guns, a woefully short-ranged Sea Sparrow launcher, and an ASROC launcher on its (at the time) oversized hull, it looked painfully inadequate. Lurking in that big hull, however, was possibly the quietest surface ship in service with a sonar array that rivaled that on the newest American attack subs. The Spruance was designed to find and kill subs before they could attack, even with horizon missiles. The primary ASW weapon of the Spruance is not ASROC, as in earlier ships, but its LAMPS helicopters, giving it a standoff range of over 60 miles. Even better, the Spruances from the outset were designed for modular replacement of sensors and weapons, allowing upgrades as newer equipment became available. This flexibility equipped with Tomahawk and HARPOON missiles and Mk41 VLS systems. Despite the addition since its design, the Spruance, even in its improved form is first and foremost an Anti-Sub platform.

Ship Type: DD -- Surface Combatant Max Speed: 35 knots General Armor: Light Engineering Armor: Medium Bridge Armor: Light Sensor Armor: Light Displacement: 5916 tons Damage Points: 195 Length: 171.7 m Crew: 346 Maximum Sea State: 6 Detection Signatures side bow stern 96 92 99 Passive Sonar 25 Active Sonar 25 40 Visual 238 296 238 Infra-red 138 226 168 Radar 208 266 208 Air Facilities: Hangar X 2 Medium Aircraft Pad with Haul-Down X 1 Medium Helo Propulsion: LM 2500 COGAG Sensors: AN/SPS-40 SMA + SS + PS + PMA + PMF + PBAN/SPS-55 360 (000 - 000) AN/SPQ-9A 360 (000 - 000) AN/SLO-32(V)3 (ESM BAND 1) 360 (000 - 000) AN/SLQ-32(V)3 (ECM) SMA + SS + PS + PMA + PMF + PB AN/SLQ-25 Nixie 360 (000 - 000) TAS (Mk 23) 360 (000 - 000) AN/SPG-60 BOW (225 - 135) LN-66 360 (000 - 000) AN/SOR-19 360 (000 - 000) AN/SQS-53 BOW (225 - 135) AN/SSO-104 360 (000 - 000) Mk 91 FCS Radar STRN (045 - 315) Mk 91 FCS ElectroOptical STRN (045 - 315) Mounts: 127mm/54 Mk45 c20 BOW (225 - 135) 127mm/54 Mk45 c20 STRN (045 - 315) Mk36 SRBOC c6 PS (225 - 315) Mk36 SRBOC c6 S (045 - 135) Mk141 c4 PS (180 - 360) Mk141 c4 SS (000 - 180) 12.7mm MG c100 PEA (180 - 315)

12.7mm MG c100 PEF (225 - 045) 12.7mm MG c100 SEA (045 - 180) 12.7mm MG c100 SEF (000 - 135) Mk29 NATO Sea Sparrow c8 STRN (045 - 315) Mk15 Block 1 CIWS c4 SS + PS + Mk15 Block 1 CIWS c4 SWF (315 - 135) Mk50 Mod 2 Decoy Launcher c1 PA (180 - 270) Mk50 Mod 2 Decoy Launcher c1 SA (090 - 180) 25mm/87 Mk38 Bushmaster c15 PS (225 - 315) 25mm/87 Mk38 Bushmaster c15 S (045 - 135) 324mm Mk32 SVTT Triple c3 PS (225 - 315) 324mm Mk32 SVTT Triple c3 S (045 - 135) Mk41 VLS (3) (Spruance) c61 360 ( 000 - 000 ) Communications: Link 11 AN/WSC-3 URN-25 Link 14 VHF (Sec) UHF (Sec) AN/WSC-3A LAMPS III Ship Datalink Fuel Storage: Gas Fuel X 1650 Aviation Fuel X 16 Magazines: Mk-50 ALWT c12 20mm Mk-15 Mod 1 CIWS Burst c20 20mm Mk-15 Mod 1 CIWS Burst c20 127mm/54 Mk-42/Mk-45 c400 Mk36 SRBOC Magazine c96 SLQ-49 Magazine c8 Spruance (VLS) c290 Ship Flags: Refuel Astern In x 2 Refuel from Port x 2 Refuel from Starboard x 2 Replenish from Port x 1 Replenish from Starboard x 1 Nuclear Shock Resistant Helo in-flight refuel capable

#### **DDG 51 Arleigh Burke**

The US Navy's next generation destroyer, the Burke class incorporates VLS and Aegis fire control technologies from the initial design stages. Primarily intended to stop air attacks, the Burkes are also very capable anti-surface and anti-sub platforms, although the class lacks full helo facilities. Able to launch standard ZRM SAMs, Tomahawk and HARPOON SSMs, and potentially VL ASROC anti-sub weapons, the Burkes can be mission tailored merely by altering their weapons loadout. Future weapons can also be easily installed as long as they fit in the Mk41 launch cells, as the digital fire control systems are easily adapted to new weapons.

By 1996, with most of the old CGs, DDGs, and FFGs being scrapped or decommissioned, the Burkes will make up the bulk of out light carrier group escorts, with Spruances retained in the ASW role. The Burke is inferior to the newer Ticonderoga cruisers only in its slightly smaller weapons capacity and lack of helo facilities.

Ship Type: DDG -- Surface Combatant Max Speed: 35 knots General Armor: Medium Engineering Armor: Medium Bridge Armor: Light Sensor Armor: Light Displacement: 6625 tons Damage Points: 210 Length: 153.8 m Crew: 303 Maximum Sea State: 6 **Detection Signatures** side stern bow Passive Sonar 95 98 96 Active Sonar 25 25 40 Visual 242 287 242 Infra-red 142 217 172 Radar 212 257 212 Air Facilities: Pad with Haul-Down X 1 Medium Helo Open Parking X 1 Medium Aircraft Propulsion: LM 2500 COGAG Sensors: AN/SPS-67 360 (000 - 000) AN/SPG-62 (Mk-99) BOW (225 - 135) AN/SPG-62 (Mk-99) STRN (045 - 315) AN/SPS-64(iv) 360 (000 - 000) AN/SPY-1D 360 (000 - 000) AN/SLQ-32(V)3 (ESM BAND 1) 360 (000 - 000) AN/SLQ-32(V)3 (ECM) 360 (000 - 000) AN/SLQ-25 Nixie 360 (000 - 000) AN/SQR-19 360 (000 - 000) AN/SQS-53 BOW (225 - 135) AN/SLO-32(V)3 (ESM BAND 2) 360 (000 - 000) AN/SSQ-104 360 (000 - 000) LowLight TV 360 (000 - 000) Mounts: 127mm/54 Mk45 c20 BOW (225 - 135) Mk36 SRBOC c6 PF (270 - 360) Mk36 SRBOC c6 SF (000 - 090) Mk141 c4 PS (180 - 360) Mk141 c4 SS (000 - 180) 12.7mm MG c100 PEA (180 - 315) 12.7mm MG c100 PEF (225 - 045) 12.7mm MG c100 SEA (045 - 180)

12.7mm MG c100 SEF (000 - 135) Mk41 VLS (1) c29 360 (000 - 000) Mk41 VLS (2) c61 360 (000 - 000) Mk15 Block 1 CIWS c4 BOW (225 - 135) Mk15 Block 1 CIWS c4 STRN (045 - 315) 25mm/87 Mk38 Bushmaster c15 PEA (180 - 315) 25mm/87 Mk38 Bushmaster c15 SEA (045 - 180) 324mm Mk32 SVTT Triple c3 PS (225 - 315) 324mm Mk32 SVTT Triple c3 S (045 - 135) Communications: Link 11 AN/WSC-3 Link 14 Link 4A VHF (Sec) UHF (Sec) AN/WSC-3A LAMPS III Ship Datalink Standard Command DL (Aegis) Fuel Storage: Aviation Fuel X 10 Diesel Fuel X 1500 Magazines: Mk-50 ALWT c12 20mm Mk-15 Mod 1 CIWS Burst c20 20mm Mk-15 Mod 1 CIWS Burst c20 127mm/54 Mk-42/Mk-45 c400 Mk36 SRBOC Magazine c96 Arleigh Burke c138 Ship Flags: Refuel Astern In x 2 Refuel from Port x 2 Refuel from Starboard x 2 Replenish from Port x 1 Replenish from Starboard x 1 Helo in-flight refuel capable

#### FFG 7 Perry

A radical departure from previous frigate design philosophies, the Perry class missile frigates provide adequate all-around capability for a reasonable price. Carrying a Mk13 launcher in place of the ASROC carried on earlier designs, the Perry's have fair air defense capability using standard 1 MR missiles, as well as an anti-ship capability using HARPOONs.

Early construction FFG's, most of which are now in reserve, have hangar facilities which can accommodate the Seasprite LAMPS I, but not the larger Seahawk LAMPS III. Later flights can carry two Seahawks, giving them a much improved standoff ASW capability. With the retirement of the Adams and Coontz class destroyers, Perrys will be forced to take places in carrier battle groups (something they are not really capable of doing) until sufficient numbers of Arleigh Burke class destroyers become available. These ship have an aluminum superstructure and only one propeller. They were originally designed to fulfill the "low end" (quantity over quality) obligations of the US Navy.

Several allied nations now produce versions of the Perry class with slightly different loadout and sensors.

Ship Type: FFG Surfa	ice Con	nbatant				
Max Speed: 33 knots						
General Armor: Light						
Engineering Armor: Ligh	t					
Bridge Armor: Light						
Sensor Armor: Light						
Displacement: 3169 tons						
Damage Points: 102						
Length: 135.6 m						
Crew: 217						
Maximum Sea State: 5						
Detection Signatures		bow	side	stern		
Passive Sonar	95	96	98			
Active Sonar	22	39	22			
Visual	219	276	219			
Infra-red	119	206	149			
Radar	189	246	189			
Air Facilities:						
Hangar X 2 Smal	l Aircra	ıft				
Pad X 1 Small H	elo					
Propulsion: LM-2500 (Du	ual) Sin	gle Sha	ft			
Sensors:						
AN/SPS-55 360	( 000 -	000)				
STIR 360 (000 -	- 000 )					
AN/SPS-49(V)4 360 (000 - 000)						
AN/SLQ-25 Nixi	ie 360 (	( 000 - (	) ( 000			
AN/SQR-19 360	( 000 -	000)				
AN/SQS-56 BOV	N (225	5 - 135 )	)			
AN/SLQ-32(V)2	(ESM ]	BAND	1) 360	( 000 - 000 )		
AN/SLQ-32(V)2 Sidekick (ECM) 360 (000 - 000)						
Mk 92 Mod 2 360 (000 - 000)						
Mounts:						
Mk36 SRBOC c6 PF (270 - 360)						
Mk36 SRBOC c6 SF (000 - 090)						
12.7mm MG c100 PS (180 - 360)						
12.7mm MG c100 SS (000 - 180)						
Mk15 Block 0 CIWS c3 STRN ( 045 - 315 )						
76mm/62 OTO Melara Comp c13 SMA + SS + PS + PMA + PMF +						
Mk13 Mod 4 c40 BOW (225 - 135)						
324mm Mk32 SVTT Triple c3 PS (225 - 315)						
324mm Mk $32$ SVTT Triple c3 S (045 - 135)						

Communications: AN/WSC-3 URN-25 Link 14 VHF (Sec) UHF (Sec) AN/WSC-3A Fuel Storage: Aviation Fuel X 64 Diesel Fuel X 587 Magazines: Mk-46 NEARTIP c12 Mk-50 ALWT c6 20mm Mk-15 Mod 0 CIWS Burst c20 Mk36 SRBOC Magazine c96 O.H.Perry c18 Ship Flags: Refuel Astern In x 2 Refuel from Port x 1 Refuel from Starboard x 1 Replenish from Port x 1 Replenish from Starboard x 1 Passive or Single Stabilizers

# **APPENDIX B – SCENARIO LIST**

Global Conflicts 1 Dawn Patrol (Russia): 1 squadron Assault on Zion (Israel): 3 small surface vessels White Death (Chile): 1 squadron A Naval Border War (Ecuador): 2 squadrons, 3 small merchant ships, 1 diesel sub Operation Ratcatcher (Sweden): 3 squadrons, 1 diesel sub Ichon Again (US): 1 squadron Lightning Bolt (South Africa): 2 squadrons, 2 diesel subs Break the Blockade (Britain): 2 squadrons, 1 nuclear sub To Protect the Queen (Britain): 1 squadron, 2 nuclear subs, 1 diesel sub Okinawa (US): 2 squadrons, 3 nuclear subs Malvinas Part II (Britain): 2 squadrons, 1 nuclear sub Blood Feud (Taiwan): 1 squadron Taking of Sakhalin (Japan): 1 squadron, 3 diesel subs Black Sea Fleet (Russia): 2 squadrons, 1 nuclear sub, 1 diesel sub A Fight to the Death (US): 1 squadron, 1 nuclear sub **Global Conflicts 2** Halfway to Haifa (US): 2 squadrons, 2 nuclear subs Attack on Kamchatka (US): 1 squadron, 1 nuclear sub Battle for Khusestan Part I (US): 1 squadron Battle for Khusestan Part II (US): 1 squadron Battle for Tehran (US): 1 squadron Return to Yankee Station (US): 1 squadron, 2 nuclear subs Bengali Bridges (US): 1 squadron, 1 nuclear sub Red Sea Rescues (US): 2 squadrons, 1 nuclear sub Those Futile Fjords (Soviets): 4 squadrons, 1 nuclear sub The PLO Returns (Israel): 1 squadron The Merge (US): 2 squadrons, 2 nuclear subs Pretorian Gold (US): 1 squadron, 1 nuclear sub Hunters (Soviets): 1 squadron, 1 nuclear sub, 1 diesel sub Killers (US): 2 squadrons, 2 nuclear subs Sea of Okhotsk (US): 1 squadron, 3 nuclear subs **Global Conflicts 3** Opening Moves (NATO): 3 squadrons, 4 diesel subs Vodka or Sake (Soviets): 1 squadron, 2 nuclear subs Rum Punch (US): 5 air squadrons, 1 aircraft Panama Hats (US): 2 squadrons, 1 surface vessel (cutter) Linchpin - Red (NATO): 1 squadron, 5 nuclear subs Neutrality Violated (Soviets): 1 aircraft Nordic Revenge (Soviets): 1 squadron Retaking the Diego Garcia (US): 1 squadron, 2 nuclear subs Airlane Gambit (US): 1 nuclear sub, 2 surface vessels (frigate) Thief in the Night (US): 1 squadron, 6 nuclear subs Battle of the Bay of Bengal (US): 3 squadrons, 1 nuclear sub Bay of Pigs Part II (US): 3 air squadrons, 1 squadron Polar Bears (US): 1 squadron, 1 nuclear sub Second Battle of Tsushima Straights (Soviets): 1 squadron, 4 nuclear subs Linchpin – Blue (US): 2 squadrons, 2 nuclear subs Cold War Air Lane Raiders (US): 1 squadron Reinforcing the Northern Flank (NATO): 2 squadrons, 2 nuclear subs Car Carrier Convoys (US): 11 surface vessels (6 merchant, 3 destroyers, 2 frigates) Tremors (US): 3 squadrons, 16 surface vessels (7 tankers, 6 containers, 1 nuclear sub, 1 cutter, 1 cruise liner) Enemy on Island (US): 3 air squadrons, 3 nuclear subs Watch that First Step (US): 5 surface vessels (1 destroyer, 2 nuclear subs, 2 cutters)

Midway Revisited (US): 1 squadron Bring Along Some Friends (US): 1 squadron Vietnam Escort (US): 2 squadrons, 1 nuclear sub Fish in a Barrel (US): 1 squadron Black Sea Surprise (US): 2 nuclear subs Visit to Valdez (US): 1 squadron, 2 nuclear subs, 2 surface vessels (cutters) Battle of the North Sea (NATO): 2 squadrons, 14 surface vessels (drilling rigs) End Run (US): 1 squadron Battle of the Western Approaches (NATO): 2 squadrons WestPac Sanctions (US): 5 surface vessels (2 frigates, 2 destroyers, 1 cruiser) Reunification by Force Part I (North Korea): 3 squadrons, 2 diesel subs Reunification by Force Part II (North Korea): 5 squadrons, 2 diesel subs Infiltration (North Korea): 4 surface vessels (patrol boats) Battle for the Yellow Sea (US): 1 squadron Block the Oil (Russia): 1 squadron, 3 nuclear subs, 3 surface vessels (2 frigates, 1 destroyer) Defense of a Friend (US): 1 squadron, 2 nuclear subs Phone Tap (US): 1 nuclear sub Whose Islands are They (China): 2 squadrons Australasian War Part I (ANZEF): 1 squadron, 1 diesel sub Australasian War Part II (Singapore): 3 squadrons Operation Big Bash (US): 1 squadron, 1 nuclear sub Piracy (Malaysia): 5 surface vessels (small combatants) Gunboat Diplomacy (Philippines): 9 surface vessels (small combatants) Fish Stick Theory (Malaysia): 3 squadrons **Regional Conflicts 1** Fish Net (Japan): 3 squadrons, 2 diesel subs The Rising (Japan): 3 squadrons, 2 diesel subs The Gas Line (Japan): 2 squadrons, 2 diesel subs Desperate Times (Japan): 2 squadrons, 1 diesel sub The Fruit (Japan): 4 squadrons, 1 diesel sub Fortune Cookies (UK): 1 nuclear sub Women and Children First (UK): 1 squadron, 1 nuclear sub A Fork in the Road (UK): 2 squadrons, 1 nuclear sub Yellow Surprise (UK): 2 nuclear subs, 1 frigate, 5 surface vessels The Grand Game (UK): 2 squadrons, 1 nuclear sub The Eyes of Inchon (US): 3 squadrons, 2 nuclear subs, 1 frigate Chaperones (US): 3 squadrons, 1 nuclear sub Back War (US): 2 squadrons, 3 nuclear subs A Tale of Two Oceans (US): 2 squadrons, 2 nuclear subs The Beijing Split (US): 2 squadrons **Regional Conflicts 2** Flash Point (Iran): 2 patrol boats Retribution (Iran): 4 patrol boats A Tooth for a Tooth (Iran): 3 squadrons Escalation (Iran): 4 squadrons Kilo Patrol (Iran): 2 patrol boats, 3 diesel subs Sons of Islam (Saudi Arabia): 2 squadrons David and Goliath (Iran): 2 patrol boats, 5 squadrons The Great Satan (US): 1 squadron, 1 nuclear sub, 1 cruiser Cleansing (US): 1 squadron Stand Down (Coalition): 3 squadrons Pacification (Iran): 3 squadrons Straight Jacket (Iran): 4 squadrons Oman Revisited (Iran): 2 squadrons Is a Formidable Foe (Iran): 4 squadrons Are Quite Unaccustomed to Fear (US): 2 squadrons
Winner. Cheap Shot (France): 1 squadron

Runnerup Falklands War I (UK): 1 squadron, 3 diesel subs

Runnerup Fleet EX-95-3.2 (Blue Forces): 1 squadron, 1 nuclear sub, 1 ocean survey vessel

Runnerup Newfoundlands Scouts (NATO): 3 squadrons, 3 nuclear subs

Runnerup Seward's Folly (US): 1 squadron

Runnerup The Jugular (Japan): 2 squadrons, 3 diesel subs

Runnerup Caribbean Snowstorm (US): 4 DEA boats, 2 cutter, 2 nuclear subs, 1 squadron

# **APPENDIX C – QUESTIONNAIRE DATA**

Name	N1	N2	N3	N 10001	N10002	N10003	N20000	N 30000	N21001	N21002	N21003	N22001	N22002	N22003	N31001	N31002	N31003	N32001	N32002	N32003
James	-2	-4	-3	7	9	5	7	-5	4	9	4	9	9	9	5	9	3	7	5	2
Mike	-5	-7	3	7	9	3	1	-5	3	5	1	1	1	1	7	9	5	7	7	1
Dave H.	-7	-6	-2	7	9	7	4	3	3	5	2	3	7	4	1	3	1	1	3	1
Jared	-8	1	5	4	9	4	1	4	1	3	1	1	1	1	2	6	2	5	8	5
Dave C.	-5	-7	-3	5	7	5	-5	-3	3	5	3	3	5	3	5	7	5	3	5	3
Justin	-7	-3	3	5	9	5	1	-5	5	9	5	5	9	5	3	6	3	1	4	1
Jay	-6	3	2	3	7	5	3	-3	2	4	3	4	7	4	6	9	6	4	7	5
ave.	-5.71	-3.86	1.57	5.43	8.43	4.86	2.00	-2.57	3.00	5.71	2.71	3.71	5.57	3.86	4.14	7.00	3.57	4.00	5.57	2.57
normal	-6	-3	2	5	8	5	2	-3	3	6	3	4	6	4	4	7	4	4	6	3
outlier	-8/-2	-7/3	-3/5	3/7	7/9	3/7	-5/7	-5/4	1/5	3/9	1/5	1/9	1/9	1/9	1/7	3/9	1/6	1/7	3/8	1/5
	-																			
Normalized	-1	-3	-2	6	8	4	6	-4	3	8	3	8	8	8	4	8	2	6	4	1
	-4	-6	2	6	8	2	0	-4	2	4	0	0	0	0	6	8	4	6	6	0
	-6	-5	-1	6	8	6	3	2	2	4	1	2	6	3	0	2	0	0	2	0
	-7	0	4	3	8	3	0	3	0	2	0	0	0	0	1	5	1	4	7	4
	-4	-6	-2	4	6	4	-4	-2	2	4	2	2	4	2	4	6	4	2	4	2
	-6	-2	2	4	8	4	0	-4	4	8	4	4	8	4	2	5	2	0	3	0
	-5	2	1	2	6	4	2	-2	1	3	2	3	6	3	5	8	5	3	6	4
ave.	-4.71	-2.86	0.57	4.43	7.43	3.86	1.00	-1.57	2.00	4.71	1.71	2.71	4.57	2.86	3.14	6.00	2.57	3.00	4.57	1.57
varience	3.35	8.12	4.53	2.24	0.82	1.27	8.29	7.39	1.43	4.78	1.92	6.49	9.96	6.41	4.12	4.29	2.82	5.43	2.82	2.82
Normalized	-4	-3	2	6	8	4	6	-4	2	4	0	0	8	0	4	8	2	6	4	1
outlier	-6	-6	-1	6	8	2	0	-4	2	4	1	2	6	3	6	8	4	0	6	0
dropped	-7	-5	4	6	8	3	3	2	0	2	0	0	0	0	1	5	1	4	7	0
	-4	0	-2	3	8	4	0	-2	2	4	2	2	4	2	4	6	4	2	4	4
	-6	-6	2	4	6	4	0	-4	4	8	4	4	8	4	2	5	2	0	3	2
	-5	-2	1	4	8	4	2	-2	1	3	2	3	6	3	5	8	5	3	6	0
ave.	-5.33	-3.67	1.00	4.83	7.67	3.50	1.83	-2.33	1.83	4.17	1.50	1.83	5.33	2.00	3.67	6.67	3.00	2.50	5.00	1.17
normal	-5	-4	1	5	8	4	2	-2	2	4	2	2	5	2	4	7	1	3	5	1
non-normal	-6	-5	2	6	9	5	3	-3	3	5	3	3	6	3	5	8	2	4	6	2
varience	1.22	4.89	4.00	1.47	0.56	0.58	4.81	4.56	1.47	3.47	1.92	2.14	7.56	2.33	2.89	1.89	2.00	4.58	2.00	2.14

#### **Questionnaire Data Standard Deviation Plot**



Appendix D – sample scenario summary form

Objective: Navigate your squadron to surround the peninsula and engage North Korea.

Victory conditions:	Destroy 2 destroyers
	Destroy 7 patrol boats
	No loss of US units

### Run Name: SHIP

Victory Conditions Met		
Destroy 2 DD units	yes	no
Destroy 7 PG or PCM units	yes	no
No loss of US units	yes	no
If all met time of completion	-	

Losses/ %Damaged:

North Korea

**China** 

Comments By Player/ Observations of ship characteristics

# **APPENDIX E – ALDV MISSION NEED STATEMENT** [23]

#### FOR AN

# **Advanced Logistics Delivery Ship – ALDV**

#### 1. DEFENSE PLANNING GUIDANCE ELEMENT.

The policy definition for the ALDV is based on four unclassified documents: "Forward...from the Sea," the 2001 Quadrennial Defense Review Report, the Naval Transformational Roadmap, and Sea Power 21.

With the collapse of the Cold War, the Department of the Navy developed a new policy, called "Forward...from the Sea". This document outlines a significant change in priorities from a "Blue Water Navy fighting a traditional Super Power". This policy set forth a directive for the Navy and Marine Corps team to have faster and more conflict specific responses. Most recently, the Quadrennial Defense Review Report and the Department of the Navy's new whitepaper, "Naval Transformational Roadmap," provide additional unclassified guidance and clarification on current DOD and USN defense policies and priorities.

The Quadrennial Defense Review Report identifies six critical US military operational goals. These are: protect critical bases of operations; assure information systems; protect and sustain US forces while defeating denial threats; deny enemy sanctuary by persistent surveillance, tracking and rapid engagement; enhance space systems; and leverage information technology.

The Naval Transformational Roadmap provides the US Navy's plan to support these goals using warfighting capabilities in the areas of Sea Strike – Projecting precise and persistent offensive power using strategic agility, maneuverability, ISR, and time-sensitive strikes; Sea Shield – Projecting global defensive assurance by projecting defense around allies, controlling the seas and countering threats; and Sea Base – Projecting joint operational independence using accelerated deployment and employment times and enhanced seaborne positioning of joint assets. Sea Power 21 also focuses on Sea Shield, Sea Strike and Sea Basing.

This Mission Need Statement specifically addresses the lack of an adequate logistics delivery solution that reduces cost, minimizes personnel in harms way and efficiently delivers large quantities of supplies to inland troops.

#### 2. MISSION AND THREAT ANALYSIS.

#### a. Threat.

Adversaries may range from Super Powers to numerous regional powers, and as such the US requires increased flexibility to counter a variety of threat scenarios that may rapidly develop. There are two distinct classes of threats to US national security interests:

- (1) Threats from nations with a major military capability, or the demonstrated interest in acquiring such a capability. Specific weapons systems that could be encountered include ballistic missiles, land and surface launched cruise missiles, and significant land based air assets and submarines.
- (2) Threats from smaller nations who support, promote, and perpetrate activities which cause regional instabilities detrimental to international security and/or have the potential for development of nuclear weapons. Specific weapon systems include diesel/electric submarines, land-based and surface-launched anti-ship missiles, chemical/biological weapons and mines.

#### b. Required Mission Capabilities.

Enhance our ability to provide the following capabilities:

- (1) Transport supplies from off-shore seabase or logistic support (shuttle) ships to the coast.
- (2) Store dry and liquid cargo necessary to support a MEB ashore.
- (3) Assemble an Airborne Logistics Delivery System (ALDS).
- (4) Deliver supplies over the coast to inland troops by launching ALDS.

(5) Support V-22 Osprey refueling operations.

Given the following significant constraints:

- (1) Minimize personnel in harms way.
- (2) Reduce cost.
- (3) Provide an efficient and reliable supply delivery method.

#### c. Need.

Current logistics delivery methods include:

- (1) Landing Craft, Air-Cushioned (LCAC) and convoy lines
- (2) Helicopter delivery
- (3) Air-drops

These methods are costly and/or put significant numbers of personnel in harms way. Convoy lines are slow and unreliable and endanger military personnel. Using helicopters to deliver supplies has also proven itself an inadequate solution. Helicopters make easy targets, thereby endangering personnel and expensive equipment. In addition, helicopters can only carry a limited amount of supplies and must maneuver from location to location to deliver the supplies to different areas. Air-drops have the same shortcomings as helicopters, but also create problems in that they need a land base from which to operate. Friendly land bases are not often nearby while performing missions in hostile territories.

There is a mission need for a system that efficiently and effectively delivers large quantities of supplies to inland troops in various locations while minimizing risk to personnel and equipment. The solution must be expendable, unmanned, safe, inexpensive, and easy to produce.

### 3. NON-MATERIAL ALTERNATIVES.

- a. Change the US role in the world by reducing international involvement.
- b. Increase reliance on foreign political and military support.
- c. Increase reliance on non-military assets and options to enhance U.S. performance of missions identified above; requiring a smaller naval force.

#### 4. POTENTIAL MATERIAL ALTERNATIVES.

- a. Create a mortar launch delivery system.
- b. Higher altitude air-drops.
- c. Assign supply delivery responsibilities to aircraft carriers.
- d. Create a new ship (ALDV) with an expendable gilder delivery system (ALDS) that replenishes from offshore base or logistic support (shuttle) ships.

#### 5. <u>CONSTRAINTS</u>

- a. The platform must be non-nuclear powered, to keep down cost and manning.
- b. The platform must minimize cost.
- c. The platform must require low manning due to high levels of automation.
- d. The ALDS must be highly producible, minimal time from design to production.
- e. The ship must be able to operate in shallow water and high sea states.
- f. The platform must support the V-22 Osprey mission.
- g. The platform must be a high speed vessel for a rapid, 'just-in-time' delivery.

## VITAE

Daniel Todd Demko was born November 22, 1980 in Pittsburgh, PA to Betty and David Demko. He graduated from Lower Merion High School in 1999. He earned his Bachelors of Science degree in Ocean Engineering at Virginia Tech in December of 2003. During Daniel's years as an undergraduate he was the Treasurer/Secretary of the Society of Naval Architects and Marine Engineers and participated in the Virginia Tech men's rowing team. He also led a team to win the 2003 Lisnyk International Ship Design Competition. Upon completion of his undergraduate education he stayed at Virginia Tech for his Master's of Science degree in Ocean Engineering. Following his graduation in May of 2005 Daniel will begin employment with John J. McMullen Associates in Alexandria, VA, the maritime sector of Alion Sciences.