# Reengineering the Naval Ship Concept Design Process

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## Abstract

Naval ship concept design is very much an "ad hoc" process. Selection of design concepts for assessment is guided primarily by experience, design lanes, rules-of-thumb, preference and imagination. Objective attributes are not adequately synthesized or presented to support efficient and effective decisions. Attributes are often qualitative, inconsistent, and not provided to design engineers in a format they can use. The design space is very large, non-linear, discontinuous, and bounded by a variety of constraints and thresholds. These problems make a structured search of design space difficult. Without a structured search, there is no rational way to measure the optimality of selected concepts relative to the millions of other concepts that have not been considered or assessed. Responsible decisions cannot be made without this information and perspective.

This paper addresses these problems in the context of a systems approach to naval ship concept design. Multiattribute value theory (MAVT) and the Analytical Hierarchy Process (AHP) are used to synthesize an effectiveness function. A Pareto Genetic Algorithm (PGA) searches design parameter space and identifies non-dominated design concepts in terms of cost and effectiveness. Design concepts are presented graphically as points on a non-dominated cost-effectiveness frontier for consideration by decision-makers. A simplified surface-combatant design demonstrates the process.

## Introduction

Despite steady improvement in design tools, and excellent progress in concurrent and systems engineering (Kramer, 1996, and Tibbitts, 1995), naval ship concept design is still very much an "ad hoc" process. Elements missing from this process are:

- A quantitative methodology for synthesizing a manageable set of critical, but dissimilar objective attributes
- An efficient method to search design space for non-dominated concepts based on these attributes
- An effective format to present these non-dominated concepts for rational selection

Critical naval ship objective attributes are mission effectiveness, cost and risk. Each of these overall attributes includes a number of specific attributes or measures such as mission-specific Measures of Effectiveness (MOEs) whose cumulative value must be synthesized in the overall measure.

Effectiveness, cost and risk are dissimilar attributes, and require different units of measure. 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. Manageable implies that only a limited number of attributes can be considered simultaneously. This requires either looking at one piece of the problem at a time, or combining similar objective attributes into an overall measure or index.

Effectiveness and risk are relatively abstract objectives that are sometimes difficult to measure quantitatively. The effectiveness of a few 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. Risk requires a similar treatment, and will be addressed in subsequent work.

MOEs describe mission effectiveness in specific scenarios. Examples of MOEs are conflict duration, territory lost or gained, casualties, and targets destroyed. Measures of Performance (MOPs) define the performance of the ship system independent of mission scenarios. Examples of MOPs are sustained speed, endurance and signatures. Design parameters (DPs) provide the physical description of the ship system. DPs determine MOPs, and MOPs determine MOEs. DPs also determine cost and risk.

Ultimately, a ship design is defined by specifying millions of DPs, in thousands of drawings, and with libraries full of technical specifications and information. Even in its simplest concept form, the definition of a balanced ship design requires many DPs. The functional relationship of these DPs cannot be described in a closed-form set of equations.

A total-system approach to ship design makes an already complex problem more complex. The goal of a total system approach is to optimize the life cycle cost-risk-effectiveness of the total ship system. This system includes the ship and everything outside the ship that either affects it or is affected by it. It usually requires an iterative and interactive process that depends on an effective concurrent engineering organization to produce a true total-system result.

The hierarchy of systems and subsystems included in a total-ship-system is rightly called a "supersystem" (Hockberger, 1996). At the bottom of this hierarchy are the detailed components and characteristics that define the ship. Many lower-level system decisions can be made at their own level or one higher. Others must be determined at the total ship level. Some compromise between global and local optimization is essential to keep the problem manageable. The number of DPs at any level must be kept to the minimum necessary to capture important interdependence. The highest level of optimization should consider only those variables that have a major impact on ship balance. Frequently combat systems, HM&E systems and ship characteristics can be grouped into synergistic packages or suites. This reduces the number of variables that must be managed early in the design process.

The primary objective of the concept design process (as defined here) is to identify non-dominated and feasible concepts for selection by decision-makers based on the objective attributes of cost, effectiveness and risk. Ideally, there should be no bias or preference for particular DPs or MOPs. They are only fundamental and intermediate parameters. Cost, effectiveness and risk are the relevant objective attributes.

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 simple two-objective (cost-effectiveness) problem. 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.

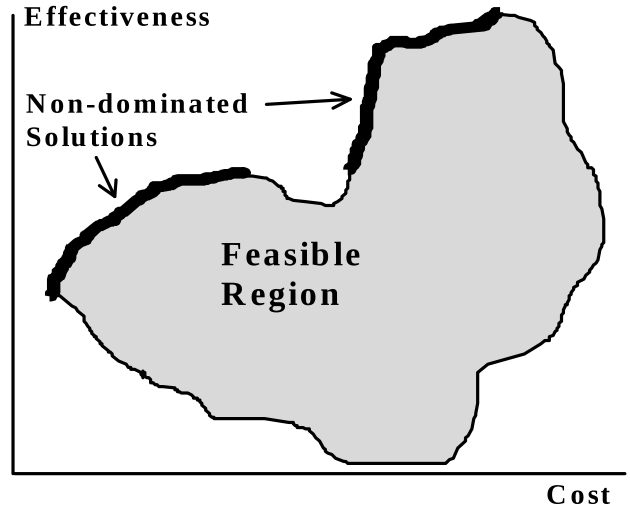


**Figure 1. Two-Objective Attribute Space**

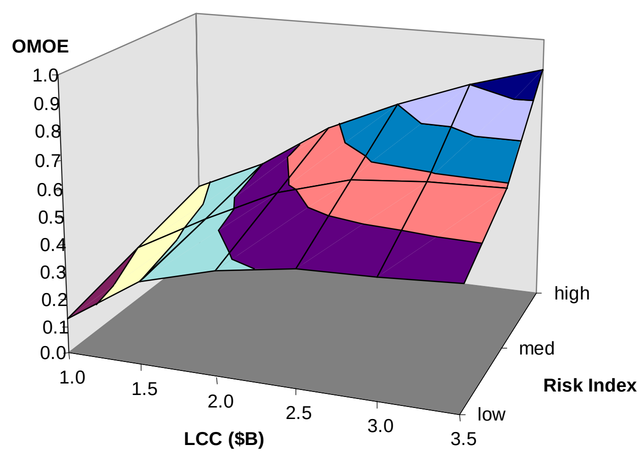


**Figure 2. Three-Objective Attribute Space**

When considering three attributes, the non-dominated frontier is a surface, as illustrated in Figure 2. Points on this surface represent feasible ships, and can be mapped to specific design parameters. With such a surface, the full range of cost-risk-effectiveness possibilities can be presented to decision-makers, "knees in the curve" can be seen graphically, trade-off decisions can be made, and specific design concepts can be chosen for further analysis.

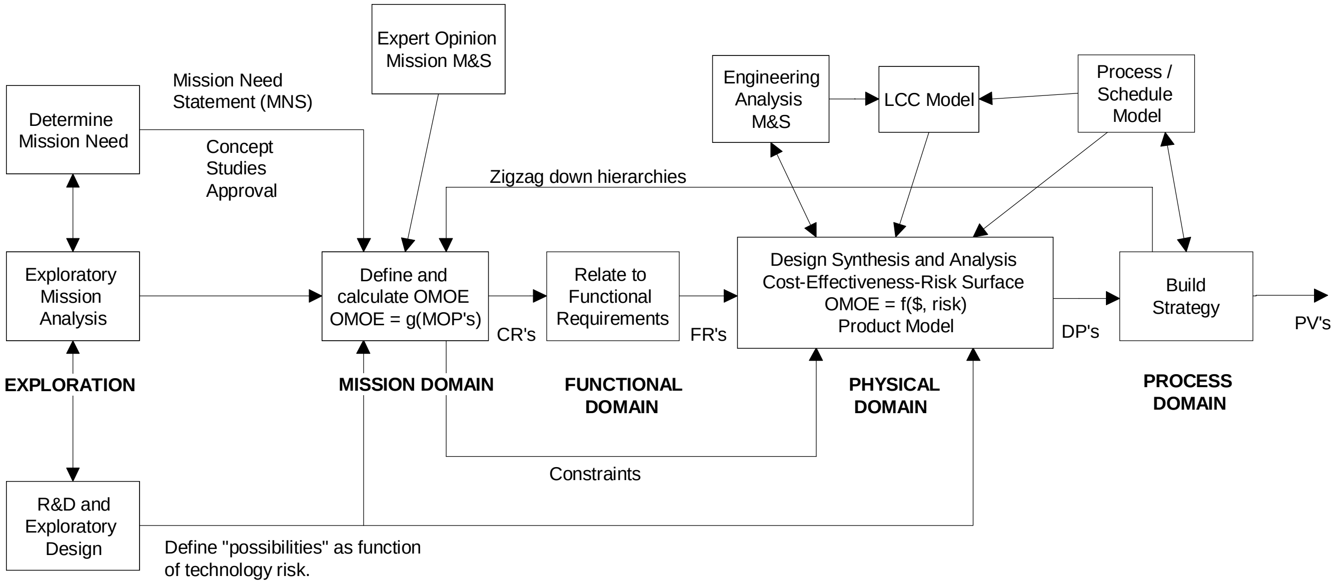


**Figure 3. Notional Concept Design Process**

## Proposed Design Process Framework

It is helpful to think of the design process as a sequential mapping between four domains as shown in Figure 3: 1) the mission or customer domain; 2) the functional domain; 3) the physical domain; and 4) the process domain (Suh, 1990). Decisions made in each domain are mapped into the subsequent domain, moving from "what" to "how" in each mapping, and then zigzagging down hierarchies in each domain as the design is defined in increasing detail. Customer requirements (CRs) are the "what" for the functional domain, functional requirements (FRs) are the "how". FRs are the "what" for the physical domain, design parameters (DPs) are the "how". DPs are the "what" for the process domain, process variables (PVs) are the "how". Results are fed back to the customer, CRs are refined, and the mapping continues. A notional top-level design hierarchy consistent with this scheme is shown in Figure 4.

**Exploration.** The naval ship design process is initiated with the definition of a mission need and direction to begin concept studies, but significant effort precedes this direction.

Exploratory mission analysis provides a description of projected world political/military environments, and maintains a time-phased assessment of the threat and future mission scenarios consistent with defense planning guidance. It determines joint force and naval force structure, identifies future mission deficiencies, and estimates the force level, mix and mission performance required of future ships.

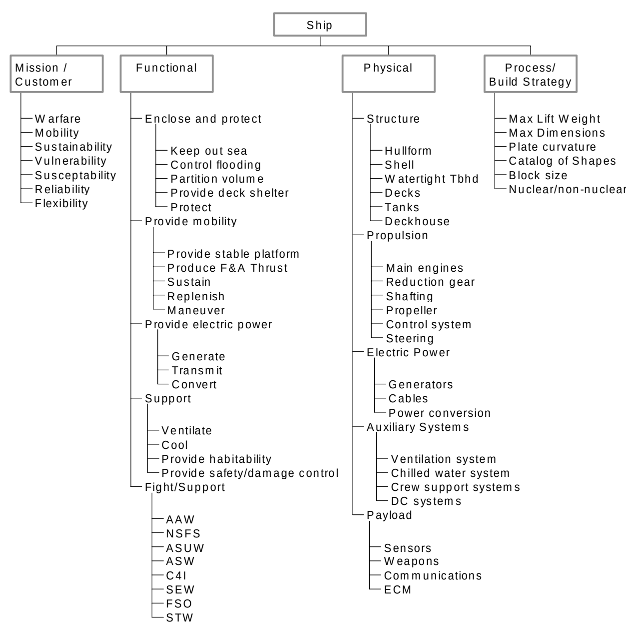


**Figure 4. Notional Top Level Design Hierarchy**

Important products of exploratory mission analysis include the Mission Need Statement (MNS), threat, required operational capabilities (ROCs), projected operational environment (POE), mission scenarios and MOEs. Also important are war-fighting model validation and sensitivity analysis including the identification of critical ship MOPs.

Research, development, technology demonstration, and exploratory design identify, develop and evaluate new systems, technology, and ship concepts. Together with proven systems and concepts these pieces must be assembled into balanced, feasible, and cost-effective ship designs that must satisfy the evolving mission need in an evolving environment. Products of R&D and Exploratory Design include new technology and systems, ship concepts, and a preliminary definition of feasible ship and system performance. Expected performance is described using upper and lower bounds on MOPs. These bounds are a function of technology risk that may be quantified and included as a system attribute.

**Mission Domain.** Customer needs and requirements are determined, and effectiveness is assessed in the Mission Domain. Initial inputs to this domain are the MNS, POE, threat definition and mission scenarios. Customer requirements (CRs) are the output. In this research, CRs are specified in three ways: 1) required operational capabilities (ROCs); 2) performance constraints, goals and thresholds; and 3) an overall mission measure of effectiveness (OMOE) index which defines mission effectiveness as a function of ship MOPs. The definition of a quantitative relationship between mission effectiveness and ship performance in the mission domain is an essential prerequisite to a disciplined search of design parameters in the physical domain. Modeling, simulation and expert opinion are used to define the OMOE as a function of MOPs. Some MOPs are binary, the ship has a capability or it doesn't. Others are continuous, such as sustained speed or endurance.

**Functional Domain.** In the Functional Domain, top level functional requirements might include enclose and protect, provide mobility, support and fight. Consideration of functional requirements is most important when new design solutions or technologies are sought and when paradigms are reevaluated.

**Physical Domain.** Design parameters define the ship in the Physical Domain. The selection, synthesis and balance of DPs determine ship MOPs, and ultimately determine mission effectiveness. Cost and risk are determined as a function of DPs and process variables (PVs).

In this research, a simple ship-synthesis model is used to synthesize and balance designs in the physical domain, and to calculate the first level of ship MOPs. Balance requires that physical and functional constraints are satisfied. A genetic algorithm (GA) is used to search DP space in the physical domain, and to generate and identify concepts on the non-dominated objective attribute frontier. More sophisticated tools, models and simulations can be used later in the design process on selected concepts to refine the designs, demonstrate feasibility, and improve MOP calculations. Analysis results are added to a design knowledge base and applied to update model parametric equations, MOP, cost and risk calculations. This provides a dynamic landscape or environment for the genetic algorithm over the course of the design process. The updated non-dominated frontier is used to reevaluate and adjust earlier top level DP decisions during the design process until further design changes are no longer cost-effective.

**Process Domain.** Critical design parameters must be related to process variables (PVs). These process variables may be synthesized in a build strategy. The build process must be refined at each level of the design hierarchy to insure feasibility and maximize producibility. PVs effect cost and risk.

## Building the OMOE Function

Early in the 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 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: 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 MOP 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 MOEs. 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 (MAUT, Keeney and Raiffa, 1976) and the Analytical Hierarchy Process (AHP, 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 (MAV) 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 a maximum 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 5. System options or alternatives comprise the bottom hierarchy level.

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 (Belton, 1986). 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 MOE(s) 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 5, 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.

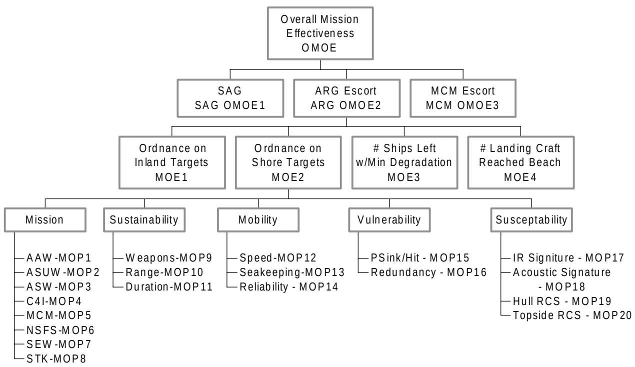


**Figure 5. Notional Top Level OMOE Hierarchy**

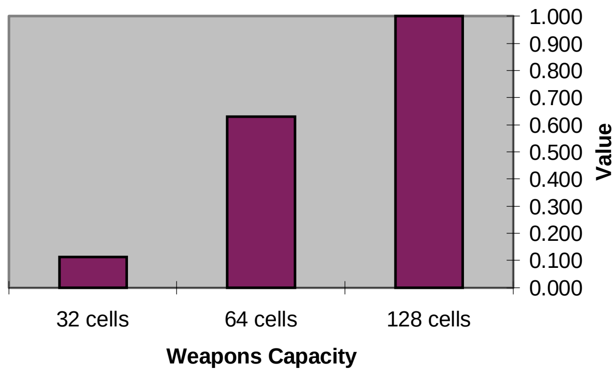


**Figure 6. Discrete MOP Value Function**

Figure 6 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 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 the 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 7 illustrates an example value index for ship sustained speed. Sustained speed is a continuous MOP, not a design parameter. 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.

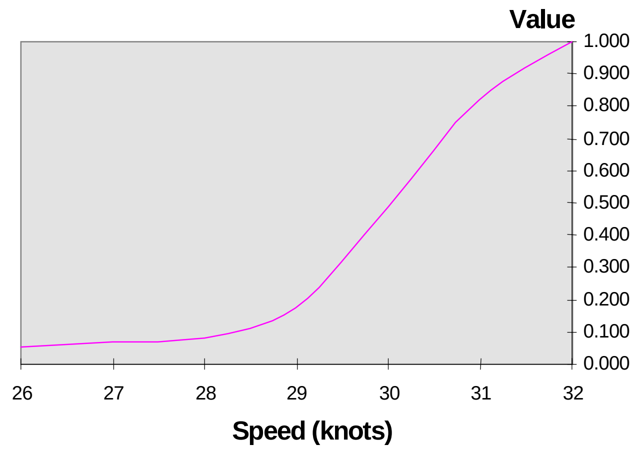


**Figure 7. Continuous MOP Value Function**

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. A maximum eigenvalue approach is used to extract and quantify average relative values and an inconsistency measurement. MOP weights calculated for the Figure 5 notional hierarchy are shown in Figure 8. An OMOE function, OMOE = g(MOP), is derived from these weights and from the MOP value functions.

## Ship Design Synthesis Model

The ship synthesis model used in this research is based on a model originally developed by Reed (1976). Reed's model was based on two earlier codes, DD07 and CODESHIP (CNA, 1971). Reed's model has been improved and updated at MIT for over two decades by a long series of naval officer students and faculty, and specifically for use with a genetic algorithm (GA) by Shahak (1998). It follows the basic process shown in Figure 9.

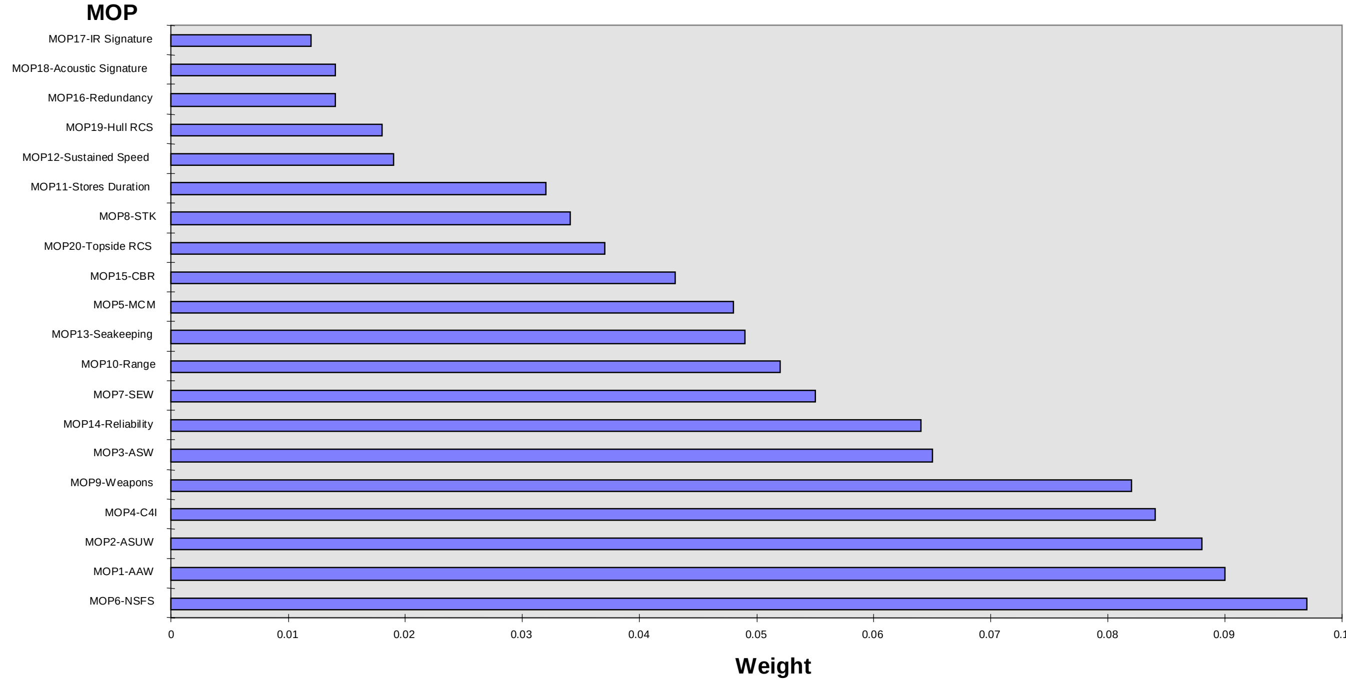


**Figure 8. Measure of Performance (MOP) Weights**

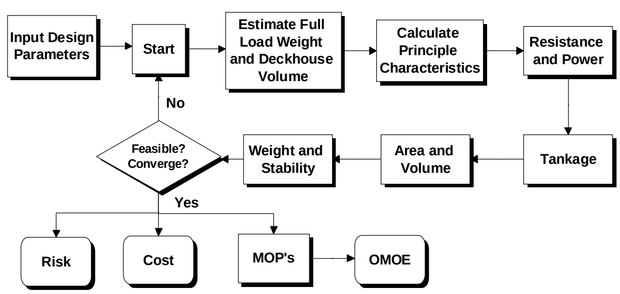


**Figure 9. Ship Synthesis Model Process**

Most recently modules have been added to interface with a payload database, and calculate acquisition cost, seakeeping index and effectiveness. It has also been updated to be more consistent with regression-based equations for weight, area and electric power as they have evolved in ASSET (DTMB, 1990). The current version is self-balancing, and written in FORTRAN 90.

In the GA application of this synthesis model, input design parameters (genes) are specified in a ship design matrix (chromosome). An example is shown in Figure 10. Design parameter descriptions 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 GA uses these results to assess fitness and breed the next generation of ship variants.

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 (Gertler, 1954). Cost is calculated using a modified weight-based algorithm. LCC as defined for this analysis includes only follow-ship acquisition cost, life cycle fuel cost and life cycle manning cost. Seakeeping is assessed using the McCreight Index.

| | | | | |
|---|---|---|---|---|
| $C_P$<br>0.61 | $C_X$<br>0.82 | $C_{\Delta L}$<br>80 | $C_{BT}$<br>2.9 | $C_{D10}$<br>11.1 |
| $C_{RD}$<br>0.2 | Cmanning<br>0.5 | AAW<br>1 | ASUW<br>2 | ASW<br>1 |
| C4I<br>1 | MCM<br>4 | NSFS<br>1 | SEW<br>1 | Weapons<br>1 |
| Range<br>3 | Stores<br>2 | Shafts<br>2 | CPS<br>1 | ICR/GT<br>1 |

**Figure 10. Design Parameter Chromosome**

**Table 1. 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; 15increments |
| 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<br>2 - Area TBMD<br>3 - Area Defense<br>4 - Limited Area Defense<br>5 - Self Defense |
| 9 - ASUW Payload | 1 - Long Range<br>2 - Medium Range<br>3 - Short Range<br>4 - Self Defense |
| 10 - ASW Payload | 1 - Area Domonance<br>2 - Adverse ASW Environment<br>3 - Good ASW Environment<br>4 - Torpedo Defense |
| 11 - C4I Payload | 1 - Advanced<br>2 - Current |
| 12 - MCM Payload | 1 - Limited Clearance<br>2 - Mine Recon<br>3 - Mine Avoidance<br>4 - Limited Mine Advoidance |
| 13 - NSFS Payload | 1 - Advanced (VGAS, NATACMS, ATWCS)<br>2 - Full<br>3 - Medium<br>4 - Minimum |
| 14 - SEW Payload | 1 - Advanced<br>2 - Current |
| 15 - Weapons Capacity (VLS) | 1 - 128 cells<br>2 - 64 cells<br>3 - 32 cells |
| 16 – Range or fuel capacity | 1 - 10000 nm<br>2 - 7000 nm<br>3 - 5000 nm<br>4 - 4000 nm |
| 17 - Stores Duration | 1 - 60 days<br>2 - 45 days |
| 18 - Shafts | 1 or 2 |
| 19 - CPS | 0 (none) or 1 (full) |
| 20 - ICR or GT | 0 (ICR) or 1 (LM2500) |
| | |

## Design Optimization

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

In the simplified design problem presented in this paper, each design variant requires 12.5 seconds on a 200 MHz PC to balance and evaluate. An exhaustive search would assess over ten trillion variants requiring over 4 million years on this machine! Random search does not require a closed-form solution and has advantages of simplicity and insensitivity to discontinuities, but it still requires many iterations, and is computationally impractical for a large design problem. Exponential random search improves the efficiency of random search, but also requires many concept iterations. Genetic algorithms (GA) offer great promise to tackle this difficult problem.

Twenty-five years ago John Holland developed a genetic algorithm to abstract and explain the adaptive processes of natural systems for use in the design of artificial systems (Goldberg, 1989). Since that time, this algorithm has been applied with success to a wide range of problems. Genetic algorithms use models of natural selection, reproduction and mutation to improve a population of individuals or variants based on the “survival of the fittest”, or in the case of Pareto Genetic Algorithms (PGAs), based on the dominance and distribution of variants (Thomas, 1998). GAs are ideally suited to optimizing discontinuous and disjointed functions, and to optimization where no closed-form function exists (or no mathematical function at all, as with experimental data). The robustness of a particular GA depends on its exploration and efficiency qualities. Exploration refers to its ability to master the design space and consistently identify the global optima. Efficiency refers to the effort required to identify the global optima. Robustness implies an effective balance between these qualities. Genetic algorithms are very robust relative to other methods.

Figure 11 illustrates the PGA process used in this application. An initial population of 200 variants is created by random selection of design variables within the design space specified in Table 1. A chromosome with 20 design parameters as in Figure 10 represents each variant. The ship variants defined by these chromosomes are balanced, and evaluated using the ship synthesis model resulting in an assessment of feasibility and objective values (OMOE and LCC) for each variant. Fitness indicates a variant’s relative dominance in the population based on OMOE and LCC. A Goldberg (1989) ranking scheme is used. Variants are sorted into layers of Pareto-dominance. Each layer contains all variants that are dominant to subsequent layers. Variants are sorted with the best variant in the highest layer getting a rank of one and the poorest in the lowest layer a rank of 200 (population size). A geometrically decreasing probability of selection is assigned to each variant based on its rank. Equivalent variants (same dominance layer) are ordered randomly within their layer, probabilities are averaged for variants in the same layer, and the same average value is ultimately assigned to each. Variants are penalized for infeasibility and for similarity to other variants. This minimizes niches and duplicate variants, and forces the selection to spread out over the objective frontier.

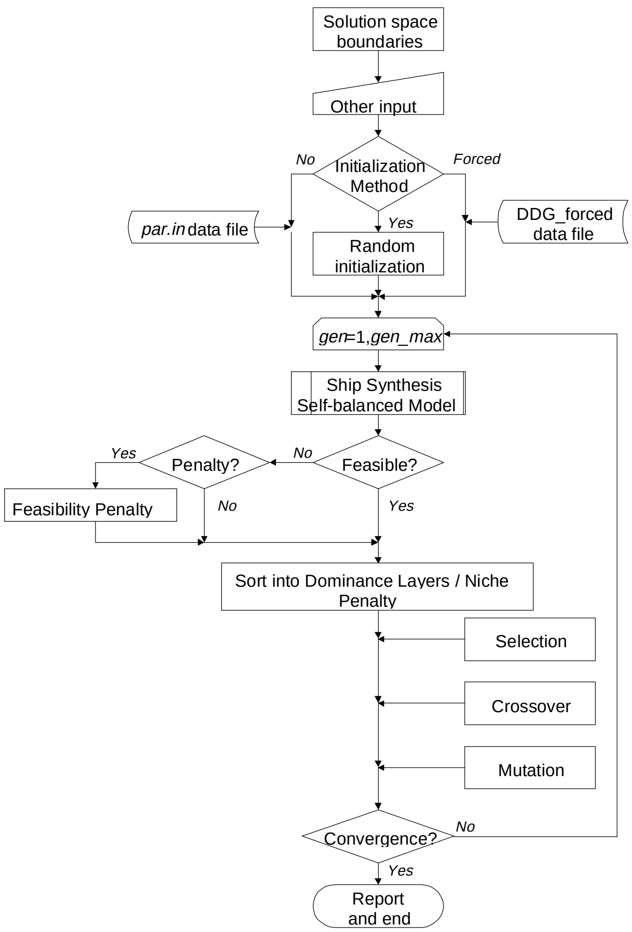


**Figure 11. Pareto Genetic Algorithm (PGA) Process**

Once selection probabilities have been assigned, selection can proceed. A roulette wheel is constructed with 200 segments representing each variant. The area of each segment is equal to the variant selection probability. Baker's (1987) selection method is used. This method "spins" 200 (population size) equally space markers once (vice spinning one marker 200 times) to select 200 variants (some multiple times) for survival and reproduction.

Once a surviving population is selected, 25 percent of these are chosen in pairs at random for crossover. 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. A small percentage of individual design parameters (genes) in the selected variants are chosen randomly to mutate. In mutation, the value of a single design parameter is replaced with a new value chosen at random. After these operations are completed, new variants in the new population are evaluated and the process cycles until convergence. Each cycle defines a new generation.

Compared to other optimization techniques, genetic algorithms are particularly well suited for generating a Pareto-optimal frontier because they improve the fitness of a population of concepts simultaneously. By penalizing for niching, this population spreads out over non-dominated values of the objective attributes, and ultimately defines the Pareto-optimal frontier.

## Surface Combatant Design

A simple surface-combatant concept design is used to evaluate and demonstrate this design methodology. A Mission Need Statement, Required Operational Capabilities (ROCs) and mission scenarios were developed for a notional Land Attack Surface Combatant. A group of warfare experts consisting of MIT naval officer students and faculty were briefed on this mission need, and an effectiveness hierarchy similar to Figure 5 was developed. Measures of Effectiveness were identified for each of three critical mission scenarios: 1) Surface Action Group (SAG); 2) Amphibious Readiness Group (ARG) escort; and 3) Mine Counter Measures (MCM) Group escort. Ship MOPs were identified for each MOE. Goals and thresholds were set for all MOEs and MOPs. The AHP was applied using questionnaires and group discussion. AHP results were used to build an OMOE function. Typical MOP value functions and MOP weights are shown in Figures 6 through 8.

Once the OMOE function was determined, critical design parameters to be varied were selected, and structured as a GA chromosome. These DPs included hull form parameters, payload packages to achieve various levels of warfare area performance, ship endurance, number of shafts, use of a Collective Protection System (CPS), propulsion gas turbine selection, and a manpower reduction factor.

**Table 2. Select Non-dominated Feasible Variants**

| | 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 |
| GM/B | .108 | .129 | .101 | .111 |
| Generators/kW | 3/3000 | 3/3000 | 3/3000 | 7/3000 |
| CPS | no | yes | full | full |
| AAW | 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 |
| ASUW | 5"/54 w/ERGM,GFCS | Harpoon, 5"/54 w/ERGM,GFCS | Harpoon,AN/SWG-1,VGAS,GFCS | TASM/TMMM, ATWCS,VGAS,GFCS |
| ASW | 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 |
| C4I | Baseline | Baseline | CEC,JTIDS, digital comm, TADIX/TACINTEL | CEC, JTIDS, digital comm, TA-DIX/TACINTEL |
| MCM | Degaussing | Degaussing | Mine avoidance sonar, degaussing | Mine avoidance sonar, Remote Minehunting System, degaussing |
| NSFS | N-ATACMS, 5"/54 w/ERGM,GFCS | N-ATACMS, 5"/54 w/ERGM,GFCS | VGAS, N-ATACMS, ATWCS | VGAS, N-ATACMS, ATWCS |
| STK | TWCS,TLAMs,UAVs | TWCS,TLAMs,UAVs | ATWCS,TLAMs,UAVs | ATWCS,TLAMs,UAVs |
| SEW | SLQ-32V2, DLS | SLQ32V2,DLS | AIEWS,DLS | AIEWS,DLS |
| VLS cells | 32 | 64 | 64 | 128 |
| Hello hangar / helos | 0 | 0 | Yes/2 | Yes/2 |
| Crew | 108 | 120 | 184 | 266 |
| Follow ship Acquisition Cost ($M) | 547.6 | 656.6 | 888.6 | 1242.3 |
| LCC ($M) | 628.3 | 943.5 | 1319.7 | 1867.5 |
| OMOE | 0.2296 | .4627 | .7523 | .9562 |

Ship manning was calculated based on historical data and reduced by a manpower reduction factor. Weight and cost for automation was increased consistent with the manpower reduction. Weight, area and power were specified for each payload package. Chromosome DPs are described in Table 1. Other DP's were held constant for all designs.

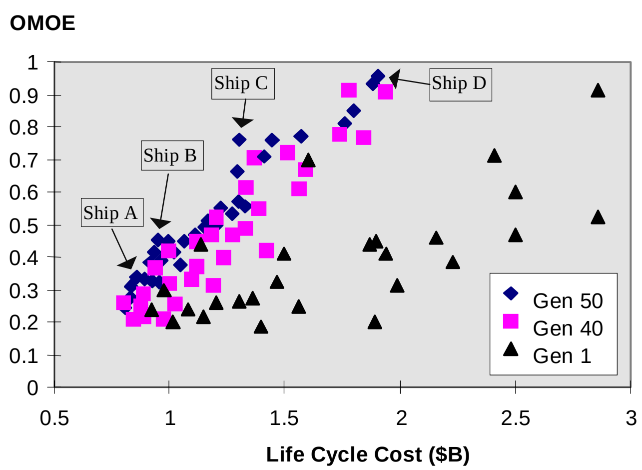


**Figure 12. OMOE/LCC Frontier**

A PGA search was completed for the design space specified in Table 1 using OMOE and LCC as objective attributes. The optimization was run for 50 generations, taking 26 hours on a 200 MHz PC. LCC was defined to include acquisition cost, discounted life cycle fuel cost and discounted life cycle manpower cost. Results of this search are presented in Figure 12. The data points represent LCC and OMOE values for a sample of feasible variants in generations 1, 40 and 50. 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 40 and finally to Generation 50. Generation 50 results approximate the design frontier. Many of these points are non-dominated.

Ships A, B, C and D are non-dominated and represent "knees in the curve". Characteristics for these ships are listed in Table 2. Variants between Ships C and D on the frontier have 2 shafts. Variants below Ship B on the frontier have one shaft. Between Ships B and C, there is a mix of one and two shaft ships. Ship D is the feasible ship with the highest OMOE.

Although non-dominated, none of these ships can be identified as "the best". Selection of the preferred design is up to the customer, but Figure 12 provides the customer with important information to make this selection: 1) the engineer can assure the customer with confidence that non-dominated variants have been identified; 2) the non-dominated frontier provides a perspective on the design space; and 3) some variants stand out as providing good value given a range of acceptable cost. In this example, Ships A, B, C and D are noteworthy.

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 $500-600M. Most war fighters would not be impressed, but it is the best for the money.
- Ship D is the high-end variant. It achieves goal performance in most MOPs. The big cost driver for ships to the right of Ship C is the addition of an S-band radar. This radar has a large ship impact due to its power (<u>seven</u> 3000 kW generators) and cooling requirements. Ship D would be an excellent candidate for an Integrated Power System (IPS), an option which is not included in the present model. As a mechanical drive ship, it is only worth the money if full TBMD capability is essential.
- Ship B is the most effective of the single shaft ships 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 reasonable low-end capability.
- Ship C stands out as a particularly sharp knee in the curve. It has excellent capability in all areas and the price is comparable to a number of variants with much less effectiveness. It is a "Best Buy", and if the acquisition cost is manageable, this would be an excellent choice.

## 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, and its implications are revolutionary. 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).

Essential future work includes:

- Integrate with a design database and product model.
- Extend to later stages of design using a dynamic landscape PGA.
- Validate the AHP/MAVT approach to define and calculate an OMOE.
- Integrate with a process/shipbuilding model.
- Extend to include risk as a third objective attribute.
- Evaluate existing ship designs using this methodology.
- Compare the GA performance to other optimization techniques.

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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