METHODOLOGY FOR OPTIMIZING COMMONALITY DECISIONS IN MULTIPLE CLASSES OF SHIPS

by

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To My Family

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NOMENCLATURE

A^t – Archive at generation t
A^* – Final archive
AMIO – Alien Migration Interdiction Operations
ASSET – Advanced Surface Ship Evaluation Tool
B - Beam
BM_T – Transverse Metacentric Radius
C – Cruise engine number
C_b – Block Coefficient
C_I – Waterplane Transverse Inertia Coefficient
C_m – Midship Section Coefficient
C_{WP} – Waterplane Coefficient
C_{VP} – Vertical Prismatic Coefficient
CC – Common cruise engine type
CER – Cost Estimating Relationship
CG – Common ship service diesel generator type
CIWS – Close In Weapon System
CM – Common midship section type
CODAD – Combined Diesel and Diesel
CODOG – Combined Diesel and Gas Turbine
Cost – Average construction cost of fleet
CS – Common superstructure type
CW – Common weapon system type
d_{ij} – Distance between *n* data points
D – Normalized distance between data points
D_{RAW} – Average distance between data points
$D(x_i)$ – Diversity operator
E – Endpoint archive
EEZ – Exclusive Economic Zone
f – Objective function
G – Ship service diesel generator number
GDO – General Defense Operations
GM_T – Transverse Metacentric Height
H – Number of helicopter hangars
I_T – Transverse Moment of Inertia of the Waterplane
k – Number of children generated per generation
K – Kernel function
KB – Height of center of buoyancy
KG – Height of center of gravity

L – Length
LMR – Living Marine Resources
M_{mut} – Mutation Magnitude
MOGA – Multiple-Objective Genetic Algorithm
MP – Percent of time engaged in mission
n – Number of independent design variables
N – Designation for no component commonality
NAVSEA – Naval Sea Systems Command
NSC – National Security Cutter
OPC – Offshore Patrol Cutter
P^t – Population at generation t
R_{mut} – Mutation Rate
SWBS- Ship Weight Breakdown Structure
t - Generation
t^* – Maximum number of generations
T – Draft
USC – United States Code
V_{max} – Maximum Speed
W – Weapon system number
WG – Weight Group
WHEC – High Endurance Cutter
WMEC – Medium Endurance Cutter
WMSL – Maritime Security Cutter Large
WMSM – Maritime Security Cutter Medium
x – Independent design variable vector
y(k) – Performance characteristic
∇ - Submerged volume

CHAPTER 1

INTRODUCTION

1.1 Overall Goal

The overall goal of this research was to apply multicriterion optimization methods to platform decisions for families of ship variants while explicitly taking into account fleet-wide savings. In this context, a platform is the set of common elements used in more than one ship class. The Optimal Design Laboratory of the Department of Mechanical Engineering at the University of Michigan has developed analytical methods for making optimal platform decisions in consumer products and the automotive industry. This research has adapted these methods and extend them to utilize the multicriterion optimization approach necessary to effectively treat naval fleet design problems. The methodology was then tested through modeling and application to determine the optimal common platform and ship designs to use for the missions of the U.S. Coast Guard's Deepwater Fleet.

1.2 Motivation

A common practice within the automotive industry is to use the same frame, engine, etc. for perhaps a light sport utility vehicle, a sedan and perhaps other variants within an automobile manufacture's line of vehicles. If this practice is so widely used in the automotive industry, why is it not utilized in naval ship design? In ship design, common hull blocks, main engines, engine rooms, ship service generators, sensors and weapons could be used to provide commonality and savings across multiple ship variants. Savings can be obtained in training of personnel, logistical support, procurement, detailed design development, and construction costs. The use of optimally determined platforms may offer part of the solution for an affordable fleet in the future.

Traditionally naval ship design has been performed on a ship class by ship class basis. Ships are generally designed in order to maximize their mission effectiveness without consideration of the detailed design of other ships in their fleet; an exception being compatible communications and weapons control. As ship designs have progressed, ships are being developed with more systematic commonality in mind. Different ship classes will have certain systems that are common to each other. The motivation behind this is to improve interoperability and decrease costs associated with design, development, construction and operation of the ships. Despite the use of commonality, the shipbuilding industry has yet to utilize platform design techniques as a standard of practice. This research develops a logical methodology to establish the optimal platforms within a family, or fleet, of ships.

The strategic design question is how many and which elements should be included in the platform definition to maximize savings without excessive degradation of the performance of the variants in the family. The use of commonality in design often comes with compromises in mission effectiveness of individual designs. A multicriterion design optimization decision results – how to maximize the savings through the use of the platform while also maximizing the performance of each of the variants within the family. In order to use platforms in ship design, one must develop a way to measure the effects of commonality decisions on each variant's performance. This research develops a system of measuring the change in performance associated with the use of a platform and comparing this to the resulting fleet-wide cost savings.

1.3 Previous Product Family Work

The development of rational, analytical methods for the definition of platforms has been the subject of a number of recent research efforts. Simpson provides an extensive survey on these efforts [Simpson 2004]. Here only some basic relevant work is reviewed.

At the University of Michigan, the Optimal Design Laboratory of the Department of Mechanical Engineering has developed optimization-based methodologies for making optimal platform decisions. Fellini et al. used information from the optimization of individual product variants to determine optimal platforms [Fellini et al. 2004]. Further work by these same authors evaluated commonality decisions while controlling performance losses. Sharing of product components was based on designer-specified loss tolerances [Fellini et al. 2005]. By combining two previous approaches, Fellini, Kokkolaras, and Papalambros developed a methodology that identifies an initial set of shared components for a platform and then evaluates that platform using performance loss standards [Fellini et al. 2006] under the tacit assumption that more platform content is better. Sensitivity measures were used to establish the platform content to consider without requiring detailed cost savings estimation.

At M.I.T.'s Engineering Design Laboratory, Gonzalez-Zugasti, Otto, and Baker used a general optimization formulation that balances the advantages of sharing components with the constraints of individual product variants to form an interactive, team-based negotiation model for designing a product family based on a common platform [Gonzalez-Zugasti et al. 1998]. In addition, Gonzalez-Zugasti and Otto explored methodologies for designing families of products built onto modular platforms [Gonzalez-Zugasti and Otto 2000]. These authors rely heavily on design team input throughout their product platform design methodology. In this methodology, the design team meets to decide which portions of the individual designs should be used as platforms. From this decision, product variants are developed. The variant designs are optimized with regard to performance and cost constraints. The optimization is performed on the variants on a "one at a time" basis rather than optimizing them concurrently.

Simpson, Maier, and Mistree have also focused their attention on product family design [Simpson et al. 2001]. Their primary focus was on scale-based product families derived from product platforms that can be derived from functional and manufacturing considerations. This methodology has been extended several times. Nayak, Chen, and

Simpson developed robust design concepts to formulate a variation-based platform design methodology [Nayak et al. 2002]. Messac, Martinez, and Simpson used a physical programming approach to optimize designs [Messac et al. 2002]. In these papers, the authors consider performance and production considerations, but do not explicitly mention cost savings considerations.

Fujita and Yoshida proposed a simultaneous optimization method for module combination and module attributes of multiple products. Their work optimized the combinatorial pattern of commonality and similarity, optimized similarities on scale-based variety, and optimized the continuous module attributes [Fujita and Yoshida 2004]. Considerations were made for performance, cost and profit of the design variants based on a fixed modular architecture. Design trends in the optimization were used to help narrow the number of design variants.

1.4 Related Ship Design Optimization Work

In 1992, the U.S. Navy began an initiative titled "Affordability through Commonality" [Bosworth and Hough 1993, Cecere et al. 1995]. The goal of this initiative was to lower the cost of fleet ownership through the use of increased commonality. The Navy defined commonality as using modularity, equipment standardization and process simplification. The authors argue that the use of commonality would ultimately lower all life cycle costs associated with design, construction and operation of the Navy's ships. Although the Navy is using this new fleet ownership strategy, it does not appear that a formal methodology has been developed to aid cost-effective commonality decision-making.

Brown and Salcedo presented a ship design optimization methodology based on life cycle cost and mission effectiveness [Brown and Salcedo 2003]. They developed a methodology for exploring the many variations that are possible in a given ship design. By using various combinations of combat systems, engine selections, hull form parameters, manning, endurance, and mobility, they efficiently explored the design space for non-dominated designs. The designs are compared using life cycle costs and a measure of mission effectiveness. A Multiple-Objective Genetic Algorithm (MOGA) optimization was used to search the design space. Their work did not consider the design of a family of ship variants, but rather gives the methodology for the optimal design of one ship class.

Zalek, Parsons and Papalambros used a multicriterion evolutionary algorithm to search the design space for monohull forms optimized with respect to calm water powering and seakeeping [Zalek et al. 2006a, Zalek et al. 2006b, Zalek 2007]. Their experience in developing a multicriterion evolutionary algorithm was a starting point for this research.

1.5 Contribution of Research

The proposed research project will serve to benefit the Naval Architecture and Marine Engineering and Mechanical Engineering design communities in several areas.

Previous work in multiobjective optimization has adopted methods to change the multicriterion problem into a single criterion optimization [Fellini et al. 2005]. In that research, they reformulated the multicriterion problem by changing one of the objectives into a constraint. The research presented here does not utilize a similar reformulation of the optimization problem. Rather, it develops a methodology to solve the multicriterion optimization directly.

In order to solve the optimization problem, a multicriterion evolutionary algorithm was developed as part of this proposed research. The solution obtained by the evolutionary algorithm is the Pareto front. This Pareto front will help designers make design decisions based on commonality savings and the resulting performance losses of the variants.

Another extension of previous Optimal Design Laboratory research is the development of an explicit platform fleet cost savings model. Until now, the actual cost savings associated with platform decisions has not been taken into account directly. Most of the effort of the research was in developing a methodology for making commonality decisions using performance loss as the main constraint [Fellini et al. 2005]. This research looks more closely at the cost savings that various commonality decisions would bring. By comparing cost savings with performance loss a designer can objectively determine how much the use of common components would benefit the cost of a fleet of vessels. Platform decisions can then be made based on both cost effectiveness and performance loss.

So far, most all of the work in the commonality design and optimization field has been related to consumer goods and, more specifically, the automotive industry. This research will expand these concepts to be used on a larger-scale marine application. Although the Navy has considered some aspects of these optimization issues in the past as part of its "Affordability through Commonality" program, this research provides a way for designers to design families of ships vice individual ship classes. This research is the first multi-ship class design optimization of its kind. The formal optimization of the design of two ship classes simultaneously using platforms and cost considerations has not been done before.

The final component of this research is a case study to test the methodology developed herein. The case study is conducted using the U.S. Coast Guard's Deepwater Fleet mission requirements and operations scenarios. The two ship classes that will be considered are the Maritime Security Cutter Large (WMSL), formerly known as the National Security Cutter (NSC), and the Maritime Security Cutter Medium (WMSM), formerly known as the Offshore Patrol Cutter (OPC). These ship classes serve this research well based on the significant overlap of their missions and designs.

CHAPTER 2

MULTICRITERION OPTIMIZATION THEORY

2.1 Basic Theory

"When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions is known as multicriterion optimization." [Deb 2001]. Single criterion optimization problems can be formulated as:

$$\begin{aligned} &\text{minimize} && F(\mathbf{x}) = f_1(\mathbf{x}) && \mathbf{x} = [x_1, x_2, \ldots, x_n]^T \\ &\text{subject to} && h_i(\mathbf{x}) = 0, && i = 1, \ldots, I \\ & && g_j(\mathbf{x}) \geq 0, && j = 1, \ldots, J \end{aligned} \tag{2.1}$$

where f_1 is a single scalar objective function or criterion and the vector $\mathbf{x}$ represents the design independent variables.

In most real world applications, optimization problems often involve multiple competing objectives. The multicriterion or multiobjective optimization problem can be formulated as

$$\begin{aligned} &\text{minimize} && \mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x}), \ldots, f_K(\mathbf{x})]^T \quad \mathbf{x} = [x_1, x_2, \ldots, x_n]^T \\ &\text{subject to} && h_i(\mathbf{x}) = 0, \qquad i = 1, \ldots, I \\ & && g_j(\mathbf{x}) \geq 0, \qquad j = 1, \ldots, J \end{aligned} \tag{2.2}$$

where $f_1, f_2, f_3, \ldots, f_K$ represent the multiple objective functions and **x** again represents the design independent variables.

Some of the multiple objective functions usually conflict with one another. As one objective function is improved some of the other objective functions often suffer. Therefore, compromises must take place in order to reach acceptable levels of satisfaction among each of the objective functions. Because of these compromises, the results of a multicriterion optimization problem differ from that of a single criterion optimization problem. A single criterion optimization will generally have only one globally optimal solution. A multicriterion solution will have many possible solutions. A given solution may be optimal for one of the objective functions, but not the others. If some of the objectives are conflicting, satisfying one objective will lead to a sacrifice of one or more of the others. No solution will be the best for all the objectives. The result of a multicriterion optimization is a Pareto optimal set.

The Pareto optimal set is composed of the non-dominated set of solutions to the problem. Each design on the Pareto front is such that no criterion can be improved without sacrificing another. An example of a convex two criterion optimization solution is shown Figure 2.1.

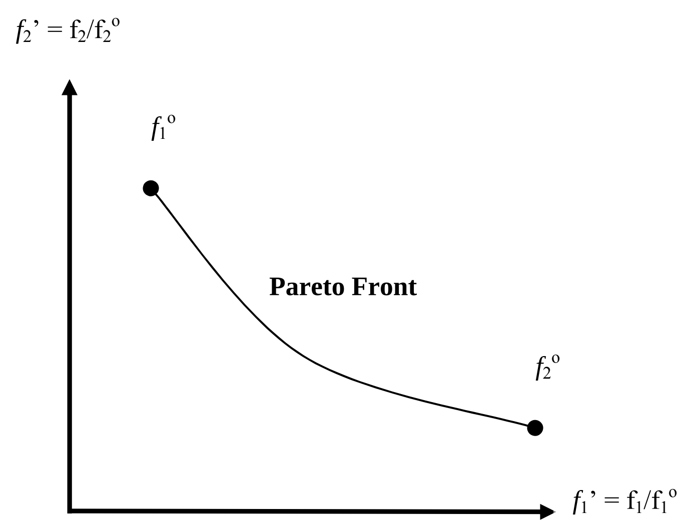

Figure 2.1 Multiobjective Optimization Solution

In Figure 2.1, f_1 and f_2 represent the two objective functions to be minimized. The Pareto front is usually bounded by the optimum solutions for f_1 and f_2 obtained considering their objective functions one at a time, f_1^o and f_2^o, respectively.

Since the objective is usually to determine which single design is the best for a particular problem, one must examine ways to choose a design from the Pareto optimal set. There are several accepted ways to accomplish this. The two methods that will be considered in the proposed research are the Min-Max solution and the Nearest to the Utopian solution.

2.2 Min-Max Solution

The Min-Max solution method provides a result that formally compromises between the competing design criteria by providing equal fractional loss relative to the best that could be achieved for those criteria. The un-weighted Min-Max solution uses a scalar preference function [Parsons and Scott 2004],

$$\mathrm{P}[f_k(\mathbf{x})] = \max_{k} \, [z_k(\mathbf{x})] \tag{2.3}$$

where z_k are the relative increments (loss) between the $f_k(\mathbf{x})$ and associated f_k^o,

$$z_k(\mathbf{x}) = |\, f_k(\mathbf{x}) - f_k^o \,| \,/\, |\, f_k^o \,|. \tag{2.4}$$

Using the Min-Max solution method, the maximum is taken over the K criteria to obtain a preference function, P. The scalar preference function P is then minimized over all $\mathbf{x}$ considering the constraints. Figure 2.2 illustrates the Min-Max solution for a problem with K=3 criteria.

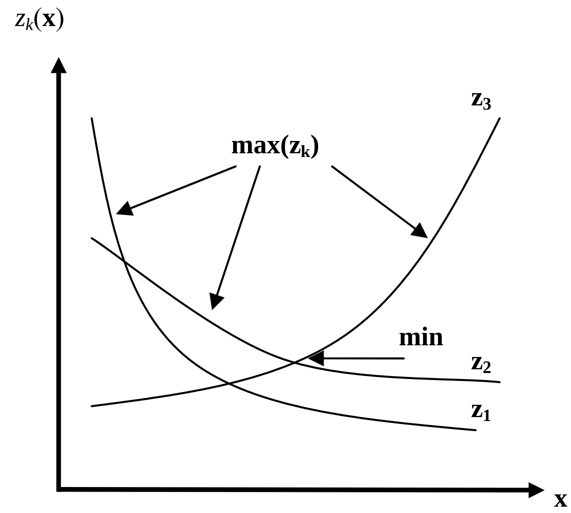

Figure 2.2 Min-Max Solution for *K*=3 Problem

The preference function P or the maximum of the z_k can be viewed in Figure 2.2. The max(z_k) is composed of three sections: the leftmost section is the segment of z_1 up to its intersection with z_2. The center section is the segment of z_2 that is between its intersections with z_1 and z_3. The rightmost segment is the portion of z_3 that starts at the intersection with z_2 and continues to the right. The minimization of P over all **x** is then determined to be at the point where $z_2 = z_3$. It is typical for the two criteria that control the conflict (f_2 and f_3) to have equal fractional loss z_i at the solution with lower z_i for the other criteria as shown.

2.3 Nearest to the Utopian Solution

The utopian solution is the best possible design that could be achieved with respect to both objective functions. This solution is not attainable, however, because of the constraints. The nearest to the utopian solution suggests that a good compromise between objective functions would be the point on the Pareto front that lies closest to the utopian solution in normalized criterion space. Figure 2.3 illustrates a nearest to the utopian solution. The optimization of the design is performed by minimizing the distance **d** from the utopian point to the Pareto front.

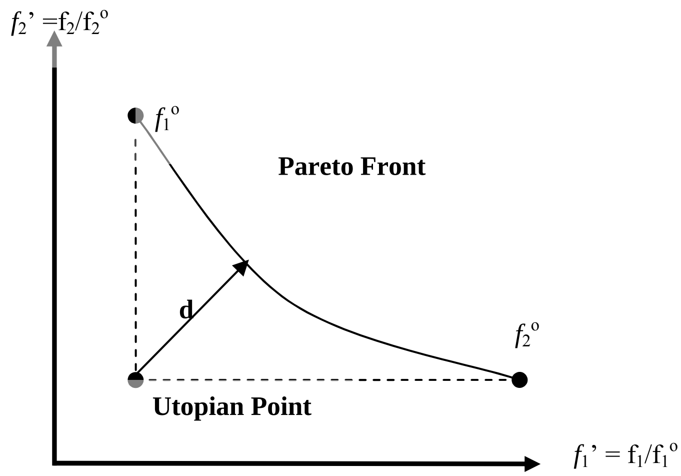

Figure 2.3 Nearest to Utopian Point Solution

2.4 Problem Formulation

For the purposes of this research, the objective functions, $f_1, f_2, f_3, \ldots, f_K$, will be limited to three. The objective functions will be:

$f_1(\mathbf{x_1}, \mathbf{x_c})$ – Ship A Mission Effectiveness/Average Ship Cost

$f_2(\mathbf{x_2}, \mathbf{x_c})$ – Ship B Mission Effectiveness/Average Ship Cost

$f_3(\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_c})$ – Net Fleet Savings from Commonality

where f_1 and f_2 are subject to the ship design constraints for their respective design as specified by naval architecture practice and the customer. The objective function f_3 is the total fleet savings realized through the use of the commonality.

The design independent variable vector **x** is composed of the following:

$\mathbf{x_1}$ = Ship A design independent variables

$\mathbf{x_2}$ = Ship B design independent variables

$\mathbf{x_c}$ = Commonality components.

The performance or mission effectiveness of the two different ship classes (i=1, 2) is related to their specific missions (j=1,…,n). The ability of each ship i to successfully accomplish each mission j is assumed to depend upon k performance characteristics y_k. The contribution of each of these performance characteristics k to the success in each mission j is characterized by a fuzzy membership function or utility $0 \leq U_{ijk}(y_k) \leq 1$. The overall mission effectiveness or performance per average ship cost is then obtained by minimum correlation inference as follows.

$$\left[\frac{Performance}{Cost}\right]_i = \sum_{j=1}^{n} \frac{MP_{ij} \min\lfloor U_{ijk}(y_k)\rfloor}{Cost_i} \tag{2.5}$$

where MP_{ij} is the percent of time that vessel i is engaged in mission j and $Cost_i$ is the average acquisition cost of vessel i.

The cost of the ship will be estimated using common ship construction cost estimating methods. The cost used in the objective functions will be the average cost of all the ships in the fleet. The primary benefit of only considering the construction cost is that it will penalize a ship from being over designed. Using components that are more effective than necessary to meet the ship's mission at a higher cost will not benefit a ship's design.

The net fleet savings function, $f_3(\mathbf{x})$ will take into consideration all fleet-wide costs directly associated with the use of common components. To demonstrate the methodology, these are limited to bulk purchase savings and construction learning curve savings. The savings function will consider all ships in each design class as contributing to the total fleet savings. The global effect of commonality on the cost of the entire fleet of ships involving the two classes A and B is used.

The design constraints consist of the typical standards that a ship must comply with in order to be safe and effective. For this research considerations were made for basic stability, weight-displacement balance and a volume check. Other design constraints may dictate operational capabilities that the ships must meet involving such systems as electronics, weapons, radar, helicopter capabilities and small boats.

The commonality components will be comprised of a set of integers that specify which ship components will be common between both ship classes. If a given commonality component is designated as common, both ships will be constrained to use that component. Each commonality component will have two or three component choices. By varying the number and combinations of the commonality components, the design space will be populated.

Common components in the design optimization will consist of weapon systems, ship service generators, cruise engines, superstructure and midship section. The various combinations of these commonality components will be used to determine which set of common components will result in the Pareto optimal designs for Ship A and Ship B.

As the various combinations of commonality are applied to the designs, the optimization program will begin to fill out the three object Pareto front or Pareto surface. Figure 2.4 shows a schematic of the expected discrete Pareto Front that will be obtained for the multicriterion optimization.

Every set of commonality components ℓ should result in a solution for Ship A_ℓ and Ship B_ℓ that will be located on a line of commonality. If a single ship were being considered for both missions, this line would be the two-objective Pareto front for Ship A_ℓ performance/cost and Ship B_ℓ performance/cost. For specific commonalities, A_1 and B_1 might share Ship A's midship section only, Ships A_2 and B_2 might share Ship A's midship section and cruise engine and so on. As more things become common amongst the ships, the savings can increase and the ship designs will tend toward each other on the Pareto surface as more effectiveness is sacrificed for commonality. Once every item on the ship is determined to be common, the result will be one design for both missions. This design is shown as point C in Figure 2.4. Once every combination of common components is used in the optimization, the discrete Pareto front will be fully populated. The Pareto front will not be continuous because of the discrete nature of the commonality variable. Rather, the Pareto front is will be a collection of discrete points as shown in Figure 2.4.

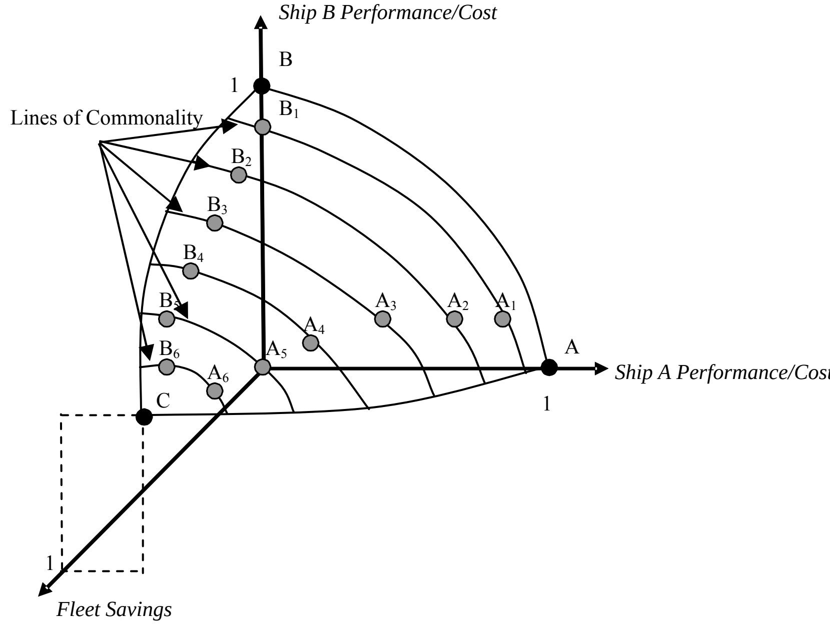

Figure 2.4 Expected Discrete Pareto Front

CHAPTER 3

U.S. COAST GUARD FLEET DESIGN MODELING

3.1 Ship Synthesis Model

For the purposes of this research, a ship synthesis model was needed. Since the goal of the optimization program would be to generate scores of ship variations with minimal input, the synthesis model had to be simple in nature. The goal was to find, adapt, or develop a synthesis model that had a limited number of basic conceptual design level inputs. If the model had too many required inputs, the need to estimate values to fill in all the inputs would be great and the results would likely suffer. A simple ship synthesis model would be adequate in providing initial point design characteristics needed for basic cost estimates and performance evaluations.

The ship synthesis model used in this research was adapted from the Performanced Based Cost Model used by the U.S. Coast Guard Engineering Logistic Center. The model was developed by the Naval Surface Warfare Center Carderock Division as a means to do comparative ship studies [Naval Surface Warfare Center 1998]. The model is capable of synthesizing frigate-sized, deep-water, white-hull cutters and reporting both acquisition and operational and support costs.

The model was developed using previously developed models of relevant ship types. The ship synthesis algorithms are based on a combination of SHOP 5 and ASSET algorithms. SHOP 5 is a Canadian developed model for monohull frigates and destroyers based on NATO frigates. ASSET is the Advanced Surface Ship Evaluation Tool used extensively within NAVSEA and represents a mixture of first principle algorithms as well as regression analysis of historical U.S. combatant ship data, included the U.S. Coast

Guard's WMEC 270 class of ships [ASSET 2005]. The model provides reasonable results for deep-water cutters with displacements of 1500 Long Tons or greater.

The Cost Estimating Relationships (CERs) for the basic construction costs were developed by SPAR Associates Inc. and are based on the U.S. Coast Guard's WHEC 378, WMEC 270, and WMEC 210 classes of ships. Additional CERs were adapted from the CERs that were developed for the U.S. Coast Guard's Great Lakes Icebreaking estimate. All costs are reported in constant year 1998 U.S. dollars.

The inputs to the U.S. Coast Guard model are design and performance based and allow the user to examine the effects of 21 variations in design. From the inputs, the program calculates ship dimensions, powering requirements, electrical load, auxiliary systems weight estimate, outfit and furnishing weight estimate, variable loads, and habitability/personnel space volumes. This information is used to determine the weight of each Ship Weight Breakdown Structure (SWBS) group, lightship displacement, growth margins, ship loads, and full load displacement. A volumetric check is also performed to ensure adequate space is allotted for necessary compartment volumes. Once the ship is balanced and has adequate volume, the program calculates the procurement costs for the lead ship and follow-on ships as well as operating and support costs for the life of the ships.

Several key factors made this synthesis model a good choice for use in this research. First, it was created for the purpose of studying the same types of ships as used as case studies for the research. The synthesis model also provided cost information which is important to the research. The weight-based cost model in the program is a real estimation tool that is used to evaluate costs of real designs. Another advantage that this model had over others was that the inputs are basic. A full understanding of the ship and its specifics is not needed in order to create a ship using this program. Detailed design information is not needed to evaluate the ships' cost and performance. The research focuses on the initial conceptual design information. Finally, the program is straight forward and understandable. The methodology and flow of calculations is easy to follow and could easily be adapted to the research.

In order to make the ship synthesis model more suited to be used in the research a number of changes were made. First, since the model was originally programmed in Microsoft Excel, it was reprogrammed in C++. The adapted synthesis model was changed to require fewer inputs than the Coast Guard model. Table 3.1 shows the independent variable used in the two models.

Table 3.1 Ship Performance Characteristic Inputs

Coast Guard Synthesis Model	Adapted Synthesis Model
Power plant type	Power plant type
Prismatic coefficient	Midship section coefficient
Block coefficient	Block coefficient
Froude length constant (circle M)	Length
Beam/draft ratio	
Maximum speed or shaft horsepower	Maximum speed
Nr of main engines	
Nr of cruise engines	
Nr of diesel-generator sets	
Total accommodations	
Range @ cruising speed	Range @ cruising speed
Cruising speed	
Endurance dry stores	
Endurance chilled stores	
Endurance frozen stores	
Endurance general stores	
Helicopter hangars (1=yes, 0=no)	Number of helicopter hangars
	Weapon system type
Combat system weight input	
Combat system variables loads input	
WG700 weapons weight	
Ratio of superstructure volume to hull volume	

The Coast Guard model allows the user to change any of the inputs listed in Table 3.1 independent of the others. The synthesis model that was adapted for this research limited the number of independent variables to the eight listed. By limiting the number of inputs to eight, the user can control the variable design space more easily and limit the number of possible ship variants to a manageable number. The remaining variables are made dependent on the eight input variables and follow logical ship design practice.

The ship synthesis model was also extended to ensure that its outputs satisfied a few naval architecture constraints. These include a more refined weight-displacement check, a basic stability check, and a more robust volume check.

The iterative process starts with initial guesses for beam, draft, and superstructure volume. As the synthesis model conducts calculations for weights, the initial guesses are updated and the iterative process continues until the calculated displacements of successive iterations are within one half of a percent of each other. As the vessel weight changes, the buoyancy requirement is met by modifying the draft.

The beam of the ship is dependent on the required stability of the ship. Chapter 11 of *Ship Design and Construction* [Parsons 2003] defines the transverse metacentric height (GM_T) using,

$$GM_T = KB + BM_T - 1.03 \cdot KG \tag{3.1}$$

where the 3% increase in KG is included to account for free surface effects. The vertical center of buoyancy (KB) is calculated here using Wobig's regression equation,

$$KB / T = 0.78 - 0.285 \cdot C_{VP} \tag{3.2}$$

The metacentric radius is calculated as follows,

$$BM_T = I_T / \nabla \tag{3.3}$$

where the transverse area moment of inertia of the waterplane, I_T, is estimated using,

$$I_T = C_I L B^3 \tag{3.4}$$

The waterplane transverse inertia coefficient, C_I, is found using the D'Arcangelo formula,

$$C_I = 0.1216 \cdot C_{WP} - 0.0410 \tag{3.5}$$

The beam is increased, if necessary, until the stability requirement is met,

$$GM_T \geq \text{Required } GM_T \tag{3.6}$$

where the required GM_T is set at 7% of the beam.

The hull volume check is performed at each design iteration. The required volume of each space is calculated and compared to the total volume of the ship. If the required volume is less than that of the actual ship's volume, the superstructure volume is decreased and vice versa. This calculation ensures that the ship is sized correctly and that there is no extra volume on the ship.

Occasionally the design inputs, as a set, may be unrealistic and not able to produce a working design. There are a few safeguards that prevent these sets of inputs from being considered in future analysis. These safeguards are designed to stop calculations when it is found that the given inputs will not generate a practical design. Two occurrences have been found to happen when unrealistic ship requirements are made. The first occurs when the required horsepower is greater than the available horsepower of the engines in the database. The engine database consists of over forty gas turbines and diesel engines. The engines range in horsepower from 600 to over 57,000 hp. If the required horsepower for maximum speed is greater than 57,000 hp, the program will stop calculations and abort that design. This usually occurs when the ship continues to grow in size from one iteration to another causing the design to diverge toward an infinite displacement. Given the discrete nature of the engine sizes, the synthesis will at times iterate between two designs. When this occurs, the iterations will continue indefinitely bouncing from one solution to the other without converging to within one half of a percent of successive weights. In order to limit the possibility of this happening, more engines were added to the database. However, there is still a chance that some designs won't converge completely. If a design conducts 100 iterations without convergence, the calculations are stopped and the design is aborted. Through repeated runs, it was found that most good designs converge in less than 10 iterations.

Once a ship's displacement converges the ship's characteristics are fully defined. At this point the cost model is used to determine the costs associated with each ship in the class. An average ship cost is calculated by summing the cost of each ship in the class and dividing by the number of ships in the class. The cost is determined using a weight-based cost model that is based on previously constructed ships and their costs.

CHAPTER 4

MULTICRITERION EVOLUTIONARY OPTIMIZATION

4.1 Design Space Search

There are many well established methodologies for solving a multicriterion optimization problem. This research uses an evolutionary (real-coded genetic) algorithm to search the design space [Goldberg 1989, Michalewicz 1996, Deb 2001, Oscyczka 2002]. The use of a genetic algorithm overcomes some of the difficulties experienced by classical nonlinear programming solution methods. Classical solution methods all have similar difficulties. These difficulties include [Deb 2001]:

1. Inability to find more than one Pareto-optimum solution per simulation run.
2. Not all Pareto-optimal solutions of non-convex criteria space problems can be found with some algorithms.
3. A prior knowledge of the problem is required in order to assign suitable weights/preferences to the objectives.

In order to use the various classical methods to solve multicriterion optimization problems, many of the methodologies require that the problem be converted to a single objective optimization. The solution that is obtained is specific to the weights/preferences used in the conversion. In order to obtain a different solution, the user must change the weights/preferences and rerun the single objective optimization problem. This process has to be repeated over and over in order to fully populate a Pareto-optimal solution set [Parsons and Scott 2004].

In order to select the proper classical solution method, a prior knowledge of what type of solution is expected may be necessary. Some solution methods are limited to only working on convex objective spaces. Should these methods be used on a non-convex solution, “shadows” may form which will omit certain sections of the Pareto-optimal set of solutions.

The weighting or factoring of some of the problems is a difficult part of the solution process. In many cases, this weighting seems to be very arbitrary. Since the solutions are greatly dependent on the weighting this may not be the best way to achieve an optimal solution, especially if objective preferences are not clearly known for the given problem. Another common problem with assigning weights/preferences to classical solution methods is that evenly spaced weights do not typically correlate to evenly spaced solutions on the Pareto front. This may make it difficult to obtain a diverse population of possible solutions for a given optimization.

In multicriterion optimization problems, it is very desirable to accomplish two tasks with each simulation run. First, it is desirable to find multiple optimal solutions; hopefully enough to fully map the Pareto front. Second, it is desirable that these solutions be diverse in that they will be widely spread in order to define the entire non-dominated solution front. The capability to address these two tasks are a unique feature of the use of genetic algorithms to solve multiobjective optimization problems. By searching the entire design space, the genetic (binary-coded) or evolutionary (real-coded) algorithms are not limited as to whether the objective space is convex or nonconvex. In addition, genetic algorithms are generally not dependent on weights/preferences which drive the search towards single solutions. Therefore, genetic algorithms do not utilize user determined weights/preferences.

By using a diversity operator, genetic algorithms can ensure that they have at each generation a population of solutions spread across the entire Pareto front [Zalek et al. 2006a]. These diversity operators measure each solution’s distance to the nearest solutions. If the distance is small, the fitness value of that solution is penalized and that solution is disadvantaged relative to other solutions. By repeating these steps, the population will spread out evenly across the Pareto front giving the designers more choices as they begin to make more advanced design decisions.

Classical solutions also have difficulties converging to a globally optimum solution. In these methods, the algorithms usually start from a random guess. From there, they use the objective function and constraints to guide the search to the optimum solution (direct search methods) or they also use first- or second-order derivatives of the objectives and constraints (gradient-based methods). The direct search methods tend to be slow because of the number of evaluations necessary to achieve convergence. The gradient-based methods are generally quicker, but become more less effective as the object functions become non-differentiable or discontinuous. The difficulties involved with each of the two search methods can be summarized as follows.

1. Convergence depends on the chosen initial guess;
2. Algorithms may get stuck in local or suboptimal solution areas;
3. Algorithms are not universally effective in solving all optimization problems;
4. Algorithms are not efficient in handling problems in a discrete search space.

Genetic algorithms do not face the obstacles that classical methodologies face with regard to convergence. Because of the stochastic nature of how they search the design space, the initial guesses have very little to do with the results. The use of natural analogy genetic principles enables a well-tuned genetic algorithm to efficiently search the entire objective space without getting stuck in local or suboptimal locations. Another way that the genetic algorithms overcome these problems is that the solution method is continuously evolving a population of multiple solutions vice one. Once a genetic algorithm finds an optimal solution, it won't stop but will genetically alter its solutions and continue searching for more non-dominated solutions.

Because of the aforementioned reasons for using genetic and evolutionary algorithms, the Department of Naval Architecture and Marine Engineering at the University of Michigan has undertaken several research projects which utilize genetic algorithms in the solution of single and multiple objective optimization [Li 1997, Li and Parsons 1998, Li and Parsons 2001, Zalek et al. 2006a, Nick et al. 2006, Daniels and Parsons 2006]. Zalek's research used an evolutionary algorithm approach to a multiobjective problem [Zalek et al. 2006a, Zalek et al. 2006b, Zalek 2007]. The experience and methods obtained through these projects has been extended in this research.

4.2 Problem Formulation without Commonality

In the marine design problem studied here, the following multicriterion design optimization will be used.

- Maximize the mission performance of the OPC mission ship relative to the average ship cost for the entire fleet
- Maximize the mission performance of the NSC mission ship relative to the average ship cost for the entire fleet.

The problem can be formulated as

$$\text{maximize} \quad \mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x}), \ldots, f_K(\mathbf{x})]^T \quad \mathbf{x} = [x_1, x_2, \ldots, x_n]^T$$

$$\begin{aligned} \text{subject to} \quad & h_i(\mathbf{x}) = 0, \quad && i = 1,\ldots,I \\ & g_j(\mathbf{x}) \geq 0, \quad && j = 1,\ldots,J \end{aligned} \tag{4.1}$$

where f_1, f_2, f_3,…, f_K represent the multiple objective functions and $\mathbf{x}$ represents the design variables. In this initial case study, the objective functions, f_1, f_2, f_3,…, f_K, will be limited to two. The objective functions will be:

$f_1(\mathbf{x_1})$ – OPC Mission Ship Effectiveness / Average Ship Cost
$f_2(\mathbf{x_2})$ – NSC Mission Ship Effectiveness / Average Ship Cost,

where f_1 and f_2 are subject to the ship design constraints for their respective designs as specified by naval architecture practice and the customer. The objective functions used relate to effectiveness and cost; a benefit/cost ratio. For this application, the constraints have been included in the synthesis model and are, therefore, not explicitly stated in the problem formulation.

As mentioned in the previous chapter, the independent variables have been limited to eight. They are power plant type, midship section coefficient, block coefficient, length, maximum speed, range at cruise speed, helicopter capacity, and weapon system type.

Mission effectiveness measures how well a design meets the mission requirements for the ship. The effectiveness of each design is modeled using fuzzy utility functions. The utility of a given ship design represents how well it performs a specific mission. It is important to note that if a design exceeds its design requirements, it will not receive more credit and since the cost of exceeding requirements will be higher, the value of its objective function will decrease due to its over design for its intended mission.

The cost of the ship will be modeled using common ship construction cost methods. The cost in the objective functions is the average cost of building a fleet of ships of that design. The primary benefit of considering the average ship construction cost is that it will penalize a ship from being over designed. Using components that are more effective than necessary for its mission at a higher cost will not benefit a ship's design.

4.3 Basic Optimization Process

An evolutionary (real-coded Genetic Algorithm) optimization process [Goldberg 1989, Michalewicz 1996, Deb 2001, Osyczka 2002] was designed to provide the Pareto front with a diverse set of solutions, which represent the best possible solutions to the multicriterion problem. The solutions should represent the entire range of independent variables in order to ensure that all possible solutions have been considered. The basic optimization process used in this research is illustrated in Figure 4.1. The details of each portion of this algorithm are described in the following subsections.

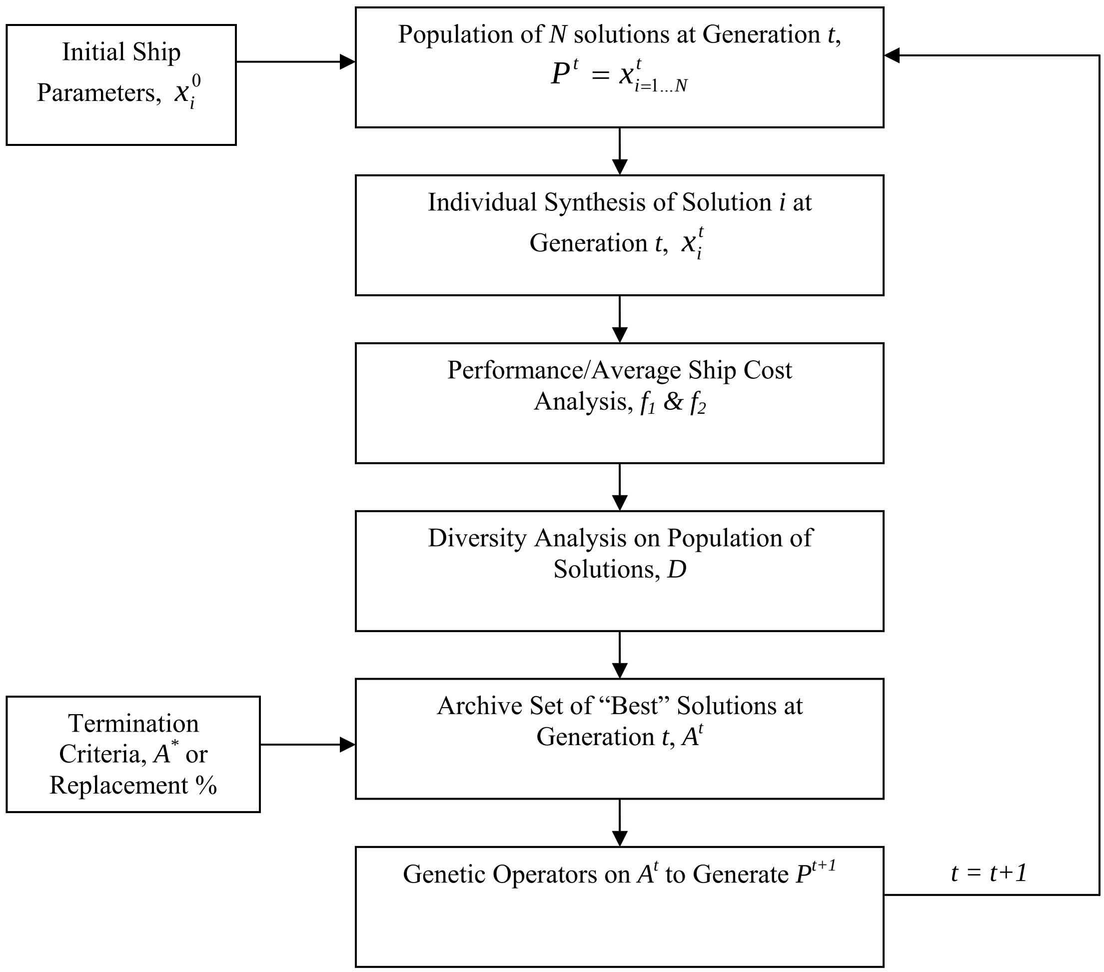

Figure 4.1 Basic Optimization Process

The optimization process is a multicriterion evolutionary algorithm based primarily on Zalek's work [Zalek et al. 2006a]. His experience and lessons learned were very helpful in the initial formulation of this research. Zalek's algorithm was based primarily on Deb [Deb 2001] and Zitzler [Zitzler et al. 2003] along with some original concepts that were developed for the specific nature of his work. Many of the procedures used in this research are standard methodologies that are common in the use of evolutionary algorithms. However, Deb's influence can be seen in the nondominance sorting algorithm and in the tournament selection method used. The use of an archive as an elitism operator was taken from the Strength Pareto Evolutionary Algorithm (SPEA) work of Zitzler.

4.3.1 Initial Ship Parameters

The initial population of ships, P^0, consists of randomly generated combinations of the n independent variables, x_i^j. The random parameters are generated using the following standard equation,

$$x_i^j = x_{lower}^j + random(0,1) \cdot (x_{upper}^j - x_{lower}^j) \tag{4.2}$$

Each set of parameters is input into the ship synthesis model and a ship is developed. Not all combinations of inputs will generate a feasible ship. If a ship is not feasible, a new set of parameters is developed and synthesized. The process continues until the minimum population of ships, N, has been created.

4.3.2 Population at Generation *t*

The population at any given generation t is set to have a minimum number of ship variants, N. There is no maximum on the number of solutions in the archive. This was done to ensure that nondominated solutions were not inadvertently left out of the solution set. By allowing the population to grow without a maximum, the user is able to search the variable space more efficiently and effectively. If an artificial criteria were used to limit the size of the population, as done by Zitzler, nondominated solutions may be lost and never recovered. In order to maintain elitism, the population at t>0 consists of the previous generation's archive and the offspring that are created in the current generation.

4.3.3 Individual Synthesis

Each set of solution parameters is input into the ship synthesis model during each generation. The synthesis model was described in detail previously.

4.3.4 Performance/Average Ship Cost

The goal of the optimization is to maximize the performance over average ship cost. One aspect of this maximization is to select ships that perform their missions well. The performance measurement of a given solution is calculated using fuzzy utility functions. The utility functions represent how effective ship i would be in performing its assigned missions j given its individual capabilities. Each objective function will be divided up by the number of individual missions j that each ship i is expected to perform. Each mission has performance attributes y_k that contribute to the successful performance of the mission. The performance attributes are assigned a fuzzy utility $0 \leq U_{ijk}(y_k) \leq 1$ that represents what percent of a given mission the ship can perform with that performance attribute y_k. Fuzzy minimum correlation inference is used to assign an overall effectiveness for each mission [Kosko 1992]. The percent of time that each ship i spends performing mission j (MP_{ij}) is multiplied by the minimum utility for that mission. The values used for the MP were obtained from the projected operational profiles of the OPC and NSC [USCG Internal]. The j mission utilities are then summed to yield the overall mission performance and this is divided by the average cost of each ship

$$\left[\frac{Performance}{Cost}\right]_i = \sum_{j=1}^{n} \frac{MP_{ij}\ \min\left\lfloor U_{ijk}(y_k)\right\rfloor}{Cost_i} \tag{4.3}$$

A ship that has the capability to perform all of its missions well will have a high measure of performance approaching one. However, the ability to perform these missions comes at a price. The more capable a ship is, the higher the cost of the ship. By dividing the performance by cost the algorithm prevents ships from being overly capable. There is a fine balance between capabilities and cost. Overly capable ships will prove costly and the performance over average ship cost will suffer as a result. On the other hand inexpensive ships will not be as mission capable and they too will have poor performance over cost.

4.3.5 Diversity Calculations

In order to ensure that a wide range of solutions is generated along the entire Pareto Front, diversity calculations are performed. The diversity calculations measure a given solution's distance from its nearest neighboring solutions.

There are three common methods of ensuring solution diversity. They are the Kernel method, nearest neighbor method, and histogram methods as described by Zitzler [Zitzler et al. 2003]. Kernel methods take the distances between solutions as an argument. The distances (d_i) are calculated from each individual solution to all the other solutions then they are put through a Kernel function, K, and summed. The sums of the Kernel functions, $K(d_i)$, represent the solution density. The nearest neighbor technique used here takes the distance of a given point to its k nearest neighbors in order to estimate the solution density. The histogram method uses a grid to define the density of solutions. The density is determined by calculating the number of solutions in a given box of the grid.

Using a method similar to that utilized by Zalek [Zalek 2007], the distance to the nearest three neighbors is calculated. The diversity operator $D(x_i)$ can be calculated in either objective function space or independent variable space. Depending on the nature of the optimization there may be a difference in the performance of these two methods. A comparison of the two methods was performed in this research to determine which method is more suitable for this optimization and this study will be discussed in the next chapter. Distances, d_{ij}, between solutions in n-dimensional space are calculated using,

$$d_{ij} = \sqrt{(x_i^1 - x_j^1)^2 + \ldots + (x_i^n - x_j^n)^2}\ . \tag{4.4}$$

The average of the three closest solutions, D_{raw}, is calculated and then normalized by dividing by the maximum value of D_{raw} for all solutions in the population.

$$D_{RAW}(x_i) = (d_i^1 + d_i^2 + d_i^3)/3 \tag{4.5}$$

$$D(x_i) = D_{RAW} / \max\{D_{RAW}(x_1),\dots,D_{RAW}(x_N)\} \tag{4.6}$$

Using the three nearest neighbors ensures that pairs of solutions that are each others neighbors will not be penalized for have a single close neighbor. By only using the three nearest neighbors a localized diversity is calculated.

Identical solutions are not considered in the calculation of diversity. By eliminating duplicate solutions, the diversity of the population is more easily maintained. Duplicate solutions run the risk of dominating the genetic processes and creating additional duplicates. The goal of creating a broad range of solutions along the Pareto front makes identical solutions an undesirable outcome.

4.3.6 Archiving

The archiving of best solutions serves three important purposes. First, it creates the pool of potential parents for tournament selection and the evolutionary generation of offspring. Second, it allows for the measurement of how much the Pareto front is progressing from one generation to the next. Finally, it serves as the elitism operator for the algorithm.

The archive is developed using standard dominance sorting techniques. Each solution in the population is compared to every other solution to check for dominance. Dominance occurs when a solution, x_1, is no worse than another solution, x_2, in all objectives and the solution, x_1, is strictly better than the other solution, x_2, in at least one objective. When both of these conditions occur, a solution is said to dominate the other solution. The set of solutions that are not dominated by any other solutions are called the nondominated set of solutions.

The archive is generally made up of the nondominated set of solutions. However, during the early generations it may consist of lower ranked solutions in order to reach a minimum number of solutions. As the solutions become more refined, the number of nondominated solutions increases and eliminates the need to carry lower ranked solutions in the archive. There is no maximum to the size of the archive. If the Pareto front were limited in size, the fine details of the Pareto front might not become apparent. Interesting trends along the front might not become visible with a limited number of data points. These trends might include knuckles or even gaps in the front as will be seen.

4.3.7 Termination Criteria

The optimization process has two conditions under which it will terminate. The user can set a maximum number of generations, t^*. When the program completes t^* generations it will stop and output a final archive, A^*. By selecting a maximum number of generations, the user prevents the optimization from running indefinitely. A second stopping condition exists when the archive becomes stagnant. The solutions in the archive carry markers which indicate if they have been carried over from previous generations or if they are newly generated offspring. If 99% of the solutions from one archive to the next are the same, the program stops and outputs a final archive. This saves computation time and only allows the optimization to continue as long as it is creating new solutions along the Pareto front.

4.3.8 Genetic Operators

The archived solutions in A make up the potential parent solutions in the mating pool. Once the archive has been created, those solutions are compared in a tournament selection process [Michalewicz 1996, Li and Parsons 1998]. In tournament selection, archived solutions are randomly paired together. Each pair of solutions is compared using two tests. The first test asks if either solution dominates the other. If one solution dominates the other, the dominant solution is placed in the mating pool. If neither solution dominates the other, another test is performed. In this test, each of the objective criteria are added together along with the solution's diversity value. The sum of these values is compared to the sum of the values from the other solution in the pair. The solution with the higher sum is selected for the mating pool. In earlier generations, the first test is more likely to determine which solution in a pair will become a parent. As the archive is filled entirely with nondominated solutions, the second test tends to distinguish between the two solutions. In essence, early in the optimization process, the goal is to generate more nondominated solutions. Later in the process the goal shifts to creating more diverse solutions.

The optimization process creates a minimum of *k* child solutions per generation. As the archive grows beyond the minimum, more child solution will be developed in proportion to the size of the archive. For every child that is created two parents are needed. The crossover operator is used on the parents to create an offspring. Arithmetic crossover is applied to the real number variables using,

$$x_{child}^{j} = \alpha \cdot x_{parent1}^{j} + (1-\alpha) \cdot x_{parent2}^{j} \tag{4.7}$$

The weighted parent blending factor α is randomly selected between 0 and 1. This serves as a means to weigh which parent more heavily influences the characteristics of the offspring. If α is exactly 0.50 then the resultant variable will be exactly half way between that of the parents. For discrete variables, α is used again. In this case, if α is less than 0.50, the value of the first parent is chosen and if α is greater than or equal to 0.50, the value of the second parent is chosen.

One problem with the crossover operator is that the child solutions will always be between the parent solutions, which does not aid in the generation of a diverse set of solutions. As a result, the optimization process also utilizes a mutation operator that allows for a more global search of the variable space. There are two parts to the mutation operator. The first part is the mutation rate R_{mut}, and the second is the mutation magnitude, M_{mut}.

$$R_{mut}(t) = 0.15 \cdot e^{1.2 \cdot (t/t^*)} \tag{4.8}$$

$$M_{mut}^{j}(t) = (2 \cdot random(0,1) - 1) \cdot \frac{1}{2 \cdot e^{(t/t^*)}} \cdot (x_{upper}^{j} - x_{lower}^{j}) \,. \tag{4.9}$$

The mutation is set up similar to Zalek's work in that the rate of mutation starts out small with a large mutation magnitude for earlier generations. This allows for a broad search of the variable space. As the generations progress toward the termination condition, the rate of mutation is increased exponentially, while the mutation magnitude is decreased exponentially. This allows for a more local search for new design solutions. By searching closer to existing solutions, the optimization process essentially looks to fill in the gaps between existing solutions creating a more refined Pareto front.

The mutation operation is randomly applied the entire set of child solutions with replacement. Some solutions may be mutated multiple times while other may not be mutated at all. The mutation of real variables is performed using,

$$(x_i^j)^{t+} = (x_i^j)^t + M_{mut}^{j}(t) \;\; \text{if} \;\; x_{lower}^{j} \le (x_i^j)^{t+} \le x_{upper}^{j} \,. \tag{4.10}$$

If the mutated value falls outside of the selected limits for that variable, it is discarded and another mutation is attempted. Failed mutations do not count toward the total number of mutations,

$$Number\ of\ Mutations = R_{mut} \cdot n \cdot k \tag{4.11}$$

where n is number of independent design variables and k is number of child solutions.

Many variations to the genetic operations are possible; a few variations were studied in this research. For example, the mutation rate and magnitude vary exponentially with the generation number. An alternative method might be to set them as constants or vary them linearly. The analyses performed will be discussed in the next chapter.

4.4 Case Study

A two-objective case study was performed to test the methodology incorporated into the optimization program. The study utilized the U.S. Coast Guard's Deepwater Fleet. Specifically, the Operational Requirements of the Maritime Security Cutter Large (WMSL), formerly known as the National Security Cutter (NSC), and the Maritime Security Cutter Medium (WMSM), formerly known as the Offshore Patrol Craft (OPC), were used to create a multicriterion optimization problem. (The first NSC was actually launched in September 2007 and the OPC is currently being designed.) The mission requirements for these two real classes of ships will be used extensively in this research to examine the validity of the optimization methodologies. Table 4.1 shows the actual design characteristics of both ships [USCG Website 2006]. (Note: Changes in designs may have taken place since the information in Table 4.1 was obtained.)

Table 4.1 A Comparison of Design Characteristics

Characteristics	NSC	OPC
Number of cutters	8	25
Length overall	418'	Estimate 350'
Maximum beam	54'	Estimate 51'
Navigational draft	21'	Estimate 21'
Displacement	4300 LT	Estimate 3000 LT
Sprint speed	28 kts	26.5 kts
Sprint speed range	2,600 nm	1,550 nm
Sprint speed endurance	3.91 days (94 hrs)	2.5 days (60 hrs)
Economical speed	8 kts	9 kts
Economical speed range	12,000 nm	9,000 nm
Endurance	60 days	45 days
Propulsion plant	2 Diesels, 1 Gas Turbine	4 Main Diesel Engines
Bow thruster	Yes	Yes
Gun for weapon system	57mm Gun	57mm Gun
Gunfire control	Mk-160/Mk 46/SPQ-9B	Mk-160/Mk 46/SPQ-9B
Operating days away from port	230	230
Mission days/year	200-220	200-220
Berthing capacity limit	148	106
Number of helicopter hangars	2	2

In this portion of the case study, the mission requirements of the two ships were combined into one ship requirement. The goal of the study was to find the Pareto optimal set of solutions that would satisfy the mission needs of both ships. In other words, if only one class of ships that maximized its ability to satisfy both ships' missions were to be built, what would the Pareto front look like.

For the purposes of this case study, the design parameters for the eight independent variables were set to approximately +/- 10% of the actual ship design characteristics as set by the Performance Specifications [USCG Internal]. The design ranges can be seen in Table 4.2. (Note: The Performance Specifications may have taken place since the information in Table 4.2 was obtained.)

Table 4.2 Independent Variable Ranges

Independent Variables	Variable Ranges
Power plant type	1 or 2
Midship coefficient	0.75-0.99
Block coefficient	0.45-0.85
Length	270'-470'
Max speed	19-31 knots
Range @ cruising speed	8000-14000 nm
Number of helicopter hangars	1 or 2
Weapons system type	1, 2, or 3

The Power plant type inputs are 1 or 2 which represent either a four (two cruise, two sprint) diesel engine (CODAD) plant or a two cruise diesel engine and one sprint gas turbine (CODOG) plant, respectively. The Weapons system type inputs of 1, 2, or 3 represent a 46 mm gun, a 57 mm gun, or both a 57 mm gun and Phalanx Close In Weapon System (CIWS).

4.5 Fuzzy Utility Functions

The utility function values for a baseline solution were set according to Table 4.3.

Table 4.3 Definition of Baseline Optimization Utility Functions

Mission	Attribute	OPC y_k	Utilities Utility $U(y_k)$	NSC y_k	Utilities Utility $U(y_k)$
Defense	Maximum speed	<20	0	<26	0
		20-22	0.5*(V-20)	26-28	0.5*(V-26)
		>22	1	>28	1
	Number of hangars	1	1	1	1
		2	1	2	1
	Weapon system	1	1	1	0.6
		2	1	2	0.8
		3	1	3	1
	Range	<9000	0	<12000	0
		>9000	1	>12000	1
Drug	Maximum speed	<20	0	<22	0
		20-22	0.5*(V-20)	22-28	0.1667*(V-22)
		>22	1	>28	1
	Number of hangars	1	0.85	1	0.5
		2	1	2	1
	Weapon system	1	1	1	1
		2	1	2	1
		3	1	3	1
	Range	<9000	R/9000	<12000	R/12000
		>9000	1	>12000	1
LMR	Maximum speed	<20	0	<22	0
		20-22	0.5*(V-20)	22-28	0.1667*(V-22)
		>22	1	>28	1
	Number of hangars	1	0.92	1	0.57
		2	1	2	1
	Weapon system	1	1	1	1
		2	1	2	1
		3	1	3	1
	Range	<9000	R/9000	<12000	R/12000
		>9000	1	>12000	1
AMIO for OPC or GDO for NSC	Maximum speed	<20	0	<26	0
		20-22	0.5*(V-20)	26-28	0.5*(V-26)
		>22	1	>28	1
	Number of hangars	1	0.85	1	0.5
		2	1	2	1
	Weapon system	1	1	1	0
		2	1	2	0
		3	1	3	1
	Range	<9000	R/9000	<12000	0
		>9000	1	>12000	1

Each ship has four primary missions. The OPC and NSC each perform the National Defense, Drug Iinterdiction and Living Marine Resources (LMR) missions. The OPC also conducts the Alien Migration Interdiction Operations (AMIO) while the NSC performs General Defense Operations (GDO) [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. For each mission four ship attributes were selected to describe each ship's ability to perform these missions. The four attributes were maximum speed, number of helicopter hangars, weapon systems and endurance range. [It is important to note that the values/functions found in Table 4.3 do not necessarily reflect the opinions of the U.S. Coast Guard. They were established by the author for academic purposes.]

4.5.1 National Defense

The Coast Guard is "a military service and a branch of the armed forces of the United States at all times" as established by the United States Code (USC) (14 USC 1). It is required to "maintain a state of readiness to function as a specialized service in the Navy in time of war" (14 USC 2) and to operate as a service to the Navy when directed to by the President (14 USC 3). It is also authorized to assist the Department of Defense in performance of any activity that the Coast Guard is qualified (14 USC 141, 145). In 1994, the Coast Guard's defense missions were more clearly defined to include Maritime Interception Operations and Deployed Port Operations, Security and Defense. The National Defense mission is accomplished using surveillance, detection, interception and sustained presence. These abilities are accomplished with a combination of maximum speed, aerial asset capabilities, weapon systems and range [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. Figure 4.2 through 4.5 show the assigned fuzzy utility for each of the ship attributes.

The utilities shown in Figures 4.2 through 4.5 show the relative importance of each attribute in accomplishing the National Defense mission for each vessel. From these graphs, it can be seen that achieving the required maximum speed for each ship is important although some variance is accepted. At least one helicopter hangar is absolutely necessary to perform the mission. Weapon system 1 fulfills the OPC's role in the mission, but only satisfies a portion of the NSC's role. In order to maintain a sustained presence for the National Defense mission both ships must meet their minimum required ranges.

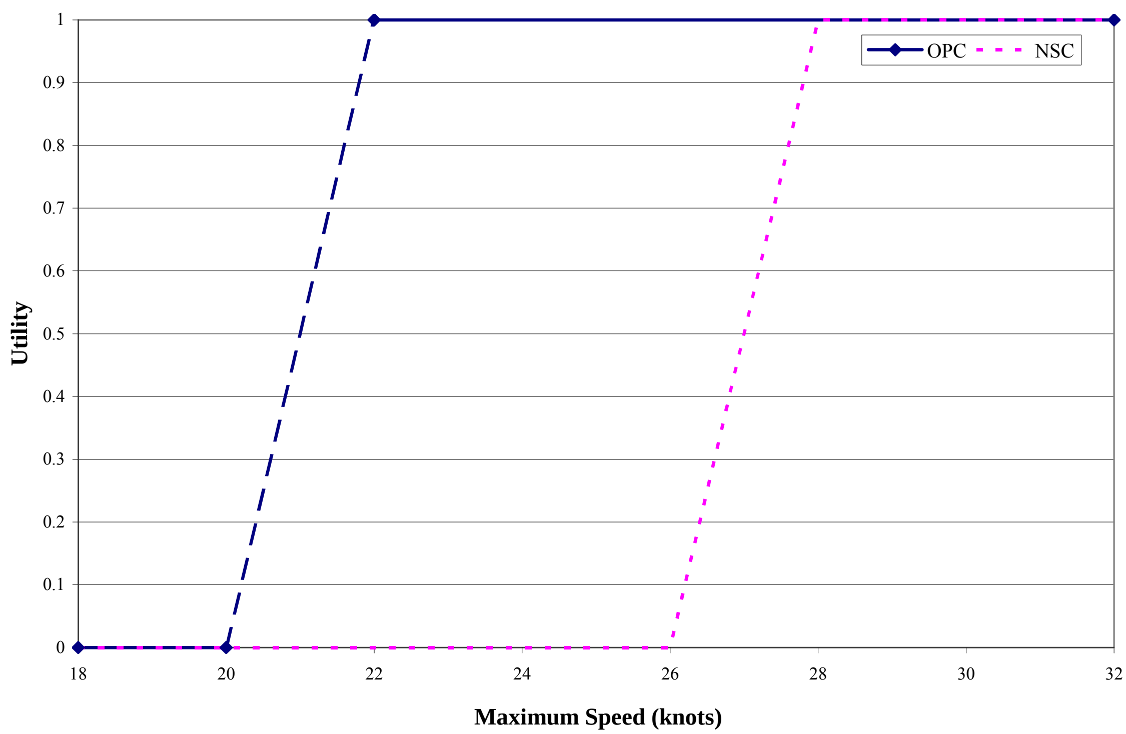

Figure 4.2 Maximum Speed Utility for the National Defense Mission

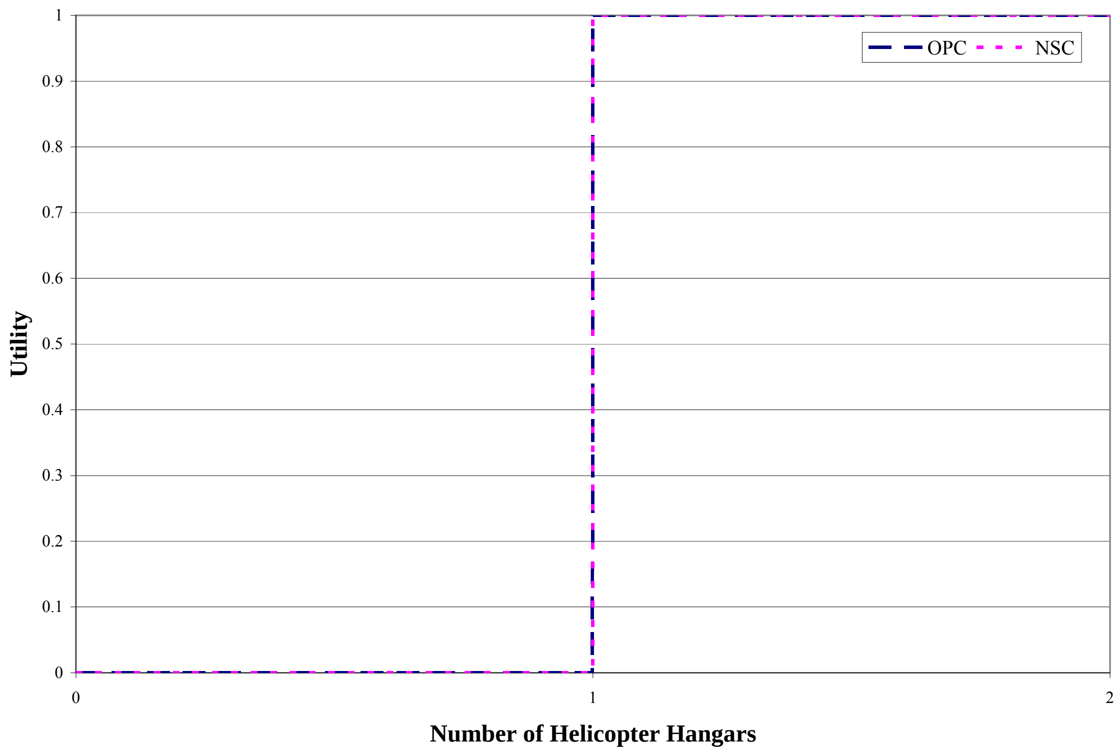

Figure 4.3 Helicopter Hangar Utility for the National Defense Mission

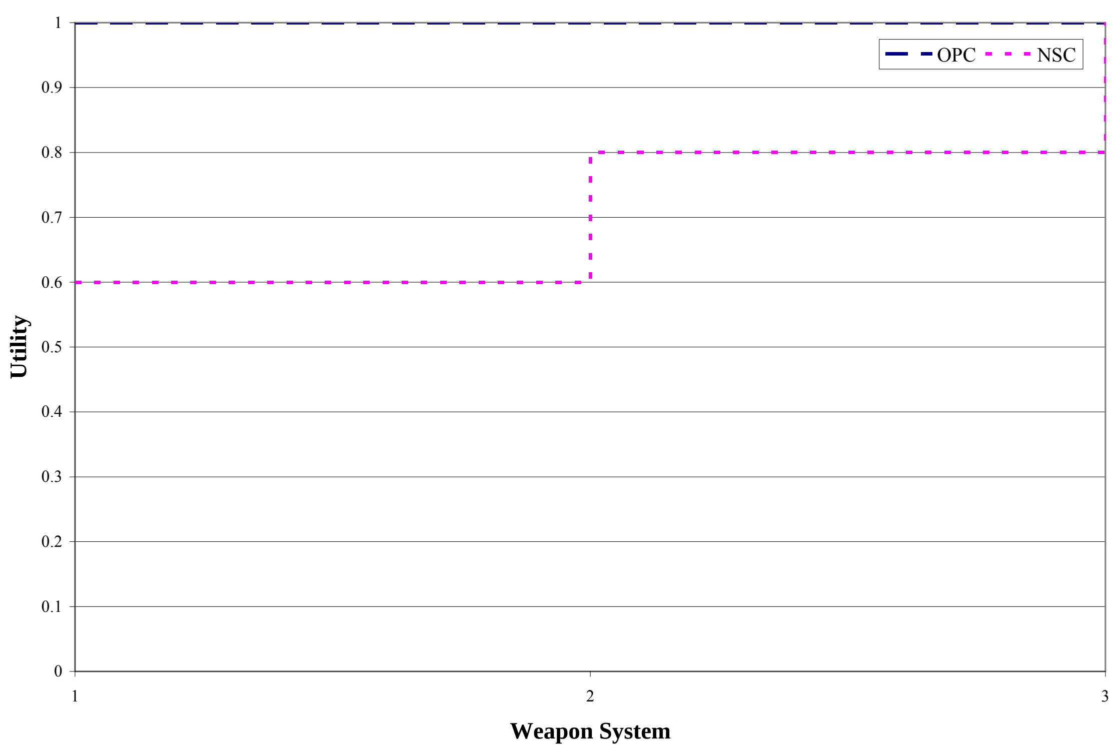

Figure 4.4 Weapon System utility for the National Defense Mission

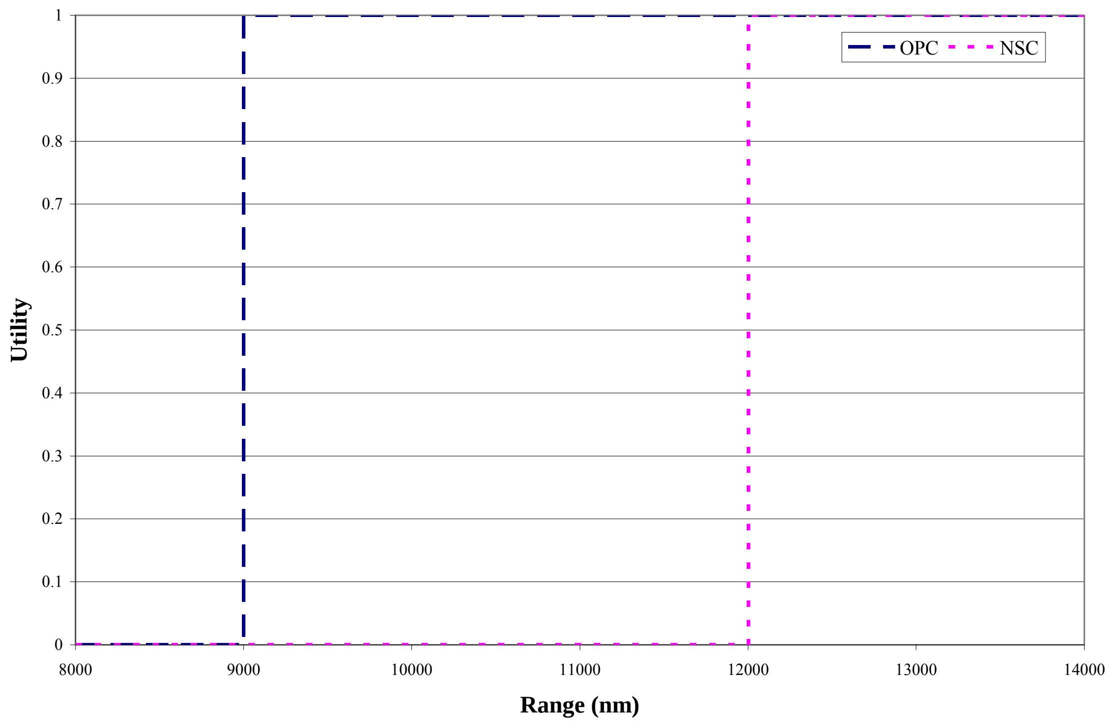

Figure 4.5 Range Utility for the National Defense Mission

4.5.2 Drug Interdiction

The Coast Guard is the lead agency for maritime drug interdiction. Drug Interdiction operations rely heavily on the ability to detect, intercept and board vessels for compliance with U.S. and International law. These boardings are essential in deterring and interdicting drug shipments at sea. By maintaining a presence on the high seas, smugglers are required to develop new, more costly methods in order to continue the illegal transport of drugs [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. Figure 4.6 through 4.9 show the fuzzy utility values for each of the four ship attributes being used to assess each ship's mission performance in the Drug Interdiction mission.

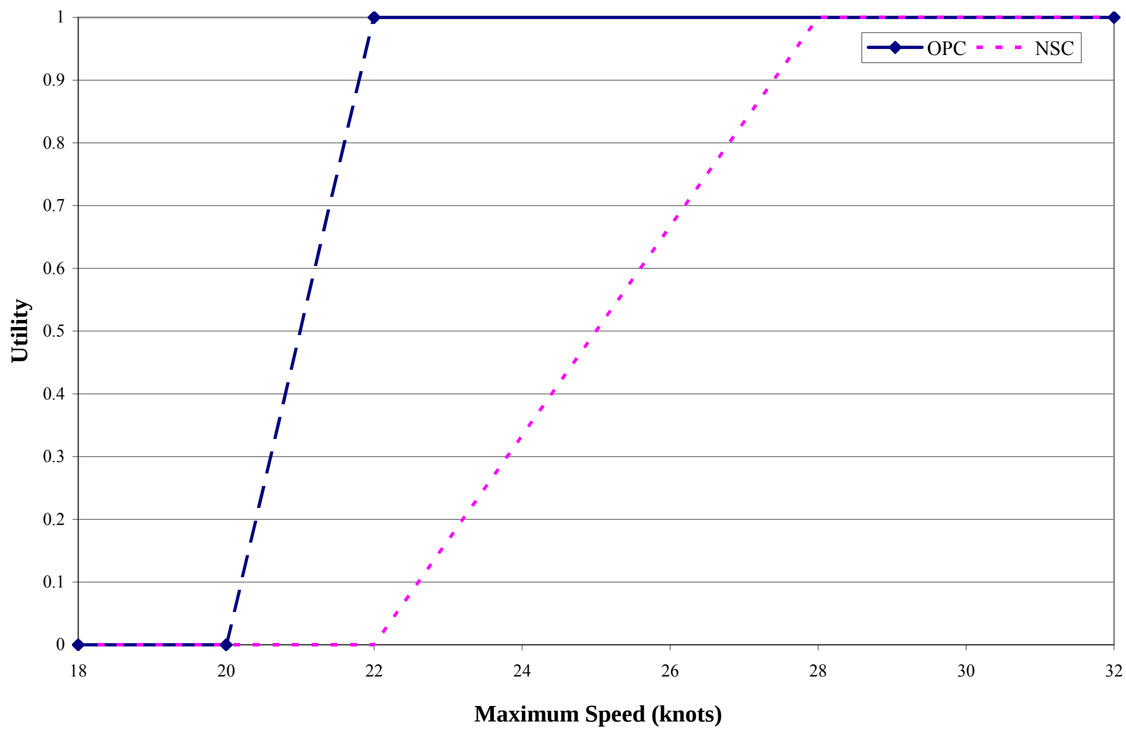

Figure 4.6 Speed Utility for the Drug Interdiction Mission

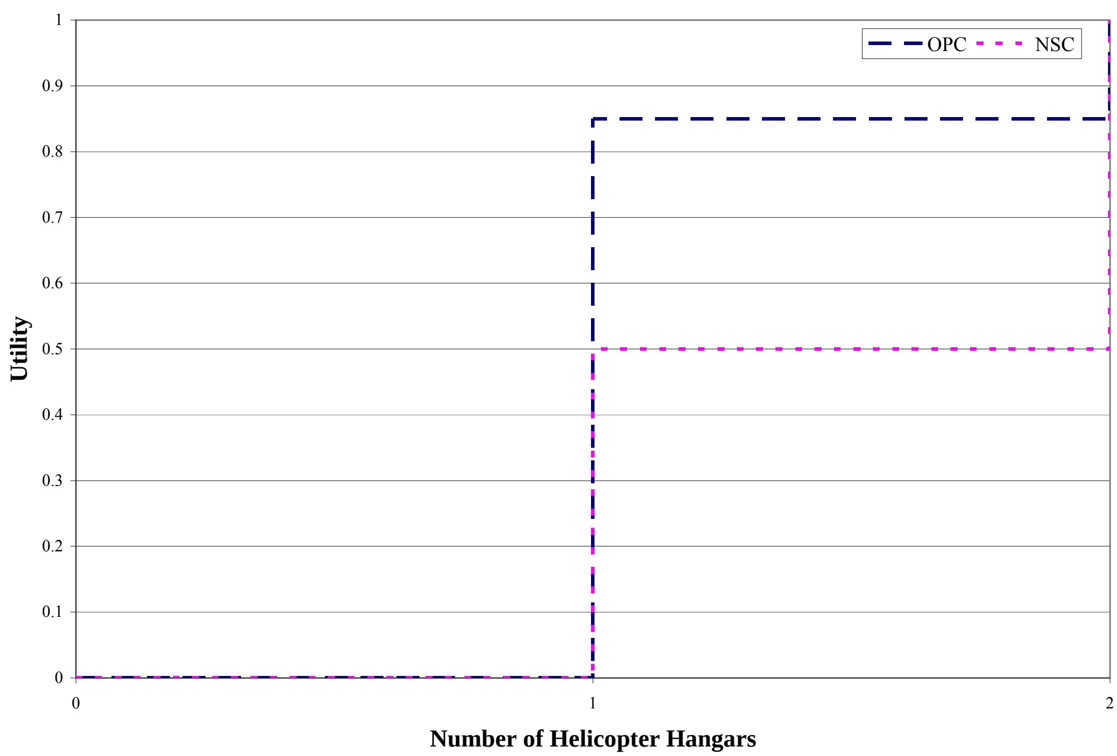

Figure 4.7 Helicopter Hangar Utility for the Drug Interdiction Mission

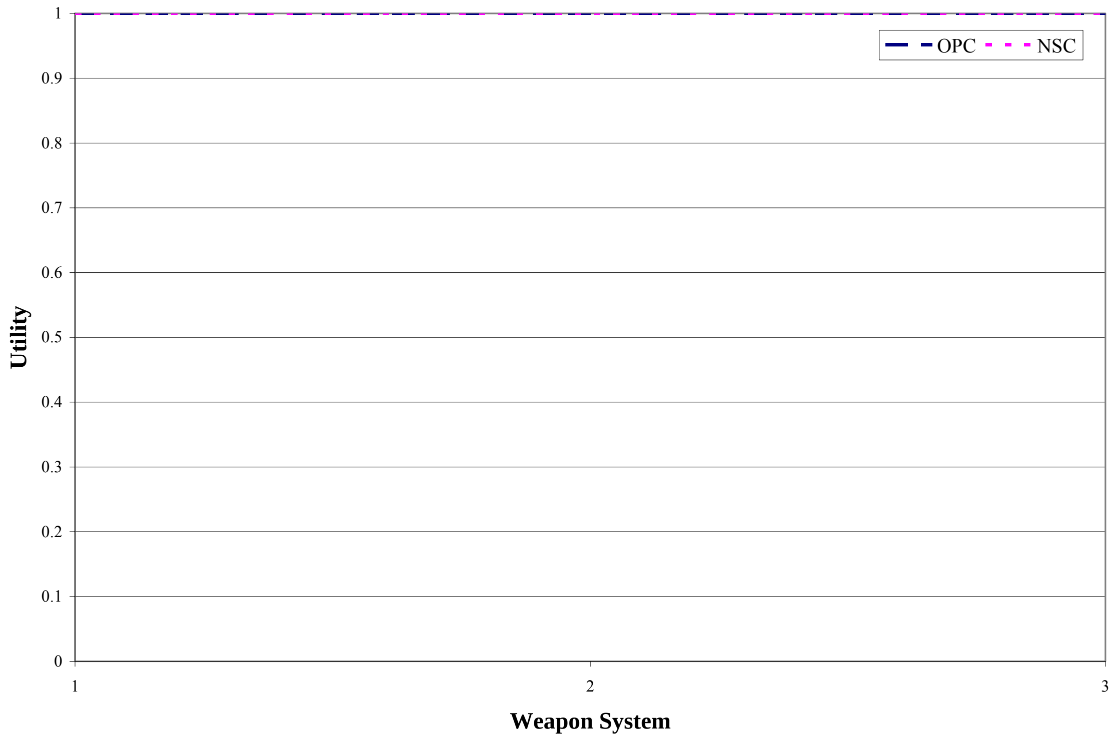

Figure 4.8 Weapon System Utility for the Drug Interdiction Mission

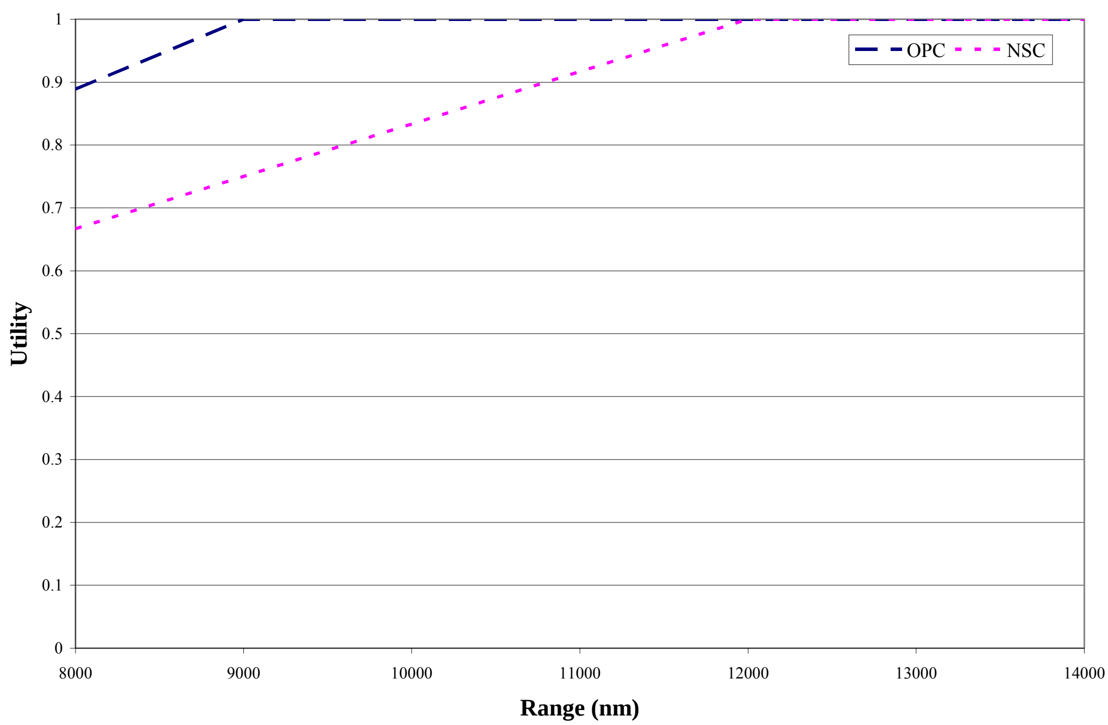

Figure 4.9 Range Utility for the Drug Interdiction Mission

Figures 4.6 through 4.9 show the importance of each ship attribute in accomplishing the Drug Interdiction mission. For this mission the maximum speed of the vessel is not as important as for the National Defense mission as shown by the more gradual slope for the NSC. The number of helicopter hangars is more important for this mission. In order to conduct a wide range of surveillance on the high seas, the fast aerial assets will be used extensively. Weapons are generally not too important to this mission and only act as a means for intimidation if close contact with the smugglers is made. Because a majority of the Drug Interdiction mission occurs in the Caribbean, land is always nearby. Therefore, ships have the ability to refuel more often which makes the need for a long range less important.

4.5.3 Living Marine Resources

The U.S. Coast Guard provides law enforcement support to the conservation and management of our Nation's living marine resources. These resources are vital to the fragile ecosystem as well as the $67 billion (1995 estimate) that they annually contribute to the U.S. economy through commercial and recreational fisheries. In order to protect these resources, the Coast Guard must maintain a presence in the U.S. Exclusive Economic Zone (EEZ) and its borders. In order to deter illegal or unauthorized activities harmful to this maritime resource, the Coast Guard must detect and intercept vessels for boarding and inspections [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. Figures 4.10 through 4.13 show the need for maximum speed, aerial capabilities, weapon systems and range in the enforcement of fisheries laws.

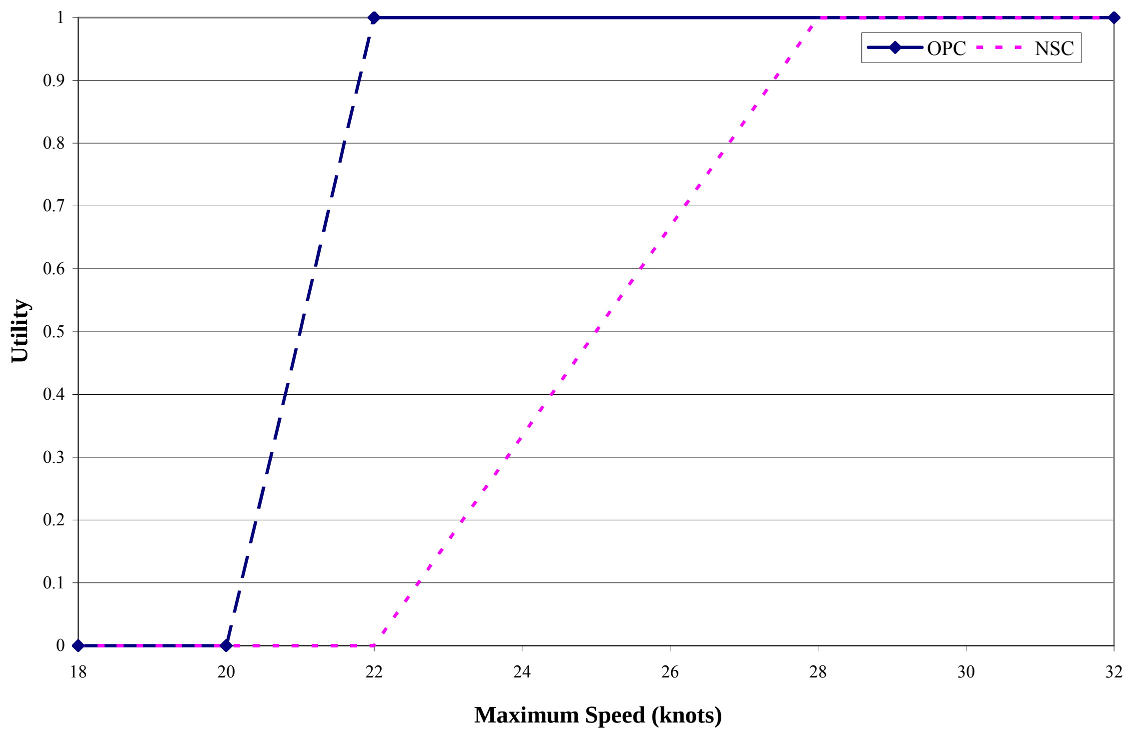

Figure 4.10 Maximum Speed Utility for the Living Marine Resource Mission

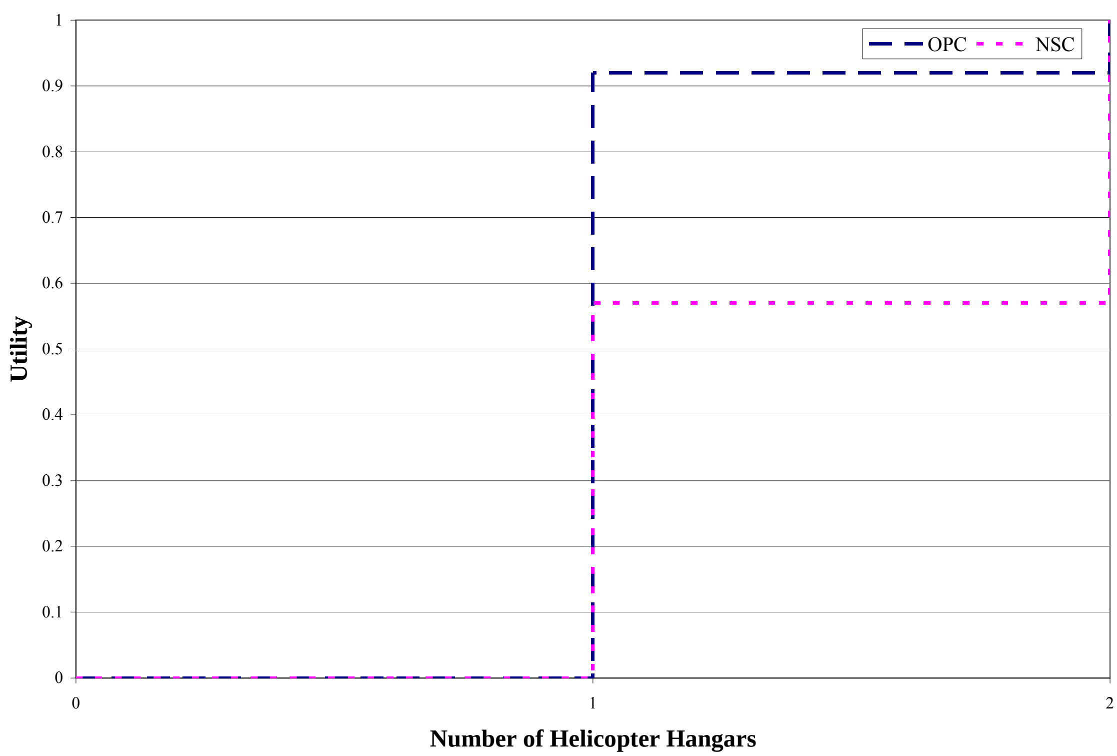

Figure 4.11 Helicopter Hangar Utility for the Living Marine Resource Mission

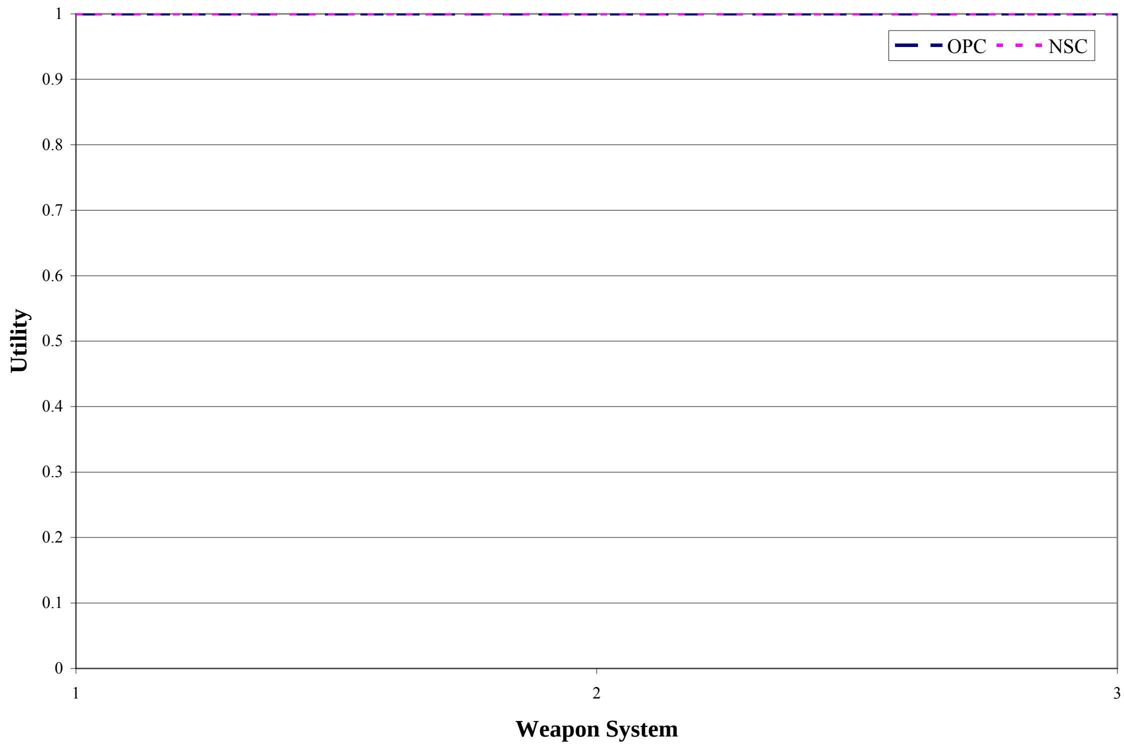

Figure 4.12 Weapon System Utility for the Living Marine Resource Mission

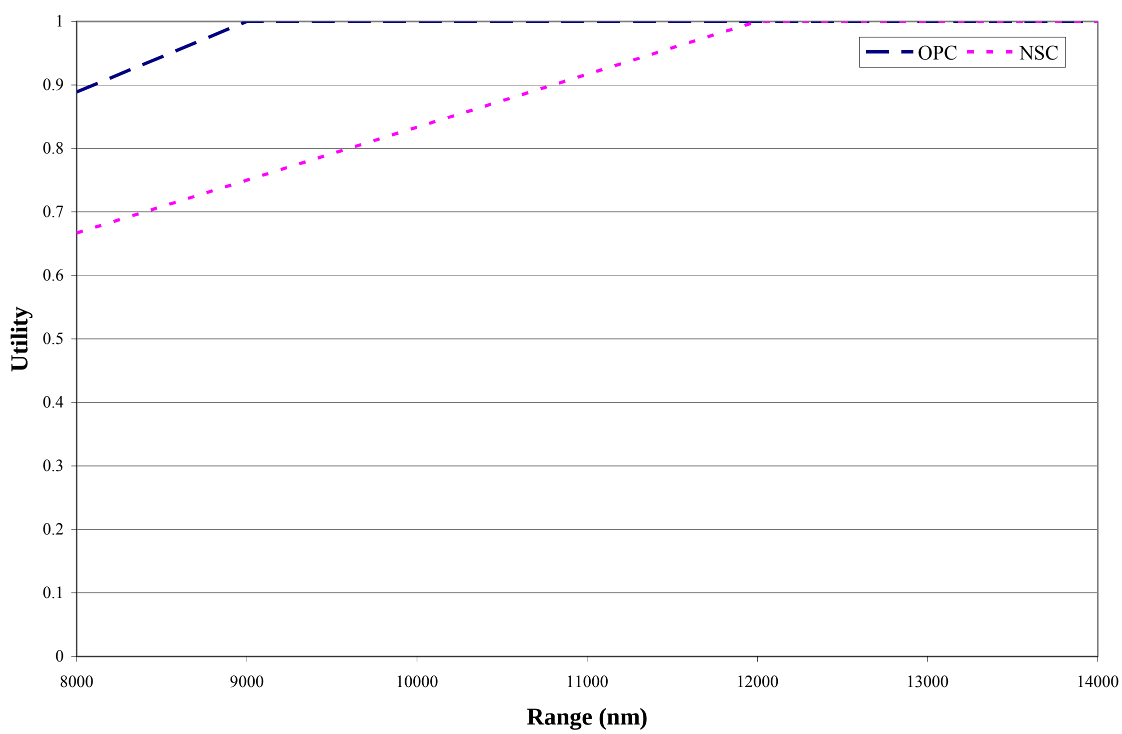

Figure 4.13 Range Utility for the Living Marine Resource Mission

The fuzzy utility values for the Living Marine Resource mission are very much the same as for the Drug Interdiction mission since the missions are very similar. The only difference is in the importance of having a second helicopter hangar. This attribute is not quite as important for the Living Marine Resource mission as the utility shows.

4.5.4 Alien Migration Interdiction Operations

The OPC is also tasked with the Alien Migration Interdiction (AMIO) mission. This mission is conducted in order to enforce U.S. migration laws. The need for this mission has grown significantly in the past 20 years. Basically, it is designed to deter the illegal flow of migrants into the U.S. In order to accomplish this mission, the Coast Guard must maintain a presence in areas where migration is likely. In addition to maintaining a presence, the ability to detect vessels carrying migrants and intercept them is crucial to the success of this mission [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. Figures 4.14 through 4.17 show the utilities associated with OPC attributes for the AMIO mission.

4.5.5 General Defense Operations

The General Defense Operation (GDO) mission is a broad category. In addition to the National Defense mission described earlier, possible general defense missions might include surveillance, forward presence, amphibious ready group escort, sealift protection, sea lines of communication control, noncombatant evacuation, naval special forces warfare, combat operations, anti-terrorism and disaster relief. These operations are normally in support of the Navy [US Coast Guard Memorandum 1995, US Department of Transportation Memorandum 1996]. Figures 4.14 through 4.17 show the utilities associated with NSC attributes for the GDO mission.

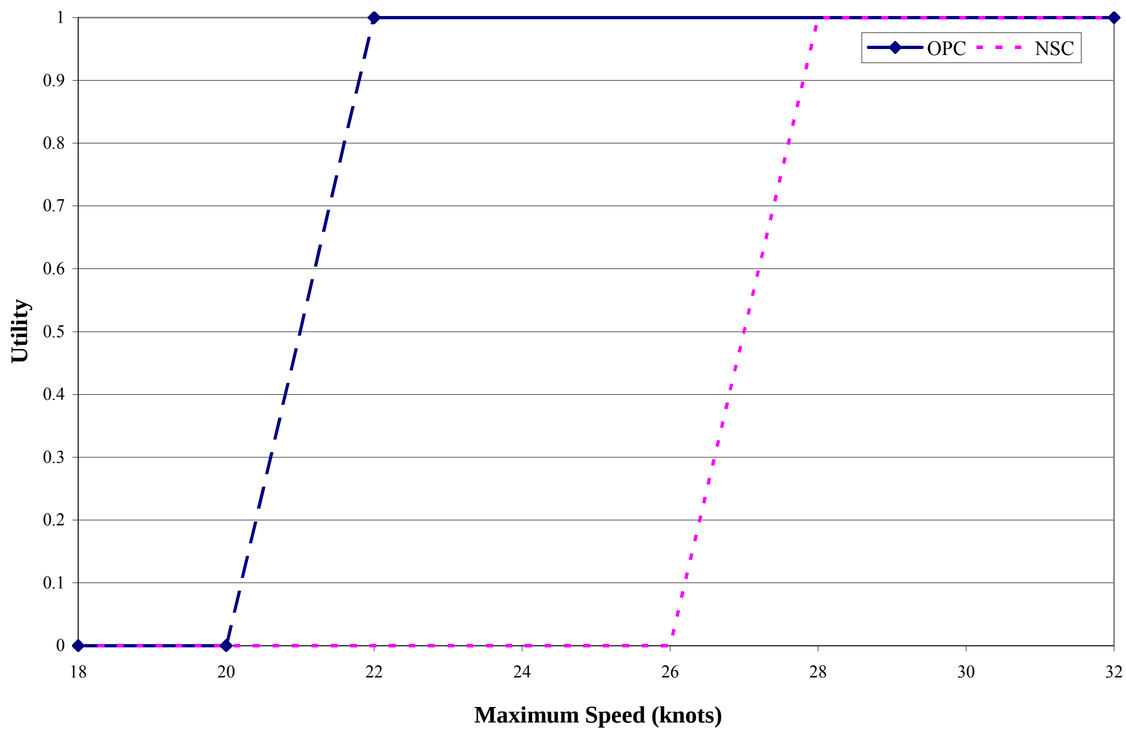

Figure 4.14 Maximum Speed Utility for the AMIO/GDO Missions

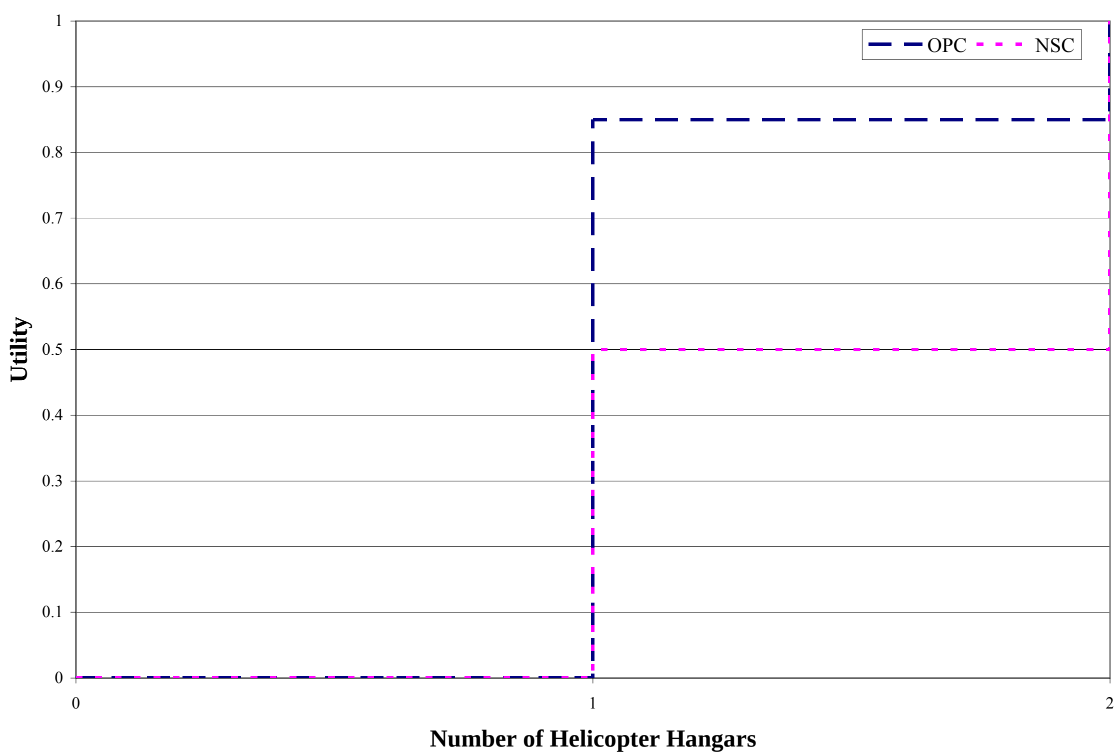

Figure 4.15 Helicopter Hangar Utility for the AMIO/GDO Missions

Figure 4.16 Weapon System Utility for the AMIO/GDO Missions

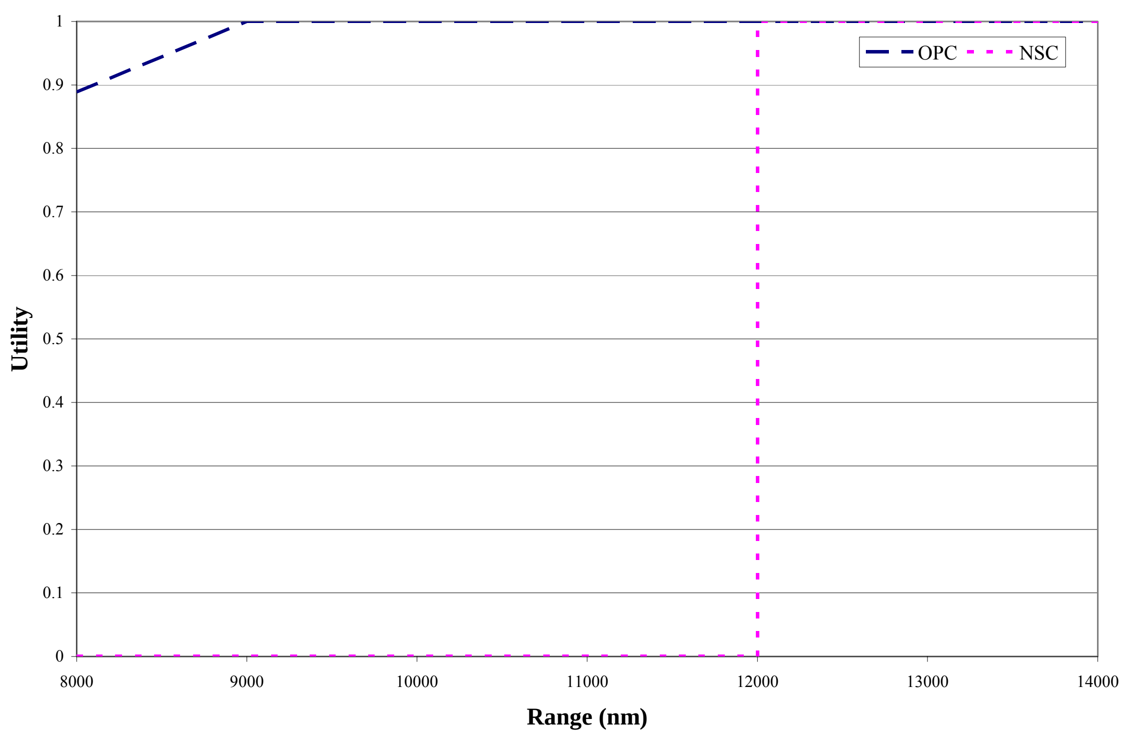

Figure 4.17 Range Utility for the AMIO/GDO Missions

The OPC's AMIO mission fuzzy utility values are the same as those for the Drug Interdiction mission. The NSC's GDO mission fuzzy utility values closely resemble those used for the National Defense mission. The main difference is the fuzzy utility assigned for the weapon system. Because of the need to operate in higher threat environments, the NSC must be equipped with offensive and defensive warfare capabilities. Speed and range are important because of the likelihood of steaming with the Navy.

CHAPTER 5

MULTICRITERION OPTIMIZATION WITHOUT COMMONALITY

The purpose of this chapter is to analyze the multicriterion optimization problem of designing vessels to meet both the NSC and OPC missions in a single vessel class design. This initial investigation provided an opportunity to test the synthesis model and the optimization algorithm, develop an understanding of the tradeoffs in vessels designed for these two missions, and revealed candidates for commonality between classes designed for each of the individual missions.

The optimization was run with the following minimum settings: archive size-50, population size-150, and number of offspring per generation-100. The maximum number of generations was set at 200 and a termination condition of <1% new solutions in the archive was used. Given these parameters, the optimization program was run and results analyzed.

5.1 Population History

A population history was generated for this baseline solution. At generation 108, the termination condition was met and the program stopped. Figure 5.1 shows the results of the baseline run in object function space. The populations of solutions at generations 0, 54, and 108 are shown. Population 0 shows the results of the random selection of input variables. The ships are spread throughout the objective space. This illustrates the effectiveness of the random input generation function used in the optimization process. The goal of population 0 is to randomly generate a variety of ships that represent a broad range of possible ship designs. This initial population generally does not have high values in either objective function. Many of the solutions have zero NSC effectiveness.

Population 54, midway through the optimization, shows a progression of the designs toward higher objective function values. The initial formation of a Pareto front can be seen as more nondominated solutions have been created. The crossover and mutation operations appear to be effective in searching the design space for possible solutions. Mutation rates are increasing and the mutation magnitudes are decreasing. This allows for a more localized search of the design space and the start of a more clearly defined Pareto front. Population 108, the final set of solutions, shows a very distinct formation of a Pareto front. The Pareto front is densely populated as the search for new solutions has become more localized through the use of the genetic and diversity operators. The solutions cover a broad range of inputs which is a strong indication that the diversity operator has successfully served its purpose.

Overall, the optimization run demonstrates the behaviors that were expected of it. The run took approximately 4 minutes to complete on a 1.73 GHz PC running a compiled C++ code.

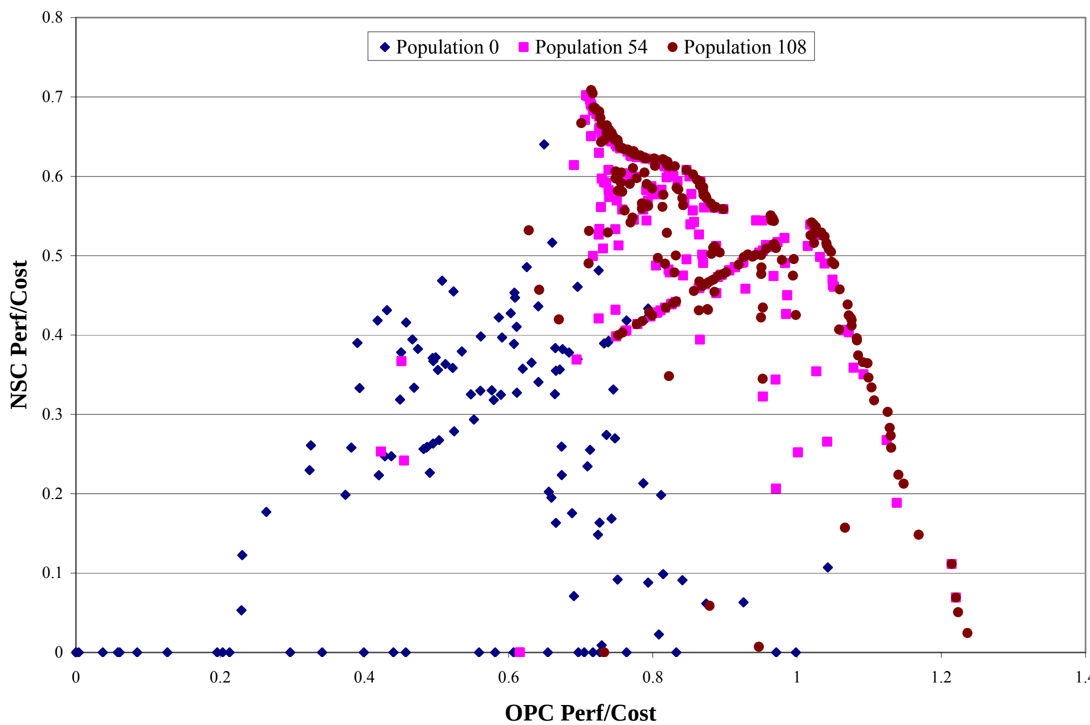

Figure 5.1 Population History of a Baseline Optimization Run

One interesting trend that appears in Figure 5.1 is the formation of a line roughly perpendicular to the middle of the Pareto front. Upon examination, this line is revealed to be the transition point from designs with one helicopter hangar to designs with two hangars. All of the designs on that line and to its right have one hangar. Designs to the left of the line have two hangars.

5.2 Baseline Run Characteristics

By only plotting the nondominated solutions from the baseline run some more interesting characteristics can be seen. Figure 5.2 shows the Pareto front of the baseline optimization run. Point A shows the best NSC mission design and point D shows the best OPC mission design. The solutions found between point A and D make up compromise solutions. Two interesting areas appear in the Pareto front. Region B shows a gap in the Pareto front. This gap consistently appears in all runs. This gap is caused by the change from two helicopters to one and the resulting reduction in beam possible with the removal of one of the parallel hanger bays. This transition will be described in more detail in later sections. A knuckle in the Pareto front can be seen at point C. This knuckle can be subtle like in Figure 5.2 or more distinct in other runs. The cause of this knuckle is due in large part to ship service generator selection. The synthesis model uses data from real generators to outfit the ships. The knuckle seen at point C is the transition from one generator to another. The weight and size of the generators at this transition change by a relatively large amount. This translates to a change in cost and eventually leads to the knee in the Pareto front. By populating the ship service generator database with a greater variety of generators, this knuckle could possibly be eliminated. However, the existence of this knuckle shows the methodology’s sensitivity to the discrete data supplied.

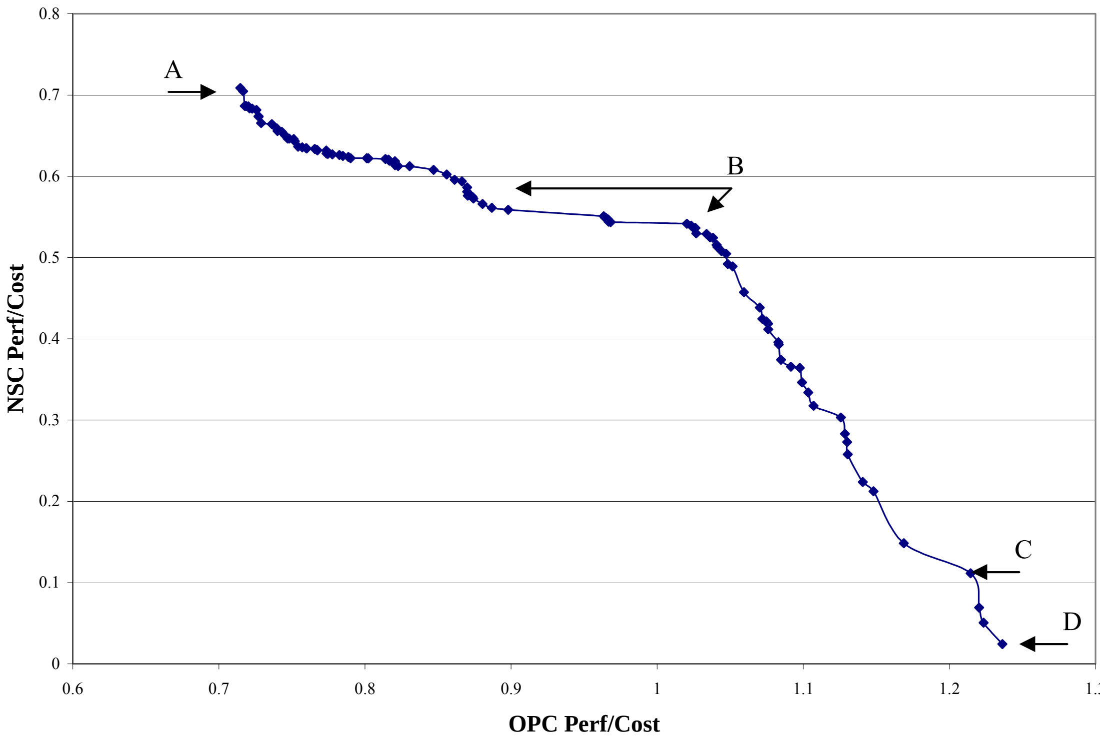

Figure 5.2 Baseline Optimization Run Pareto Front

Table 5.1 shows the design characteristics of point A, B, C, and D as seen in Figure 5.2. The following abbreviations are used:

W = Weapons system number

H = Number of helicopter hangars

C = Cruise engine item number

G = Diesel generator item number.

The cruise engine and diesel generator numbers designate which item they are in the respective database. The engine size increases with higher values. These numbers have little meaning otherwise. In general, the larger, faster, more capable ships are at the best for the NSC mission left end of the Pareto front and the smaller, slower, less capable ships are at the best for the OPC mission right end of the front, as expected.

Table 5.1 Design Characteristics for Baseline Run

Point	L ft	B ft	Vmax kts	Range nm	W	H	C	G	OPC Perf	NSC Perf	Cost $mil	OPC/ Cost	NSC/ Cost
A	401	54	28.0	12035	3	2	9	3	100.0	99.1	139.9	0.715	0.709
B (left)	352	54	26.3	9076	1	2	9	3	100.0	62.2	111.4	0.898	0.559
B (right)	340	42	25.4	9082	1	1	7	1	89.7	47.6	87.9	1.020	0.542
C (left)	304	41	22.8	9097	1	1	7	1	89.7	11.4	76.7	1.169	0.148
C (right)	315	41	22.6	9162	1	1	7	0	89.7	8.2	73.8	1.215	0.111
D	323	42	22.1	9142	1	1	7	0	89.7	1.8	72.5	1.236	0.024

Numerous runs were performed to ensure that the optimization program produced repeatable results. Due to the stochastic nature of the evolutionary optimization algorithm, individual runs are not identical to each other. However, the trends displayed on the Pareto front are very repeatable as seen in Figure 5.3. Here four individual runs were performed and the plots of the final Pareto fronts are displayed on the same graph. The upper left hand portion of the graph shows a very strong similarity among the four runs all the way down to approximately 1.1 on the OPC performance/cost axis. At this point, the data points become a bit more sparse and the different runs show some minor differences. There is a tendency for more designs to appear in the upper left portion of the curve. The reason for this is in the nature of the optimization. Basically, a ship that is over designed will meet its mission requirements with a penalty for excessive cost. Ships that are good at performing the NSC mission will also serve the OPC mission very well. On the other hand, ships that serve the OPC mission efficiently do not generally perform well in the NSC mission. As a result, the ships at the upper left portion of the curve tend to do better in tournament selection than the lower right ships. The diversity operator helps even this out some, but not without some unbalance in the results. Some efforts were made to alleviate this and these will be discussed in later sections. Overall, there is a strong correlation within the four individual runs.

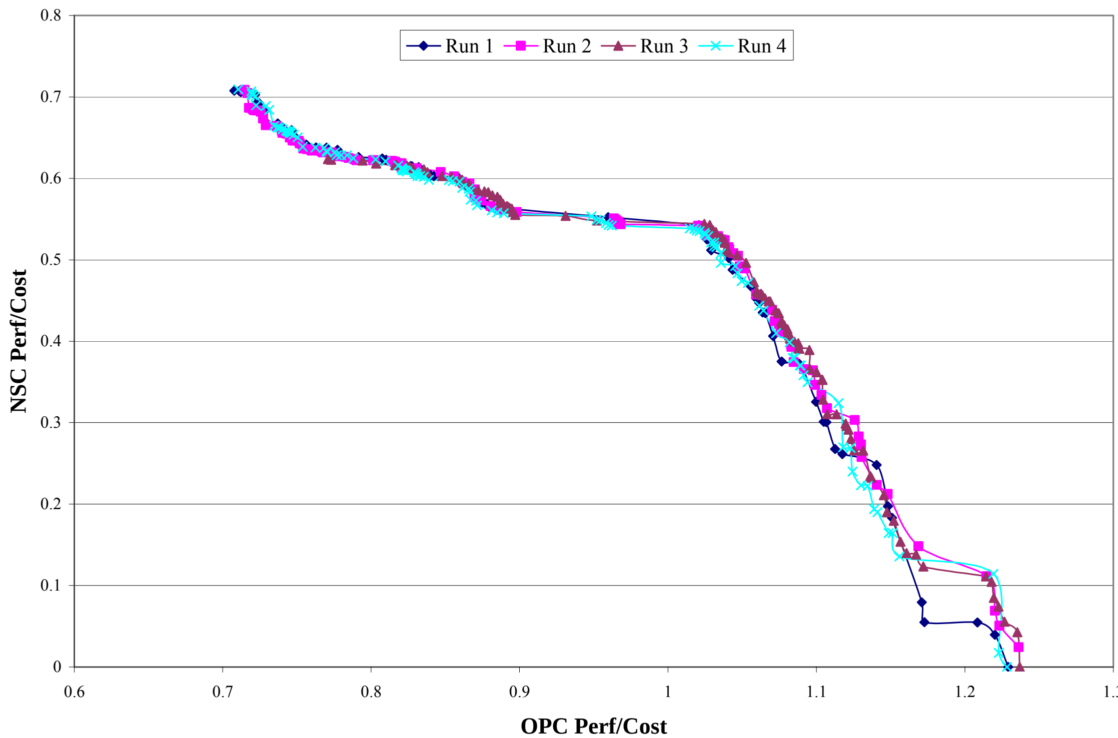

Figure 5.3 Repeatability Study using Baseline Optimization Conditions

In order to fully understand the results, a series of plots was created that show the affects of the independent variable values on the shape and regions of the Pareto front. Figures 5.4 through 5.8 show the trends of the independent variables length, maximum speed, endurance range, weapons systems, and number of helicopters in the optimization results.

The results of all of these plots are intertwined through the overall ship designs. For example, the gap in the middle of the Pareto front is the transition from one hangar designs to two hangar designs. When a second hangar is added, the required beam necessary to accommodate the two hangars is 54'. Ships with one hangar tend to have a beam of about 42'. This drastic increase in beam requires the ships to increase in length in order to meet the speed requirements. In addition to the second hangar, the gap also shows an increase in maximum speed from one side to the other. Again the desire to increase speed necessitates some increase in length. The gap represents an increase in length of about 10' as seen on the length study curve. The range requirement is higher for the NSC than it is for the OPC, therefore, the range increases from right to left on the

Pareto front. The selection of weapon systems shows an interesting trend. Only ships that are near the optimal design for the NSC have the most advanced weapons system. Near that end point, the weapon system becomes the controlling factor in the overall utility and, therefore, the selection of the more advanced system becomes optimum.

The makeup of the set of solutions for the baseline condition is very broad. About half of the solutions have one hangar. Weapons system 3 was selected on only 12% of the ships with weapons system 1 on the rest. The lengths ranged from 294’-412’, speeds from 22-28 knots and ranges from 8000-12000 nm.

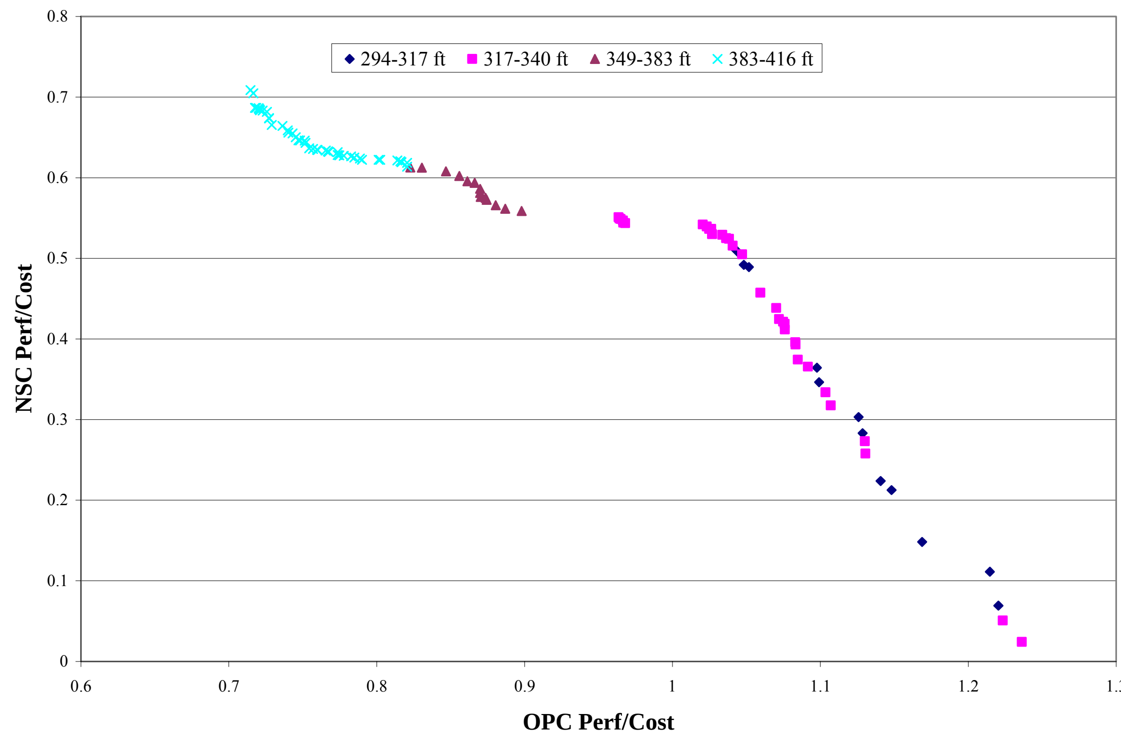

Figure 5.4 Detailed Study of Baseline Optimization Results for Ship Length

The distribution of length along the Pareto front generally increases from right to left. However, the length does not increase monotonically as can be seen in Figure 5.4. The performance values and cost of the solutions are made up of many characteristics. Some of these characteristics complement each other nicely while others do not. This results in a fine balance of factors each having their own affect on the performance values and cost of the solutions.

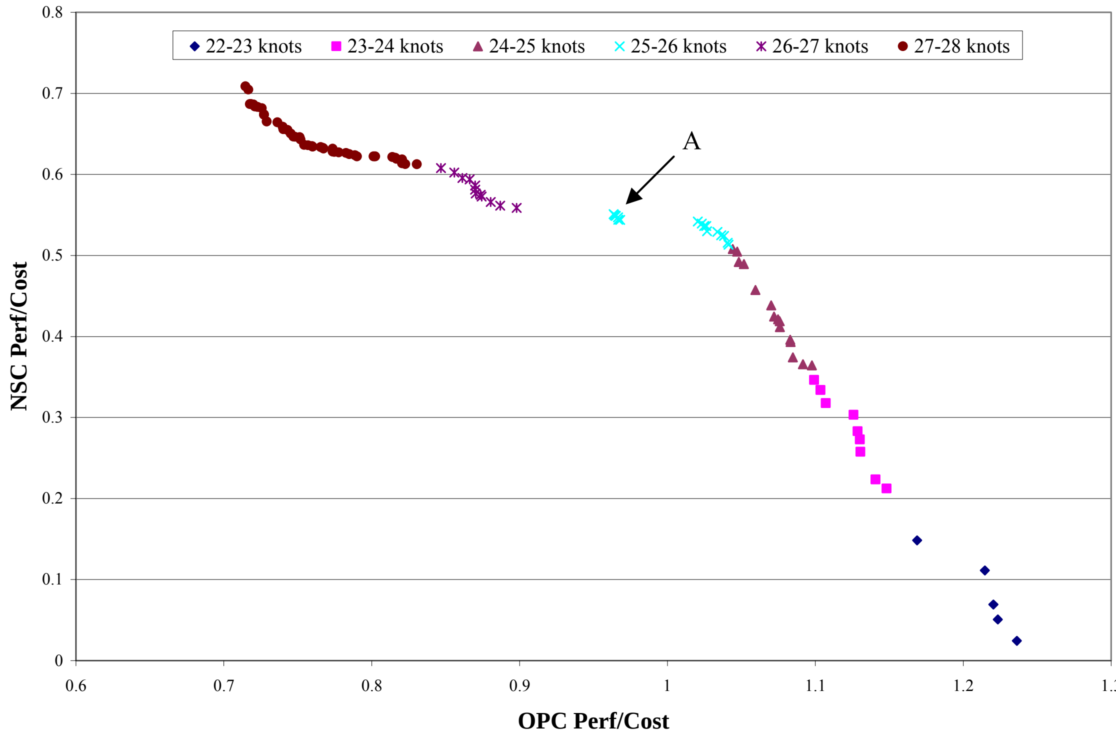

Figure 5.5 Detailed Study of Baseline Optimization Results for Ship Speed

Figure 5.5 shows that the distribution of maximum speed along the Pareto front is monotonic except for the solutions marked with an A. These ships have slightly smaller speeds that the solution to the immediate right of those marked A. More explanation on the reason for this will be found in the discussion of Figure 5.6 which follows.

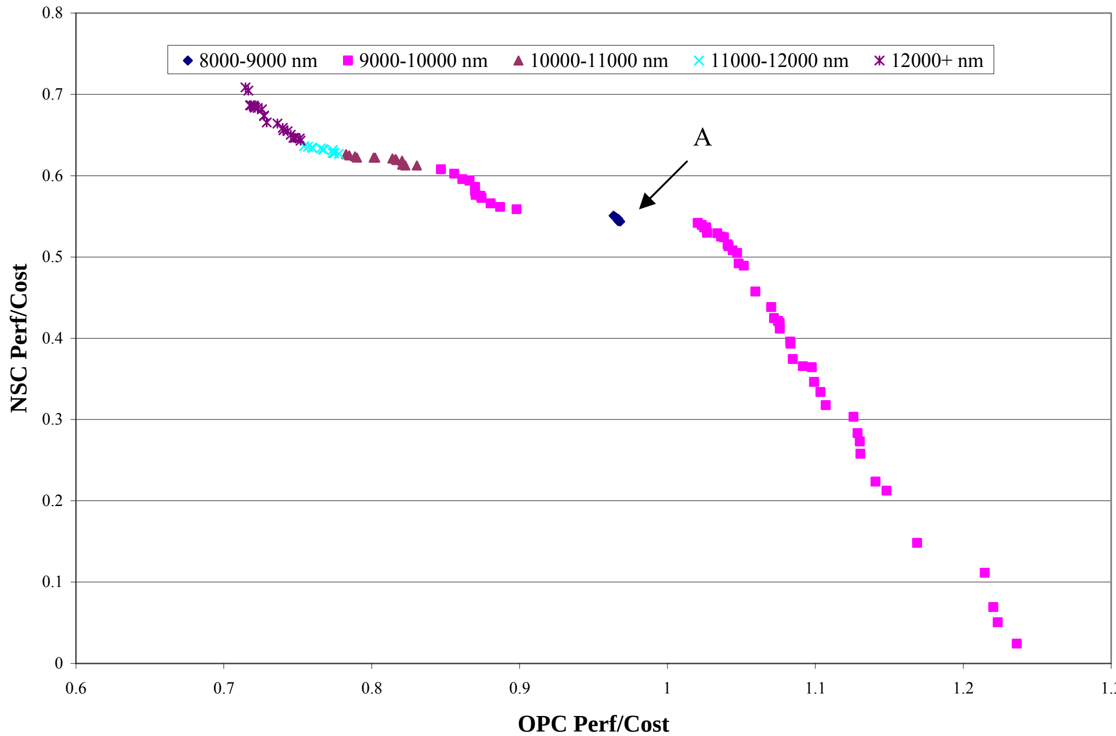

Figure 5.6 Detailed Study of Baseline Optimization Results for Ship's Range

Although not monotonic, the range generally increases from right to left along the Pareto front. Figure 5.6 shows a small cluster of solutions that do not follow the expected trend. The ships labeled with an A are the only solutions along the Pareto front with ranges less than 9000 nm. As mentioned previously, they also have a lower maximum speed than the ship to their immediate right. As a result, they will have lower OPC performance and NSC performance values than the ship to their right. However, since they have smaller ranges and maximum speeds, they will cost slightly less which results in higher performance over cost values than the ship on their right. The solutions that make up cluster A are not influenced solely by their small ranges. Their performances are also driven by maximum speed and number of hangars. Again, the fine balance of characteristics allowed for these distinctly different solutions to occur.

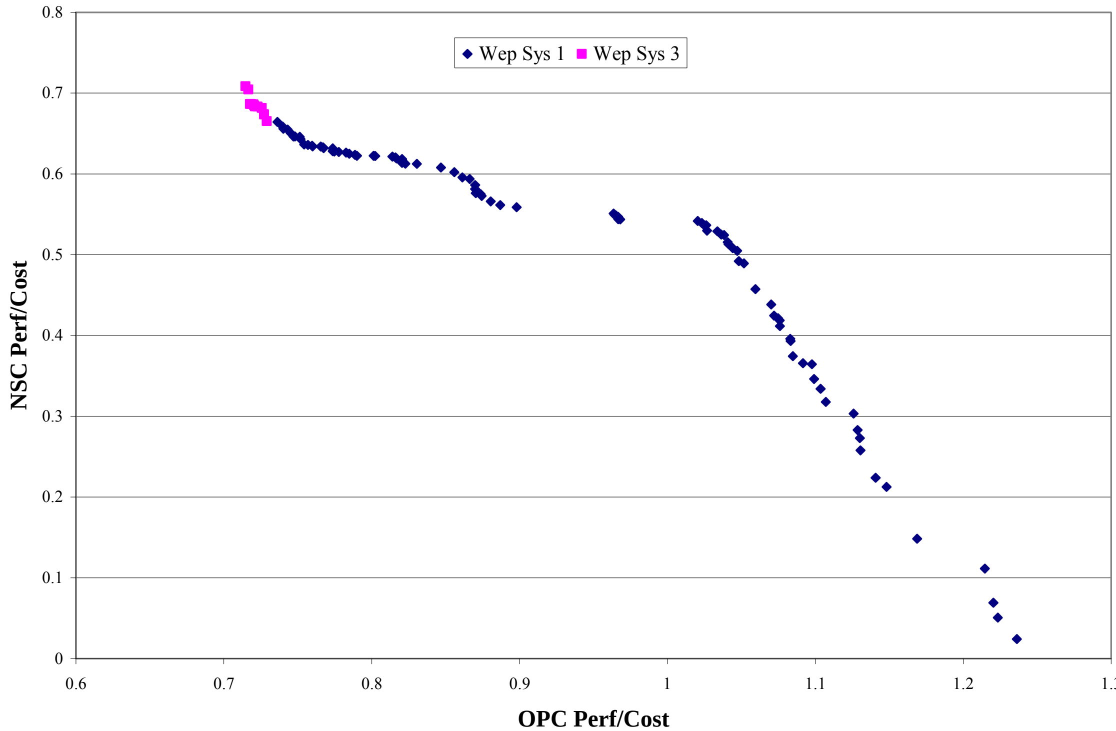

Figure 5.7 Detailed Study of Baseline Optimization Results for Ship's Weapons System

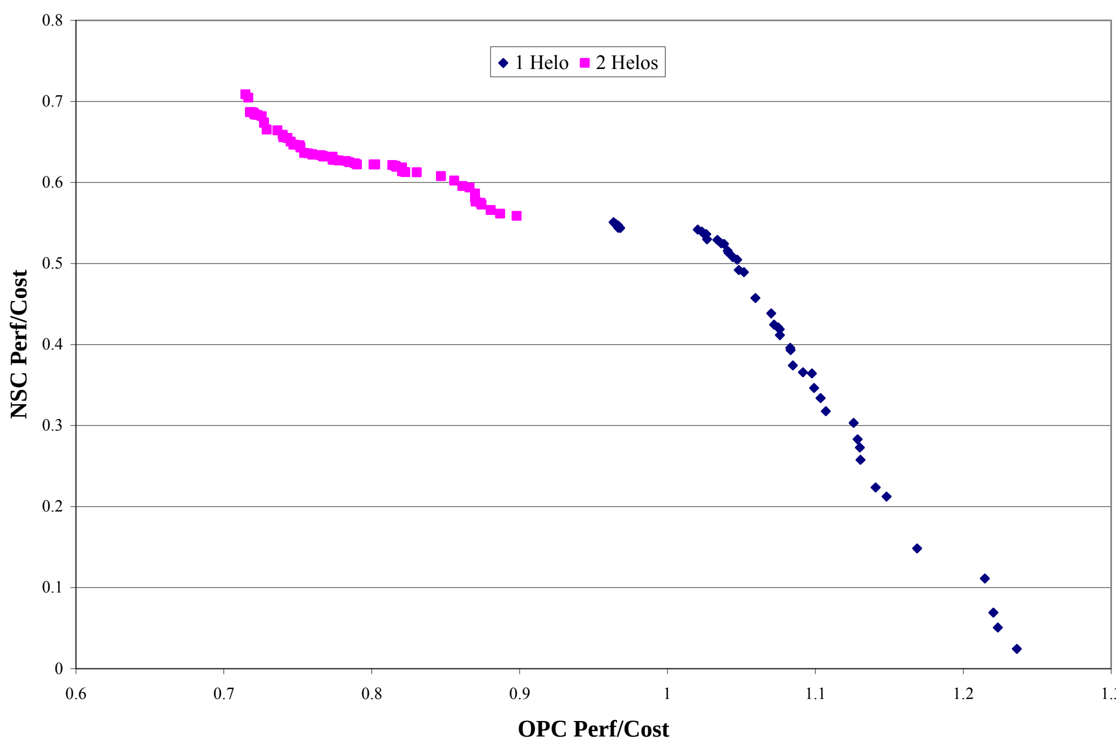

Figure 5.8 Detailed Study of Baseline Optimization Results for Number of Helicopter Hangars

5.3 Speed Utility Study

To illustrate the sensitivity of the optimization methodology to the choice of the fuzzy utility functions by the designer, the utility function values were modified for each of the four mission attributes (speed, number of helicopter hangars, weapon systems, and range).

The first utility functions that were modified were for maximum speed. The baseline NSC National Defense and General Defense Operations speed utilities shown in Figure 4.2 and 4.14 were made broader by varying them at a rate of 0.1667*(V-22) for speed between 22 and 28 knots as for the other NSC missions and as shown in Figure 5.9. This change did little to change the results from the baseline case as seen in Figure 5.10. This shows that maximum speed was not controlling influence on the optimization. The modified results also show a change in the distribution of solutions along the Pareto front. One specific region where this occurred is near the upper left hand portion of Figure 5.10. Because of the sparse distribution of results and the stochastic nature of the optimization, the results in this area were not quite as good as the baseline. The gap near the middle of the Pareto front shows a slight improvement over the baseline results. Again, this is a result of the stochastic nature of the optimization.

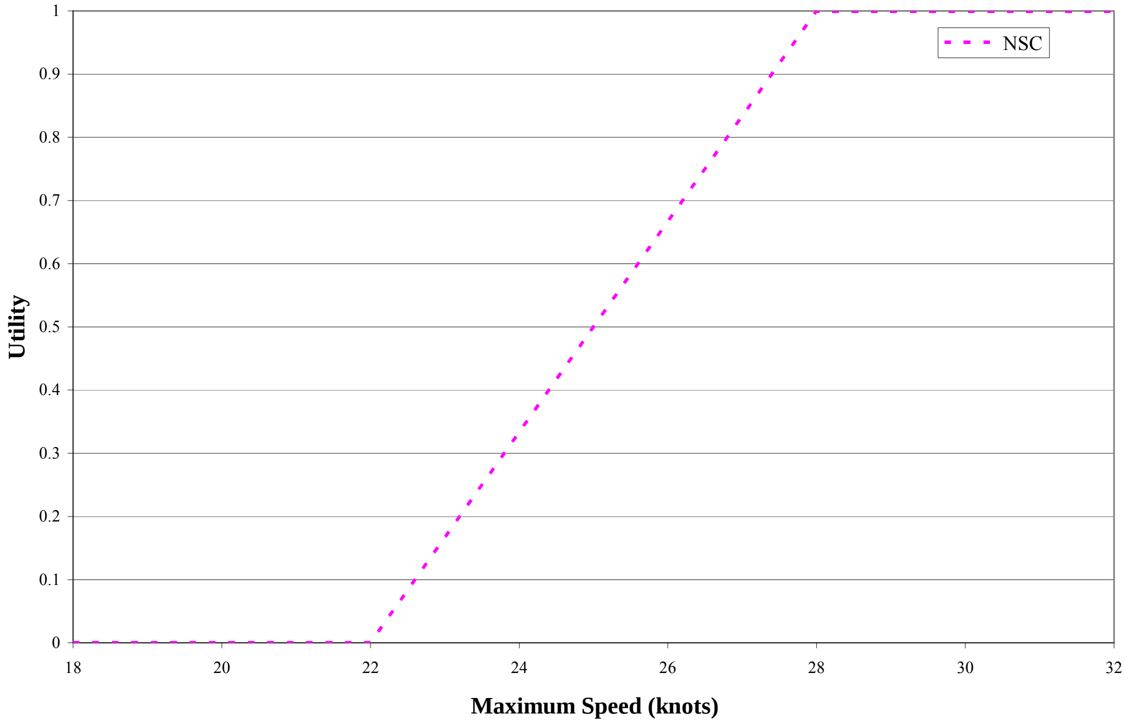

Figure 5.9 Modified NSC Speed Utility

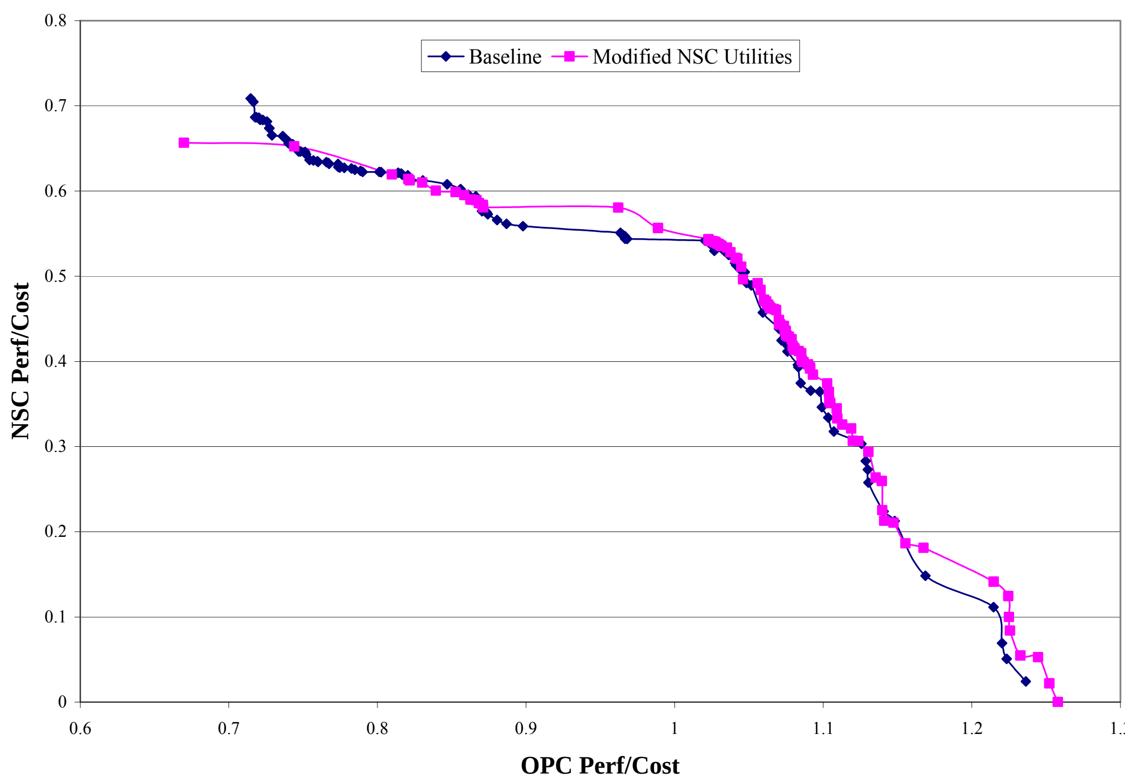

Figure 5.10 Speed Utility Study

5.4 Helicopter Hangar Utility Study

Modifications were made to the utility functions assigned to the number of hangars. The baseline helicopter utility values for one helicopter on the NSC shown in Figures 4.7, 4.11, and 4.15 were increased from 0.50, 0.57 and 0.50 to 0.75, 0.82 and 0.75 for the Drug Interdiction, Living Marine Resources, and General Defense Operations (GDO) missions, respectively. Figure 5.11 shows these utilities graphically. The result of this change was somewhat dramatic. All solutions had only one hangar due to its higher value and all used weapon system 1. The lengths of the solutions ranged from 298'-349'. All ranges were around 9000 nm and the maximum speed of all solutions was 26 knots. By increasing the utility for the one hangar, the optimization tended toward one very distinct type of ship. Figure 5.12 shows the results compared to the baseline results. The shape of the curve shows the effect of having solutions with only one hangar on the optimization. The lower left hand ships were unchanged, but the mid-plot ships show an increase in the NSC objective function. This is due to the increase in NSC performance for one hangar solutions and the significant decrease in cost associated with only one hangar.

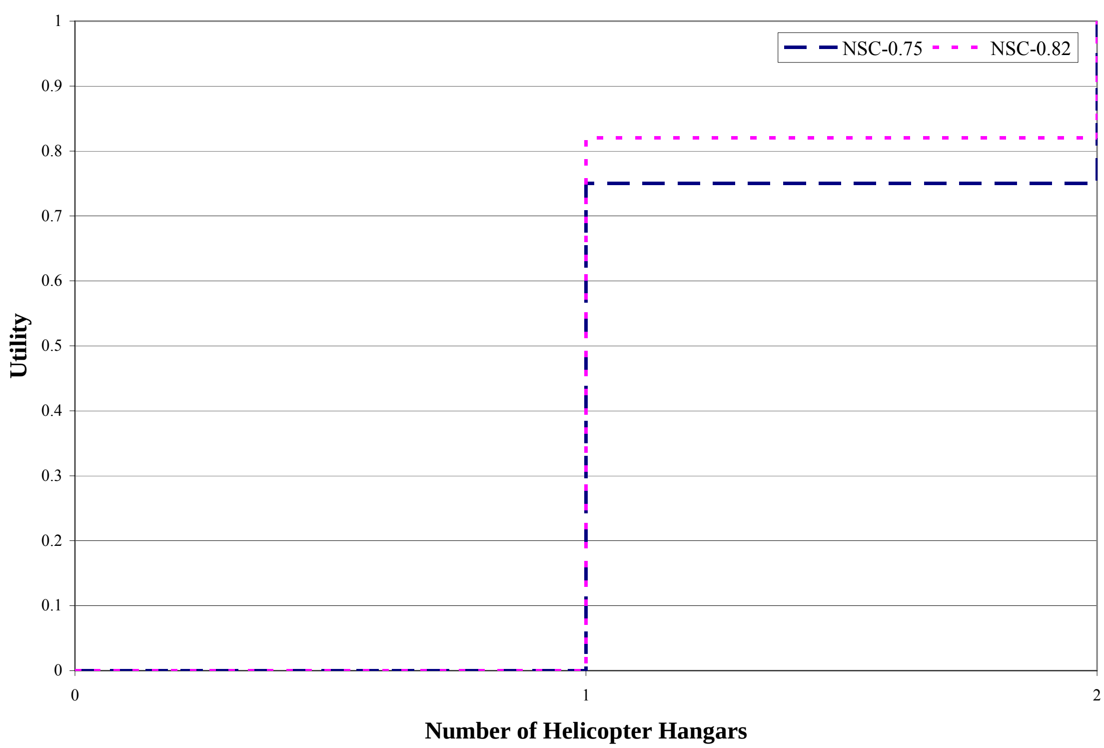

Figure 5.11 Modified NSC Helicopter Hangar Utility

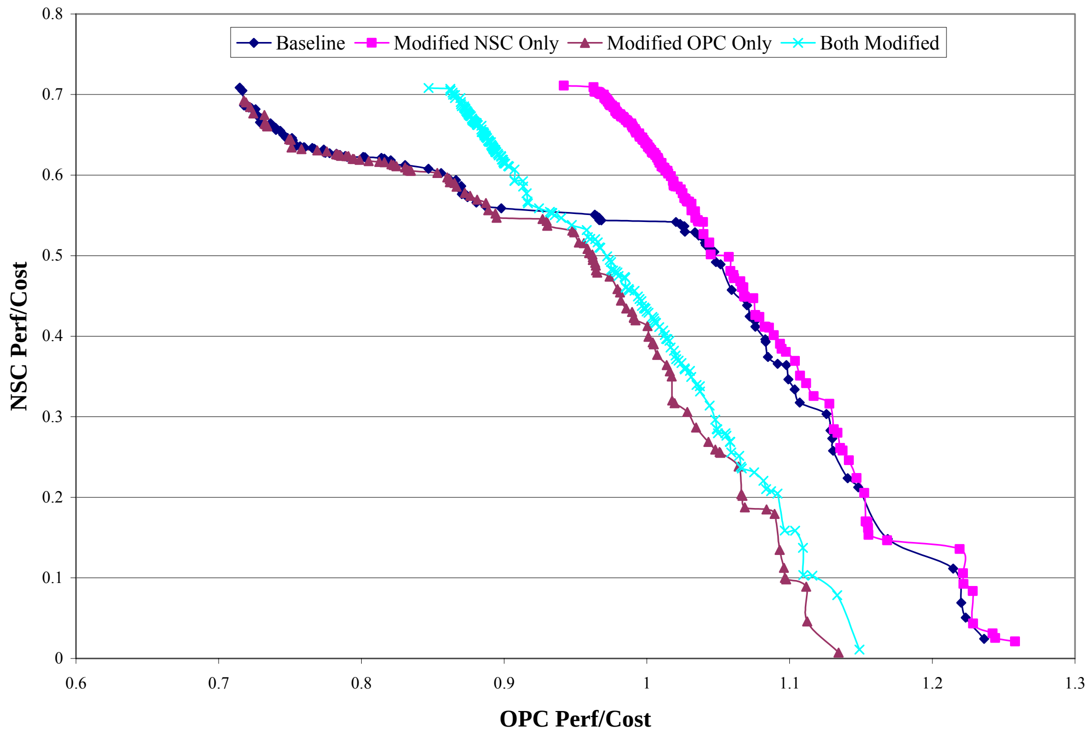

Figure 5.12 Helicopter Hangar Utility Study

Next the baseline utility functions for the OPC's one hangar case shown in Figures 4.7, 4.11, and 4.15 were decreased from 0.85, 0.92 and 0.85 to 0.75, 0.82 and 0.75 for the Drug Interdiction, Living Marine Resources, and the Alien Migration Interdiction Operations (AMIO) missions, respectively. The modified OPC utilities are shown in Figure 5.13. The results showed that OPC performance in each solution was maximized. All solutions had two hangars. The weapons systems breakdown was 10% for weapons system 3, 2% for weapon system 2 and the rest were weapon system 1. The length, speed and range characteristics ranged similar to the baseline condition. Figure 5.12 shows that the solution is similar to the two hangar baseline solutions on the left end of the Pareto front. Because all solutions have two hangars, the OPC performance increases over that of the baseline's one hangar solutions. However, the effect of the increase beam on cost reduces the OPC objective function value in that region of the curve.

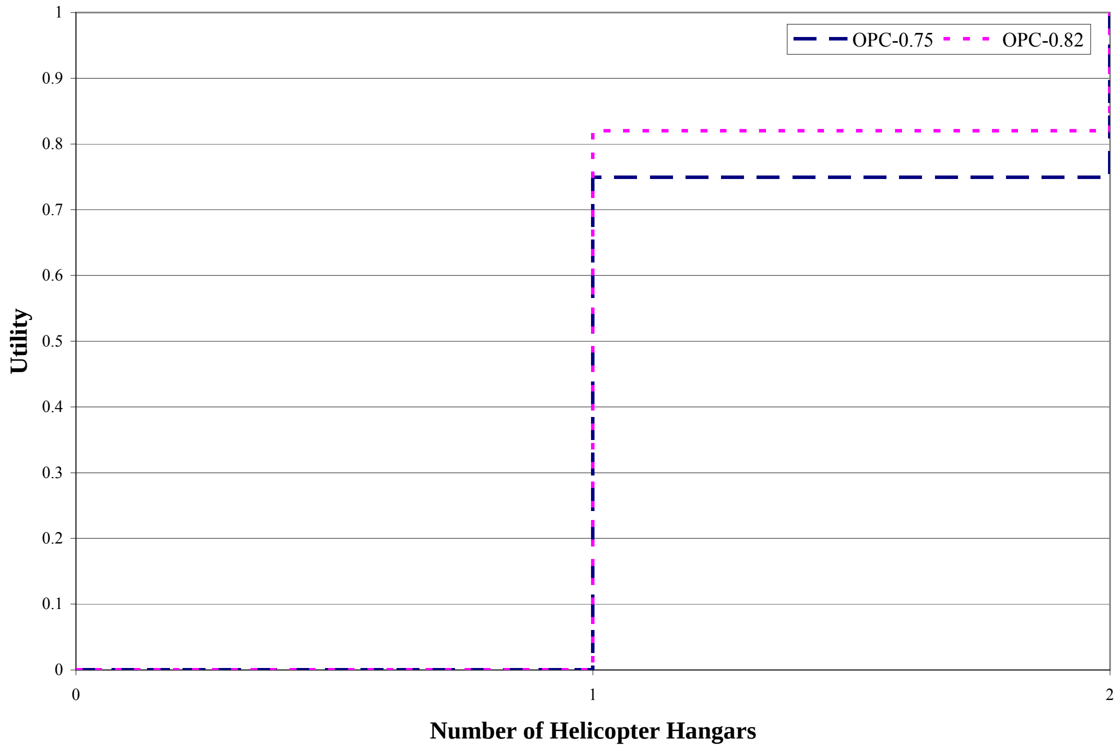

Figure 5.13 Modified OPC Helicopter Hangar Utility

The third modification to the helicopter hangar utility was to make them equal for both ships. The OPC and NSC utilities for one hangar were 0.75, 0.82 and 0.75 for the Drug Interdiction, Living Marine Resources, and AMIO/GDO missions, respectively. The number of hangars in the Pareto front solutions were split roughly in half. Weapon system 1 was used in all but 1 solution. The lengths were very limited ranging from 321'-346', speeds ranged from 22-26.5 knots, and the range was around 9000 nm for all solutions. Recall that the typical baseline results have one hangar solutions in the lower right portion of the plot and two hangar solutions in the upper left. For this scenario that was switched. The lower right hand ships had two hangars while the upper left hand ships had one. This trend follows closely what was learned in the other helicopter hangar utility scenarios. Figure 5.12 shows the results of having equal helicopter hangar utilities for both ships as being a combination of their individual modifications.

5.5 Weapon System Utility Study

The baseline weapon system utility was modified by lowering the NSC National Defense utilities for weapon system 1, 2, and 3 shown in Figure 4.4 from 0.6, 0.8, and 1.0 to 0.25, 0.50 and 1.0, respectively. The modified fuzzy utility functions can be seen in Figure 5.14. The results were very similar to the baseline optimization as shown in Figure 5.15. The NSC performance was less for the lower right hand portion of Pareto front due to the decrease in utility for weapon system 1 solutions.

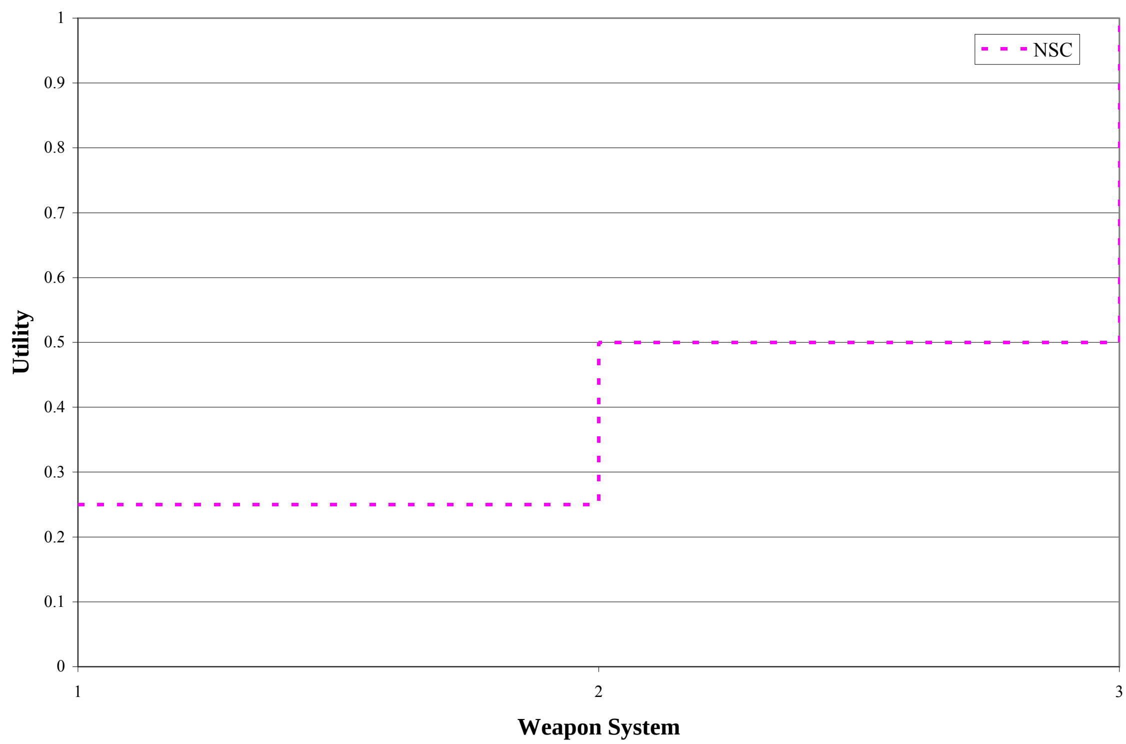

Figure 5.14 Modified NSC Weapons Utility for the National Defense Mission

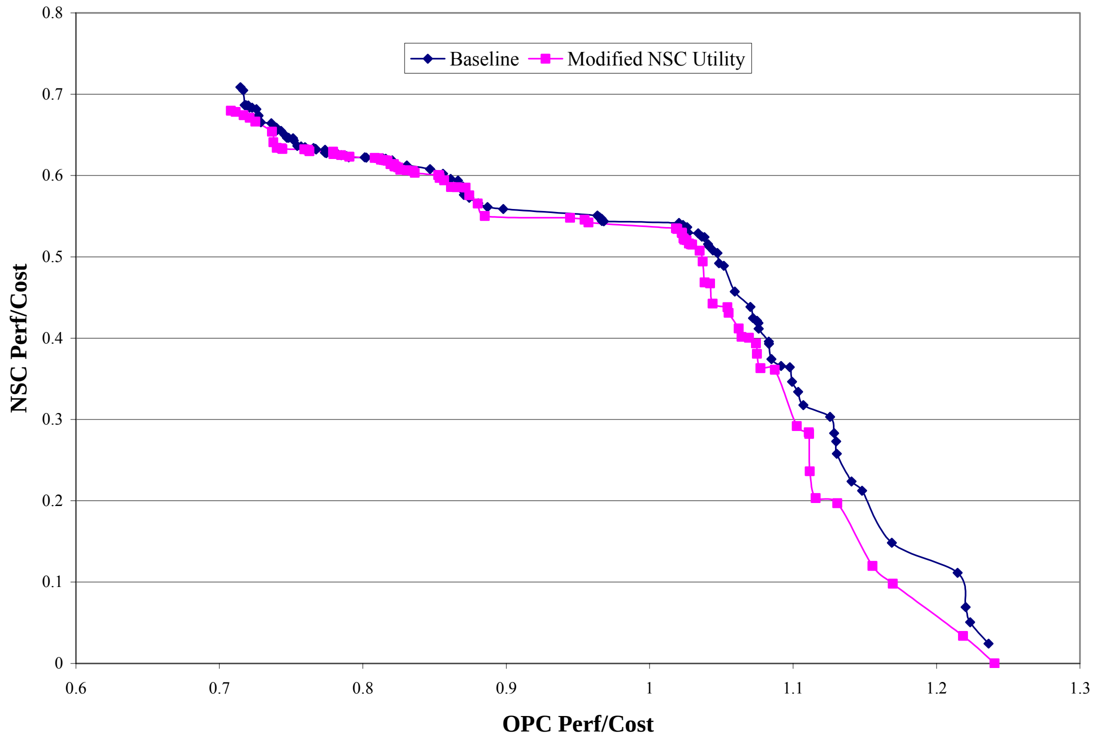

Figure 5.15 Weapons System Utility Study

5.6 Range Utility Study

Lastly, the range utility functions were changed. The first change was to make the baseline National Defense and GDO missions' range utility for the NSC and the National Defense mission's range utility for the OPC, as shown in Figures 4.5 and 4.17, decrease more gradually. Rather than have the range utility equal zero for less than the required range, it was changed to decrease as a percent of the required range as seen in Figure 5.16. The result was similar to the baseline except approximately half of the solutions used weapon system 3. Figure 5.17 shows the effect of this change as compared to the baseline solution. The upper left hand portion of the graph shows an increase in utility associated with the increased number of weapon system 3 solutions. The lower right portion of the plot shows a slight increase in the objectives as a result of the increase in range utility.

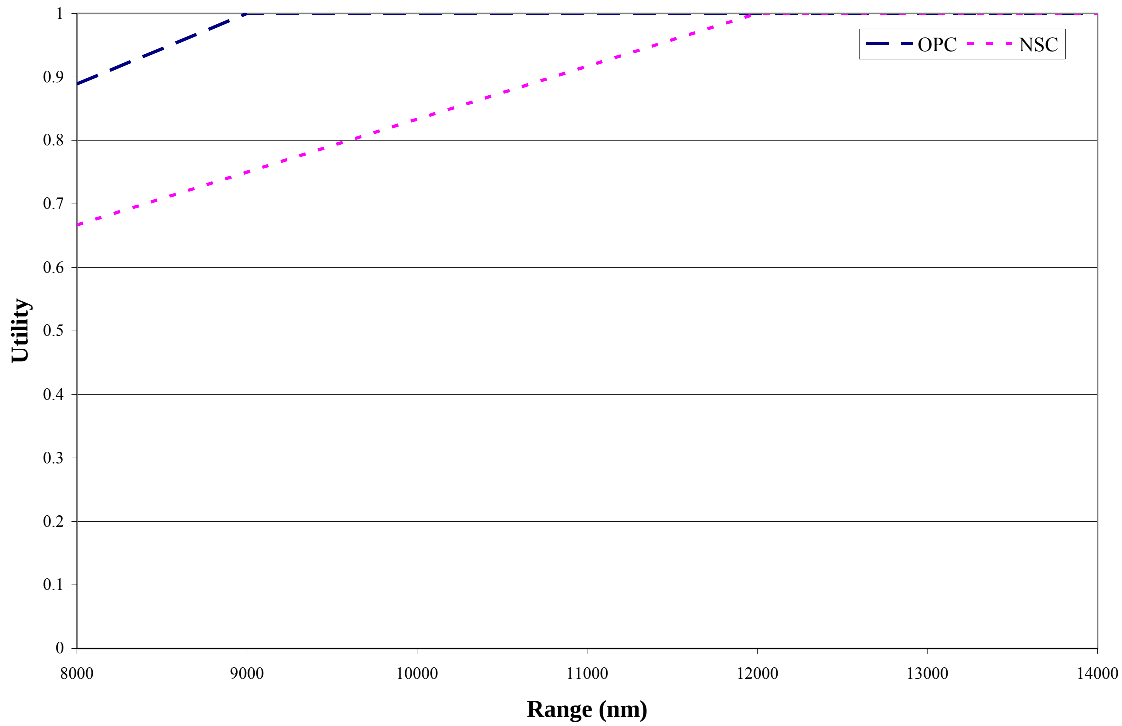

Figure 5.16 Modified Range Utilities 1 for the National Defense and General Defense Operation Missions

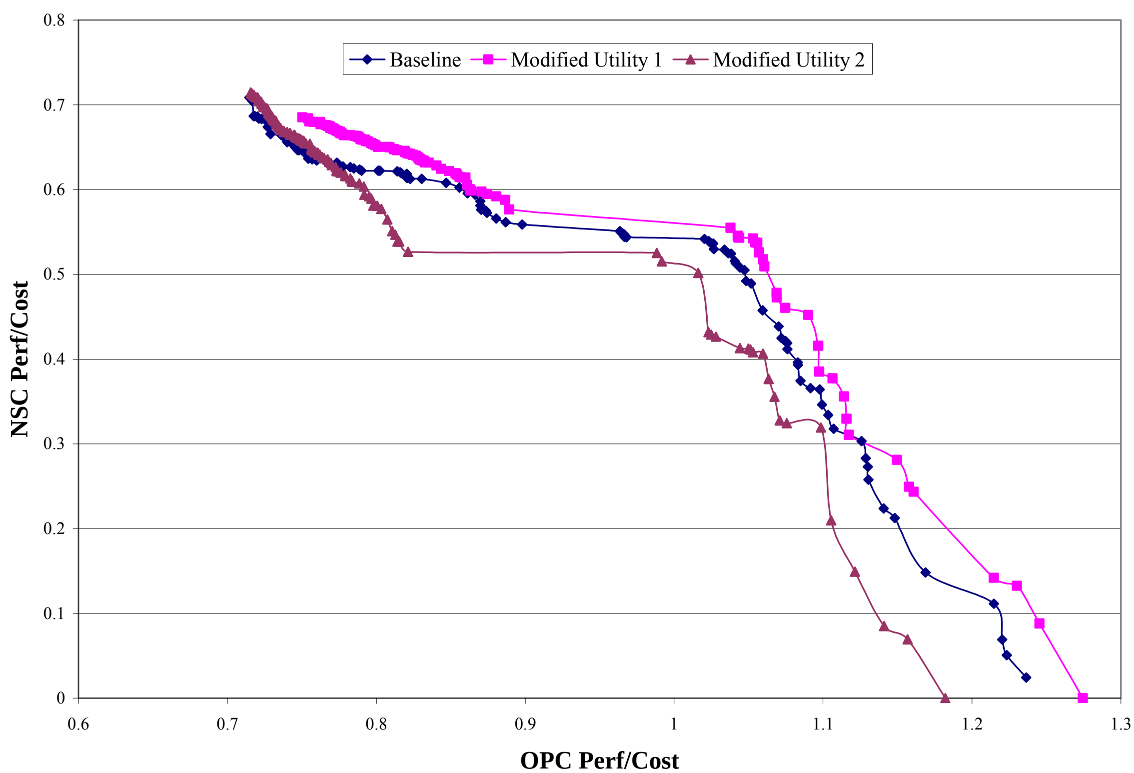

Figure 5.17 Range Utility Study

A second change increased the steepness of the range utility. Rather than taking the utility as a percent of the required range, the utilities were changed to have double slope as seen in Figure 5.18. This resulted in lower utilities overall. The biggest effect that this had was to drive the ship lengths up. About 85% of the ships were over 400' long and had 2 helicopter hangars. Weapon system 3 was used in about a third of the solutions. Figure 5.17 clearly shows the large number of solutions at the upper left. The solution is similar to the baseline at the most upper left hand region of the Pareto front, but quickly falls below the baseline once the ranges fall below 12000 nm. The remainder of the front has similar shape to the baseline, but has lower objective function values as a result of the steeper range utility.

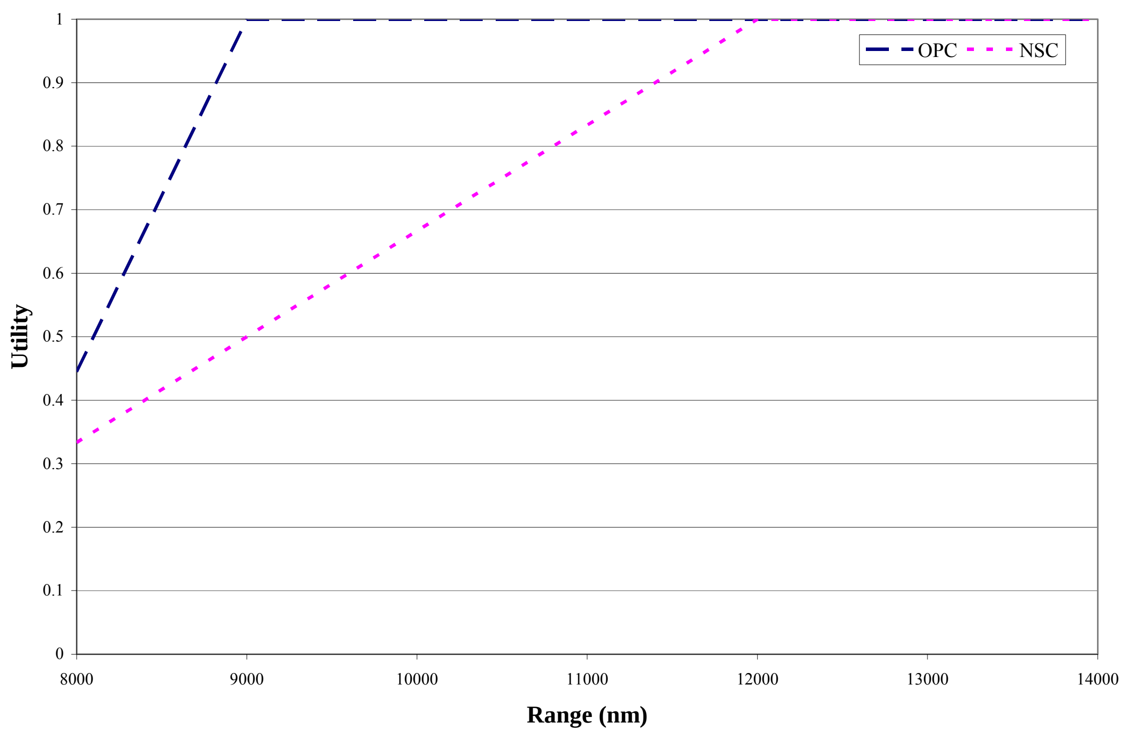

Figure 5.18 Modified Range Utilities 2 for the National Defense and General Defense Operation Missions

5.7 Mutation Rate and Magnitude Studies

The mutation rate and mutation magnitudes were examined to ensure that the selected method was best suited for this study. As mentioned in Chapter 4, the mutation rate increases exponentially as defined in eq. 4.8 while the mutation magnitude decreases exponentially as defined in eq. 4.9. The purpose of this is to search globally early in the optimization and more locally later in the optimization. The goal during the early generations is to establish a broad range of solutions while initially developing a Pareto front. As the optimization moves forward, the goal is to refine the Pareto front and establish any unique characteristics it may have. This is accomplished by using a more localized search that works to increase the number of solutions on the Pareto front making it more densely and diversely populated.

Other mutation strategies were investigated and compared to the exponential methods. Linear and constant mutation rates were examined in this study and can be seen in Figure 5.19.

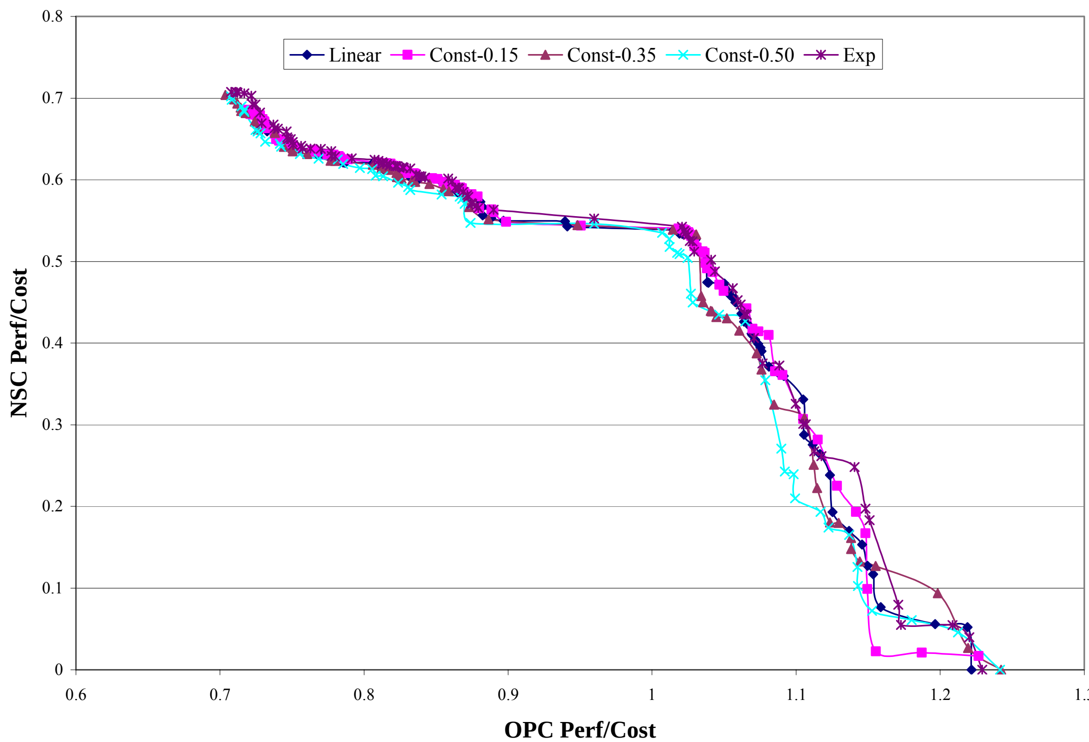

Figure 5.19 Mutation Rate Study Results

The linear mutation rate varied using

$$R_{mut}(t) = 0.15 + \left({t}/{t^*} \right) \cdot (0.50 - 0.15) \tag{5.1}$$

while the constant values used were 0.15, 0.35 and 0.50.

Initial analysis of the plot shows a good correlation among the results. However, as more runs were performed some concerns developed. Each of the constant mutation rate values had a tendency to result in stopping at the <1% new solutions termination condition prior to filling the archive with nondominated solutions. Thus, some rank 2 solutions appeared in the final archive, which reduced the number of Pareto solutions below the minimum desired number of 50. This result was deemed unacceptable and constant mutation rates were not examined further.

With little difference being noticed in the results of the linear and exponential mutation rates, further analysis was performed. After completing ten sets of optimizations for both linear and exponential mutation rates, some interesting results were observed. Table 5.2 shows the statistical data for the number of generations to termination and number of ships in the final archive for the ten runs. The run using an exponential mutation rate were far more consistent in their performance. The efficiency of the exponential mutation rate was also more apparent throughout the ten runs. The linear mutation rates had a significantly different number of ships and generations from one run to the next. The consistency of the exponential mutation rate is viewed as a positive characteristic of its performance and, therefore, makes it more suitable for this application.

Table 5.2 Statistical Data from Mutation Rate Study

	Linear	Exponential
Average Number of Generations	139	101
Average Number of Ships in Archive	152	100
Average Optimization Run Time (minutes)	7	4
StDev Number of Generations	51	20
StDev Number of Ships	42	10

Both linear and exponential mutation magnitudes were also studied to determine which method is better for this application. A plot comparing the results can be seen in Figure 5.20.

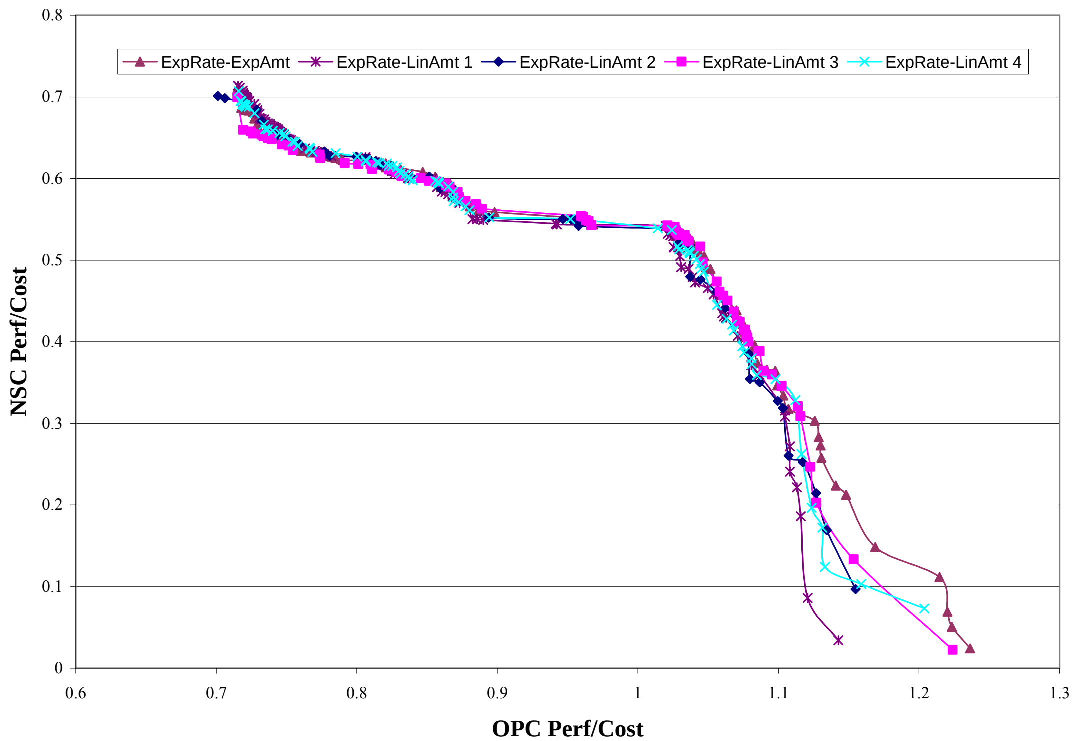

Figure 5.20 Mutation Magnitude Study

The plots show that the linear mutation magnitude does not do a consistently good job at optimizing the solutions in the lower right hand portion of the object function space for five individual optimizations. There is no obvious reason why this happens. One possible explanation is that the rate of decline in magnitude for the linear case is a bit slower than for the exponential case. This allows the exponential magnitude to do a finer search of the design space sooner in the optimization. The <1% new solution termination occurs before the linear mutation magnitude has the ability to complete a fine search of the design space.

5.8 Diversity Operator Study

Chapter 4 discussed how the diversity operator calculates the distance of each solution to the nearest three solutions. This calculation is performed using an *n*-dimensional distance in variable space. A series of eight (four each) optimization runs were performed to compare the results of calculating diversity in the independent variable space versus calculating it in objective function space. The results in Figure 5.21 show that there is little to no difference in the use of either method for this problem. Runs Var 1-4 have diversity calculated in the independent variable space, while runs Object 1-4 have it calculated in object function space.

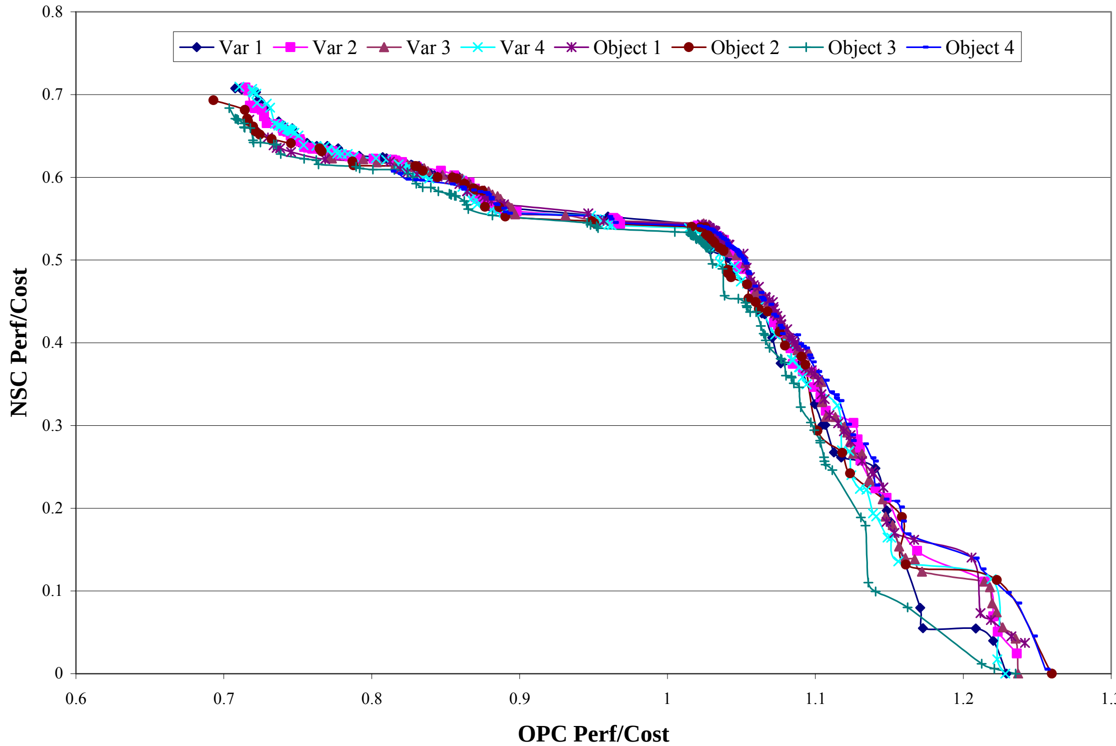

Figure 5.21 Variable Space vs. Objective Space

5.9 Normalized versus Raw Data Study

During the dominance check and the tournament selection, the optimization algorithm uses normalized performance over cost values for the two objective functions. A series of eight (four each) optimizations was performed to determine if using the normalized values produced better results than using the raw objection function values. Figure 5.22 shows the results of this comparison. Both methods have areas of the curve where they appear to perform better at optimizing solutions. The raw data method seems to consistently find better solutions in the lower right hand area of the Pareto front. In the upper left hand portion of the front, the raw data method does not always find results that extend all the way to the "best" NSC solution. The data shows that in several cases the maximum length is only ~360', well short of the maximum allowable length of 470' and the best NSC mission design length of 401'. The normalized method results seem to extend further up to the left of the front. Many of the normalized method solutions have lengths >410'. By reaching these longer lengths the ships will vary more in other ways. They will have different weapon systems, more helicopter capabilities, longer ranges and generally greater maximum speeds. However in contrast, the normalized method is a bit inconsistent in the lower right hand portion of the front.

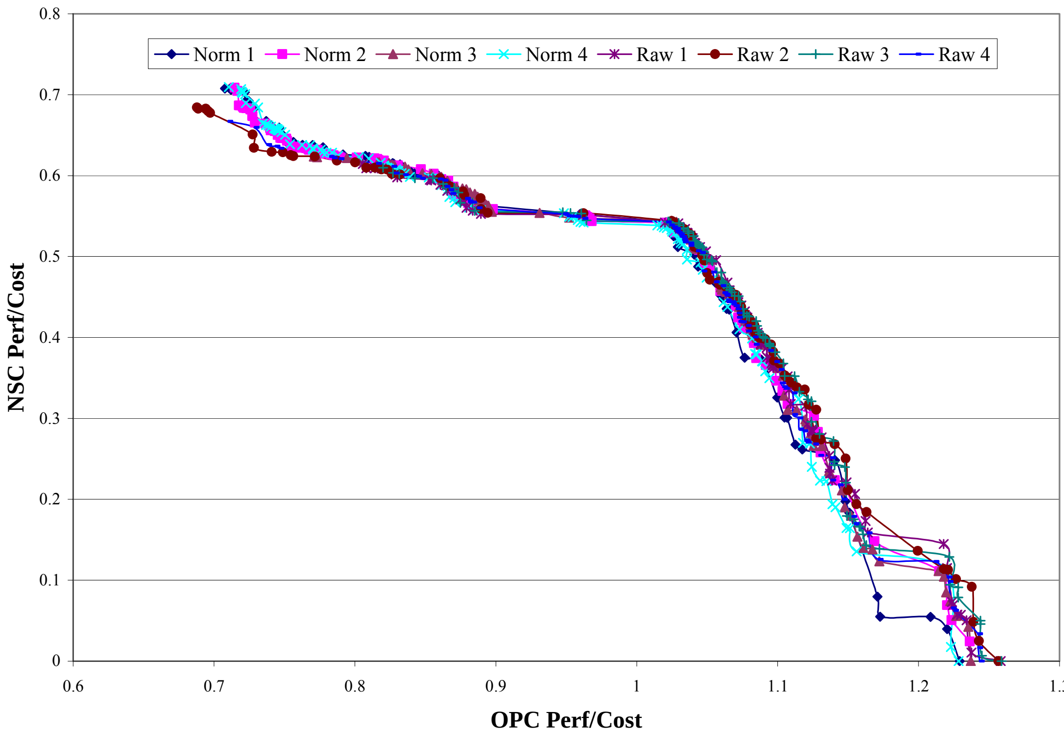

Figure 5.22 Normalized vs. Raw Data Results

The primary reason for this difference in the two methods has to do with the tournament selection criteria. Once enough generations have been run to completely fill the archive with nondominated solutions, the tournament selection relies on the sum of the objective functions and diversity to distinguish between solutions. Using the raw data method, the sums tend to favor the OPC type ships (lower right hand portion of the front) due to their numerically higher (≅1.2) raw performance/cost values. The normalized method tends to favor the NSC type ships (upper left hand portion of the front) on a relative basis since the absolute magnitude of the performance values are normalized. The tournament selection tends to pick the favored solution when an OPC and NSC type solution are compared. Figure 5.23 shows the sum of the objective functions using the different methods along the entire range of solutions and clearly shows which portions of the curve are favored by which method.

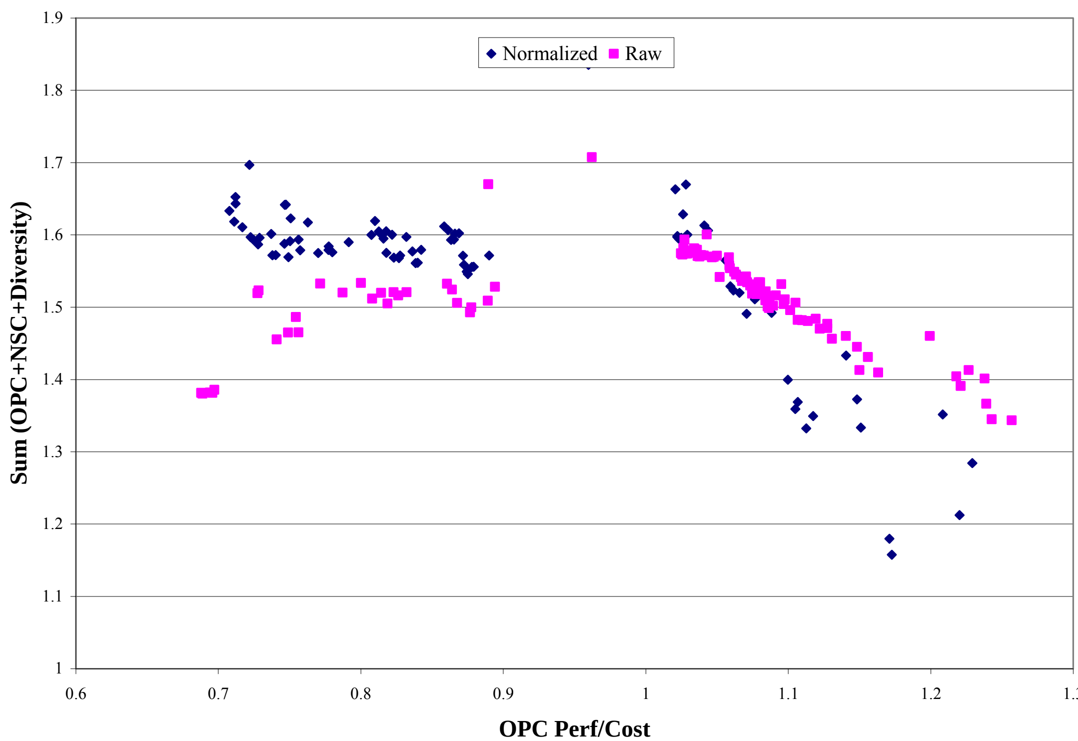

Figure 5.23 Comparison of Normalized versus Raw Data Method Tournament Selection Sums

The normalized method ships tend to consistently have more diverse solutions than the raw data method solutions. At the same time, the raw data method ships tend to be more consistent from run to run in the lower right hand portion of the front. It is difficult to decide which is more important. For this application, the ability to achieve a diverse solution set was felt to outweigh the need for more consistent results in the lower right hand portion of the front. If the solutions are not diverse in all independent variables, then the optimization will not effectively serve its purpose. Therefore, using the normalized results for tournament selection was judged more suitable for this application.

5.10 Min-Max Solution /Nearest to the Utopian Solution

Chapter 4 described two methods to determine which solutions along the Pareto front may be the best compromise solutions if only one ship class were to be designed to satisfy both missions. The Min-Max solution and the Nearest to the Utopian solution have been chosen to be viable methods for this research.

The Min-Max solution method for the baseline optimization is shown in Figure 5.24. Here the values for $z_k(x)$ as defined in eq. 2.4 are superimposed on the normalized baseline run results. The intersection point of the z_1 and z_2 curves, the minimum of the maximum z_i, gives the Min-Max solution for this optimization. This solution can also be found from the intersection of the (0.5, 0.5) to (1.0, 1.0) line and the Pareto front in the normalized objection function space. This solution achieves about 78% of the best object function value possible for each mission.

The Nearest to the Utopian solution for the baseline optimization run can be seen in Figure 5.25. The baseline solution is the same as throughout Chapter 5. Figure 5.25 shows the results as normalized and scales the x and y axes to be the same length. This modified view of the results gives a more real perspective of which solution is the Nearest to the Utopian solution. The Min-Max solution is also shown as the intersection of the 45 degree line and the Pareto front in this re-scaled normalized object function space. The two standard compromise designs are significantly different in this particular case.

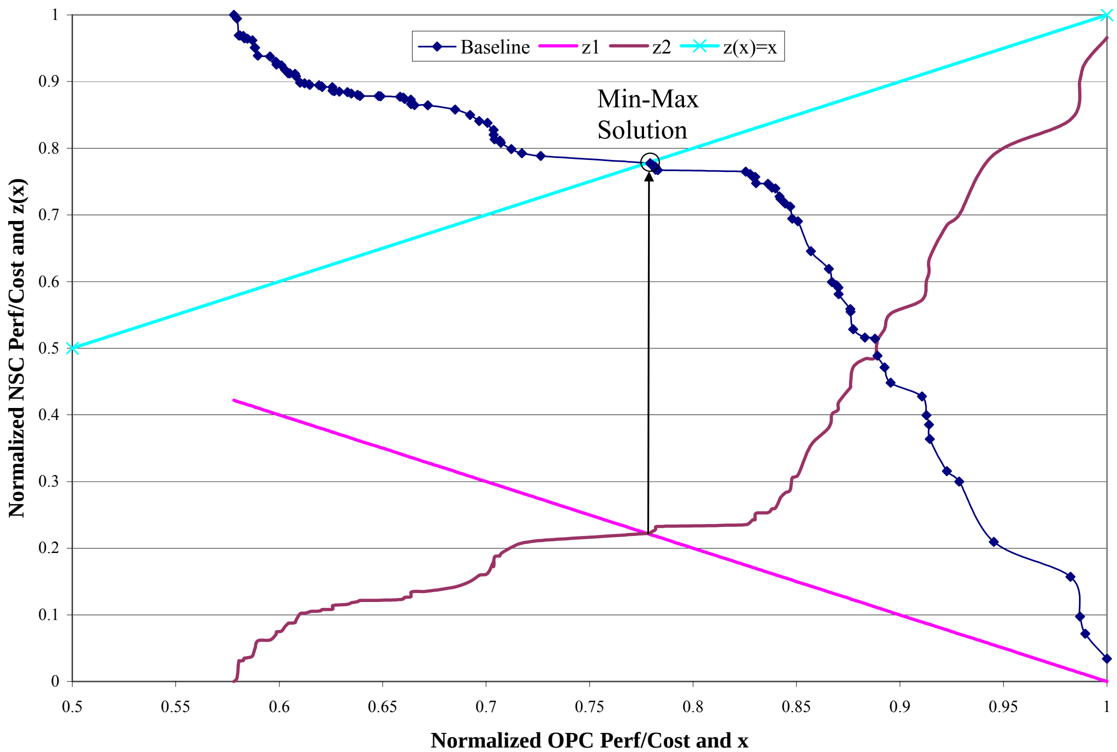

Figure 5.24 Min-Max Solution

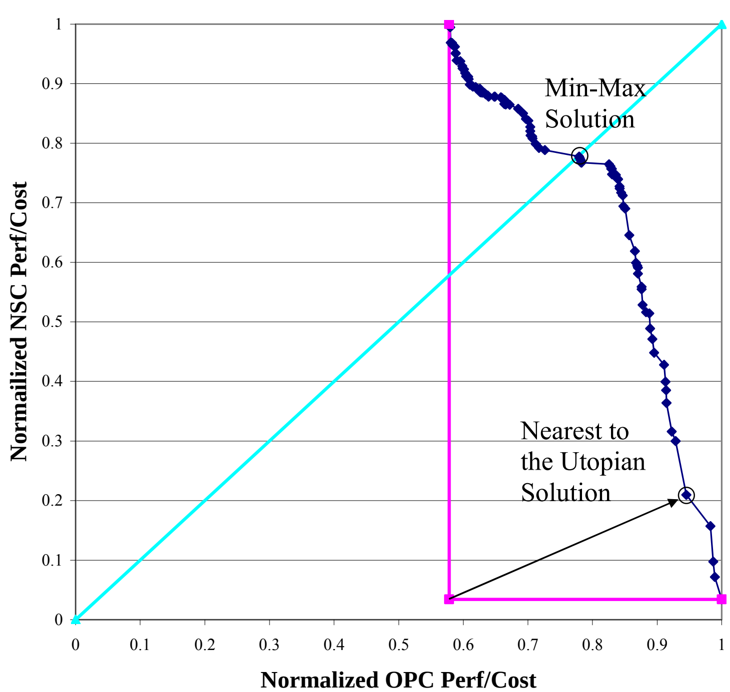

Figure 5.25 Nearest to the Utopian Solution

5.11 Commonality Options

Further evaluation of the baseline optimization results showed some important trends relative to possible commonality choices. Figure 5.26 shows a breakdown as to which areas of the Pareto front had certain components as common. The different areas show the different combinations of weapon systems, ship service generators and cruise engines. All baseline Pareto front ships were made up of one of the four possible combinations of these three components.

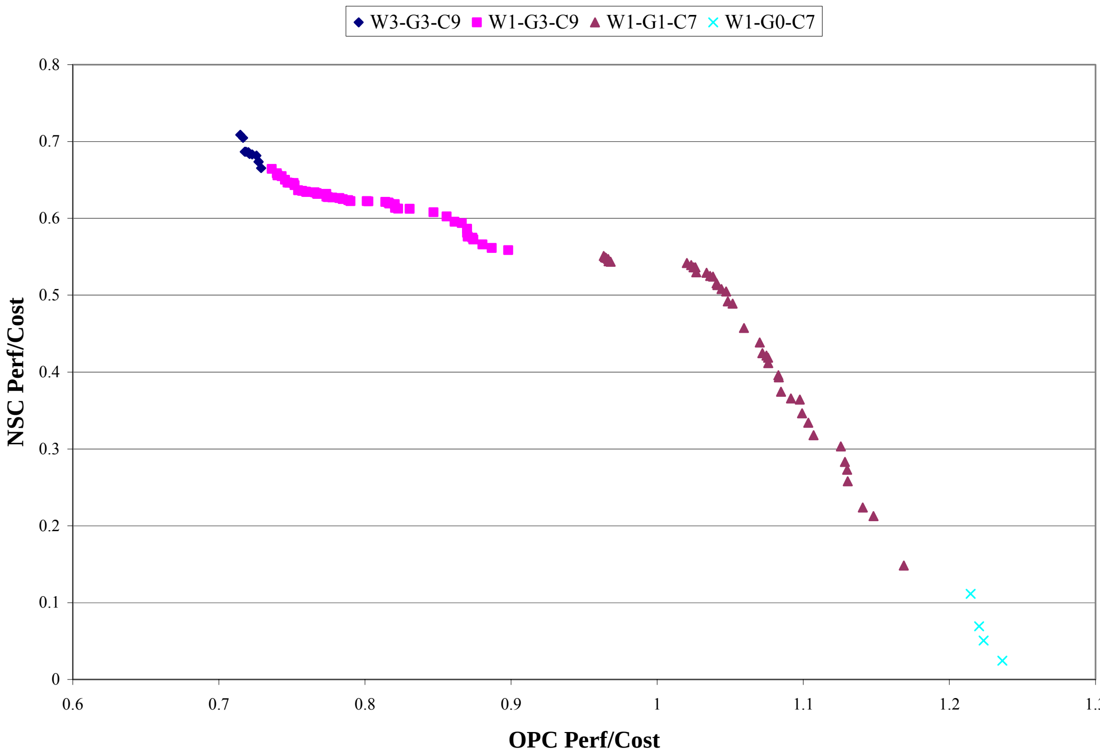

Figure 5.26 Natural Commonality within Pareto Front Solutions

The baseline results revealed several key factors to guide the determination of what components should be considered for common use. For components such as generators and cruise engine only a few different choices were ever selected from their respective databases. In addition, the superstructure volume produced by the synthesis model closely correlated with the number of hangars. Once the number of hangars was determined, the superstructures had little volume variation. Thus, the volumes of the superstructures could be easily made common as either the smaller (one hangar) size or the larger (two hangar) size. A similar trend was noticed with hull depth and beam ranges. Solutions tended to have two sets of depth and beam depending on the number of hangars present. Thus, midship section became a logical choice to make common. Further details of the commonality choices used in this research will be discussed in Chapter 6.

CHAPTER 6

MULTICRITERION OPTIMIZATION WITH COMMONALITY

6.1 Problem Formulation with Commonality

The problem formulation with commonality is similar to the optimization seen in Chapter 4. The only difference is that a fleet commonality savings objective, also to be maximized, is added.

$$\text{maximize} \qquad \mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x_1}, \mathbf{x_c}), f_2(\mathbf{x_2}, \mathbf{x_c}), f_3(\mathbf{x})]^T$$
$$\mathbf{x} = [\mathbf{x_1}, \mathbf{x_2}, \mathbf{x_c}]^T = [x_1, x_2, \ldots, x_n]^T$$

$$\text{subject to} \qquad h_i(\mathbf{x}) = 0, \qquad i = 1,\ldots,I$$
$$g_j(\mathbf{x}) \geq 0, \qquad j = 1,\ldots,J \tag{6.1}$$

where f_1, f_2, f_3 represent the multiple objective functions and $\mathbf{x}$ represents the design independent variables. The objective functions are:

$f_1(\mathbf{x}_1, \mathbf{x_c})$ – OPC Mission Ship Effectiveness /Average Ship Cost
$f_2(\mathbf{x}_2, \mathbf{x_c})$ – NSC Mission Ship Effectiveness /Average Ship Cost
$f_3(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x_c})$ – Net Fleet Savings from Commonality

where f_1 and f_2 are subject to the ship design constraints for their respective designs as specified by naval architecture practice and the customer. The specific formulation of f_1 and f_2 was discussed in Chapter 4.

The problem constraints that are used are not explicitly stated. Instead, they are integrated into the ship synthesis model as part of the optimization process. The weight-displacement balance, basic stability requirements and volume check were all discussed in Chapter 3.

The ship design variables in $\mathbf{x}_1$ and $\mathbf{x}_2$ were discussed in Chapter 3 and remain the same. The commonality variable vector or commonality string, $\mathbf{x}_c$, will be introduced below.

6.2 Basic Optimization Process

In order to add commonality, the basic optimization process seen in Chapter 4 needed to be extended. A few elements were added to create families of designs with a particular commonality. These elements include a commonality string, parallel optimization runs, the archiving of endpoints, the fleet savings calculation and a second dominance sort which includes all three design objectives. The complete optimization process can be seen in Figure 6.1. The specific descriptions of each of the new elements will be discussed in detail in subsequent sections of this chapter.

6.2.1 Commonality Strings

This optimization uses a string of *n* possible common design components. Each of these *n* possible common design components will have multiple options for commonality. The commonality string designates which design components to make common along with which component option to use for each optimization run. An example of a commonality string is

$$\mathbf{x}_c = [0\ 2\ 0\ 1\ 3]^T.$$

There are five design components that are considered for the use in common in this commonality string. These five elements can be whatever the designer feels would be good candidates to make common among a family of designs. In this example, 0 indicates that the component will not be common while non-zero numbers indicate that commonality will be used for that component. If a design component is not required to be common, the optimization is free to use whichever element it chooses to optimize the design. So, components two, four and five will all be common for the above example family of designs. Each of the components may have any number of options for commonality. The commonality string above designates the second option for component two and designates that component four and five use options one and three, respectively.

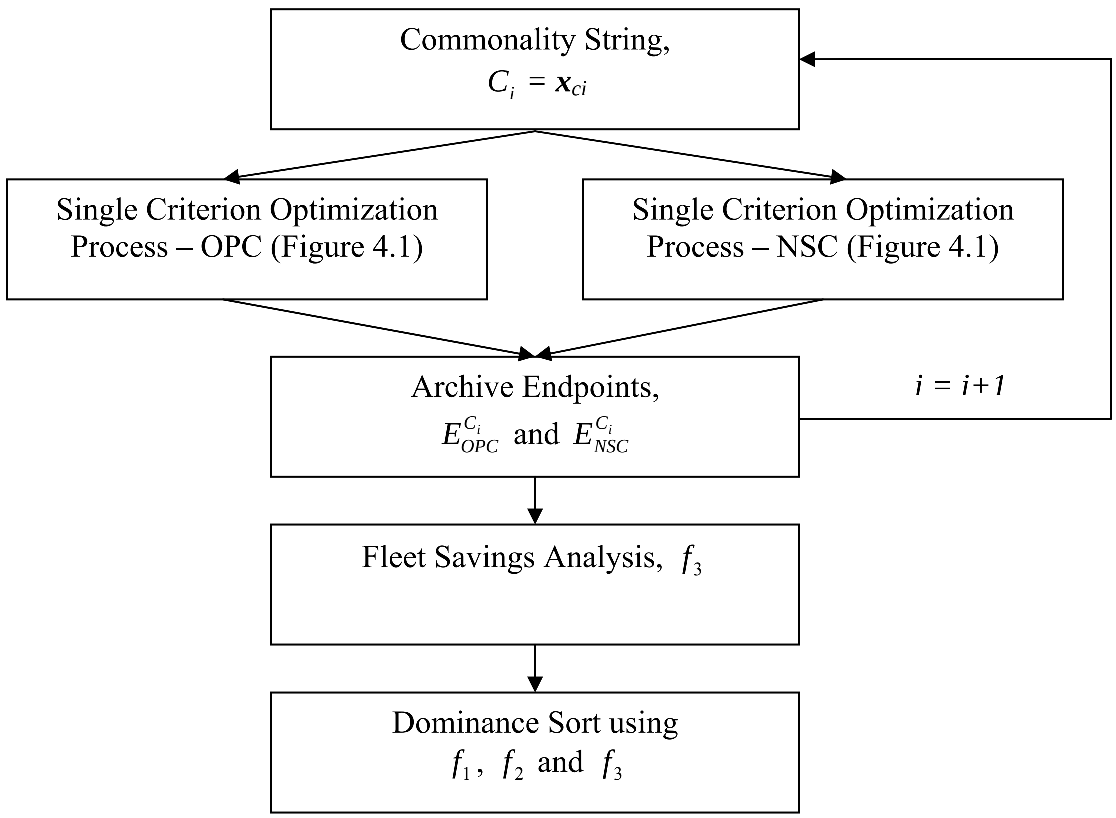

Figure 6.1 Basic Optimization Process with Commonality

If each of the n possible components has the same number of commonality options, m, the number of possible commonality strings will be $(m+1)^n$, which accounts for the possibility that a component may be considered not common. If the components have varying numbers of options for commonality then the number of possible commonality strings is $(m_1+1)(m_2+1)\ldots(m_n+1)$.

For this study, the number of common components used was five. The five common components are weapon systems, ship service generators, cruise engines, superstructure and midship section. The selection of these components was designed to provide a broad range of possible commonality. Each of these elements affects the designs in a different way.

For each possible common component, the number of different options to choose from was determined from the optimal characteristics revealed by the results of the two-criterion optimization runs without commonality. These results were discussed in detail in Chapter 5.

There are three possible weapon systems that can be used in each design. Using weapon systems for commonality is relatively simple because it is an independent variable. By simply designating which one is to be used, the synthesis model designs a family of ship variants using only the designated weapon system. The difference from one weapon system to another is primarily through its weight and cost. The weight of the weapon system will obviously have some impact on the designs, but does not affect the design too much. The weapons systems options are listed in sequence in Table 6.1.

Table 6.1 Common Weapon System Characteristics

Weapons	Weapons weight in Ltons	Ammunition weight in Ltons	Combat Systems Weight in Ltons
46mm gun	11.22	10.10	73
57mm gun	14.04	11.40	75
57mm and CIWS	23.48	23.48	84

The ship service generators are a little more complex in their impact in the overall design of the ships. Since the choice of ship service generators is a dependent variable, its implementation is different from that of the weapon systems. If no generator is designated as common, the number of generators used in each design will be four and the ship synthesis will select a generator to be used in each design. However, if the generators are designated as common, the ship synthesis selects the number of generators required to meet electrical load requirements of the ships. The effect of the generators goes beyond just weight considerations. In addition to accounting for the weight of the generators, the synthesis must also allocate space for the generators in the design. The two objective baseline runs that were discussed in the previous chapter showed that only three of the twelve generators in the database were ever used in Pareto front designs. The characteristics of these generators are listed in sequence in Table 6.2.

Table 6.2 Common Ship Service Generator Characteristics

kW Rating	Engine RPM	SPC (FP) in lb/HP-hr	Total wt of DG in Ltons	Length of DG set in feet
250	1800	0.39	5.07	6.0
304	1200	0.35	8.00	7.9
444	1800	0.38	6.89	7.6

The cruise engines showed another aspect of the use of commonality. The choice of cruise engines limits the number of possible designs that could meet the cruise speed requirement. The choices made for weapon system and generator did not have firm requirements associated with them. While they may have impacted the mission performance of the designs, they were not required to meet a design requirement as seen with the cruise engines. Similar to the ship service generators, the choice of cruise engine is a dependent variable and cannot simply be designated without further consideration. The ship synthesis was permitted to run as if no commonality were chosen. Once it had a ship designed, it checked to see if the engine used was the desired common engine. If it were, the design was kept. If not, the design was discarded. This process allowed for the iterative ship design process to take place while ensuring that the cruise engines satisfied the cruise speed requirements. During the iterative process, the synthesis model changes engines as needed to ensure the correct engine is being used for each design. If the common cruise engine is forced into the design, the iterative process is disrupted and the synthesis model may not work as intended. Even though this process is not an efficient way to create designs, it is more reliable in creating good designs that meet the required commonality. The two objective baseline cases consistently used only two types of cruise engines on the Pareto front designs. Their characteristics are shown in sequence in Table 6.3.

Table 6.3 Common Cruise Engine Characteristics

HP Rating	SPC (FP) in lb/HP-hr	Weight in Ltons	Length in feet	Width in feet	Height in feet	Volume in ft^3
1931	0.34	3.95	9.48	4.25	4.68	188.4
2481	0.34	7.6	13.11	4.98	6.2	405

To this point, all the commonality components have dealt with specific shipboard equipment. In order to show another side of commonality in design, construction savings was considered. Two areas of commonality, superstructure and midship section, were used to show the effectiveness of this optimization methodology.

As noted in Chapter 4, the baseline runs showed that all the ships on the Pareto front basically had one of two narrow ranges of superstructure volume. The superstructure is primarily a function of the number of helicopter hangars on the ship. In addition to the number of hangars, the beam of the ship (B) is also related to the design of the superstructure. These characteristics along with the volume of the superstructure make up a commonality component. By using the superstructure as a common component both independent variables and dependent variables are being designated. The number of helicopter hangars is an independent variable while the beam and volume of the superstructure are dependent variables calculated in the iterative ship synthesis model. The synthesis was allowed to calculate the beam and superstructure volume as if no commonality was being used. Once calculated, the values were overwritten to the necessary values for the designated commonality and the process was continued. The characteristics associated with the two common superstructure choices can be seen in sequence in Table 6.4.

Table 6.4 Common Superstructure Characteristics

Designation	Volume in ft^3	Beam in feet	Number of Helicopter Hangars
Small	60,000	40	1
Large	113,000	54	2

The final component that was considered to be common was the midship section of the ships. This would enable the use of a common hull block(s) near amidships in both designs. Again, the size of the midship section was largely dependent on the number of helicopter hangars on the ships. Other midship section related characteristics included the midship coefficient (C_m), depth of the hull (D) and the beam of the ship. Again, this commonality component consists of independent (number of hangars and C_m) and dependent variables (D and B). Similar to above, the depth and beam of the ship were determined in the iterative process and changed when necessary to satisfy the commonality requirement. The characteristics used for the common midship sections are listed in sequence in Table 6.5.

Table 6.5 Common Midship Section Characteristics

Designation	C_m	Depth in feet	Beam in feet	Number of Helicopter Hangars
Small	0.99	23	40	1
Large	0.99	27	54	2

Given the five possible commonality components and the choices associated with each, the total number of possible commonality strings was 432. However, some of these had conflicting requirements. For example, a large superstructure requires two helicopter hangars and a 54’ beam while a small midship section requires one hangar and a 40’ beam. Obviously both of these requirements cannot be satisfied at the same time. So options with this combination were eliminated from consideration. Similarly, a small superstructure and large midship section was also eliminated as infeasible. Other combinations of commonality were eliminated because they were counterintuitive. For example, designs using the smaller cruise engine could not adequately power ships with the large midship sections or large superstructures. As a result, the optimization program would spend excessive time trying to populate itself with ships of this nature. Instead of looking for ships that are infeasible, the optimization eliminated these inconsistent combinations of commonality. As a result of eliminating infeasible commonality choices, there were only 288 commonality strings remaining.

6.2.2 Optimization Process

The optimization process is similar to the one seen in Figure 4.1. A few changes were made, however, in order to make this process more efficient in solving the three criterion optimization process. The most obvious change is that the optimization is run for the OPC and NSC mission designs in parallel rather than at the same time. Since finding only the endpoints of the two objective Pareto front is the goal for this problem, it is possible to optimize for each objective at a higher precision when independent of the other. The dominance sorting and tournament selection processes are performed using only the respective objective for each mission ship. This single objective sorting allows for an efficient search for the best OPC ship and the best NSC ship for each commonality string.

6.2.3 Archive Endpoints

Each individual optimization produces the two objective Pareto front endpoints for each commonality string. Since this optimization can be run for any number of ship classes, the number of endpoints will be equal to the number of ship classes that are being considered. The endpoints are the ship designs that have the highest value of performance over cost for each of the required missions.

6.2.4 Fleet Savings

In each optimization in which commonality was applied, a fleet savings was calculated. By using common engines and/or weapon systems, savings can be found in a variety of ways. For example, savings can be realized is in crew training, spare parts, generation of manuals, and in engineering integration of components.

If a fleet of ships all have a particular common component, training of crew members can be simplified. If a crew member were to transfer from one class of ship to another he/she would not have to be retrained on the engine or weapon system resulting in a savings of time and money. Instead of having to conduct training on multiple engines or weapon systems for crew members within a fleet of ships, only one school would be necessary for each. Savings could be realized in training facilities and staff.

Depending on the location of the home ports of the ships within the fleet, commonality can lead to a significant savings in spare parts. If ships of two classes of ships are located near each other, the need for two sets of spare parts can be eliminated. This results in a savings in purchasing the spare parts as well as storing the spare parts. Shore based maintenance may also be a source of commonality savings in that they will only have to service one type of engine or weapon system.

When an engine or weapon system is installed on a ship there is a nonrecurring cost associated with that installation. If commonality is used in a fleet of ships, the cost of this installation will only occur once and can be spread out over the entire fleet of ships. If no commonality is used, the cost may occur for each class of ships and be spread out over smaller numbers of ships. In addition to engineering design at installation, administrative savings can be made. Engine manufacturers generate owner's manuals for each ship. The cost of this can be reduced if only one type of manual is needed.

If a fleet of ships is able to use the same superstructure or midship section design, savings can be found in the construction learning curve as well as the design of those areas of the ships. As shipyards construct sections of a ship, there are lessons learned that helps them become more efficient in their work. This efficiency will save them time and money in the construction process. The more common pieces that they construct, the more they will learn and significant savings can be made through this form of commonality.

The fleet savings modeled in this case study was based on either the savings as a result of bulk purchasing or the savings associated with a construction learning curve. The savings model was limited to these two types of savings. The following sections will explain how the fleet savings for each commonality option was calculated. As a designer learns more about the ships and how they will be operated, manned and where they will be located, other types of savings can be added to the fleet savings model.

6.2.4.1 Weapon System Savings

The savings associated with the commonality of the weapon systems was limited to the bulk purchase for the entire fleet. In calculating the fleet savings for the use of a common weapon system, the cost of the fleet of ships with commonality was compared to the cost of a fleet of ships that were designed with no commonality. The optimization was run using very small parameter ranges that focused on each of the endpoints of the baseline curve. In doing so, it ensured that the ships designed were best suited for their specific missions. This resulted in baseline ships for both the National Security Cutter (NSC) and the Offshore Patrol Craft (OPC) missions. The commonality savings also incorporates a percent savings associated with bulk purchasing. Figure 6.2 shows the assumed rate of decreased cost as a function of number of units purchased for weapon systems 1 and 2. The assumed savings for using weapon system 1 or 2 common was linear from zero for one ship to 10% at 33 ships.

The fleet savings associated with using common weapon systems 1 and 2 is the sum of the NSC Fleet Savings

$$\#NSCs * \begin{bmatrix} wg700Cost^{0}_{NSC} * (1.0031 - 0.0031 * \#NSCs) - \\ wg700Cost^{i}_{NSC} * (1.0031 - 0.0031 * \#ships) \end{bmatrix} \tag{6.2}$$

and the OPC Fleet Savings

$$\#OPCs * \begin{bmatrix} wg700Cost_{OPC}^{0} * (1.0031 - 0.0031 * \#OPCs) - \\ wg700Cost_{OPC}^{i} * (1.0031 - 0.0031 * \#ships) \end{bmatrix} \tag{6.3}$$

where

wg700Cost – material cost of one weapon system

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#ships – total number of ships being built (33).

The superscript *0* represents the NSC and OPC designs that were designed without commonality. The superscript *i* represents the current ship being considered.

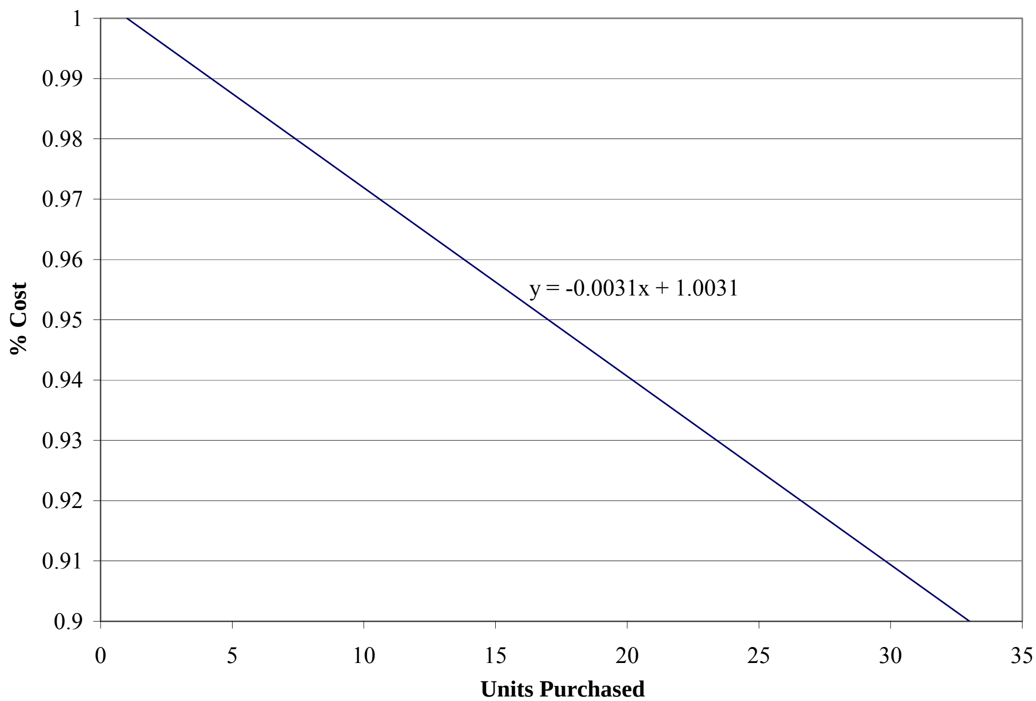

Figure 6.2 Weapon System 1 and 2 Cost Savings Schedule

Figure 6.3 shows the rate of decreased cost as a function of the number of units purchased for weapon system 3. The assumed savings for using weapon system 3 was linear from zero for one ship to 20% at 33 ships.

The fleet savings associated with using common weapon system 3 is the sum of the NSC Fleet Savings

$$\#NSCs * \begin{bmatrix} wg700Cost^{0}_{NSC} * (1.0063 - 0.0063 * \#NSCs) - \\ wg700Cost^{i}_{NSC} * (1.0063 - 0.0063 * \#ships) \end{bmatrix} \tag{6.4}$$

and the OPC Fleet Savings

$$\#OPCs * \begin{bmatrix} wg700Cost^{0}_{OPC} * (1.0063 - 0.0063 * \#OPCs) - \\ wg700Cost^{i}_{OPC} * (1.0063 - 0.0063 * \#ships) \end{bmatrix} \tag{6.5}$$

where

wg700Cost – material cost of one weapon system

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#ships – total number of ships being built (33).

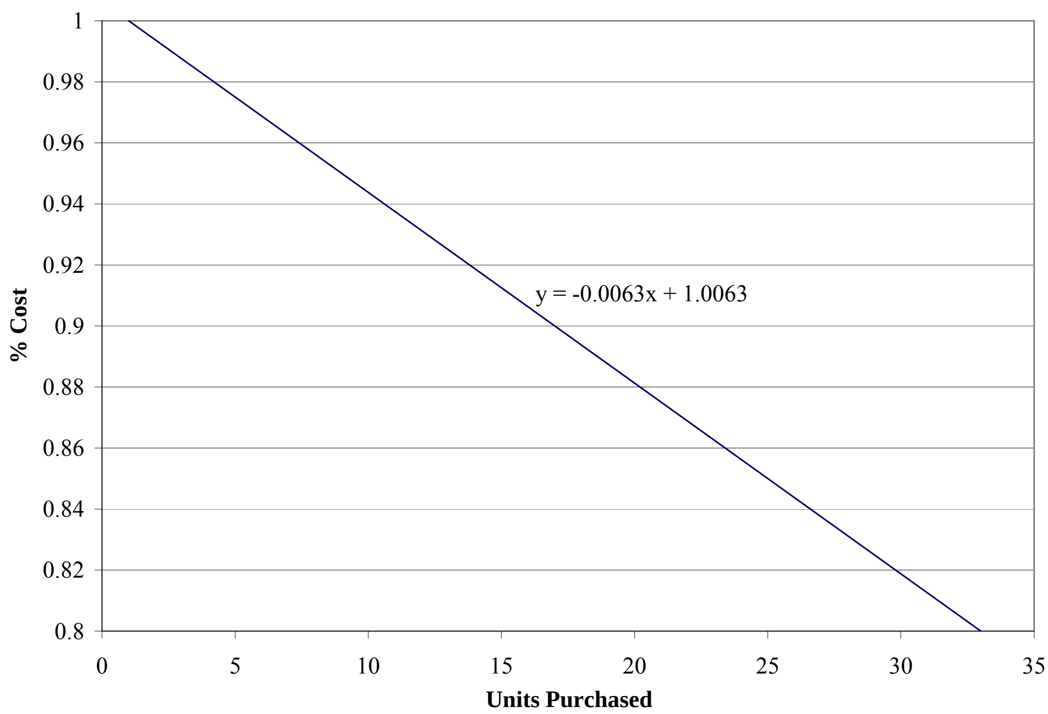

Figure 6.3 Weapon System 3 Cost Savings Schedule

6.2.4.2 Ship Service Generator Savings

The savings associated with using common ship service generators was performed in much the same way as the weapon system. A cost schedule was created based on the number of units purchased and the savings was the difference between the ships with no commonality and those with common generators. Because the number of generators is not constant for all ships, however, the savings had to include the number of generators purchased. The assumed cost schedule as a function of the number of generators purchased is shown in Figure 6.4. The assumed savings associated with using a common ship service generator was from zero for four generators to 10% at 132 generators total on all 33 ships.

The fleet savings associated with using a common ship service generator is calculated as the sum of the resulting NSC savings

$$\#NSCs*\#Gens_{NSC}*\left[\begin{array}{l}\dfrac{wg300Cost^{0}_{NSC}}{\#Gens^{0}_{NSC}}*(1.0008-0.0008*\#NSCs*\#Gens^{0}_{NSC})-\\ \dfrac{wg300Cost^{i}_{NSC}}{\#Gens^{i}_{NSC}}*(1.0008-0.0008*(\#NSCs*\#Gens^{i}_{NSC}+\#OPCs*\#Gens^{i}_{OPC}))\end{array}\right] \tag{6.6}$$

and the OPC savings

$$\#OPCs*\#Gens_{OPC}*\left[\begin{array}{l}\dfrac{wg300Cost^{0}_{OPC}}{\#Gens^{0}_{OPC}}*(1.0008-0.0008*\#OPCs*\#Gens^{0}_{OPC})-\\ \dfrac{wg300Cost^{i}_{OPC}}{\#Gens^{i}_{OPC}}*(1.0008-0.0008*(\#NSCs*\#Gens^{i}_{NSC}+\#OPCs*\#Gens^{i}_{OPC}))\end{array}\right] \tag{6.7}$$

where

wg300Cost – material cost of ship service generators for one ship

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#Gens – number of generators (varies).

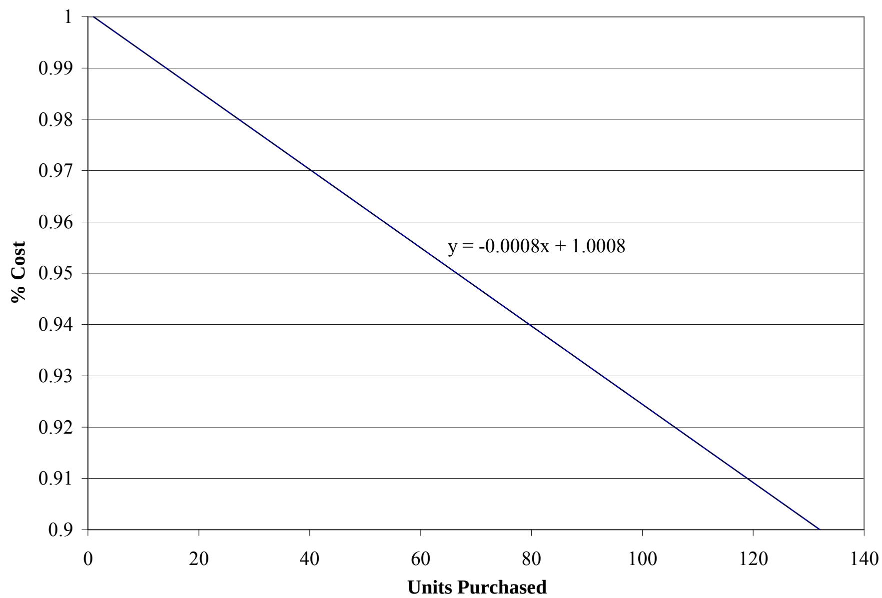

Figure 6.4 Ship Service Generator Cost Saving Schedule

6.2.4.3 Cruise Engine Savings

Again, a cost schedule was created for the savings associated with using common cruise engines. Figure 6.5 shows the assumed cost schedule as a function of number of engines purchased. The cost savings associated with using common cruise engines was linear from zero for 2 engines to 15% for 66 engines for all 33 ships.

The fleet savings associated with using a common cruise engines is calculated as the sum of the resulting NSC savings

$$2*\#NSCs*\begin{bmatrix} 0.6*wg200Cost_{NSC}^{0}*HPRatio_{NSC}^{0}*(1.0023-0.0023*2*\#NSCs)- \\ 0.6*wg200Cost_{NSC}^{i}*HPRatio_{NSC}^{i}*(1.0023-0.0023*2*\#ships) \end{bmatrix} \quad (6.8)$$

and the OPC savings

$$2*\#OPCs*\begin{bmatrix} 0.6*wg200Cost_{OPC}^{0}*HPRatio_{OPC}^{0}*(1.0023-0.0023*2*\#OPCs)- \\ 0.6*wg200Cost_{OPC}^{i}*HPRatio_{OPC}^{i}*(1.0023-0.0023*2*\#ships) \end{bmatrix} \quad (6.9)$$

where

0.6 – fraction of wg200 that is for engines

wg200Cost – material cost of propulsion system

HPRatio – fraction of ship power used for cruise engines

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#ships – total number of ships being built (33).

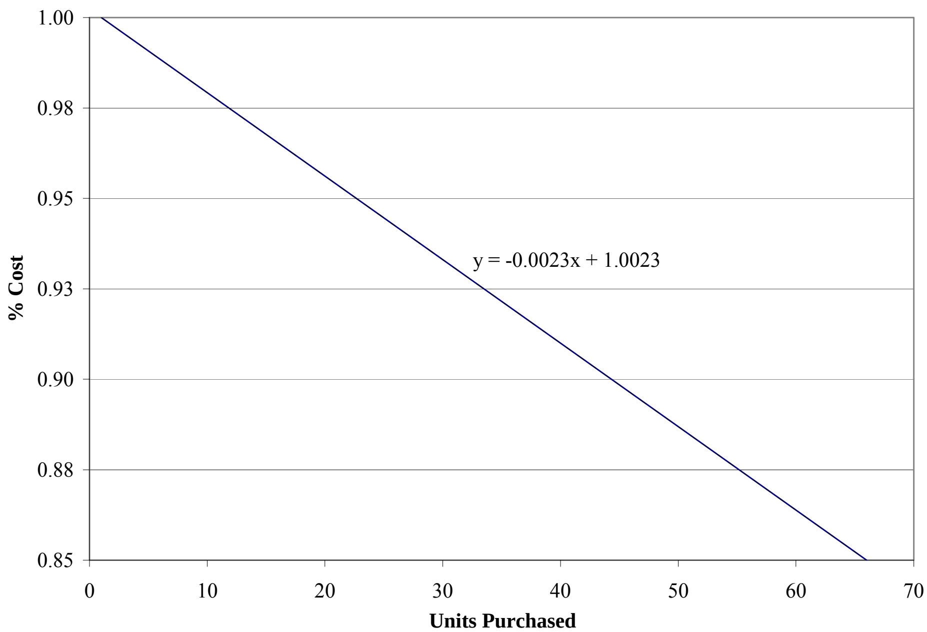

Figure 6.5 Cruise Engine Cost Savings Schedule

6.2.4.4 Superstructure and Midship Section Savings

The savings assumed for the common superstructures and midship sections was limited to construction labor costs. By applying a learning curve to the labor cost of construction, savings can be calculated by summing the savings for the NSC and the OPC. For a common superstructure, the savings was based upon the assumed fraction of the weight group 100 cost that is superstructure and the assumed learning curve rate. The NSC common superstructure savings is

$$\frac{\# NSCs}{\# ships} * \left[\begin{array}{l} ((wg100Cost_{NSC}^{0} * SSRatio_{NSC}^{0} * (\sum_{i=1}^{8} Learn)) + (wg100Cost_{OPC}^{0} * SSRatio_{OPC}^{0} * (\sum_{i=1}^{25} Learn))) - \\ (\frac{\# NSCs * (wg100Cost_{NSC}^{0} * SSRatio_{NSC}^{0} + \# OPCs * wg100Cost_{OPC}^{0} * SSRatio_{OPC}^{0}}{\# ships} * (\sum_{i=1}^{33} Learn)) \end{array} \right]$$

(6.10)

and the OPC common superstructure savings is

$$\frac{\# OPCs}{\# ships} * \left[\begin{array}{l} ((wg100Cost_{NSC}^{0} * SSRatio_{NSC}^{0} * (\sum_{i=1}^{8} Learn)) + (wg100Cost_{OPC}^{0} * SSRatio_{OPC}^{0} * (\sum_{i=1}^{25} Learn))) - \\ (\frac{\# NSCs * (wg100Cost_{NSC}^{0} * SSRatio_{NSC}^{0} + \# OPCs * wg100Cost_{OPC}^{0} * SSRatio_{OPC}^{0}}{\# ships} * (\sum_{i=1}^{33} Learn)) \end{array} \right]$$

(6.11)

where

wg100Cost – material cost of a ship hull and superstructure

SSRatio – ratio of superstructure weight to ship weight

Learn – Learning Curve rate

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#ships – total number of ships being built (33).

The midship section hull blocks savings was calculated in the same way assuming that 20% of the group 100 cost can be made common. The NSC common midship section savings is

$$\frac{\# NSCs}{\# ships} * \left[\begin{array}{l} ((wg100Cost_{NSC}^{0} * MSRatio_{NSC}^{0} * (\sum_{i=1}^{8} Learn)) + (wg100Cost_{OPC}^{0} * MSRatio_{OPC}^{0} * (\sum_{i=1}^{25} Learn))) - \\ (\frac{\# NSCs * (wg100Cost_{NSC}^{0} * MSRatio_{NSC}^{0} + \# OPCs * wg100Cost_{OPC}^{0} * MSRatio_{OPC}^{0}}{\# ships} * (\sum_{i=1}^{33} Learn)) \end{array} \right]$$

(6.12)

and the OPC common midship section savings is

$$\frac{\#OPCs}{\#ships}*\left[\begin{array}{l}((wg100Cost^{0}_{NSC}*MSRatio^{0}_{NSC}*(\sum_{i=1}^{8}Learn))+(wg100Cost^{0}_{OPC}*MSRatio^{0}_{OPC}*(\sum_{i=1}^{25}Learn)))-\\ (\frac{\#NSCs*(wg100Cost^{0}_{NSC}*MSRatio^{0}_{NSC}+\#OPCs*wg100Cost^{0}_{OPC}*MSRatio^{0}_{OPC}}{\#ships}*(\sum_{i=1}^{33}Learn))\end{array}\right]$$

(6.13)

where

wg100Cost – material cost of a ship hull and superstructure

MSRatio – ratio of midship section weight to ship weight (0.2)

Learn – Learning Curve rate

#NSCs – number of NSCs in class (8)

#OPCs – number of OPCs in class (25)

#ships – total number of ships being built (33).

Another form of savings may also occur. In some instances, a pair of designs may have a common component despite not having it required to be common. This can occur with the weapon systems, ship service generators and cruise engines, but is very unlikely with the superstructures and midship sections. When this occurs, the resulting savings is calculated as described in the equations above.

6.2.4.5 Total Fleet Savings

The total fleet savings that results from the use of commonality in the designs was calculated by summing up each of the savings associated with each of the common components.

6.2.5 Dominance Sorting

At this point in the three-criterion optimization, the endpoint archive has two designs for each commonality string. One design represents the best NSC mission design and the other represents the best OPC mission design for the designated commonality. The fleet savings for each pair of ship classes has been calculated relative to the pair of ship classes that were designed with no commonality. In order to determine which of these designs is the best, another dominance sort was performed. In the two-criterion part of the optimization process, dominance sorting was used to determine which designs were on the Pareto front and to help select potential parents during each generation. The dominance sort was performed each generation until the optimization was complete. In that dominance sort, ships were compared using the first two objective criteria of the optimization.

$f_1(\mathbf{x_1})$ – OPC Mission Ship Effectiveness /Average Ship Cost

$f_2(\mathbf{x_2})$ – NSC Mission Ship Effectiveness /Average Ship Cost

In the three-criterion case, each commonality string was optimized individually to produce the two Pareto front endpoints corresponding to these two objective functions. To this point in the overall process, the individual commonality string results were never compared to each other. With a value calculated for the associated fleet savings, the dominance sorting can be made using all three objective criteria.

$f_1(\mathbf{x_1}, \mathbf{x_c})$ – OPC Mission Effectiveness /Average Ship Cost

$f_2(\mathbf{x_2}, \mathbf{x_c})$ – NSC Mission Effectiveness /Average Ship Cost

$f_3(\mathbf{x_c})$ – Net Fleet Savings from Commonality

As before, the ships are compared to each other to determine whether they are dominated or not. A ship is not dominated if at least one of one of its objective criteria is greater than that of the other ship. The ships were compared to each other in pairs. Each pair will have an NSC mission design, an OPC mission design and a fleet savings, which is the same for both ships in the pair. Dominance was determined by comparing the NSC mission designs using f_1, the OPC mission design using f_2, and each pairs' f_3. The solutions that make up the nondominated set of solutions are the final three-criterion discrete Pareto front anticipated in Figure 2.4.

CHAPTER 7

FLEET OPTIMIZATION WITH COMMONALITY

7.1 Case Study

Similar to the two-objective case study shown in Chapter 5, the optimization was run with the following minimum settings: archive size-50, population size-150, number of offspring per generation-100. The maximum number of generations was set at 200 and the termination condition was not used in order to ensure that the Pareto fronts of each individual run progressed the same amount.

This chapter will first outline and present the results for the final discrete Pareto surface for the three-objective commonality optimization for the vessels designed for the NSC and the OPC missions. The analysis methodology and the detailed results will then be analyzed in more detail in the remaining sections.

7.2 Final Unique Design Pareto Set Results

Figure 7.1 shows the endpoints for each of the 288 commonality strings. The results group themselves into three sections. The uppermost section consists of 128 NSC designs. The middle section consists of 160 NSC designs. The remaining section near the bottom makes up the 288 OPC designs. The reason that the NSC designs are split into two sections is due to the nature of the commonality that is being forced into the designs.

The 160 NSC designs in the middle of the plot have certain defining characteristics. First, 144 of those designs have a small superstructure, a small midship section or both designated as common. The remaining 16 designs have no commonality designated for the superstructure or the midship section but have the smaller cruise engine designated as common. These three characteristics are all indicative of smaller vessels. All 160 designs have only one helicopter hangar, which is a requirement for the small superstructure and midship section commonalities. In order to meet the cruise speed requirement, the use of the smaller common cruise engine tends to need smaller vessels. Because of the way the fuzzy utility functions have been set, the single hangar tends to be the driving performance factor. As a result, all NSC designs with one hangar have ranges near 9000 nm. The weapons systems and generators selected for these designs do not influence this tendency toward the middle of the graph. If the fuzzy utility functions were modified different results may be achieved.

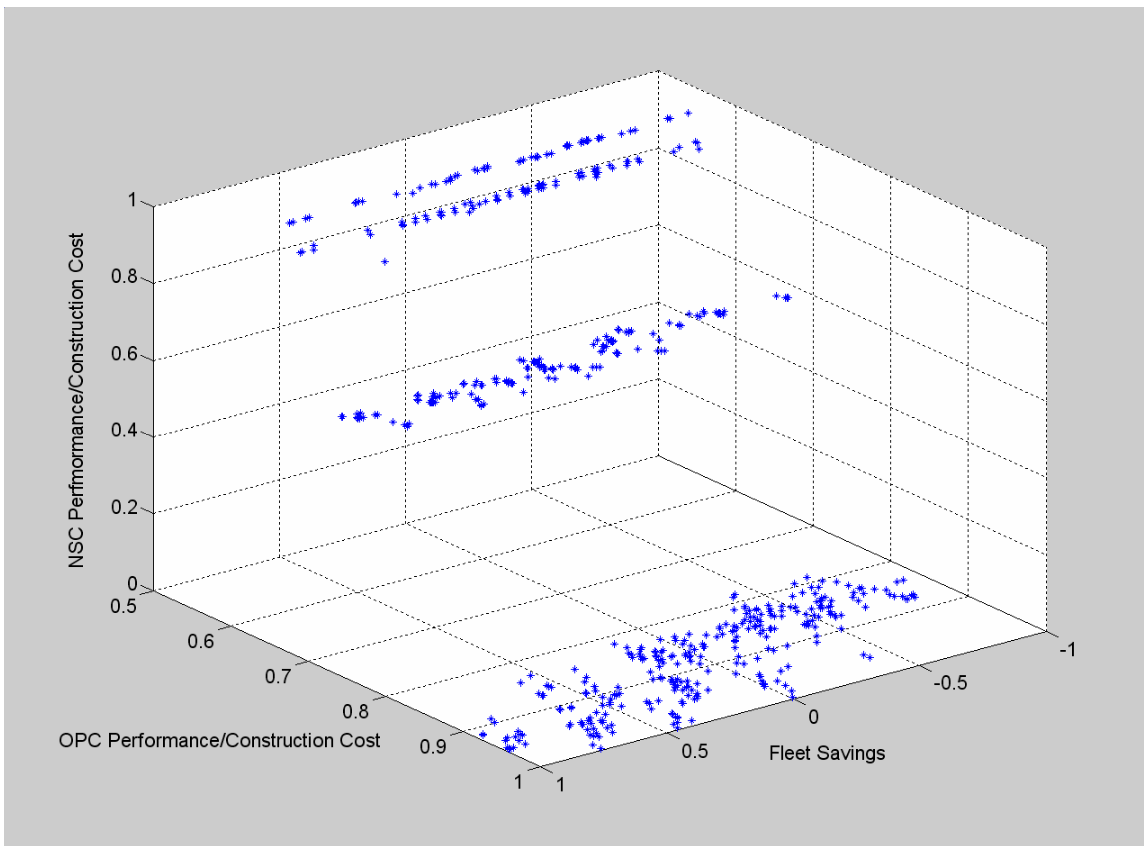

Figure 7.1 Optimization Run Endpoints prior to Dominance Sorting

When the results in Figure 7.1 are subjected to a dominance sorting to obtain those design pairs in the discrete Pareto Set anticipated in Figure 2.4 and then analyzed in detail to reveal those unique vessel designs there remain only twelve pairs of ship designs. Figure 7.2 shows the final Pareto front composed of the best OPC and best NSC baseline ships and the twelve pairs of non-dominated ships determined to be distinctly different in the overall results shown in Figure 7.1. The best NSC design and the best OPC designs, slightly improved results from the study in Chapter 5, are shown on the zero Fleet Savings from Commonality base plane. Also identified are the NSC_{10} and OPC_{10} design pair that produced the best Fleet Savings. The attractive design pair NSC_6 and OPC_6 that provide the best Fleet Savings that could be achieved without incurring the large drop in NSC performance that results from the move from two helicopter hangers to one. These results will be analyzed further below.

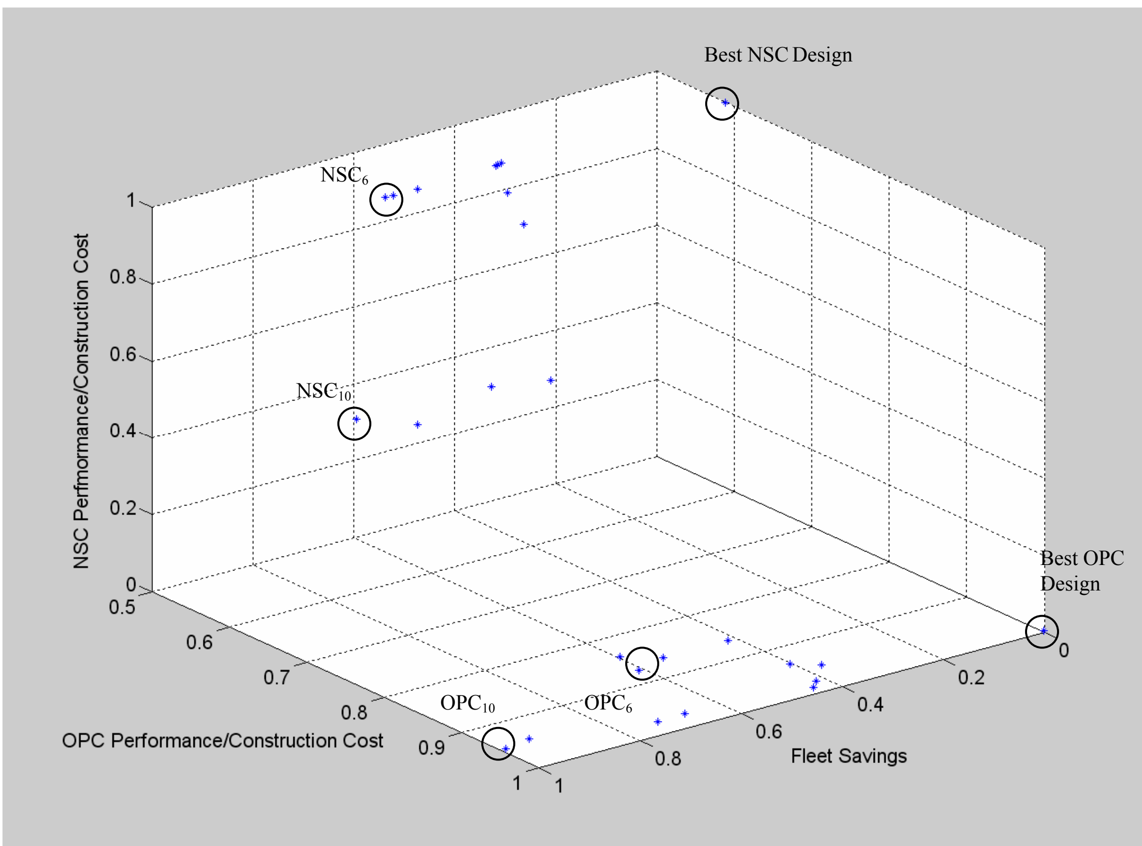

Figure 7.2 Pareto Front Showing Distinctly Different Ships Only

Table 7.1 shows the corresponding commonality strings and the resulting OPC and NSC solutions that make up this final discrete Pareto front. The designations are for the commonality assignment for the Weapons System (CW), ship service generators (CG), cruise engines (CC), superstructure (CS), and midship sections blocks (CM). The N here indicates that no commonality was assigned.

Table 7.1 Pareto Front Commonality Strings with Corresponding OPC and NSC Ship Numbers

CW	CG	CC	CS	CM	OPC Ship #	NSC Ship #
N	1	N	N	N	3	3
N	1	N	N	Large	4	4
N	1	N	Large	N	6	6
N	1	N	Large	Large	7	7
1	1	1	Small	Small	10	10
1	1	N	N	N	12	12
1	1	1	N	Small	13	13
1	1	1	Small	N	14	14
1	1	1	N	N	16	16
2	1	N	N	N	20	20
3	1	N	N	N	21	21
3	1	N	Small	N	22	22

7.3 Analysis of Results of All Feasible Commonality Strings

One assumption that is often made with the use of commonality is that it is always good. It is accepted that in using common components there will be a loss in performance. Much research has been done to measure how much performance will be lost in applying common components to designs. However, the loss in performance is assumed to be outweighed by the cost savings associated with using common components. This cost savings is the driving force behind the use of commonality in design. Figure 7.3 is the same 3-D plot seen in Figure 7.1 from a different perspective.

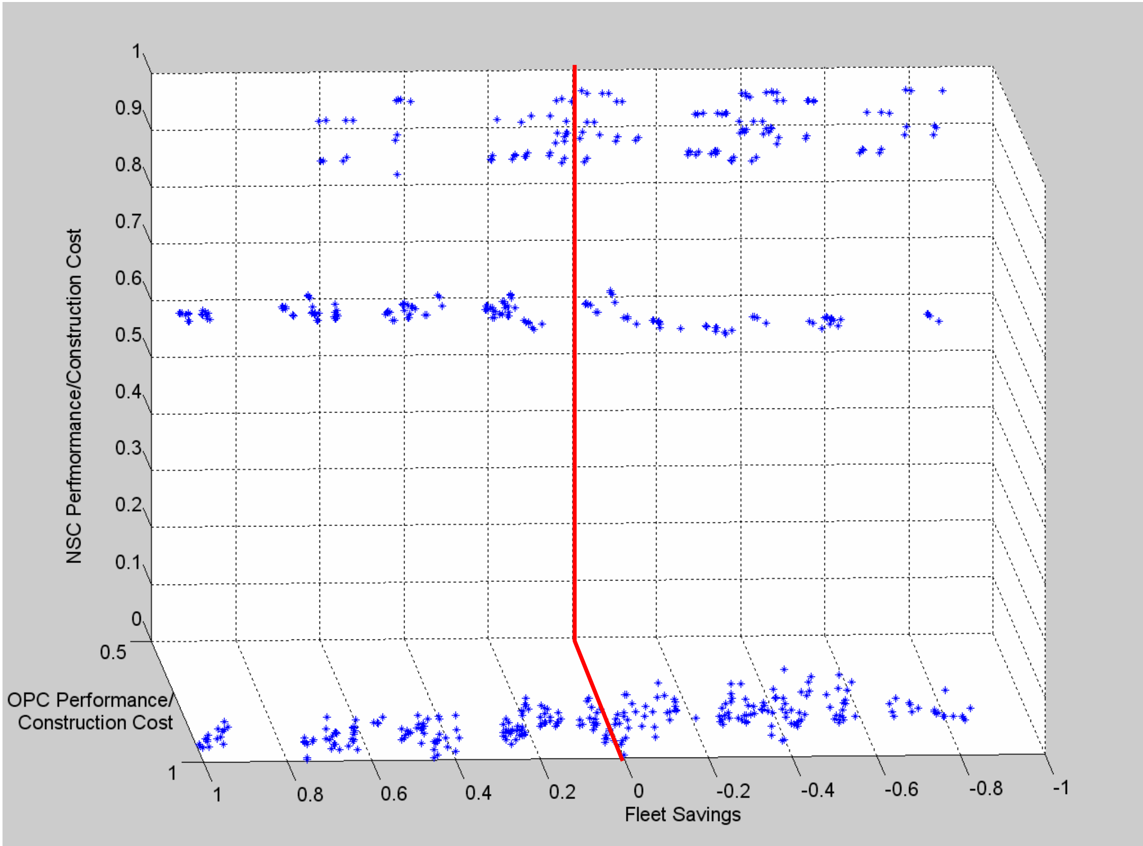

Figure 7.3 Optimization Run Endpoints prior to Dominance Sorting – Alternate View

This new perspective more clearly shows that not all commonality is good. In 127 of the 288 designs that were found during the optimization process, a negative net fleet savings occurred. This negative fleet savings is a result of over designing the OPC. The OPC that was designed without any commonality had the least expensive weapon system, generator and cruise engine used in the solutions. These components enabled the OPC to meet its performance requirements. If more expensive options for each of these components are forced into the design through commonality, the OPC will still meet its performance requirements but at more cost. Even though bulk savings will occur, the cost of the more expensive components will be more expensive overall. The result is that if the more expensive weapon systems, generators or cruise engines are made common, the OPC will have a negative savings. By using common weapon system 2 or 3, the OPC had negative weapon system savings in just over half of the commonality strings (144 occurrences). Common generators 1 and 3 resulted in negative generator savings for the

OPC (144 occurrences). Similarly when the larger cruise engine was made common, the OPC had a negative cruise engine savings as well (118 occurrences). Making the superstructure common never resulted in a negative superstructure savings for either ship. A common midship section resulted in a negative midship savings for 87 of the 288 pairs of ships. This occurred each time the larger midship section was common (64 times) and about a quarter of the time when the smaller midship section was common 23 times). The reason that these pairs resulted in a negative savings is due to the designation of the common midship section sizes. The larger midship section was sized so that the midship sections of all baseline optimization solutions were smaller. This was done to ensure that it would not limit the size of the ships in the optimization. The smaller common midship section was made slightly larger than the smallest OPC designs in the baseline run. Again, this was done in order to not force the OPC designs into being smaller in size and possibly making lots of designs infeasible. All of this translates into more cost for the slightly oversized midship sections.

It is important to realize that just because the savings may be negative for one or more of these components does not necessarily mean that the overall fleet savings for that pair of ships will be negative. For the weapon systems, generators and cruise engines only the OPC designs had negative savings. The NSC designs for each of those designs had a positive savings value. For a common weapon system 2, the net fleet weapon system savings was always positive despite the negative savings for the OPC design. In addition, if positive savings were achieved in other common components, the overall savings could still be positive.

Because of the relative costs of each of the components that are considered for commonality among the designs, some are more influential than others. Table 7.2 shows the relative importance of each component in its potential to create savings. The components with the greatest potential for large commonality savings are ship service generators, cruise engines and superstructure. These large savings are possible when the smallest generators and cruise engines are designated as common. The cruise engines and generators can also have large negative savings values. Using the largest cruise engine or generator as common will result in the greatest negative savings values. A common superstructure, which always results in a positive savings, has the largest savings when the smaller option is used. The midship section and weapon systems have a much smaller impact on savings, either positive or negative. Again, smaller options tend to result in positive savings and larger options tend to result in negative options due to class over design.

Table 7.2 Relative Influence of Components on Savings

Positive Savings		Negative Savings	
Component	Relative Importance	Component	Relative Importance
Generators	1.000	Cruise Engines	1.000
Cruise Engines	0.748	Generators	0.864
Superstructure	0.465	Midship Section	0.115
Midship Section	0.100	Weapon System	0.029
Weapon System	0.016	Superstructure	0.000

7.4 Analysis of Groupings on the Discrete Pareto Front

Once the dominance sorting is performed, the discrete three-dimensional Pareto front appears as shown in Figure 7.4, which consists of 20 pairs of non-dominated ship designs.

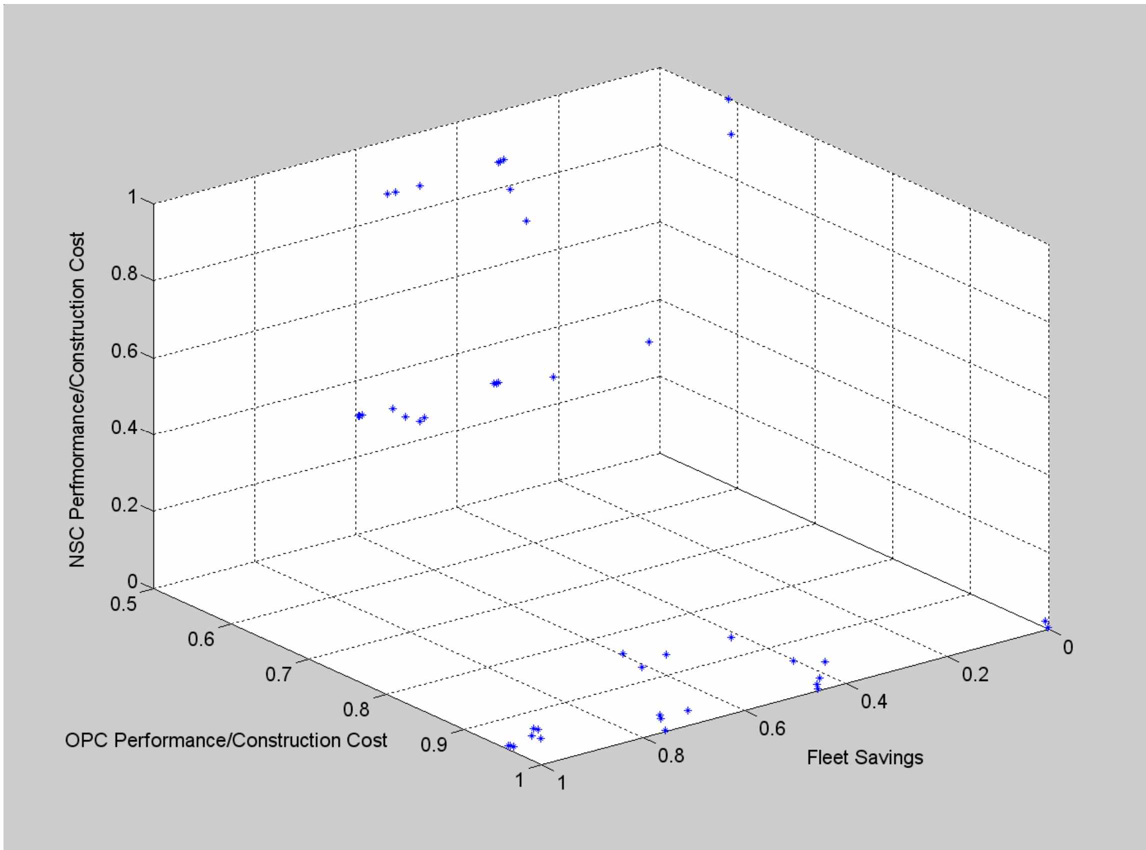

Figure 7.4 Discrete Pareto Front

If the plot in Figure 7.4 is rotated, it shows that the solutions group themselves into four bands. The four bands appear at Fleet Savings values of 0-0.01, 0.42-0.46, 0.55-0.76 and 0.94-1.00. Figure 7.5 shows the plot from a different perspective.

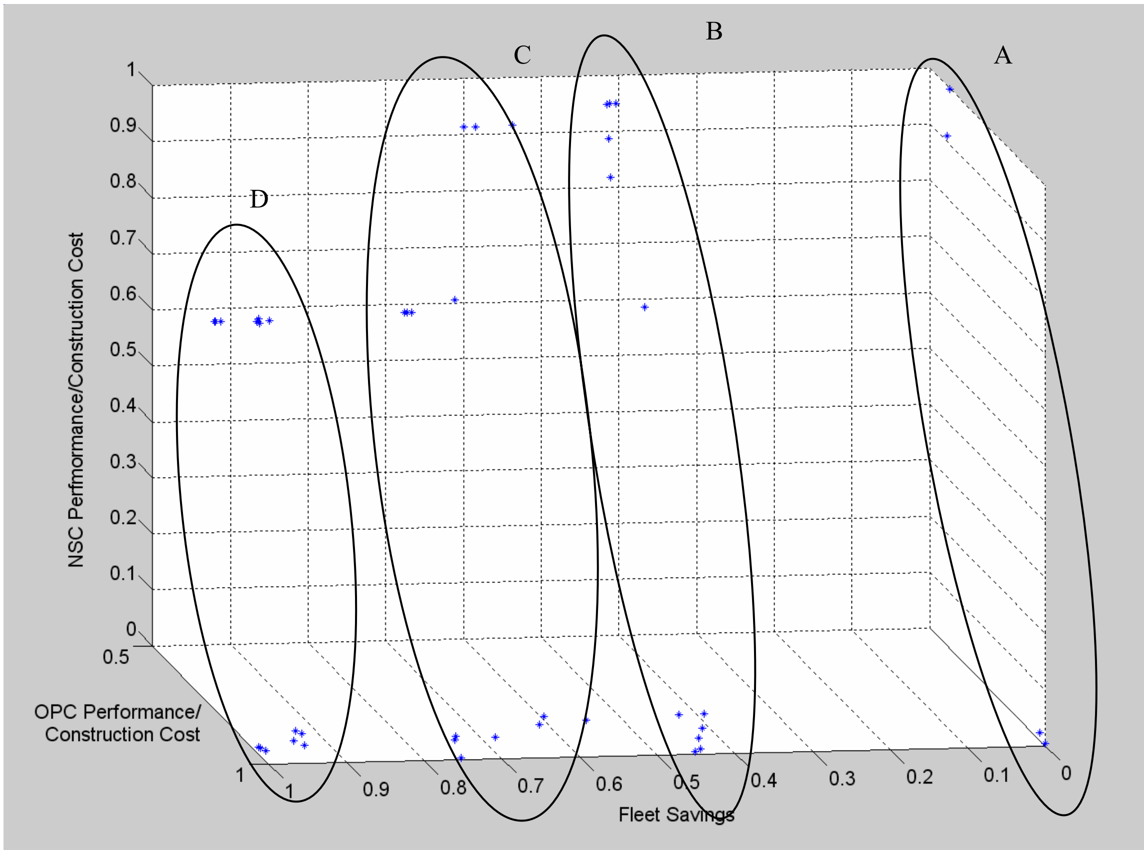

Figure 7.5 Pareto Front – Alternate View

The band labeled A consists of two pairs of solutions. One of the pairs is the baseline case which has no commonality and therefore no fleet savings. The other solution has weapon system 1 designated as common. The common weapon system results in small fleet savings. Table 7.3 shows the commonality make-up of group A (N indicates no commonality).

Table 7.3 Commonality Summary for Group A

	Weapon System	Generator	Cruise Engine	Superstructure	Midship Section
1	N	N	N	N	N
2	1	N	N	N	N

The next group of solutions, B, consists of six pairs of solutions. The small common generator appears in all but one pair of solutions. Additionally, the weapon systems and midship sections may be common which result in relatively small impacts on savings compared to the common ship service generator. In addition to the common midship section, the sixth pair actually had weapon system 1 and the smaller cruise engines common despite their not being designated as common. This natural commonality allowed this solution to achieve the highest fleet savings in group B. Table 7.4 shows a commonality summary of the ships in group B.

Table 7.4 Commonality Summary for Group B

	Weapon System	Generator	Cruise Engine	Superstructure	Midship Section
1	3	1	N	N	N
2	N	1	N	N	Large
3	N	1	N	N	N
4	2	1	N	N	N
5	1	1	N	N	N
6	N	N	N	N	Small

Group C consists of seven pairs of ships. Table 7.5 shows the commonality breakdown of group C. Every pair of ships in group C has at least two common components, five pairs have three while one has four common components. The small common ship service generator appears in all seven pairs. Natural commonality appeared in the fifth and seventh pairs of ships. Both ships in the fifth pair use weapon system 1 while both ships in pair seven use the smaller cruise engines. In both cases, the overall fleet savings benefits from this natural commonality. One trend that becomes evident for the higher savings values in group C is the use of smaller options of commonality. As discussed previously, the OPC tends to have negative savings when larger components are used. In some cases these negative values can be outweighed by other common components. This can be seen in the half of group C with lower fleet savings. In order to obtain higher fleet savings values, smaller components must be designated as common.

Table 7.5 Commonality Summary for Group C

	Weapon System	Generator	Cruise Engine	Superstructure	Midship Section
1	N	1	N	Large	Large
2	3	1	N	Large	N
3	N	1	N	Large	N
4	1	1	1	N	N
5	N	1	1	N	Small
6	1	1	1	N	Small
7	1	1	N	N	Small

The final group, D, has seven pairs of ships. In this group, fleet savings is maximized by selecting the smaller component options. Large impact savings is obtained by routinely using common ship service generators, cruise engines and superstructures. All seven pairs of ships used weapon system 1 and the smaller cruise engine regardless of whether or not it was designated as common. The required use of the small superstructure made the NSC ships tend to be smaller and thus they were optimized with the smaller cruise engines and weapon systems. Again, this natural commonality resulted in high fleet savings values for each of the pairs. Table 7.6 shows the commonality components for the ships in group D.

Table 7.6 Commonality Summary for Group D

	Weapon System	Generator	Cruise Engine	Superstructure	Midship Section
1	N	1	1	Small	N
2	1	1	1	Small	N
3	N	1	N	Small	N
4	1	1	N	Small	N
5	1	1	1	Small	Small
6	1	1	N	Small	Small
7	N	1	1	Small	Small

7.5 Similarity Analysis of Discrete Pareto Front

Despite having different commonality strings, two ships may have virtually the same characteristics. This occurs when one ship has no commonality designated for one or more components and the other ship uses commonality for those components. The ships without the commonality may optimize to similar characteristics. Take for example the commonality strings 111NN and N1NNN. Both strings have no commonality designated for the superstructure or the midship section and both use a common ship service generator. The commonality designations for weapon system and cruise engine are different for the two ships. One chooses no commonality while the other chooses option 1 for both weapon system and cruise engine. When the best NSC and best OPC designs are found for these commonality strings, how different will they really be? If the weapon system and cruise engine for the second ship are both designed to be choice 1 then the two ships will be virtually the same ship. This may not be the case for the NSC and OPC at the same time. One may be very similar to another ship while the other is very different from the corresponding ship in a pair.

In order to make a rational comparison of similarity between ships, an *n*-dimensional distance formula was used to determine how different the ships are from a practical naval architecture viewpoint.

$$Similarity = 1 - \sqrt{\frac{(x_i^1 - x_j^1)^2}{x_{\max}^1} + \ldots + \frac{(x_i^n - x_j^n)^2}{x_{\max}^n}} \tag{7.1}$$

The formula calculates how similar two ships are to each other. It would not be appropriate to compare all ships to each other. If two ships do not have the same commonality designations for superstructure and midship section, they should not be compared. By designating either of these components as common, the ship will use the associated values. The ship synthesis will have been overridden to ensure commonality. Because of this alteration of the design, a ship that does not have its superstructure or midship section designated as common cannot be similar to one that does.

The Pareto set of solutions consisted of 20 pairs of ships. Comparisons were possible for seven combinations of superstructure and midship section commonality. Of these seven combinations, only six were found in the Pareto set of solutions. Table 7.7 shows the commonality combinations and which ship numbers coincide with each.

Table 7.7 Possible Commonality Combinations for Similarity

Group	Superstructure	Midship Section	Ship Numbers
1	N	N	1-3-11-12-16-20-21
2	N	Small	2-8-13-17
3	N	Large	4
4	Small	N	5-9-14-18
5	Small	Small	10-15-19
6	Large	N	6-22
7	Large	Large	7

The ships in each group of the same commonality combination were compared using the similarity equation (eq. 7.1). The results for the OPC and designs can be seen in Table 7.8.

Table 7.8 Similarity Values for OPC Designs

Ship #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1.000																					
2		1.000																				
3	0.976		1.000																			
4				1.000																		
5					1.000																	
6						1.000																
7							1.000															
8		0.977						1.000														
9					0.951				1.000													
10										1.000												
11	0.980		0.991								1.000											
12	0.954		0.974								0.973	1.000										
13		0.994						0.978					1.000									
14					0.995				0.948					1.000								
15										0.999					1.000							
16	0.972		0.991								0.990	0.981				1.000						
17		0.989						0.973					0.991				1.000					
18					0.991				0.960					0.987				1.000				
19										0.985					0.985				1.000			
20	0.666		0.666								0.666	0.665				0.666				1.000		
21	0.331		0.332								0.332	0.333				0.333				0.664	1.000	
22						0.333																1.000

Each ship across the top of Table 7.8 is compared to each of the ships in its respective group. The value shown is a measure of similarity of the two solutions. The higher the similarity value, the more similar the ships are to each other. Each ship can only be compared to the ship at the top of the column and not to other similar ships within that column. Analysis of Table 7.8 shows that that there are ten distinctly different OPC solutions on the Pareto front. Each group can be analyzed individually to examine the similarities in there designs. Tables 7.9 through 7.14 show the characteristics of the OPC solutions from each group.

Table 7.9 Group 1 Characteristics for the OPC (Superstructure-N, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
1	N	N	N	276	38	0.469	0.987	22.02	9036	1	1	7	0	0.999	0.000
3	N	1	N	280	38	0.460	0.988	22.26	9042	1	1	7	0	0.999	0.439
11	1	N	N	279	38	0.460	0.990	22.09	9015	1	1	7	0	1.000	0.007
12	1	1	N	286	38	0.451	0.989	22.1	9000	1	1	7	0	0.996	0.446
16	1	1	1	282	38	0.458	0.987	22.13	9037	1	1	7	0	0.997	0.708
20	2	1	N	279	38	0.466	0.989	22.02	9025	2	1	7	0	0.99	0.441
21	3	1	N	293	38	0.458	0.989	22.09	9032	3	1	7	0	0.95	0.427

Table 7.9 shows that ships 20 and 21 have weapon system 2 and 3, respectively, making them distinctly different from the other solutions in this Group 1. The remaining ships all have weapon system 1 and Table 7.8 shows that the similarity between them is very strong. Therefore, ships 1, 3, 11, 12 and 16 are all virtually the same design with ship 16 having the highest values for performance over cost and fleet savings. The three best solutions from Group 1 that are distinctly different are ships 16, 20 and 21.

Table 7.10 Group 2 Characteristics for the OPC (Superstructure-N, Midship Section-Small)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
2	N	N	N	280	40	0.462	0.990	22.01	9002	1	1	7	0	0.997	0.451
8	N	1	1	276	40	0.472	0.990	22	9004	1	1	7	0	0.997	0.752
13	1	1	N	280	40	0.463	0.990	22.12	9026	1	1	7	0	0.997	0.76
17	1	1	1	283	40	0.464	0.990	22.14	9024	1	1	7	0	0.993	0.757

As shown in Table 7.8, the four solutions in Table 7.10 are virtually the same design. Ship 13 has a slightly better performance over cost with equal fleet savings making it the best of the four ships. Table 7.11 shows the characteristics of the lone ship in Group 3.

Table 7.11 Group 3 Characteristics for the OPC (Superstructure-N, Midship Section-Large)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
4	N	1	N	279	54	0.450	0.990	22.08	9056	1	2	11	0	0.875	0.435

A strong correlation between ships 5, 9, 14 and 18 was seen in Table 7.8. Table 7.12 shows that all of the designs in this Group 4 have very similar characteristics. Ship 9 has the highest performance over cost but lacks in fleet savings. Ship 14 has a performance only slightly less than ship 9 but has the highest fleet savings making it the best overall design in group 4.

Table 7.12 Group 4 Characteristics for the OPC (Superstructure-Small, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
5	N	1	N	292	40	0.462	0.990	22.15	9013	1	1	7	0	0.959	0.954
9	N	1	1	281	40	0.480	0.989	22.06	9003	1	1	7	0	0.962	0.943
14	1	1	N	293	40	0.461	0.989	22.08	9008	1	1	7	0	0.958	0.956
18	1	1	1	290	40	0.466	0.990	22.13	9020	1	1	7	0	0.959	0.945

Table 7.13 shows that Group 5 has three very similar designs. Of these designs, ship 10 is determined to be the best. Ship 10 has a strong performance over cost and a slightly better fleet savings than the other ships in the group.

Table 7.13 Group 5 Characteristics for the OPC (Superstructure-Small, Midship Section-Small)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
10	N	1	1	293	40	0.463	0.990	22.04	9008	1	1	7	0	0.957	1.000
15	1	1	N	293	40	0.462	0.990	22.04	9004	1	1	7	0	0.958	0.998
19	1	1	1	290	40	0.468	0.990	22.02	9004	1	1	7	0	0.958	0.992

The similarity values in Table 7.8 show that there are two distinctly different ships in Group 6. Table 7.14 shows that ship 6 has weapon system 1 while ship 22 has weapon system 3 making them distinctly different. Table 7.15 shows the characteristics of the lone ship in Group 7.

Table 7.14 Group 6 Characteristics for the OPC (Superstructure-Large, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
6	N	1	N	353	54	0.450	0.990	22.03	9006	1	2	7	0	0.878	0.615
22	3	1	N	350	54	0.451	0.990	22.02	9011	3	2	8	0	0.843	0.599

Table 7.15 Group 7 Characteristics for the OPC (Superstructure-Large, Midship Section-Large)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
7	N	1	N	349	54	0.450	0.990	22.04	9018	1	2	8	0	0.868	0.552

Similar analysis can be performed for the NSC solutions. Similar to Table 7.8, the similarity values for the NSC ships can be seen in Table 7.16. Again, the ships are grouped together based on which superstructure and midship sections were designated as common.

Table 7.16 Similarity Values for NSC Designs

Ship #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1.000																					
2		1.000																				
3	0.968		1.000																			
4				1.000																		
5					1.000																	
6						1.000																
7							1.000															
8		0.975						1.000														
9					0.971				1.000													
10										1.000												
11	0.330		0.327								1.000											
12	0.326		0.321								0.926	1.000										
13		0.977						0.953					1.000									
14					0.973				0.992					1.000								
15										0.981					1.000							
16	0.111		0.105								0.423	0.454				1.000						
17		0.990						0.966					0.987				1.000					
18					0.864				0.857					0.864				1.000				
19										0.986					0.994				1.000			
20	0.667		0.665								0.660	0.652				0.324				1.000		
21	0.972		0.993								0.327	0.322				0.105				0.665	1.000	
22						0.995																1.000

Analysis of Table 7.16 shows that that there are eleven distinctly different NSC solutions on the Pareto front. Each group can be analyzed individually to examine the similarities in there designs. Tables 7.17 through 7.22 show the characteristics of the NSC solutions from each group.

Table 7.16 shows that there are four distinct NSC solutions in group 1. Table 7.17 shows that the ships in Group 1 can be sorted by weapon system and number of helicopter hangars. Ships 1, 3 and 21 all share the same components. Ship 21 has the slightly higher performance over cost value, however, ship 3 has a higher fleet savings. Ship 3 seems to be the best choice. Ship 16 and 20 are each distinctly different than each of the other designs. Ships 11 and 12 show strong similarities to each other. Ship 11 is a little different in that it uses a different ship service generator than the other because it was not designated as common. Despite having the best performance, ship 11 is not the best design of these two ships when savings is considered. Instead, ship 12 is the best overall design with high performance over cost and fleet savings values. Group 1 has four distinctly different superior designs: 3, 12, 16, and 20.

Table 7.17 Group 1 Characteristics for the NSC (Superstructure-N, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
1	N	N	N	399	54	0.453	0.989	28	12016	3	2	9	3	1.000	0.000
3	N	1	N	412	54	0.455	0.988	28.01	12019	3	2	9	0	0.982	0.439
11	1	N	N	374	54	0.465	0.989	28	12090	1	2	9	3	0.92	0.007
12	1	1	N	366	54	0.452	0.988	27.65	11292	1	2	9	0	0.869	0.446
16	1	1	1	333	39	0.457	0.988	25.42	9015	1	1	7	0	0.745	0.708
20	2	1	N	399	54	0.453	0.990	28	12032	2	2	9	0	0.928	0.441
21	3	1	N	410	54	0.457	0.989	28.01	12069	3	2	9	0	0.983	0.427

Table 7.18 confirms that the four NSC designs in Group 2 are very similar. Of these four ships there is only a slight difference in their lengths and ranges. Other than that they are virtually the same. Ship 13 is the best design based on the higher performance over cost value. Table 7.19 shows the characteristics of the lone ship in Group 3.

Table 7.18 Group 2 Characteristics for the NSC (Superstructure-N, Midship Section-Small)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
2	N	N	N	293	40	0.510	0.990	25.44	9024	1	1	7	1	0.705	0.451
8	N	1	1	290	40	0.522	0.990	25.45	9001	1	1	7	0	0.707	0.752
13	1	1	N	299	40	0.501	0.990	25.45	9000	1	1	7	0	0.707	0.76
17	1	1	1	296	40	0.506	0.990	25.43	9011	1	1	7	0	0.707	0.757

Table 7.19 Group 3 Characteristics for the NSC (Superstructure-N, Midship Section-Large)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
4	N	1	N	410	54	0.457	0.990	28.01	12020	3	2	9	0	0.983	0.435

Table 7.16 showed a very strong similarity in the Group 4 designs which is confirmed by Table 7.20. Ship 18 has a different length than the others but is virtually the same otherwise. Ship 14 has both the highest performance over cost and fleet savings value making it the best design in Group 4.

Table 7.20 Group 4 Characteristics for the NSC (Superstructure-Small, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
5	N	1	N	346	40	0.464	0.990	25.3	9008	1	1	7	0	0.701	0.954
9	N	1	1	350	40	0.450	0.989	25.25	9001	1	1	7	0	0.71	0.943
14	1	1	N	347	40	0.450	0.987	25.21	9009	1	1	7	0	0.707	0.956
18	1	1	1	291	40	0.450	0.989	25.45	9003	1	1	7	0	0.697	0.945

Ships 10, 15 and 19 which compose Group 5 are nearly identical in terms of characteristics as shown in Table 7.21. Ship 10 is the best overall design with the highest performance and savings values.

Table 7.21 Group 5 Characteristics for the NSC (Superstructure-Small, Midship Section-Small)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
10	N	1	1	306	40	0.450	0.990	25.43	9002	1	1	7	0	0.69	1.000
15	1	1	N	302	40	0.459	0.990	25.42	9001	1	1	7	0	0.69	0.998
19	1	1	1	303	40	0.456	0.990	25.44	9003	1	1	7	0	0.69	0.992

Table 7.22 shows that Group 6 ships 6 and 22 are very similar. Both ships have the same value for performance over cost while ship 6 has a higher fleet savings making it the better choice. Table 7.23 shows the characteristics of the lone ship in Group 7.

Table 7.22 Group 6 Characteristics for the NSC (Superstructure-Large, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
6	N	1	N	395	54	0.452	0.989	28.01	12013	3	2	9	0	0.935	0.615
22	3	1	N	395	54	0.451	0.990	28.01	12069	3	2	9	0	0.935	0.599

Table 7.23 Group 7 Characteristics for the NSC (Superstructure-Large, Midship Section-N)

Ship #	CW	CG	CC	L (ft)	B (ft)	Cb	Cm	Vmax (kts)	Range (nm)	W	H	C	G	Perf/ Cost	Fleet Savings
7	N	1	N	394	54	0.451	0.990	28	12005	3	2	9	0	0.936	0.552

A final analysis of the similar designs for both the OPC and the NSC revealed that there are twelve distinctly different pairs of designs on the final discrete Pareto front. Based on the groupings listed in Table 7.7, the best OPC and NSC designs from each group were examined and matched with their corresponding ship based on common components. There were three ships that did not have a corresponding ship that was considered the best in its group. As a result OPC ship 3, and NSC ships 21 and 22 were included to ensure an even number of OPC and NSC solutions.

7.6 Analysis of Final Discrete Pareto Front

Figure 7.2, repeated here as Figure 7.6, shows the final discrete Pareto front composed of the best OPC and best NSC baseline ships and the twelve pairs of ships determined to be distinctly different on the discrete Pareto front shown in Figure 7.3.

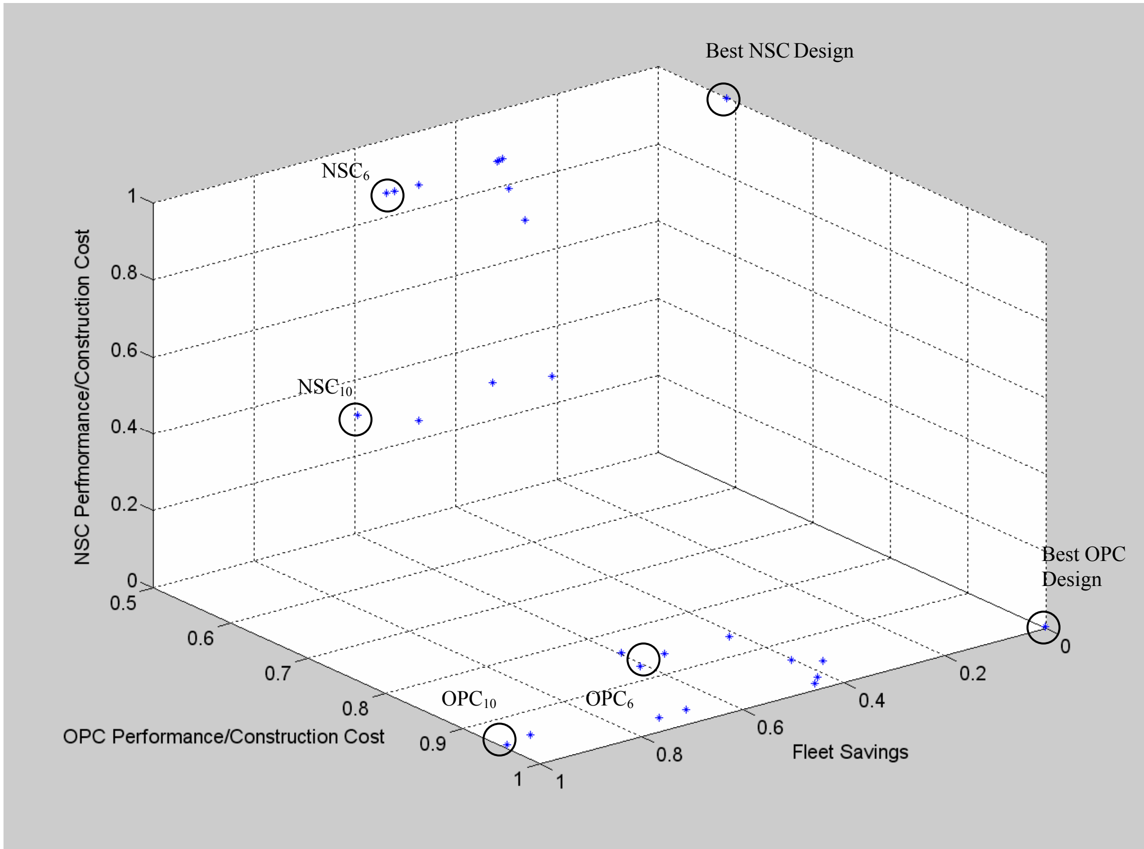

Figure 7.6 Pareto Front Showing Distinctly Different Ships Only

Table 7.24, a repeat of Table 7.1, shows the corresponding commonality strings and the resulting OPC and NSC solutions that make up this final Pareto front.

Table 7.24 Pareto Front Commonality Strings with Corresponding OPC and NSC Ship Numbers

CW	CG	CC	CS	CM	OPC Ship #	NSC Ship #
N	1	N	N	N	3	3
N	1	N	N	Large	4	4
N	1	N	Large	N	6	6
N	1	N	Large	Large	7	7
1	1	1	Small	Small	10	10
1	1	N	N	N	12	12
1	1	1	N	Small	13	13
1	1	1	Small	N	14	14
1	1	1	N	N	16	16
2	1	N	N	N	20	20
3	1	N	N	N	21	21
3	1	N	Small	N	22	22

The results seen in Table 7.24 show some interesting trends. First, each pair of ships remaining on the final Pareto front has the small ship service generator designated as common. As seen in Table 7.2 common small generators have the greatest influence on fleet savings. Generally speaking, the use of the small generators has little to no impact on performance. It may add weight, and therefore cost, to NSC ships that need more than four generators to meet the electrical load requirements. However, the performance will not suffer and the net fleet savings will benefit greatly from this choice.

There is no clear cut best choice for common weapon systems. Five of the twelve pairs of ships on the Pareto front have weapon system 1, which provides for good savings with some loss in performance for the NSC. Weapon system 2 can be seen in one pair of ships and has a slight positive affect on savings and a loss of performance for the NSC. Weapon system 2 does not benefit the OPC's performance while increasing its cost. Two pairs of ships have weapon system 3. Weapon system 3 has a negative fleet savings while completely satisfying the requirements of the NSC. Again, the OPC suffers with the use of weapon system 3 because on increased cost with no performance gain. The remaining four pairs do not designate a common weapon system and no fleet savings is realized from the weapon system. However, the NSC and OPC will be able to meet requirements without unnecessary costs.

Eight of the twelve pairs do no designate a common cruise engine. Even though the ships will not benefit from the cost savings, this can be good. Each ship is able to optimize its performance when able to use the engine that is best suited for its requirements. One third of the designs have the small cruise engine as common. This maximizes cruise engine savings. However, the performance of the NSC tends to suffer from the use of the small cruise engines. As mentioned previously, a small cruise engine tends to require a smaller ship in order to meet the cruise speed requirements. By forcing the NSC to be smaller its performance declines. Its range has to be smaller and it can only have one helicopter hangar. The OPC is not affected in this manner.

As seen in Table 7.2, common superstructures never result in a negative fleet savings. Only five of the twelve solutions realize a savings from the use of a common superstructure. Generally speaking, the smaller common superstructure does not hinder the performance or cost of the OPC. The smaller common superstructure will again limit the NSC in size and this will cause a decline in performance. The larger superstructure adds unnecessary costs to the OPC without a comparable increase in performance. By not designating a common superstructure, the OPC and NSC designs can be optimized to maximize there performance and cost. However, no superstructure savings can be realized.

The common midship section has little effect on savings, but can influence performance and cost. Similar to the superstructure, the small midship section hinders the performance of the NSC. The larger midship section benefits the NSC while at the same time adding cost and possibly hurting the performance of the OPC. A common midship section was designated in only 4 of the twelve pairs of ships on the final Pareto front.

Analysis of the results illustrates how finely balanced the three objectives can be. What tends to benefit the fleet savings the most hurts the performance of the NSC. At the same time, what maximizes the NSC performance tends to not produce large savings and increase the cost of the OPC. In order to maximize all three objective functions a balance in common components must be made.

Perhaps the most attractive pair of designs from this study is the two designs indicated as OPC_6 and NSC_6 on Figure 7.6. This pair of designs is commonality 3 in Group C of Table 7.5 and OPC ship 6 and NSC ship 6 in Table 7.24. This pair of designs has the smaller ship service diesel generators and the large superstructure in common. This pair has the highest fleet savings from commonality possible before the NSC designs take a large loss in performance/cost and, thus, this might be the most likely choice for a design team. This commonality achieves 61.5% of the maximum fleet savings considered, but the performance of the OPC and NSC remain at 100% of their maxima. The characteristics of OPC ship 6 and NSC ship 6 are shown in Table 7.25 along with OPC ship 10 and NSC ship 10, also indicated on Figure 7.6, which have the highest net fleet savings on the final Pareto front. It is worth noting that because of the strong similarity of OPC ship 10 and NSC ship 10, consideration should be made to build a single ship to perform both ship missions. A single ship would achieve even more fleet savings as all components would be common.

Table 7.25 Design Characteristics for Selected Ships on the Final Pareto Front

Point	L (ft)	B (ft)	Vmax (kts)	Range (nm)	W	H	C	G	OPC Perf	NSC Perf	Cost ($mil)	Fleet Savings ($mil)
OPC_6	353	54	22.03	9006	1	2	7	0	100	0.382	88.4	45.7
NSC_6	395	54	28.01	12013	3	2	9	0	100	100	141.0	45.7
OPC_{10}	293	40	22.04	9008	1	1	7	0	89.7	0.657	72.6	74.4
NSC_{10}	306	40	25.43	9002	1	1	7	0	89.7	47.6	91.0	74.4
Best OPC	276	38	22.02	9036	1	1	7	0	89.7	0.243	69.6	0
Best NSC	399	54	28	12016	3	2	9	3	100	99.9	131.8	0

7.7 Repeatability of Results

Initial attempts to obtain good reliable results used a method similar to the optimization without commonality seen in Chapters 4 and 5. An entire Pareto font was found for each combination of commonality components. The OPC and NSC endpoints for each commonality optimization were then used to calculate savings and the three objective dominance sort was performed. This method proved to be flawed in that the results were not adequately repeatable. Because of the stochastic nature of the optimization, it was very possible that the true endpoints of the Pareto front might not be found. Instead some of the endpoints came up short. As a result, the three objective dominance sort would eliminate good combinations of commonality based on there low values. Each of these runs would take about 24 hours to complete on a 1.73 GHz PC running a compiled C++ code and the results varied greatly.

The first attempt to remedy this was to find three sets of endpoints for each combination of commonality. Once all endpoints were found, the code would perform a repairing of endpoints in order to create the best possible pair of endpoints possible for each commonality string. Next, the fleet savings was calculated and the dominance sort was performed. Although the results were better, they still had a strong variation in which combinations would appear on the Pareto front. Another problem with this method was that it took about 3 x 24 = 72 hours to complete. Table 7.26 shows the distribution of results for this optimization method.

Table 7.26 Distribution of Results for Full Optimization Method – 3 Iterations – 200 Generations

CW	CG	CC	CS	CM	Run 1	Run 2	Run 3	Run 4	Run 5
1	1	1	N	N	X	X	X	X	X
1	1	N	N	N	X	X	X	X	X
2	1	N	N	N	X		X	X	
3	1	N	N	N	X	X	X	X	X
3	1	2	N	N				X	
1	1	1	N	Large	X	X	X	X	X
1	1	N	N	Large				X	
3	1	2	N	Large	X	X	X	X	
3	1	N	N	Large	X				X
N	1	2	N	Large			X		
1	1	1	Small	N	X	X	X	X	X
1	1	1	Small	Small	X	X	X	X	X
2	1	1	Small	Small			X		
1	1	N	Large	N	X	X	X	X	X
2	1	N	Large	N	X	X		X	
3	1	N	Large	N		X		X	
N	1	N	Large	N	X				
1	1	N	Large	Large			X	X	
2	1	N	Large	Large					X
3	1	N	Large	Large					X
N	1	N	Large	Large		X			
			Pairs Found in Run		12	11	12	14	10
			Total Combinations		21	21	21	21	21
			% Found		57.1%	52.4%	57.1%	66.7%	47.6%

This Full Optimization Method was run five times. For each run the distinctly different set of solutions were found. For the five runs there were a total of 21 combinations of commonality found on the final Pareto surfaces. On average, each run was able to find

12 of those combinations, or 57.1%. The results for these five runs can be seen in Figure 7.7.

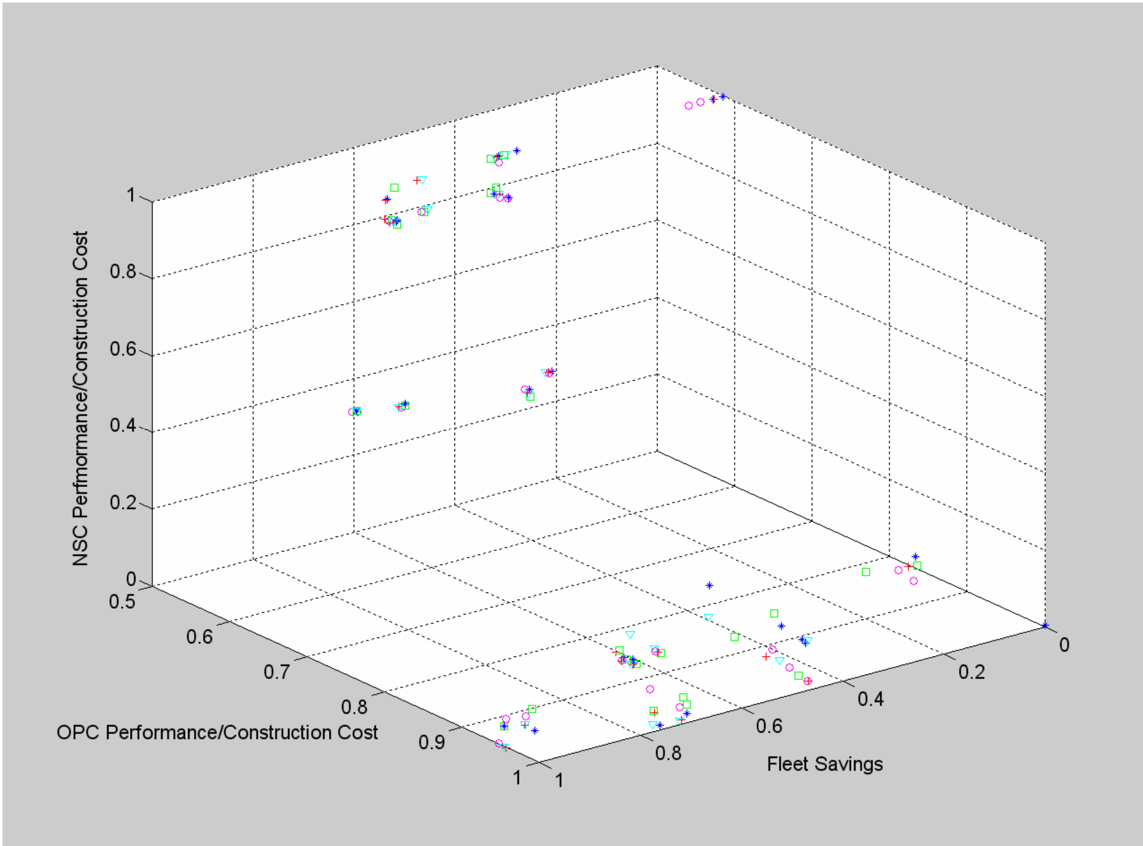

Figure 7.7 Pareto Front of Full Optimization Method (5 Runs)

The NSC endpoints are very closely packed together for the five sets of data on the plot. This shows a good correlation of results for the NSC. However, Figure 7.7 also shows the variation of data points for the OPC endpoints. The OPC data points for the five different runs are more widely distributed. Less repeatability can be seen in this area.

The Parallel Optimization Method described in Chapter 6 proved to have more repeatable results while taking less time to complete each run. Instead of finding the entire Pareto front for all 288 combinations of commonality, this method searches for each endpoint individually. One downfall to this method is that two optimizations must be run for each commonality string. However, there is a much greater confidence that the endpoints are as close to the maxima as possible without an exhaustive search. In addition to the improvement in repeatability, this method took about 47 hours to complete.

Table 7.27 Distribution of Results for Parallel Optimization Method – 200 Generations

CW	CG	CC	CS	CM	Run 1	Run 2	Run 3
1	1	1	N	N	X	X	X
1	1	N	N	N	X	X	X
2	1	N	N	N	X	X	X
3	1	N	N	N	X	X	X
N	1	N	N	N	X	X	X
1	1	1	N	Small	X	X	X
1	1	N	N	Large		X	
N	1	2	N	Large			X
N	1	N	N	Large	X	X	
1	1	1	Small	N	X	X	X
1	1	1	Small	Small	X	X	X
1	1	N	Large	N		X	X
2	1	N	Large	N		X	X
3	1	N	Large	N	X	X	X
N	1	N	Large	N	X		
2	1	N	Large	Large		X	
N	1	N	Large	Large	X	X	
		Pairs Found in Run			12	15	12
		Total Combinations			17	17	17
		% Found			70.6%	88.2%	70.6%

Table 7.27 shows the distribution of results for the three Parallel Optimization runs. The results show a stronger correlation of results from one run to another. The three optimization runs found 16 total combinations of commonality on the final Pareto surfaces. On average, each individual run found 13 of those 17 commonality strings on its final Pareto surface, or 76.4%. The results for these three runs can be seen in Figure 7.8.

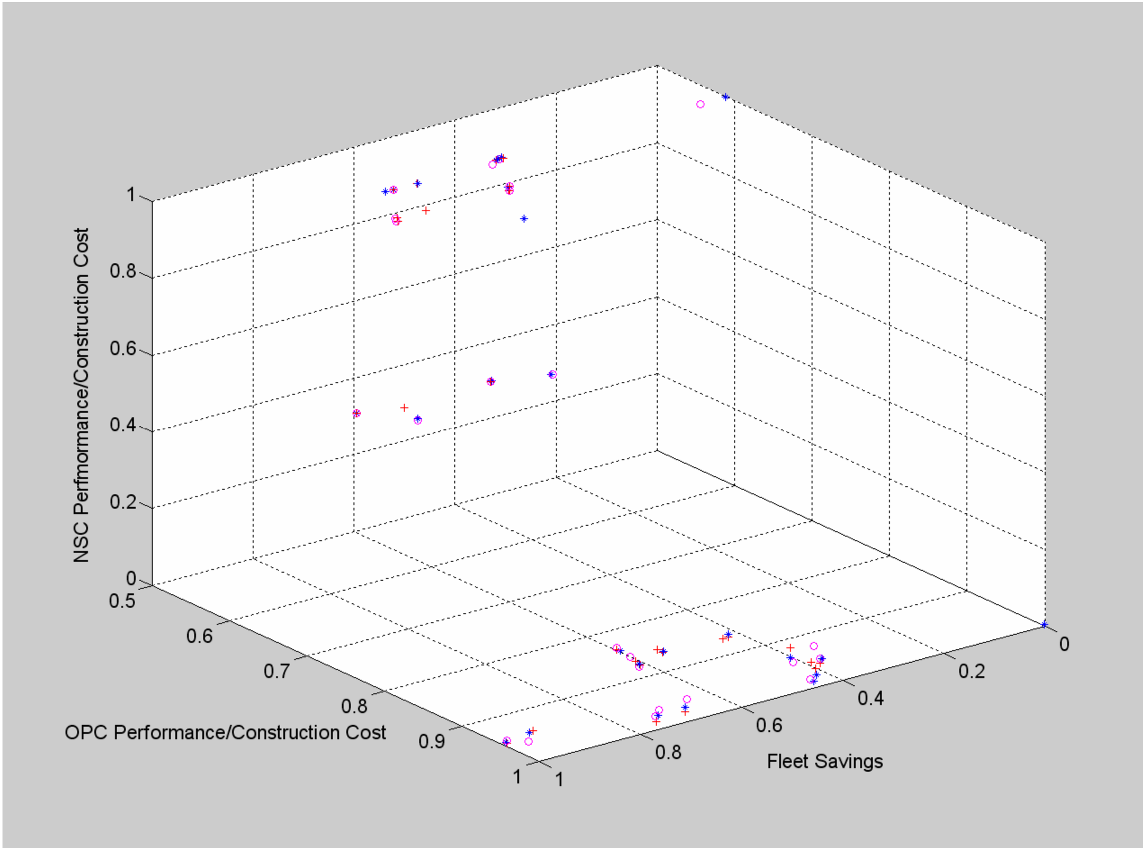

Figure 7.8 Pareto Front of Parallel Optimization Method - 200 Generations (3 Runs)

The Parallel Optimization Method shows a good correlation of data for both the NSC and OPC endpoints. The data points for both ships are tightly clustered together indicating that this method has good repeatability.

Further efficiency might be possible with some sacrifice in results by decreasing the number of generations per commonality string. Table 7.28 shows the effects of using 50, 100 and 150 generations. The time required to perform runs using 50, 100 and 150 generations is about 14, 25 and 36 hours, respectively. Thus, significant time savings can be obtained if some sacrifice in results is acceptable.

Table 7.28 Distribution of Results for Parallel Optimization Method – Varying Generations

CW	CG	CC	CS	CM	50 Gens Run 1	50 Gens Run 2	50 Gens Run 3	100 Gens Run 1	100 Gens Run 2	100 Gens Run 3	150 Gens Run 1	150 Gens Run 2	150 Gens Run 3
1	1	1	N	N	X	X	X	X	X	X	X	X	X
1	1	2	N	N	X								
1	1	N	N	N		X	X	X	X	X	X	X	X
2	1	1	N	N	X								
2	1	N	N	N			X	X	X		X	X	
3	1	1	N	N	X								
3	1	N	N	N		X	X	X		X			X
N	1	N	N	N					X		X	X	
1	1	1	N	Small	X	X	X	X	X	X	X	X	X
1	1	N	N	Large	X	X		X	X	X	X	X	X
2	1	N	N	Large						X			X
3	1	2	N	Large		X		X					
3	1	N	N	Large					X			X	
N	1	2	N	Large			X						
N	1	N	N	Large						X	X		X
1	1	1	Small	N	X	X	X	X	X	X	X	X	X
1	1	1	Small	Small	X	X	X	X	X	X	X	X	X
N	1	1	Small	Small						X			
1	1	1	Large	N							X		
1	1	N	Large	N	X	X	X	X	X	X		X	X
2	1	N	Large	N	X			X	X	X	X		X
3	1	N	Large	N				X		X	X		X
N	1	N	Large	N		X	X		X			X	
1	1	N	Large	Large				X	X				
2	1	N	Large	Large			X						
3	1	N	Large	Large							X		X
N	1	N	Large	Large	X	X		X	X	X	X		
Pairs Found in Run					11	11	11	14	14	14	14	11	13
Total Combinations					18	18	18	20	20	20	19	19	19
% Found					61.1%	61.1%	61.1%	70.0%	70.0%	70.0%	73.7%	57.9%	68.4%

Figures 7.9 through 7.11 show the final Pareto fronts for the Parallel Optimization Method using 50, 100 and 150 generations, respectively.

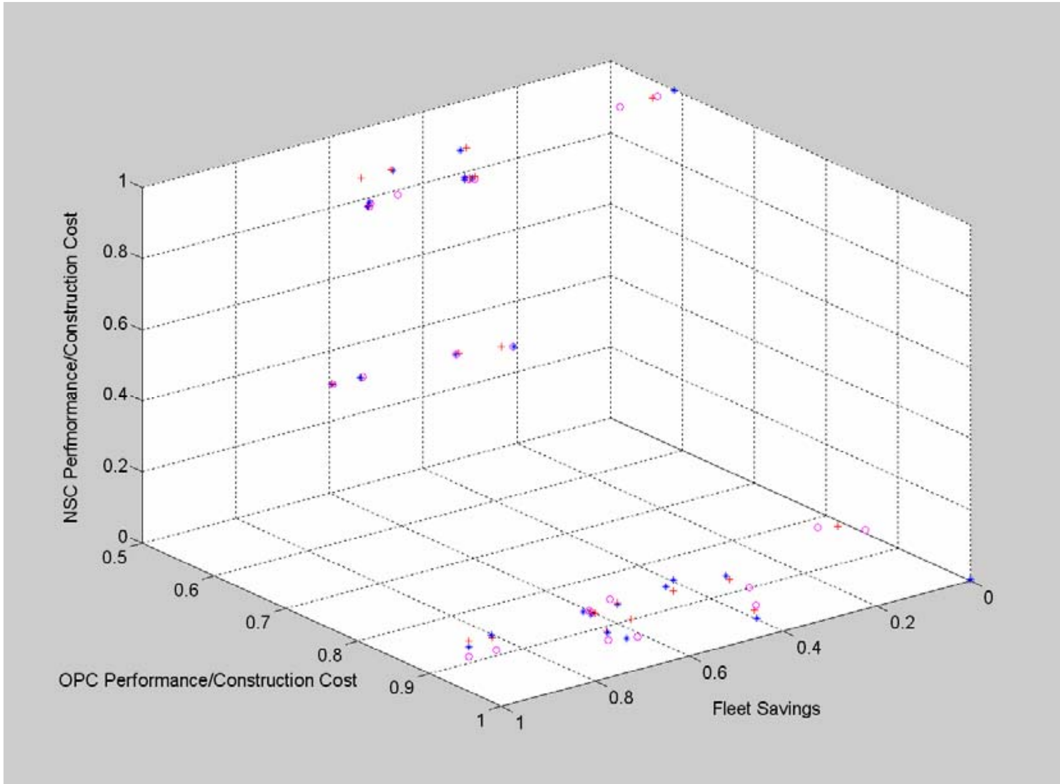

Figure 7.9 Pareto Front of Parallel Optimization Method - 50 Generations (3 Runs)

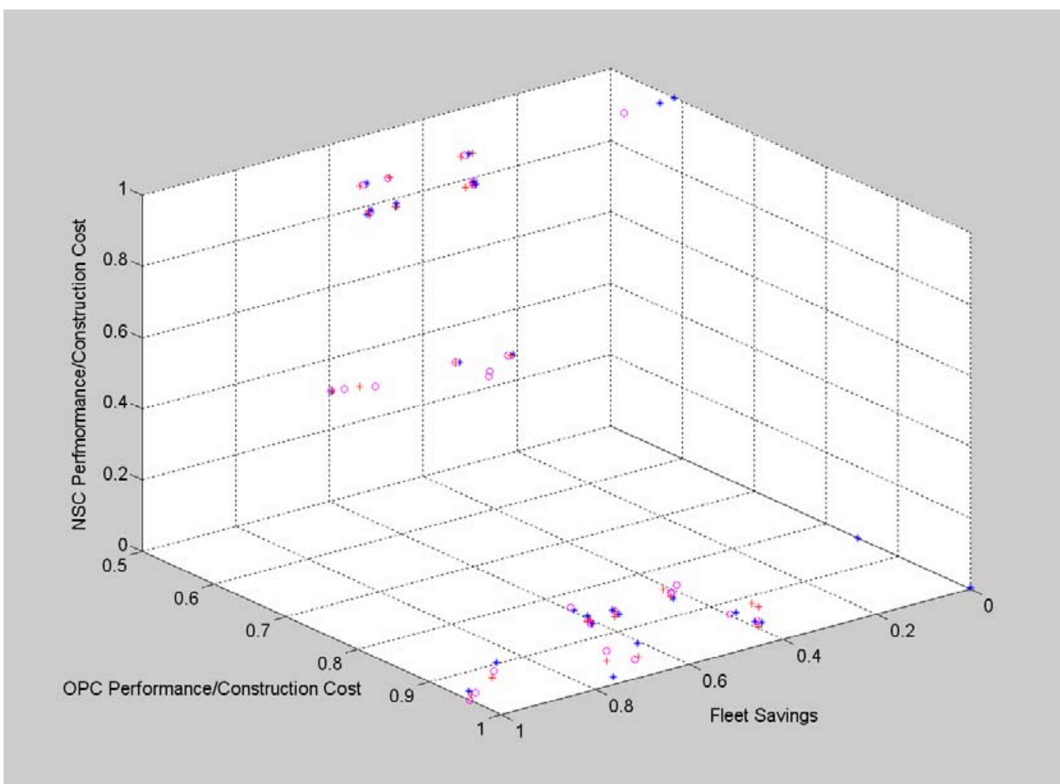

Figure 7.10 Pareto Front of Parallel Optimization Method - 100 Generations (3 Runs)

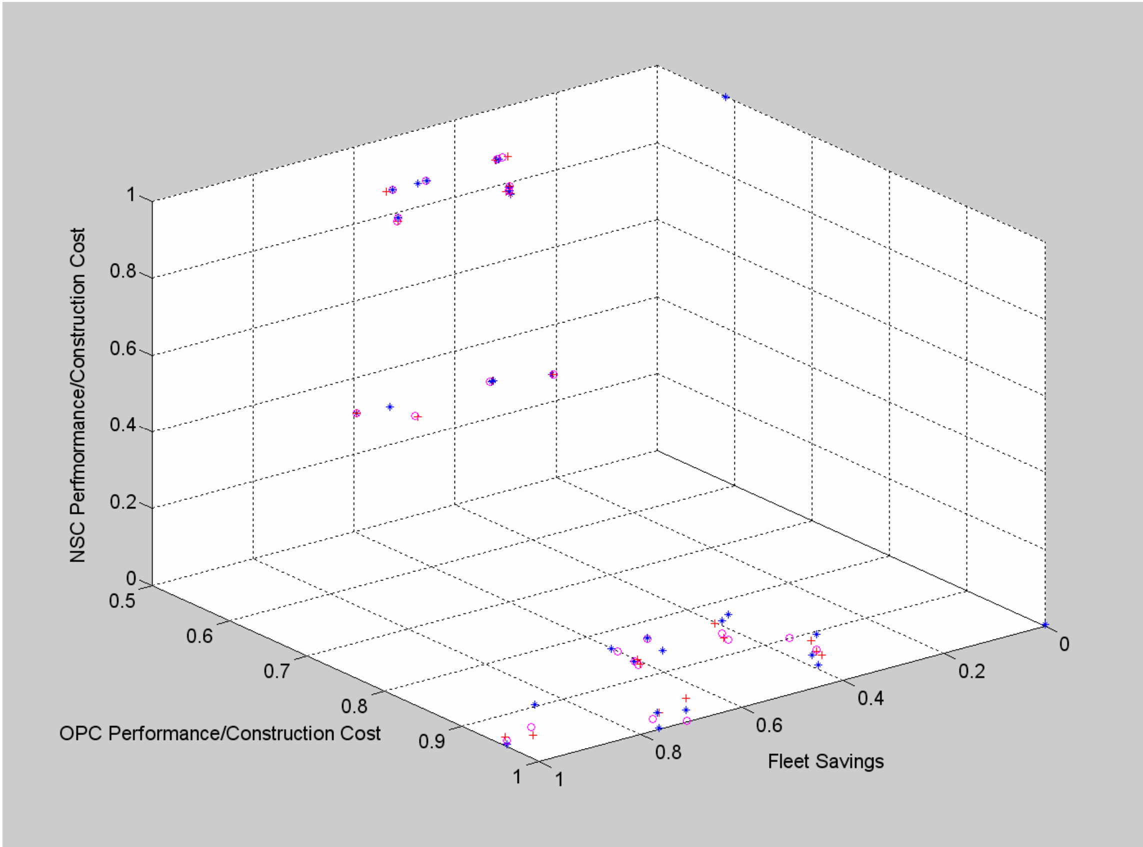

Figure 7.11 Pareto Front of Parallel Optimization Method - 150 Generations (3 Runs)

In order to quantify the improvement in the endpoints objective values, the results for each commonality string were examined and compared to the other methods. Table 7.29 compares the performance /cost values of the Parallel Optimization Method to the Full Optimization Method. The performance/cost values for all 288 commonality strings were compared to the highest values of all 15 Full Optimization runs (5 runs with 3 iterations each). Table 7.29 shows that each subsequent increase in the number of generations increased the performance/cost values for the endpoints. This increase in values was consistent throughout the entire 288 optimizations as shown by the small standard deviations for each number of generations. The 200 generation runs increased, on average, 253 OPC endpoints and 197 NSC endpoints. This is nearly all of the OPC endpoints and about 70% of the NSC endpoints.

Table 7.29 Comparison of Results for Parallel Optimization Method – Varying Generations

		OPC	NSC
50 Gens	Average % of Baseline Values	99.6%	99.3%
	Standard Deviation of Average % for all 288 Commonality Strings	0.767	1.647
	# of Improved Endpoint Values out of 288 Possible Endpoints	73	106
100 Gens	Average % of Baseline Values	100.3%	99.7%
	Standard Deviation of Average % for all 288 Commonality Strings	0.713	1.653
	# of Improved Endpoint Values out of 288 Possible Endpoints	182	156
150 Gens	Average % of Baseline Values	100.5%	100.0%
	Standard Deviation of Average % for all 288 Commonality Strings	1.030	1.491
	# of Improved Endpoint Values out of 288 Possible Endpoints	239	189
200 Gens	Average % of Baseline Values	100.6%	100.1%
	Standard Deviation of Average % for all 288 Commonality Strings	0.786	1.475
	# of Improved Endpoint Values out of 288 Possible Endpoints	253	197

By searching for only the endpoints, the Parallel Optimization Method improves the objective values, repeatability and efficiency of the optimization. Ideally the optimization would be more repeatable, but due to the stochastic nature of the process there will always be some variance in the results.

CHAPTER 8

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

The methodology developed and demonstrated in this research should prove to be a valuable tool in making good commonality decisions. It provides a logical procedure for the use of commonality in design while taking into consideration performance loss, cost and fleet savings. In much of the literature about the use of commonality there is a basic recognition that the use of common components in design hinders the performance of a product. This loss in performance is accepted because of the savings associated with using common parts. Prior to this research, the amount of savings is never really quantified. Instead, it has usually been assumed that the use of commonality always results in savings. This research showed that positive savings is not always realized. If poor commonality decisions are made in design, products could cost more and perform less.

The mission performance model relied on the use of fuzzy utility values. Performance was determined using four design characteristics for each of four mission area and applying the corresponding fuzzy utility value to each. Sensitivity studies showed that the choice of these utilities can have significant impact on the resulting optimal designs. A designer could also modify this model to include more design characteristics or even more mission areas. The fuzzy utilities could be replaced with another tool, such as Brown's Measures of Performance (MOP) which are essentially fuzzy utilities [Brown and Salcedo 2003], for awarding value to a given design characteristic. In short, the mission performance good easily be expanded or modified to meet the needs of a given designer.

Commonality decisions were limited to five components in this work. Each of these components was integrated into the design in a slightly different manner to show the versatility of the methodology and modeling. In this research there were a finite number of commonality options from which to choose. As a result, an exhaustive search was used to determine which commonality choices were the best. If more commonality choices were available, another genetic algorithm could be used to more efficiently search for the dominant commonality combinations.

Bulk purchasing and construction learning curves were used to determine the savings associated with the use of commonality. The savings model was intentionally kept relatively simple. Other forms of savings could be realized as well. These could include training of personnel, technical design costs, administrative savings, facility costs and spare parts. The type of savings and the number of different factors to consider varies with each product being designed. A designer may choose to make the savings model very elaborate when detailed information of these other forms of savings is available or it may be kept simple as seen in this research.

Using the logical methodology described in this research will enable a designer to present much more complete analysis of commonality decisions in design. Designers can expand the optimization model in many ways to adapt it to their particular needs. Regardless of how crude or elaborate it may become, the overall process can follow that developed here.

The case study used to test the methodology revealed some interesting insights into the naval architecture aspects of the optimal use of commonality in this situation. These are summarized here.

1. The optimization was sensitive to the discrete nature of the cruise engine and ship service generators databases. The resulting two-dimensional Pareto front contained gaps resulting from the shift from one generator to another

within the database. Adding additional generators to provide a more continuous array of generators is expected to reduce this tendency.

2. The results were sensitive to the specific assignments of the fuzzy utilities for the effect of the performance characteristics on the vessel missions and there is a fine balance among the independent variables in achieving an optimum solution. This indicates that the methodology is sensitive to the problem definition and that there is considerable value in formal optimization in this situation.

3. Even though there were a large number of cruise engines and ship service generators in the respective databases, only two cruise engines and three ship service generators were ever present in the designs on the two-objective Pareto front. This provided a logical and effective way to reduce the number of options for the commonality study.

4. The synthesis model included the use of either Combined Diesel and Diesel (CODAD) propulsion plants or Combined Diesel or Gas Turbine (CODOG) plants. Even though the current NSC design uses a CODOG plant, the analysis produced only CODAD designs for the Pareto front design for both the NSC and the OPC missions. This is attributed to the consideration of acquisition cost and not life-cycle cost in the denominator of the performance/cost measure, which was a decision made to ensure independence of the performance over cost and the fleet savings objectives. Testing with life-cycle cost in place of acquisition cost did produce some Pareto front designs, at the left NSC end, with CODOG plants.

5. The use of performance over cost is key to ensuring that a design is penalized for the over-design of the less capable vessel being considered for commonality. This is a normal commercial approach to design, but not necessarily the approach used in naval design where performance is usually

given a higher priority than cost. This shift in measuring performance may be important for naval ship affordability in the future.

6. The overall design of the vessels considered in the case study was heavily driven by the choice of the number of helicopter hangers since the aerial assets are key to the mission performance of these vessels. This shift from designs with one helicopter hangar to designs with two parallel helicopter hangars also affected beam, length through the speed requirement, superstructure volume, etc. The discrete jump in the Pareto front at this transition produced a significant discrete shift in vessel size and cost. The final discrete three-objective Pareto front includes two distinct bands of NSC mission designs resulting primarily from the use of one or two helicopter hangars.

7. The vessels on the Pareto front in the two-objective study were generally monotonic in the major characteristics from the low capability OPC end of the Pareto front to the more capable NSC end of the front, but not always. In some cases for length, speed, and range this was not the case indicating the fine balance within the overall design to produce a non-dominated design.

8. The use of common (smaller) ship service generators provided the largest fleet savings; the use of common (smaller) cruise engines provided the next largest fleet savings.

9. The study of the designs on the two-objective Pareto front revealed that the designs tended to have one of two basic superstructure sizes depending upon the number of helicopter hangars. This led to the consideration of a common superstructure as one of the commonality options. The use of a common superstructure always produced a fleet savings.

10. The study of the designs on the two-objective Pareto front revealed that many of the designs tended to have essentially the same midship sections (beam, depth, C_M, etc.). This led to the consideration of common midship section hull blocks as one of the commonality options. This did not, however, provide important fleet savings.

11. Most likely the best design choice for the case study would be the pair of designs on the discrete Pareto front (designs NSC_6 and OPC_6 in Figure 7.6) that result in the greatest fleet savings while still maintaining the high performance/cost for the NSC mission design possible with the use to two helicopter hangars. These design achieve 61.5% of the possible savings while achieving 100% of the mission performance for both designs.

12. The pair of designs resulting in the highest fleet savings through commonality (designs NSC_{10} and OPC_{10} in Figure 7.2) were so close in basic characteristics, as shown in Table 7.25, that there should probably be a single vessel design for both missions with the additional savings from total commonality.

The optimization methodology can be extended further with respect to its designated use, use of more common components, and the use of more elaborate cost savings functions. The methodology described in this research can be applied to non-Naval ship classes, the automobile industry and other consumer products. Each of these industries can benefit from the use of this logical optimization methodology. The case study that was used in this research used Coast Guard ships. Commercial ship design can also be applied to this methodology helping to lower the cost of portfolios of designs. This research limited the number of possible common components to five. Further investigation could be conducted which examines the use of other common components. The cost savings functions were limited to bulk purchasing and construction learning curves. As mentioned above, there are many other forms of savings that could be realized through the use of commonality. More research is possible in the examination and application of these forms of savings.

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