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Multiple-Objective Optimization in Naval Ship Design

ABSTRACT

This paper presents an optimization methodology that includes three important components necessary for a systematic approach to naval ship concept design. These are:

- An efficient and effective search of design space for non-dominated designs
- Well-defined and quantitative measures of objective attributes
- An effective format to describe the design space and to present non-dominated concepts for rational selection by the customer

A Multiple-Objective Genetic Optimization (MOGO) is used to search design parameter space and identify non-dominated design concepts based on life cycle cost and mission effectiveness. A non-dominated frontier and selected generations of feasible designs are used to present results to the customer for selection of preferred alternatives. A naval ship design application is presented.

INTRODUCTION

This paper describes the application of multiple-objective genetic optimization to a naval ship design problem. Various options and variables exist for combat system selection, engine selection, hull form parameters, manning, endurance and mobility. Critical objective attributes considered are mission effectiveness and cost. These are calculated for each design. Risk requires a similar treatment, and will be addressed in subsequent work.

Effectiveness, cost and risk are dissimilar attributes, and require different metrics. They cannot rationally be combined into a single objective attribute. They must be presented individually, but simultaneously in a manageable format for tradeoff and decision-making. They are relatively abstract objectives that are sometimes difficult to measure quantitatively. The effectiveness of a few naval ship concepts can be analyzed using war gaming and other complex models, but this approach is not practical when evaluating many concepts in a structured search of design space. This paper presents a methodology for calculating an Overall Measure of Effectiveness (OMOE) index using expert opinion to synthesize diverse inputs such as defense guidance, mission requirements, threat, war game results and experience.

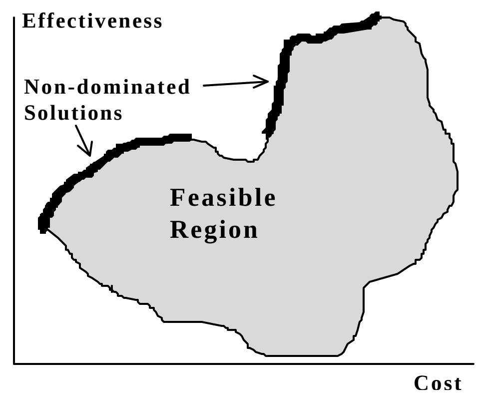

Figure 1. **Two-Objective Attribute Space**

A non-dominated solution, for a given problem and constraints, is a feasible solution for which no other feasible solution exists which is better in one objective attribute and at least as good in all others. Figure 1 illustrates this concept for a two-objective (cost-effectiveness) problem. In this notional example, cost is minimized and effectiveness is maximized. The heavy curve represents non-dominated solutions or the Pareto-optimal frontier. The preferred design should always be one of these non-dominated solutions. Its selection depends on the decision-maker's preference for cost and effectiveness. This preference may be affected by the shape of the frontier and cannot be rationally determined a priori.

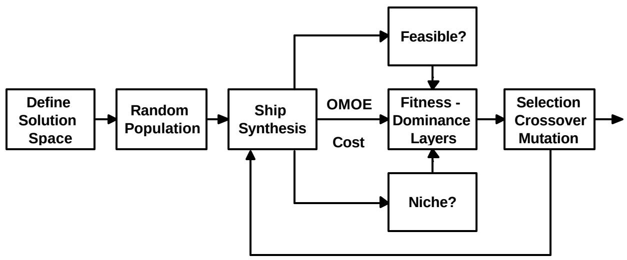

Figure 2. Optimization Process

The multiple objective optimization process used in this application is illustrated in Figure 2. An initial population of designs is created by random selection of design variables within the design space. In the application described in this paper, a chromosome or design vector with 26 design parameters represents each design. The ships defined by these chromosomes are balanced, and evaluated using a ship synthesis model. This produces a cost and OMOE value for each design. Next, designs are sorted into layers of dominance. Each layer contains designs that are dominant to subsequent layers. A geometrically decreasing probability of selection is assigned to each design based on its layer. Designs are penalized for infeasibility. After selection probabilities are calculated, selection of the next generation is performed. Once a surviving population is selected, pairs are selected at random for crossover of design parameters (genes), and a small percentage of genes in selected design chromosomes are chosen randomly to mutate. These genetic operations produce new and, on the average, better designs. After these operations are completed, the designs in the new population are sent to the ship synthesis model and the process cycles until convergence. Each cycle defines a new generation. The final generations of this process converge to a non-dominated or Pareto frontier.

OBJECTIVE ATTRIBUTES

Overall Measure of Effectiveness (OMOE)

Early in the naval ship design process, designers and engineers require a working model to quantify operators' and policy-makers' definition of mission effectiveness, and define its functional relationship to ship and ship system measures of performance (MOPs). This quantitative assessment of effectiveness is fundamental to a structured optimization process.

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

An alternative to modeling and simulation is to use expert opinion directly to integrate these diverse inputs, and assess the value or utility of ship MOPs in an OMOE function. This can be structured as a multi-attribute decision problem. Two methods for structuring these problems dominate the literature: Multi-Attribute Utility Theory (Keeney and Raiffa 1976) and the Analytical Hierarchy Process (Saaty 1996). In the past, supporters of these theories have been critical of each other, but recently there have been efforts to identify similarities and blend the best of both for application in Multi-Attribute Value Theory (MAVT) functions (Belton 1986). This approach is adapted here for deriving an OMOE.

The analytical hierarchy process (AHP) is a tool developed by Saaty (1996) for solving multi-attribute decision problems. It uses a hierarchical structure to abstract, decompose, organize and control the complexity of decisions involving many attributes, and it uses informed judgment or expert opinion to measure the relative value or contribution of these attributes and synthesize a solution. Pair-wise comparison and an eigenvalue approach extract and quantify this relative value. The method allows and measures inconsistency in value measurement, and is able to consider quantitative and qualitative attributes.

A hierarchy is a simplified abstraction of the structure of a system used to study and capture the functional interactions of its attributes, and their impact on total system behavior or performance. It is based on the assumption that important system entities or attributes, which must first be identified, can be grouped into sets, with the entities of one group or level influencing the entities of the neighboring group or level. One can conceptualize a hierarchy as a bottoms-up synthesis of influence on the top level behavior of a system, or as the top down distribution of influence of top level behavior to low level attributes. Alternatives are compared in terms of the lowest level attributes and this comparison is rolled up through hierarchy levels to an assessment of relative overall system behavior or performance.

The first step in building an AHP hierarchy is to identify critical attributes affecting the decision or system behavior. The level of detail of these attributes depends on the decision being made. These attributes are then organized into a hierarchy structure that follows a logical breakdown or categorization as shown in Figure 3. In this application, system measures of effectiveness (MOPs) comprise the bottom hierarchy level.

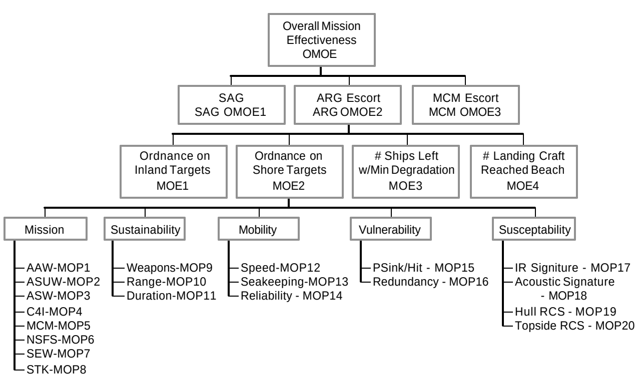

Figure 3. **Notional Top Level OMOE Hierarchy**

Next, the relative influence of each attribute on system performance and attribute values for each alternative must be estimated. Saaty recommends a nine level dominance scale for the pair-wise comparison of attribute influence on higher level attributes. This results in a "ratio scale" comparison of attributes. Pair-wise comparison or cardinal values may be used to assign attribute values for each alternative. Pair-wise comparison generates more information than is necessary with individual absolute measurements or estimates. The AHP synthesizes and evaluates the consistency of this redundant information and calculates best-fit relative values.

Although the AHP was developed primarily for comparison of management alternatives, it has also proven to be a robust method for application in MAVT. The AHP provides a structured method for deriving an additive weighted value function, and by careful application can also be used to derive non-linear attribute value or utility without the more cumbersome lottery comparison approach.

The OMOE function must include all important effectiveness/performance attributes, both discrete and continuous, and ultimately be used to assess an unlimited number of ship alternatives. Successful application AHP/MAVT to this problem requires a very structured and disciplined process as follows:

1. **Identify, define and bound decision attributes.** Identify critical mission scenarios. Identify Measures of Effectiveness (MOEs) for each mission scenario. Establish goals and thresholds for all MOEs. Identify ship MOPs critical to mission scenario MOE assessment and consistent with the current design hierarchy level. Set goals and thresholds for these MOPs.

2. **Build OMOE/MOP hierarchy**. Organize MOEs and MOPs into a hierarchy as shown in Figure 3, with specific ship MOPs at the lowest level. Association with the performance of a discrete system may define some MOPs. Others are continuous performance variables such as sustained speed.

3. **Determine MOP value and hierarchy weighting factors.** Use expert opinion and pair-wise comparison to determine MOP value and the quantitative relationship between the OMOE and MOPs.

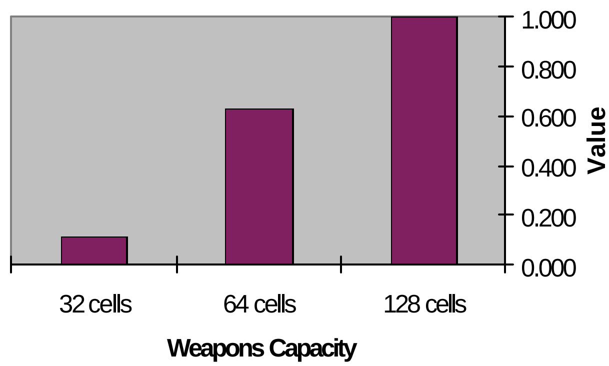

Figure 4. Discrete MOP Value Function

Figure 4 illustrates an example value index for ship weapons capacity derived using pair-wise comparison. In this model weapons capacity is both a discrete MOP, where it represents the performance associated with this capacity, and a discrete design parameter. The metric for this MOP is the number of vertical launch missile cells. The MOP threshold is 32 cells, and the MOP goal is 128 cells. Thresholds represent absolute minimum acceptable performance. Goals typically represent either a point of diminishing marginal value or a technology limitation. The pair-wise comparison is structured to compare the relative value of MOP options to achieve a particular MOE (Ordnance on shore target, etc.) in a specific scenario.

Figure 5 illustrates an example value index for ship sustained speed. Sustained speed is a continuous MOP. It is a function of the ship design, primarily the hull form and installed power. The threshold for this MOP is 26 knots, and the goal is 32 knots. Pair-wise comparison is accomplished for discrete values of speed at one knot increments, and a value function is fit to these results to calculate intermediate values. Again, the pair-wise comparison is structured to compare the relative value of MOP options to achieve a particular MOE (Ordnance on target, etc.) in a specific scenario.

Once MOP value is determined for all MOPs, pair-wise comparison is used to determine MOP and MOE hierarchy weights. In this case the pair-wise comparison is structured to compare the relative value of achieving the goal in the first MOP or MOE and only the threshold in the second, versus achieving only the threshold in the first MOP and the goal in the second. This pair-wise comparison is accomplished at all levels of the hierarchy. An eigenvalue approach is used to extract and quantify average relative values and an inconsistency measurement. An OMOE function, OMOE = g(MOP), is derived from these weights and from the MOP value functions.

Life Cycle Cost

Life Cycle Cost (LCC) as defined for this analysis includes only follow-ship acquisition cost, life cycle fuel cost and life cycle manning cost. Annual life cycle costs are discounted to the base year, using an annual discount rate of 7%. Construction costs are estimated for each weight group using weight-based equations adapted from an early ASSET cost model (NSWC Carderock 1990). The base year is assumed to be 2000. Historical costs are inflated to the base year using a 5% average annual inflation rate from 1981 data. Producibility is also considered in the construction cost equations. Producibility factors are based on hull form characteristics, machinery room volume, and deck height.

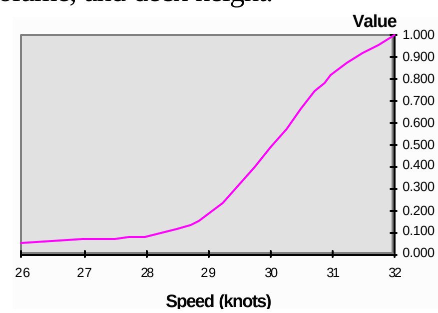

Figure 5. Continuous MOP Value Function

SHIP SYNTHESIS MODEL

The ship synthesis model used in this research is based on a model originally developed by Reed (1976). Reed's model was improved and modified specifically for use with a single objective genetic algorithm by Shahak (1998), and subsequently for a multiple-objective genetic optimization (MOGO) by Brown and Thomas (1998). Figure 6 illustrates the basic process used in this model. Most recently modules have been added to interface with a payload database, and calculate acquisition cost, seakeeping index and effectiveness.

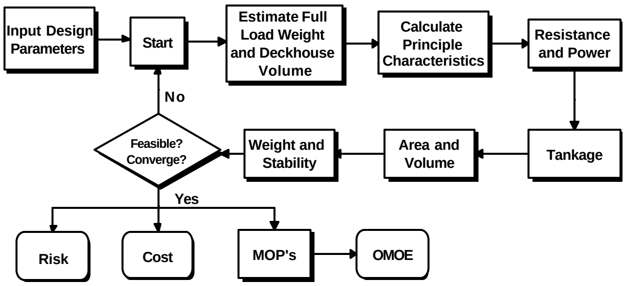

Figure 6. Ship Synthesis Model

In the genetic optimization application of this synthesis model, input design parameters (genes) are specified in a ship design vector (chromosome). Design parameters, ranges and increments for a guided missile destroyer (DDGx) application are listed in Table 1. Specific payload systems with weight, area and power requirements are associated with each payload description. The ship is balanced and resulting MOPs, OMOE, and Life Cycle Cost (LCC) are calculated. The MOGO uses these results to assess fitness and select the next generation of ship designs.

Table 1. DDGx Design Parameter Descriptions

Design Parameter	Description
1 - Prismatic Coefficient (Cp)	0.5-0.7; 20 increments
2 - Maximum Section Coefficient (Cx)	0.7-0.9; 20 increments
3 - Displacement to Length Ratio ($C_{\Delta L}$)	60.0-90.0; 15 increments
4 - Beam to Draft Ratio (C_{BT})	2.8-3.7; 9 increments
5 - Length to Depth Ratio (C_{D10})	10.0-15.0; 10 increments
6 - Raised Deck Ratio (C_{RD})	0.0-0.4; 4 increments
7 - Manning Factor ($C_{Manning}$)	0.5-1.0; 5 increments
8 - AAW Payload	1 - Theater TBMD 2 - Area TBMD 3 - Area Defense 4 - Limited Area Defense 5 - Self Defense
9 - ASUW Payload	1 - Long Range 2 - Medium Range 3 - Short Range 4 - Self Defense
10 - ASW Payload	1 - Area Domonance 2 - Adverse ASW Environment 3 - Good ASW Environment 4 - Torpedo Defense
11 - C4I Payload	1 - Advanced 2 - Current
12 - MCM Payload	1 - Limited Clearance 2 - Mine Recon 3 - Mine Avoidance 4 - Limited Mine Advoidance
13 - NSFS Payload	1 - Advanced (VGAS, NATACMS, ATWCS) 2 - Full 3 - Medium 4 - Minimum
14 - SEW Payload	1 - Advanced 2 - Current
15 - Weapons Capacity (VLS)	1 - 128 cells 2 - 64 cells 3 - 32 cells
16 – Range or fuel capacity	1 - 10000 nm 2 - 7000 nm 3 - 5000 nm 4 - 4000 nm
17 - Stores Duration	1 - 60 days 2 - 45 days
18 - Shafts	1 or 2
19 - CPS	0 (none) or 1 (full)
20 - ICR or GT	0(ICR) or 1 (LM2500)

Balance requires that physical and functional constraints are satisfied. The ship must float. It must have adequate stability, volume, area, electric power, etc. It must provide required capabilities and satisfy minimum thresholds for performance. The ship synthesis model uses regression-based equations for weight, volume, area and electric power. Resistance is calculated using Gertler/Taylor Standard Series (1954). Seakeeping is assessed using the McCreight Index.

OPTIMIZATION

Ship design optimization is not a new concept, but it poses difficult computational problems (Leopold 1965, Mandel and Leopold 1966, Mandel and Chryssostomidis 1972). As discussed previously, ship

ship design space is non-linear, very discontinuous, and bounded by a variety of constraints and thresholds. These attributes inhibit effective application of mature gradient-based optimization techniques including Lagrange multipliers, steepest ascent methods, linear programming, non-linear programming and dynamic programming. Genetic algorithms are very effective with this type of problem and design space. They provide an additional advantage in multiple objective problems because they work with a population of individual designs, and the population can be forced to spread out over the non-dominated frontier in a single optimization.

The genetic or evolutionary algorithm in this optimization uses decimal floating-point gene coding and a finite resolution and range or set of values for design variables. Although a binary-encoded alphabet offers some advantages, and its use is widely accepted, an optimization of the genetic algorithm parameters (optimization of the optimization) has demonstrated improved speed and quality of the Pareto-frontier using decimal coding (Salcedo 1999). Similar improvements in speed for floating-point representation have been demonstrated by Michalewicz (1992).

Fitness is the ultimate objective attribute for the genetic optimization. Fitness is based on dominance layer ranking adjusted for solution infeasibility and niching (or grouping). Dominance in this model is based on two objective attributes: cost and effectiveness.

Infeasibility can be managed in different ways. In Michalewicz, constraints applied to linear systems are resolved by *GENOCOP (GEnetic algorithm for Numerical Optimization for COnstrained Problems)*. This method converts a set of equations and inequalities to expressions limiting each gene value as a function of the other gene values. When the algorithm selects a particular gene to mutate or to crossover, it can only select values within the specified range, and thus the chromosome remains feasible at all times. Another method for dealing with infeasibility is “recovery”. When the algorithm finds a non-feasible chromosome, it randomly selects a gene, and returns a value from the domain of that particular gene that makes the chromosome feasible and thus recovers the individual. For large and complex systems, this process is impractical. The time that the random generation process requires creating a new gene to recover each infeasible chromosome is prohibitive.

A third alternative for dealing with infeasibility is a “penalty function” (Goldberg 1989, Horn and Nafpliotis 1993). This alternative applies a penalty to one or more objective attributes for a particular chromosome based on the degree of infeasibility of the chromosome. Instead of preventing or eliminating an infeasible chromosome, a chromosome may survive despite its infeasibility if its objective attributes are good enough to be dominant after a penalty is applied. In this way, superior genetic material is kept in the gene pool for crossover with other chromosomes.

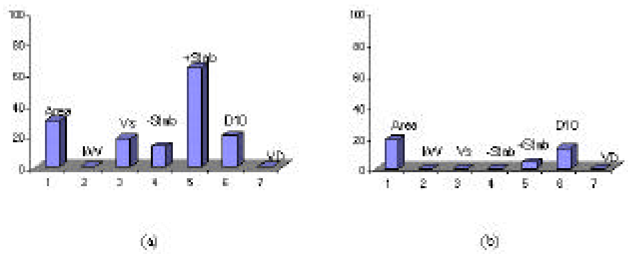

Figure 7. Number of Infeasible Chromosomes

In this optimization, the penalty is applied only to the effectiveness objective attribute. The penalty is based on the percentage of error from the various constraints imposed on the system. The greater the deviation from its allowed domain, the larger the penalty applied to it. Feasibility constraints considered in this ship model include sufficient functional area (Area), electric power (kW), sustained speed (Vs), intact stability (+/- Stab), sufficient ship depth (D10), and deckhouse volume. Figure 7 summarizes the chromosome feasibility status at the start (a) and end (b) of a typical optimization for a population size of 200. At the start of the optimization, excessive stability or "stiffness" is the most limiting constraint. By the end, the number of infeasible chromosomes is greatly reduced and the primary constraints are functional area and depth.

A niching operator is used to improve the quality of the non-dominated frontier by increasing the probability of selection of individuals in sparsely covered areas of the frontier and decreasing the selection of individuals in areas that are already densely occupied. A sharing region or box is assigned to individuals on the frontier. Individuals occupying the same sharing region are redundant or “equivalent class” solutions. Redundant individuals that occupy the same sharing region are penalized. This forces the solution to spread out over the frontier. The size of the niche box determines the sharing region for each individual. The size of the niche box and the niche penalty were determined in an optimization of algorithm parameters. Share regions of 0.1% to 3% of the objective attribute ranges were considered in this optimization. Optimum niche box dimensions for this problem were found to be $3.2M x 0.0037 or 0.3% x 0.6%. This optimization of the optimization was based on a frontier quality function that considers the final spacing of individuals, their combined optimality and the range of the frontier.

Figure 8 shows selections of non-dominated frontiers for a range of niche box dimensions. Figure 8(a) is a very sparse frontier. Figure 8(b) is denser, but with reduced range at the low cost end. Figures 8(c) and 8(d) show frontiers with good spacing, range and optimality. The optimum niche box values chosen fall in between these two alternatives.

Once objective attributes have been calculated and penalized, dominance layers are built one at a time by extracting dominant individuals until all remaining individuals are dominated. Each layer is set aside and the process repeated for the remaining individuals. The worst fitness is assigned to the last layer. The number of layers is dependent on the variety of dominance within a generation of individuals. The number of layers varies throughout the optimization process. In the last generation, or once the convergence criteria is met, the first layer approximates the non-dominated frontier. Because some dominant individuals may be lost in random selection, a record of dominant individuals created over the entire optimization is maintained. These are used to augment the dominant individuals in the final generation.

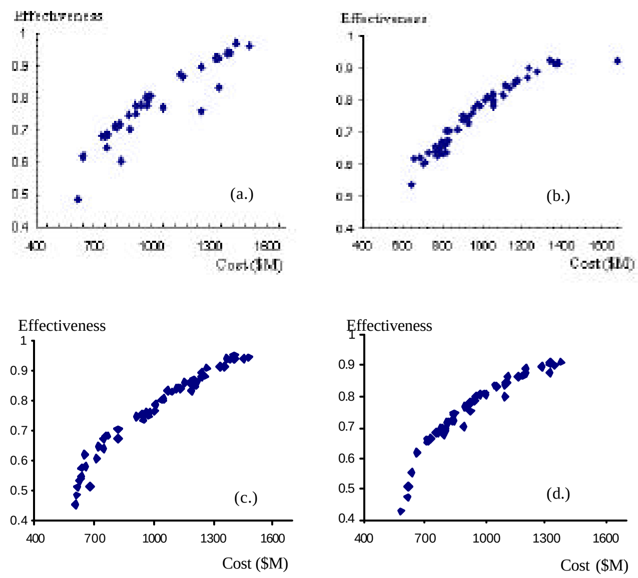

Figure 8. Comparison of non-dominated frontiers with different niche box sizes. (a) niche box 20 x 0.02. (b) niche box 10 x 0.01. (c) niche box 5 x 0.005. (d) niche box 2.5 x 0.0025.

Based on an individual’s rank in the dominance sort, *i*, a probability of selection is assigned. The fittest individual receives the highest probability of selection, and the least fit individual receives the lowest. Equivalent designs (same dominance layer) are ordered randomly within their layer, probabilities are averaged for designs in the same layer, and the same average value is assigned to each. Equivalent designs (same dominance layer) are ordered randomly within their layer, probabilities are averaged for designs in the same layer, and the same average value is assigned to each. The fitness scaling function is a geometric series where the probability of selection is:

$$P_i = A_1 \cdot P_s^{i-1} \qquad (1)$$

where *i* varies from one to the population size, A_1 is a constant, and P_s is the *selection pressure.* Ps has a value between zero and one. The sum of all probabilities must add to unity, so A_1 is a dependent variable:

$$A_1 = \frac{1 - P_s}{1 - P_s^{pop\_size}} \qquad (2)$$

As P_s approaches the unity, the probability becomes uniform. At this limit, all individuals have the same probability of selection:

$$P_i(P_S = 1) = \frac{1}{pop\_size} \qquad (3)$$

As P_s approaches the zero, the probability of selecting only the first individual approaches one.

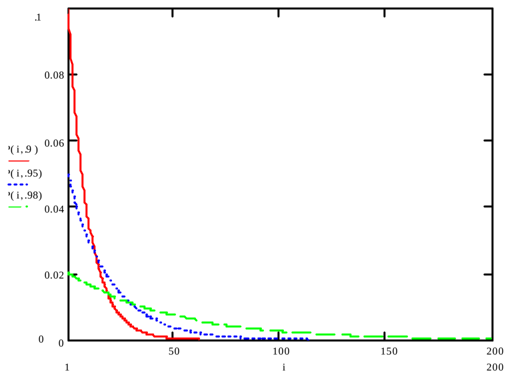

Figure 9. Effect of varying selection pressure on selection probability

Figure 9 illustrates the effect of selection pressure on probability of selection for a population size of 200 and selection pressures of 0.9, 0.95 and 0.98. In this study, a non-uniform selection pressure is used where the sele ction pressure is decreased linearly with the number of generations:

$$P_S = -0.06 \cdot \frac{gen}{gen\_\max} + P_{SO} \qquad (4)$$

An initial selection pressure, P_{s0}, of 0.98 was found to give optimum frontier quality results.

Once probabilities of selection have been assigned, the selection operator is applied. This operator selects designs from the current generation to be in the next generation. Classical selection and *stochastic universal sampling*, Baker's method (1987), were considered in the optimization of the optimization. Baker's method consistently outperformed classical selection. This method "spins" 200 (population size) equally- spaced markers once (vice spinning one marker 200 times) to select 200 for survival and reproduction.

Crossover and mutation are the next genetic operators applied to the selected population of individuals. Once a surviving population is selected, a percentage of these are chosen in pairs at random for crossover. The probability of selection for crossover used in this optimization is 0.51. A cut is made at a random location in the chromosomes of each pair. Design parameters below the cut are swapped between the parents producing new variants or offspring.

A small percentage of individual design parameters (genes) in the selected variants are also chosen randomly to mutate. In mutation, the value of a single design parameter in a single chromosome is replaced with a new value chosen at random. Mutation insures that periodically the entire design space is sampled to look for global optima and avoid premature convergence to a local optimum (exploration versus exploitation). The probability of at least one mutation in a chromosome is called the probability of update (P_{UP}). In this study, a non-uniform mutation algorithm is used. The probability of a mutation is decreased geometrically to zero over the total number of generations in the optimization. The initial probability of update selected for this optimization is 0.06.

When operations on the new generation are complete, the new chromosomes are sent to the ship synthesis model for assessment and the cycle is repeated. The optimization is stopped after adequate convergence to the non-dominated frontier or after 200 generations.

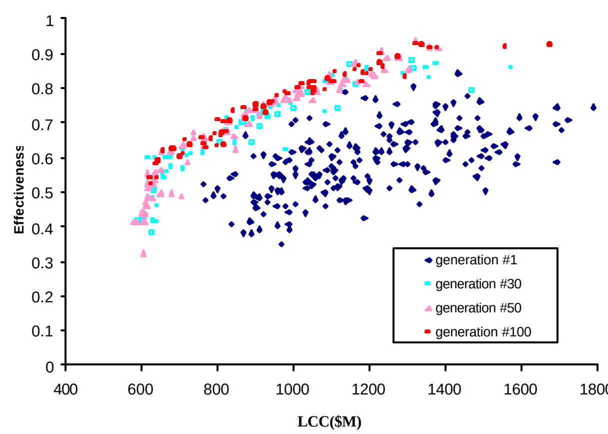

Figure 10. N-D Frontier for DDGx with 200 individuals (feasibl e and infeasible)

NAVAL SHIP APPLICATION

A Multiple-Objective Genetic Optimization (MOGO) was completed for a notional guided missile destroyer (DDGx). The design space for this ship is described in Table 1. Overall mission effectiveness (OMOE) and life cycle cost (LCC) are the objective attributes. The optimization was run for 100 generations with a population of 200 ships. Results are presented in Figure 10. The data points in Figure 10 represent LCC and OMOE values for feasible and infeasible individuals. Generation 1 is a random selection of design parameters. Convergence to a non-dominated frontier can be seen in the evolution from Generation 1 to Generation 50 and finally to Generation 100. Generation 100 results approximate the non-dominated frontier. Figure 11 shows the same results for feasible designs only.

None of these ships can be identified as "the best". Selection of the preferred design is up to the customer, but Figures 10 and 11 provide the customer with important information to make this selection: 1) the engineer can assure the customer with confidence that non-dominated designs have been identified; 2) the non-dominated frontier provides a perspective on the entire design space; and 3) some designs stand out as providing good value given a range of acceptable cost. In this example, Ships A, B, C and D are noteworthy. Data for these ships are provided in Table 2.

Ships A, B and C are non-dominated designs and represent "knees in the curve" or extreme alternatives. The dividing line in Figure 11 between Ship B and Ship C separates one shaft ships from two shaft ships. Ship C is the feasible ship with the highest OMOE. Ship A is the low-end non-dominated ship. Ship B is at a "knee in the curve" and can be considered a "best buy", particularly if cost is limited. Ship D is a dominated design and although it costs more, it does not give more effectiveness for the money than Ship C.

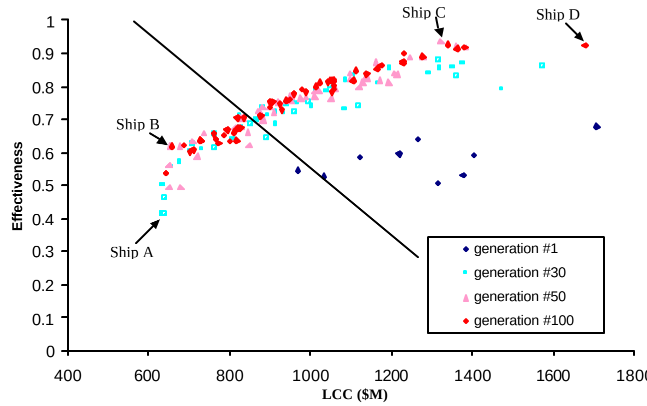

Figure 11. N-D Frontier for DDGx (feasible only)

Table 2. Select Non-dominated Feasible Designs

	Ship A	Ship B	Ship C	Ship D
LBP (ft)	422.8	440.4	520.9	588.5
Beam (ft)	52.5	59.9	55.5	75.0
D10 (ft)	36.8	40.0	35.9	52.6
Draft (ft)	17.5	21.2	19.8	24.2
Displacement (lton)	5524.2	6713.8	8899.2	16612
Shafts	1	1	2	2
Range (nm)	4000	5000	7000	10000
Sustained Speed (knt)	27.1	27.0	31.0	29.2
Stability (GM/B)	.108	.129	.101	.111
Generators (kW)	3/3000	3/3000	3/3000	7/3000
Collective Protection System (CPS)	no	Full	Full	Full
Anti-Air Warfare (AAW) Systems	RAM,SPS-49,CIWS,SDS	ESSM,SM,SPS-49,X-Band radar, Mk92 MFCS	ESSM,SM,SPY-1D, X-Band radar,Mk99 GMFCS	ESSM,SM,SPY-1D, X and S Band radar, GMFCS
Anti-Surface Warfare (ASUW) Systems	5"/54 w/ERGM,GFCS	Harpoon, 5"/54 w/ERGM,GFCS	Harpoon,AN/SWG-1, VGAS,GFCS	TASM/TMMM,ATWCS ,VGAS,GFCS
Anti-Submarine Warfare (ASW) Systems	1.5m sonar, SSTD, helo haven, SVTT,NIXIE	5m sonar(passive), SSTD, NIXIE, SVTT, helo haven, VLA	5m sonar, SSTD, LAMPS MKIII,NIXIE,SVTT,VLA	5m sonar, SSTD, LAMPS MK3, NIXIE,SVTT,VLA,SQQ-89, LBVDS
Command, Control, Communications & Computers (C4I)	Baseline	Baseline	CEC,JTIDS, digital comm, TADIX/TACINTEL	CEC, JTIDS, digital comm, TADIX/TACINTEL
Mine Counter Measures (MCM)	Degaussing	Degaussing	Mine avoidance sonar, degaussing	Mine avoidance sonar, Remote Minehunting System, degaussing
Naval Surface Fire Support (NSFS)	N-ATACMS, 5"/54 w/ERGM,GFCS	N-ATACMS, 5"/54 w/ERGM,GFCS	VGAS, N-ATACMS, ATWCS	VGAS, N-ATACMS, ATWCS
Strike Systems (STK)	TWCS,TLAMs,UAVs	TWCS,TLAMs,UAVs	ATWCS,TLAMs,UAVs	ATWCS,TLAMs,UAVs
Electronic Warfare (SEW)	SLQ-32V2, DLS	SLQ32V2,DLS	AIEWS,DLS	AIEWS,DLS
Vertical Launch System (VLS) cells	32	64	64	128
Hello hangar / helos	0	0	Yes/2	Yes/2
Crew	108	120	184	266
Follow ship Acquisition Cost ($M)	547.6	596.6	888.6	1242.3
LCC ($M)	644.1	663.5	1349.7	1697.5
OMOE	0.415	0.614	.918	.917

A discussion with the customer might consider the following:

- Ship A represents a low-end alternative. It has good performance in Naval Surface Fire Support (NSFS) with other MOPs at threshold values. It represents the best alternative if acquisition cost is limited to $550M. Most war fighters would not be impressed.
- Ship B is an effective single shaft ship at a reasonable price. Its AAW and ASW systems are much more capable than Ship A and the acquisition cost is still low. It is an excellent choice for a low-end capability/low cost ship.
- Ship C is right on the high-end knee of the curve. It is a very effective. It dominates all other ships found in this optimization. It is a good choice if it is affordable.
- Ship D is not on the non-dominated frontier and is not a good choice.
- Ships between Ship B and Ship C on the frontier may all be excellent choices. There are some soft knees just inside the two shaft region that provide excellent capability and if cost is not a problem, these are excellent choices.

CONCLUSIONS

It is estimated that more than 80 percent of a naval ship's ultimate acquisition cost is locked in during concept design. For a class of ships, this means tens of billions of dollars. An "ad hoc" process for making these critical design decisions is not adequate. Figure 11 appears to be a simple and somewhat intuitive result, but it is not. Without this kind of information, we cannot make responsible decisions.

Key elements addressed by this methodology are:

- It provides a practical method for the ship designer to calculate an Overall Measure of Effectiveness (OMOE) which represents customer requirements and relates ship measures of performance (MOPs) to mission effectiveness. This is an essential prerequisite to a disciplined search of design parameters.
- It includes an efficient method to search design space for non-dominated concepts.
- It provides a consistent format for presenting and trading off a manageable set of dissimilar objective attributes (effectiveness, cost, and risk).

Optimization parameters and operators selected for this design were efficient and effective in generating a non-dominated frontier. The process of selecting these parameters will be the topic of a future paper.

The methodology described in this paper does not replace imagination and experience. It provides a practical tool to manage a complex total-system problem that cannot be managed by experience and intuition alone. It represents essential change in how we do naval ship concept design.

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