SYM-AM-19-076

PROCEEDINGS
OF THE
SIXTEENTH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

THURSDAY SESSIONS
VOLUME II

Acquisition Research:
Creating Synergy for Informed Change

May 8–9, 2019

Published: April 30, 2019

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

Capital Budgeting and Portfolio Optimization in the U.S. Navy and Department of Defense

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Abstract

This research has the explicit goal of proposing a reusable, extensible, adaptable, and comprehensive advanced analytical modeling process to help the U.S. Department of Defense (DoD) with risk-based capital budgeting and optimizing acquisitions and programs portfolios with multiple competing stakeholders while subject to budgetary, risk, schedule, and strategic constraints. The research covers topics of traditional capital budgeting methodologies used in industry, including the market, cost, and income approaches, and explains how some of these traditional methods can be applied in the DoD by using DoD-centric non-economic, logistic, readiness, capabilities, and requirements variables. Portfolio optimization for the purposes of selecting the best combination of programs and capabilities is also addressed, as are other alternative methods such as average ranking, risk metrics, lexicographic methods, PROMETHEE, ELECTRE, and others. Finally, an illustration at Program Executive Office Integrated Warfare Systems (PEO IWS) and Naval Sea Systems Command (NAVSEA) is presented to showcase how the methodologies can be applied to develop a comprehensive and analytically robust case study that senior leadership at the DOD may utilize to make optimal decisions.

Introduction

The United States Department of Defense (DoD) is always looking for better theoretically justifiable and quantitatively rigorous analytical methods for capital budgeting and portfolio optimization. Specific interest lies in how to identify and quantify the value of each program to the military and optimally select the correct mix of programs, systems, and capabilities that maximizes some military "value" (strategic, operational, economic) while subject to budgetary, cost, schedule, and risk constraints.

This research applies some private-sector and industry best practices coupled with advanced analytical methods and models to help create these methodologies. However, the uniqueness of the DoD requires that additional work be done to determine the concept of value to the military while considering competing stakeholders' needs. We still need a defensible, quantitatively robust concept of military value to use in the modeling.

The purpose of this research is to illustrate and recommend approaches of modeling methodology and development of military value metrics, and how to combine them into a defensible, reusable, extensible, and practical approach within portfolios of programs.

This research specifically showcases how capital budgeting and portfolio optimization methods can be applied in the U.S. Navy as well as across the DoD in general, where multiple stakeholders (e.g., Office of the Secretary of Defense, Office of the Chief of Naval Operations, Congress) have their own specific objectives (e.g., capability, efficiency, cost effectiveness, competitiveness, lethality) as well as constraints (e.g., time, budget, schedule, manpower) and domain requirements (e.g., balancing the needs of anti-submarine warfare, anti-aircraft warfare, missile defense). This first-step research project provides an overview of the methodology employing nominal data variables to illustrate the analytics; it will be followed up by future research with more case-specific examples using actual subject matter expert (SME) data from the Office of the Chief of Naval Operations.

Capital Budgeting

The concept of capital budgeting and portfolio optimization has far-reaching consequences beyond the DoD. Private industry can greatly benefit from the concepts and methodologies developed in this research to apply portfolio optimization to its respective capital investment portfolios. These optimized portfolios are, by definition, the best and most efficient usage of a firm's capital to generate the greatest amount of value to the entire economy while mitigating risks for the organization and keeping limited budgetary and human resource constraints in check. More technically savvy individuals can apply the same methodologies in their retirement and investment portfolios, and portfolio managers can also leverage the knowledge and insights from the research to apply efficient frontier analyses for their clients' invested portfolios.

Portfolio Optimization

A portfolio, by definition, is any combination of two or more assets, projects, capabilities, or options. The whole portfolio is usually assumed to be greater than the sum of its parts, based on outcome performance measures, expected return on investment (ROI), capabilities, and other metrics (Mun, 2015). This assumption is due to the potential risk reduction, leverage, and synergy in terms of lower cost, interoperability, and flatter learning curve when multiple programs or capabilities are combined into a more cohesive portfolio (Mun, 2015, 2016).

In today's competitive global economy, companies in the private sector are faced with many difficult decisions. These decisions include allocating financial resources, building or expanding facilities, managing inventories, and determining product-mix strategies. The U.S. military is no different. The DoD, as a whole, has oftentimes struggled with trying to find the best force mix, or optimal programs that maximize military capabilities within set budgetary, scheduling, and human resource constraints.

Such decisions might involve thousands or millions of potential alternatives. Considering and evaluating each of them would be impractical or even impossible. An optimization model can provide valuable assistance in incorporating relevant variables when analyzing decisions and finding the best solutions for making decisions. These models capture the most important features of a problem and present them in a form that is easy to interpret. Models often provide insights that intuition alone cannot. An optimization model has three major elements: decision variables, constraints, and an objective. In short, the optimization methodology finds the best combination or permutation of decision variables (e.g., which programs or capabilities the DoD should acquire and which projects to eliminate) in every conceivable way such that the objective is maximized (e.g., maximum capabilities, highest expected military value, maximum military utility) or minimized (e.g., cost risk and schedule risk) while still satisfying the constraints (e.g., budget, political, human resources, and other non-economic resources).

Obtaining optimal values generally requires that you search in an iterative or ad hoc fashion. This search involves running one iteration for an initial set of values, analyzing the results, changing one or more values, rerunning the model, and repeating the process until you find a satisfactory solution. This process can be very tedious and time-consuming even for small models, and often it is not clear how to adjust the values from one iteration to the next. Using the proposed modeling process can eliminate the negatives of searching in an iterative or ad hoc fashion.

Research Questions and Objectives

The proposed research attempts to answer the following research questions:

- Can the DoD perform credible and defensible portfolio optimization on capabilities and programs?
- How are military-based definitions of value created and used in developing optimal portfolios?
- What are the best approaches and algorithms that are most amenable to defense acquisition portfolios?

The proposed modeling methodology and process to be developed has the following objectives:

- Create and model multiple-objective optimization models based with competing stakeholders.
- Develop models based on the integrated risk management (IRM) methodology where Monte Carlo risk simulation methods will be employed to analyze risks and uncertainties in the portfolio's inputs.
- Optimize the portfolio of options (i.e., given a set of projects, programs, acquisition, or capability options with different costs, benefits, capabilities, and uncertainties, helps identify which programs or capabilities should be chosen given constraints in budget, schedule, and capability requirements, all the while considering various viewpoints from different stakeholders, including Navy leadership, field commanders, and technical engineering, and economic and strategic points of view).

Consider that, to maintain a high level of competitiveness, corporations in the private sector need to continually invest in technology, research and development (R&D), and other capital investment projects. But resource constraints require organizations to strategically allocate resources to a subset of possible projects. A variety of tools and methods can be used to select the optimal set of technology projects. However, these methods are only applicable when projects are independent and are evaluated in a common funding cycle. When projects are interdependent, the complexity of optimizing even a moderate number of projects over a small number of objectives and constraints can become overwhelming. Dickinson, Thornton, and Graves (2001) presented a model developed for the Boeing Company in Seattle to optimize a portfolio of product development improvement projects. The authors illustrate how a dependency matrix (modeling of interdependencies among projects) is applied in a nonlinear integer programming methodology to optimize project selection. The model also balances risk, overall objectives, and the cost and benefit of the entire portfolio. Once the optimum strategy is identified, the model enables the team to quickly quantify and evaluate small changes to the portfolio.

In the U.S. military context, risk analysis, real options analysis, and portfolio optimization techniques enable a new way of approaching the problems of estimating return on investment (ROI) and the risk value of various strategic real options. There are many DoD requirements for using more advanced analytical techniques. For instance, the Clinger-Cohen Act of 1996 mandates the use of portfolio management for all federal agencies. The GAO's 1997 report entitled *Assessing Risks and Returns: A Guide for Evaluating Federal Agencies' IT Investment Decision-Making* requires that IT investments apply ROI measures. DoD Directive (DoDD) 8115.01 (DoD, 2005) mandates the use of performance metrics based on outputs, with ROI analysis required for all current and planned IT investments.

DoDD 8115.bb (2006) implements policy and assigns responsibilities for the management of DoD IT investments as portfolios within the DoD enterprise where it defines a portfolio to include outcome performance measures and an expected return on investment. The DoD's *Risk Management Guidance Defense Acquisition Guidebook* requires that alternatives to the traditional cost estimation need to be considered because legacy cost models tend not to adequately address costs associated with information systems or the risks associated with them (see Mun, Ford, & Housel, 2012).

Literature Review

Portfolio Modeling in Military Applications

Optimization is a rich and storied discipline designed to use data and information to guide decision making in order to produce an optimal, or very close to optimal, outcome. However, "government agencies have been much slower to use these approaches to increase efficiency and mission effectiveness, even though they collect more data than ever before" (Bennett, 2017). For these government agencies, optimization solutions can utilize the large amounts of data from different sources to provide decision makers with alternative choices that optimally meet agency objectives.

Greiner, McNutt, Shunk, and Fowler (2001) correctly stated that standard economic measures such as internal rate of return (IRR), net present value (NPV), and return on investment (ROI) are commonly used in evaluating commercial-based R&D projects to help identify optimal choices. However, such economic measures in their commercial form are of little use in evaluating weapon systems development efforts. Therefore, this paper examines the challenges faced by the DoD in determining the value of weapon systems during the R&D portfolio selection processes.

Burk and Parnell (2011) reviewed the use of portfolio decision analysis in military applications, such as weapon systems, types of forces, installations, and military R&D projects. They began with comparing military and commercial portfolio problems in general and discussing the distinguishing characteristics of the military decision environment: hostile and adaptive adversaries, a public decision process with multiple stakeholders, and high system complexity. Based on their work, the authors observed that the "most widespread prominent feature of these applications is the careful modeling of value from multiple objectives" (Burk & Parnell, 2011). What they found surprising was that "quantitative methods of measuring and valuing risk are surprisingly rare, considering the high level of uncertainty in the military environment" (Burk & Parnell, 2011). Their analysis examined portfolio applications in more detail, looking at how military analysts model portfolio values, weight assessments, constraints and dependencies, and uncertainty and risk.

Davendralingam and DeLaurentis (2015) looked at analyzing military capabilities as a system of systems (SoS) approach. According to the authors, this approach creates significant development challenges in terms of technical, operational, and programmatic dimensions. Tools for deciding how to form and evolve SoS that consider performance and risk are lacking. Their research leveraged tools from financial engineering and operations research perspectives in portfolio optimization to assist decision making within SoS. The authors recommended the use of more robust portfolio algorithms to address inherent real-world issues of data uncertainty, inter-nodal performance, and developmental risk. A naval warfare situation was developed in the paper to model scenario applications to find portfolios of systems from a candidate list of available systems. Their results show how the optimization framework effectively reduces the combinatorial complexity of trade-space exploration by allowing the optimization problem to handle the mathematically intensive aspects of the decision-making process. As a result, the authors concluded that human decision makers can be tasked to focus on choosing the appropriate weights for risk aversion in making final decisions rather than on the mathematical constructs of the portfolio.

Sidiropoulos, Sidiropoulou, and Lalagas (2014) ran a portfolio management analysis with a focus on identifying and assessing current commercial off-the-shelf (COTS) Portfolio Analysis (PA) software products and solutions. *Risk Simulator* was used to develop portfolio models. These models were populated with relevant data and then run through an appropriate number of simulation iterations to assess candidate projects with respect to risk and Expected Military Value (EMV). The examples and models used in this paper discuss Portfolio Management Analysis (PMA) during various stages of project management and systems engineering. The goal for PMA is realized after the entire project design infrastructure is implemented and the end users' instruments are provided for implementation. The authors' intent was to identify "approaches and tools to incorporate PMA net-centric strategies to meet war fighter and business operations requirements, while continuing to maintain current levels of service, ensuring conservation of manpower and meeting infrastructure resource requirements" (Sidiropoulos, Sidiropoulou, & Lalagas, 2014).

Flynn and Field (2006) looked at quantitative measures that were under development to assess the Department of the Navy's (DoN's) portfolio of acquisitions to improve business practices through better analytical tools and models. The authors found that the DoN's time would be better served by shifting its attention from analyzing individual acquisition programs (now studied exhaustively) to analyzing a portfolio of systems as a whole. This approach is similar to the methodology employed as a best practice in the private sector. According to the research, this high-level view provides senior military leaders valuable metrics for measuring risks and uncertainties of costs, capabilities, and requirements. Armed with these metrics, senior leaders can make better choices, among a set of plausible portfolios, to satisfy the Navy's national security objectives. To support their analysis, a subset of the then-current DoN portfolio was selected by financial management and acquisition staff with which to test a methodology of portfolio analysis in the area of Mine Countermeasures, a diverse, representative system of programs. This pilot model was a multi-phase process that included gathering life-cycle cost data for the various systems to be analyzed, establishing a scoring system using subject matter experts to determine how effectively current and future systems match capabilities to requirements, and developing a means to display results by which decision makers can examine risk-reward analysis and conduct trade-offs. The researchers' ultimate goal was to assess military investments using portfolio analysis methodology.

The GAO (1997, 2007) emphasized the approach of optimizing a portfolio mix to manage risk and maximize the rate of return. Although the DoD produces superior weapons, the GAO reported that the department has failed to deliver weapon systems on time, within budget, and with desired capabilities. While recent changes to the DoD's acquisition policy held the potential to improve outcomes, programs continue to experience significant cost and schedule overruns. The GAO was asked to examine how the DoD's processes for determining needs and allocating resources can better support weapon system program stability. To do this, according to the report, the GAO compared the DoD's processes for investing in weapon systems to the best practices that successful commercial companies use to achieve a balanced mix of new products, including companies such as Caterpillar, Eli Lilly, IBM, Motorola, and Procter and Gamble. Based on the reports, the GAO found that to achieve a balanced mix of executable development programs and ensure a good return on their investments, the successful commercial companies the GAO reviewed take an integrated, portfolio management approach to product development. Through this approach, companies assess product investments collectively from an enterprise level, rather than as independent and unrelated initiatives. These commercial entities weigh the relative costs, benefits, and risks of proposed products using established criteria and methods and select those products that can exploit promising market opportunities within resource constraints and move the company toward meeting its strategic goals and objectives. In these firms, investment decisions are frequently revisited, and if a product falls short of expectations, companies make tough go/no-go decisions over time.

Wismeth (2012) noted that the Army has implemented the Army Portfolio Management Solution (APMS) to facilitate collection and analysis of information necessary to prioritize the thousands of IT investments within its portfolio. IT investments are grouped according to the mission capabilities they support: Warfighter, Business, and Enterprise Information Environment Mission Areas, each of which is led by a three- or four-star-level general officer or senior executive.

Janiga and Modigliani (2014) recommended that the DoD foster dynamic and innovative solutions for tomorrow’s warfighter by designing acquisition portfolios that deliver an integrated suite of capabilities. Program executive officers (PEOs) today often focus on executing a dozen similar but independent programs. In contrast, large commercial businesses manage integrated product lines for items ranging from automobiles and electronics to software and health services. The DoD could leverage this model as a basis for constructing portfolios of similar programs that deliver enhanced capabilities in shorter timeframes.

The Institute for Defense Analyses (IDA) prepared a document for the Office of the Director, Acquisition Resources and Analysis, under a task titled “Portfolio Optimization Feasibility Study” (Weber et al., 2003). The objective was to study the feasibility of using optimization technology to improve long-term planning of defense acquisition. The model described in this document is an example of optimization technology that can estimate and optimize production schedules of Acquisition Category I programs over a period of 18 years.

Vascik, Ross, and Rhodes (2015) found that the modern warfighter operates in an environment that has dramatically evolved in sophistication and interconnectedness over the past half century. With each passing year, the infusion of ever more complex technologies and integrated systems places increasing burdens on acquisition officers to make decisions regarding potential programs with respect to the joint capability portfolio. Furthermore, significant cost overruns in recent acquisition programs reveal that, despite efforts since 2010 to ensure the affordability of systems, additional work is needed to develop enhanced approaches and methods. Vascik et al.’s paper discussed research that builds on prior work that explored system design trade-spaces for affordability under uncertainty, extending it to the program and portfolio level. Time-varying exogenous factors, such as resource availability, stakeholder needs, or production delays, may influence the potential for value contribution by constituent systems over the life cycle of a portfolio and make an initially attractive design less attractive over time. Vascik et al. (2015) introduced a method to conduct portfolio design for affordability by augmenting Epoch-Era Analysis with aspects of Modern Portfolio Theory. The method is demonstrated through the design of a carrier strike group portfolio involving the integration of multiple legacy systems with the acquisition of new vessels.

According to DoDD 5100.96 (DoD, 2017), the DoD Space Assessment (PDSA) monitors and oversees the performance of the entire DoD space portfolio. The PDSA, in assessing space-related threats, requirements, architectures, programs, and their synchronization, advises senior DoD leadership and recommends NSS enterprise-level adjustments. It conducts an annual strategic assessment, or Space Strategic Portfolio Review (SPR) when directed, assisted by the DSC and DCAPE, to address space posture and enterprise-level issues and provides the DMAG and the secretary and deputy secretary of defense with results of the analysis, which may include prioritized programmatic choices for space capabilities.

Capital Budgeting and the Value Concept

The Traditional Views

Value is defined as the single time-value discounted number that is representative of all future net profitability. In contrast, the market price of an asset may or may not be identical to its value ("assets," "projects," and "strategies" are used interchangeably). For instance, when an asset is sold at a significant bargain, its price may be somewhat lower than its value, and one would surmise that the purchaser has obtained a significant amount of value. The idea of valuation in creating a fair market value is to determine the price that closely resembles the true value of an asset. This true value comes from the physical aspects of the asset as well as its nonphysical, intrinsic, or intangible aspects. Both aspects have the capability to generate extrinsic monetary value or intrinsic strategic value. Traditionally, there are three mainstream methodologies to valuation, namely, the market approach, the income approach, and the cost approach (see Mun, Hernandez, & Rocco, 2016, for more details). Other approaches used in valuation, more appropriately applied to the valuation of intangibles, rely on quantifying the economic viability and economic gains the asset brings to the firm. There are several well-known methodologies for intangible-asset valuation, particularly in valuing trademarks and brand names. These methodologies apply the combination of the market, income, and cost approaches just described. Although the financial theories underlying these approaches are sound in the more traditional deterministic view, they cannot be reasonably used in isolation when analyzing the true strategic flexibility value of a firm, project, or asset.

Portfolio Optimization

In today's competitive global conditions, the DoD is faced with many difficult decisions. These decisions include allocating financial resources, building or expanding facilities, managing inventories for maintenance, and determining force-mix strategies. Such decisions might involve thousands or millions of potential alternatives. Considering and evaluating each of them would be impractical or even impossible. A model can provide valuable assistance in incorporating relevant variables when analyzing decisions and in finding the best solutions for making decisions. Models capture the most important features of a problem and present them in a form that is easy to interpret. Models often provide insights that intuition alone cannot. An optimization model has three major elements: decision variables, constraints, and an objective. In short, the optimization methodology finds the best combination or permutation of decision variables (e.g., which products to sell and which projects to execute) such that the objective is maximized (e.g., in revenues and net income) or minimized (e.g., in risk and costs) while still satisfying the constraints (e.g., budget and resources).

Obtaining optimal values generally requires that you search in an iterative or ad hoc fashion. This search involves running one iteration for an initial set of values, analyzing the results, changing one or more values, rerunning the model, and repeating the process until you find a satisfactory solution. This process can be very tedious and time consuming even for small models, and it is often not clear how to adjust the values from one iteration to the next.

A more rigorous method systematically enumerates all possible alternatives. This approach guarantees optimal solutions if the model is correctly specified. Suppose that an optimization model depends on only two decision variables. If each variable has 10 possible values, trying each combination requires 100 iterations (102 alternatives). If each iteration is very short (e.g., two seconds), then the entire process could be done in approximately three minutes of computer time.

However, instead of two decision variables, consider six, then consider that trying all combinations requires 1,000,000 iterations (106 alternatives). It is easily possible for complete enumeration to take weeks, months, or even years to carry out (Mun, 2015). To run the analysis, we use the *Portfolio Optimization* tool in the ROV PEAT software application (courtesy of www.realoptionsvaluation.com). In the Portfolio Optimization section of this tool, the individual projects can be modeled as a portfolio and optimized to determine the best combination of projects for the portfolio.

The projects can be modeled as a portfolio and optimized to determine the best combination of projects for the portfolio in the *Optimization Settings* subtab. Analysts start by selecting the optimization method (Static or Dynamic Optimization). Then they select the decision variable type *Discrete Binary* (choose which Project or Options to execute with a go/no-go binary 1/0 decision) or *Continuous Budget Allocation* (returns percentage of budget to allocate to each *option* or *project* as long as the total portfolio is 100%); select the *Objective* (Max NPV, Min Risk, etc.); set up any *Constraints* (e.g., budget restrictions, number of projects restrictions, or create customized restrictions); select the options or projects to optimize/allocate/choose (default selection is *all options*); and when completed, click *Run Optimization*.

Figure 1 illustrates the *Optimization Results*, which returns the results from the portfolio optimization analysis. The main results are provided in the data grid, showing the final *Objective Function* results, final *Optimized Constraints*, and the allocation, selection, or optimization across all individual options or projects within this optimized portfolio. The top left portion of the screen shows the textual details and results of the optimization algorithms applied, and the chart illustrates the final objective function. The chart will only show a single point for regular optimizations, whereas it will return an investment efficient frontier curve if the optional *Efficient Frontier* settings are set (min, max, step size).

Figures 1 and 2 are critical results for decision makers as they allow decision makers flexibility in designing their own portfolio of options. For instance, Figure 1 shows an efficient frontier of portfolios, where each of the points along the curve are optimized portfolios subject to a certain set of constraints. In this example, the constraints were the number of options that can be selected in a ship and the total cost of obtaining these options, which is subject to a budget constraint. The colored columns on the right in Figure 1 show the various combinations of budget limits and maximum number of options allowed. For instance, if a program office in the Navy only allocates $2.5 million (see the Frontier Variable located on the second row) and no more than four options per ship, then only options 3, 7, 9, and 10 are feasible, and this portfolio combination would generate the biggest bang for the buck while simultaneously satisfying the budgetary and number of options constraints. If the constraints were relaxed to, say, five options and a $3.5 million budget, then option 5 is added to the mix. Finally, at $4.5 million and no more than seven options per ship, options 1 and 2 should be added to the mix. Interestingly, even with a higher budget of $5.5 million, the same portfolio of options is selected. In fact, the Optimized Constraint 2 shows that only

$4.1 million is used. Therefore, as a decision-making tool for the budget-setting officials, the maximum budget that should be set for this portfolio of options should be $4.1 million. Similarly, the decision maker can move backwards, where, say, if the original budget of $4.5 million was slashed by Congress to $3.5 million, then the options that should be eliminated would be options 1 and 2. While Figure 1 shows the efficient frontier where the constraints such as number of options allowed and budget were varied to determine the efficient portfolio selection, Figure 2 shows multiple portfolios with different objectives. For instance, the five models shown were to maximize the financial bang for the buck (minimizing cost and maximizing value while simultaneously minimizing risk), maximizing Naval Operations (OPNAV) value, maximizing KVA value, maximizing Command value, and maximizing a Weighted Average of all objectives. This capability is important because depending on who is doing the analysis, their objectives and decisions will differ based on different perspectives. Using a multiple criteria optimization approach allows one to see the scoring from all perspectives. The option with the highest count (e.g., option 5) would receive the highest priority in the final portfolio, as it satisfies all stakeholders' perspectives and would hence be considered first, followed by options with counts of 4, 3, 2, and 1.

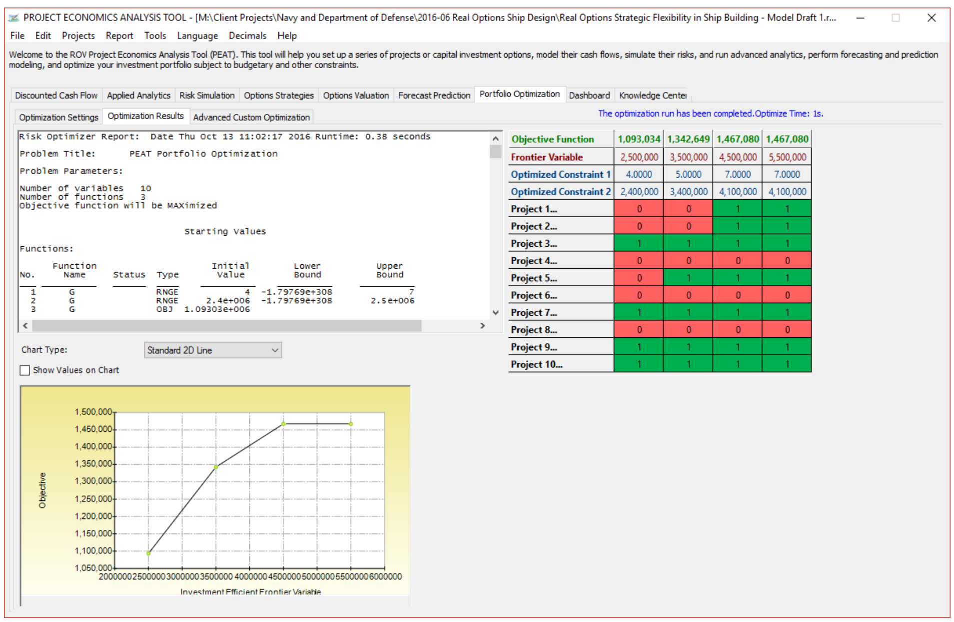

Figure 1. Portfolio Optimization Results

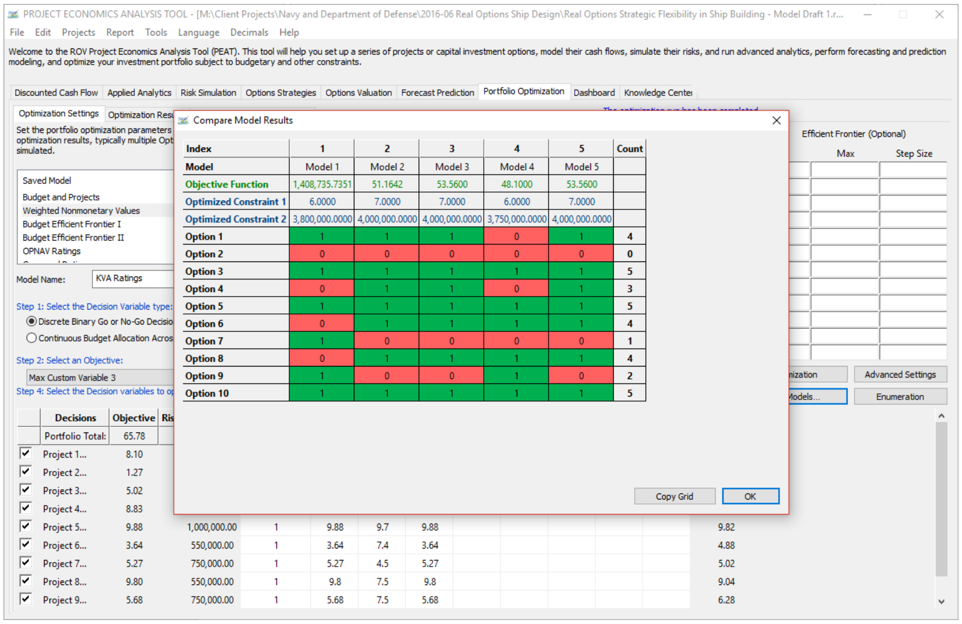

Figure 2. Multi-Criteria Portfolio Optimization Results

Alternative Analytical Approaches

Lexicographic Average Rank for Evaluating Uncertain Multi-Indicator Matrices With Risk Metrics

In many situations, projects are characterized by several criteria or attributes that can be assessed from multiple perspectives (financial, economic, etc.). Each criterion is quantified via performance values (PV), which can either be numerical or categorical. This information is typically structured in a multi-indicator matrix Q. A typical problem faced by a decision maker is to define an aggregate quality (AQ) able to synthesize the global characteristics of each project and then derive the rankings from the best to the worst base-case ranking (Mun et al., 2016). Ranking techniques can be classified as parametric and nonparametric. A parametric technique requires information about decision-maker preferences (e.g., criterion weights). According to Dorini, Kapelan, and Azapagic (2011), some examples of parametric techniques include the ELECTRE methods (Roy, 1968) and PROMETHEE—Preference Ranking Organization Methods for Enrichment Evaluations (Brans & Vincke, 1985). Nonparametric techniques, such as Partial Order Ranking (Bruggemann et al., 1999) and Copeland Scores (Al-Sharrah, 2010), do not require information from the decision maker. In general, all of these techniques are able to produce a ranking of the alternatives from the best to the worst.

Therefore, given a matrix **Q**, the selected procedure generates a ranking, defined as the base-case rank (BCR). As a result of this assessment, for each alternative, a specific rank R_i that considers the multiple perspectives defined by the decision maker is obtained. The set of R_i corresponds to the global evaluation under the first synthetic attribute, defined and named as *base ranking*, and capable of characterizing the alternatives in the base case.

However, in real-life situations, each performance value could be affected by uncertain factors. Several approaches have been presented for analyzing how the uncertainty in the performance values (the input) affects the ranking of the objects (the output; Rocco & Tarantola, 2014; Corrente, Figueira, & Greco, 2014; Hyde, Maier, & Colby, 2004; Hyde & Maier, 2006; Yu et al., 2012). The approaches, based on Monte Carlo simulation, consider each uncertain factor as a random variable with known probability density functions. As a result, the AQ of each alternative and, therefore, its ranking also become random variables, with approximated probability distributions. In such situations, the decision maker could perform probability distribution evaluations. For example, the decision maker could be interested in determining not only what the worst rank of a specific alternative is, but also its probability and volatility (risk evaluation).

In the standard approach, the probability of an alternative being ranked as in the BCR is selected as the synthetic attribute *probability* able to characterize the alternatives under uncertainty.

The stochastic nature of the AQ of each alternative could be further assessed in order to reflect the risk evaluation induced by uncertainty. In this case, it is required to compare several random variables synthesized through their percentiles and statistical moments. Several approaches have been proposed to this end, such as a simple comparison of the expected value, the expected utility (Von Neumann & Morgenstern, 1947), the use of low order moments (Markowitz, 1952), risk measures (Jorion, 2007; Mansini, Ogryczak, & Speranza, 2007; Rockafellar & Uryasev, 2000), the Partitioned Multiobjective Risk Method (PMRM; Asbeck & Haimes, 1984; Haimes, 2009), and the stochastic dominance theory (Levy, 2006), among others.

To consider the risk evaluation induced by uncertainty, each alternative is represented by the third synthetic attribute: *compliance*. This new attribute is based on a simultaneous assessment of several risk measures and some moments of each AQ distribution (Mun et al., 2016).

At this point, each alternative is assessed from three different angles:

1. Multiple decision-making perspectives that include several aspects such as economic, financial, technical, and social (*base ranking*)
2. Uncertainty propagation on performance values (*probability*)
3. A risk evaluation based on the generated probability distribution (*compliance*)

These perspectives are then used for defining a new multi-indicator matrix $\mathbf{Q}_1$ correlated to projects and synthesized using a ranking technique. However, in some situations, decision makers need to select projects following their most-preferred criteria successively. For this reason, an aggregation ranking technique that allows compensation is useless.

Therefore, the final assessment is derived using a combined approach based on a *nonparametric aggregation rule* (using the concept of average rank) for attributes 1 and 2; a simple procedure for score assignment for attribute 3; and a *lexicographic rule*. In addition, a preliminary analysis of the alternatives is performed by using a Hasse diagram (Bruggemann & Patil, 2011). To the best of the researcher's knowledge, this type of combined assessment has not been reported in the literature.

Average Rank Approach

Let P define a set of n objects (e.g., alternatives) to be analyzed and let the descriptors q_1, q_2..., q_m define m different attributes or criteria selected to assess the objects in P (e.g., cost, availability, environmental impact). It is important that attributes are defined to reflect, for example, that a low value indicates low rankings (best positions), while a high value indicates high ranking (worst positions; Restrepo et al., 2008). However, for a given problem or case study, this convention could be reversed.

If only one descriptor is used to rank the objects, then it is possible to define a total order in P. In general, given $x, y \in P$, if $q_i(x) \leq q_i(y)\ \forall i$, then x and y are said to be comparable. However, if two descriptors are used simultaneously, the following could happen: $q_1(x) \leq q_1(y)$ and $q_2(x) > q_2(y)$. In such a case, x and y are said to be incomparable (denoted by $x \| y$). If several objects are mutually incomparable, set P is called a partially ordered set or *poset*. Note that since comparisons are made for each criterion, no normalization is required.

The objects in a poset can be represented by a directed acyclic graph whose vertices are the objects $\in P$, and there is an edge between two objects only if they are comparable and one covers the other, that is, when no other element is in between the two. Such a chart is termed a Hasse diagram (Bruggemann, Schwaiger, & Negele, 1995).

A Hasse diagram is, then, a nonparametric ranking technique and can perform ranking decisions from the available information without using any aggregation criterion. However, while it cannot always provide a total order of objects, it does provide an interesting overall picture of the relationships among objects.

A useful approach to produce a ranking is based on the concept of the average rank of each object in the set of linear extensions of a poset (De Loof, De Baets, & De Meyer, 2011). Since the algorithms suggested for calculating such average ranks are exponential in nature (De Loof et al., 2011), special approximations have been developed, such as the Local Partial Order Model (LPOM; Bruggemann et al., 2004), the extended LPOM (LPOMext; Bruggemann & Carlsen, 2011), or the approximation suggested by De Loof et al. (2011).

From the Hasse diagram, several sets can be derived (Bruggemann & Carlsen, 2011). If $x \in P$,

1. $U(x)$, the set of objects incomparable with x: $U(x) := \{y \in P : x || y\}$
2. $O(x)$, the *down* set: $O(x) := \{y \in P : y \leq x\}$
3. $S(x)$, the successor set: $S(x) := O(x) - \{x\}$
4. $F(x)$, the *up* set: $F(x) := \{y \in P : x \leq y\}$

Then, the following average rank indexes are defined:

a) $LPOM(x) = (|S(x)| + 1) \times (n + 1) \div (n + 1 - |U(x)|)$

b) $LPOMext(x) = |O(x)| + \sum_{y \in U(x)} \frac{p_y^<}{p_y^< + p_y^>}$

where n is the number of objects,

$|V|$ defines the cardinality of the set V,

$p_y^< = |O(x) \cap U(y)|$, $p_y^> = |F(x) \cap U(y)|$, and $y \in U(x)$

Lexicographic Approach

A lexicographic approach allows decision makers to introduce decision rules in which they select more objects impacting on their most-preferred criteria. According to Saban and Sethuraman (2014), when two objects have the same impact on the most-preferred criteria, decision makers prefer the one with the highest impact on the second most-preferred criteria, and so forth. This lexicographic representation models the problems where decision makers strictly prefer one criterion over another or they are managing noncompensatory aggregation (Yaman et al., 2011; Pulido, Mandow, & de la Cruz, 2014).

Finally, decision makers can model their strong preferences over the criteria selected mainly because, after further analysis of the problem, they are not indifferent or only weakly sure about their preferences on the criteria taken into consideration. In other words, they will always prefer one criterion to another without considering criterion weights explicitly.

Risk Metrics and Compliance

Risk metrics are statistical indicators or measurements that allow decision makers to analyze the dispersion (volatility) of certain events or outcomes. Hence, a random variable can be evaluated using statistical moments (e.g., mean, variance, skewness, kurtosis), or risk measurements can be used to analyze extreme values, such as Value at Risk (VaR) and Conditional VaR (Bodie, Kane, & Marcus, 2009; Fabozzi, 2010; Matos, 2007; Mun, 2015).

In decision problems, risk metrics play an important role in analyzing the volatility or stability of a set of options or a portfolio of alternatives, for example, in financial risk management (Chong, 2004), portfolio risk management (Bodie, Kane, & Marcus, 2009), and enterprise risk management (Scarlat, Chirita, & Bradea, 2012), as well as a variety of other areas (Fabozzi, 2010; Szolgayová et al., 2011).

In order to determine how risky an object is and its relationship with other objects, a compliance approach is followed, that is, the definition of a set of rules to guide decision makers (Hopkins, 2011). Several approaches have been proposed for assessing the compliance. For example, Barrett and Donald (2003) propose a stochastic dominance analysis to compare probability distributions before establishing a hierarchy; Boucher et al. (2014) rely on risk metrics and forecasting to adjust models by historical performance; and Zanoli et al. (2014) analyze impacts of risk factors on noncompliance in UK farming.

The compliance approach is more user-friendly for decision making because it allows evaluating whether an object performs according to decision-makers' preferences over defined risk metrics. The basic idea is to dichotomize the risk continuum (Hopkins, 2011). Therefore, the higher the compliance with a defined risk metric, the higher the alignment with the decision-makers' preferences. Similar approaches are considered by Scarlat, Chirita, and Bradea (2012) and Tarantino (2008) relying on key risk indicators.

Multicriteria Analysis

In addition to uncertainty and flexibility, another complexity appears when decision makers need to introduce potentially conflicting decision criteria (quantitative or qualitative, monetary and nonmonetary) into project management, such as legal (taxes, compliance, social responsibility, etc.), environmental (level of pollution, noise, watershed issues, etc.), economic (level of economic growth, national income, inflation, unemployment, etc.), and social (number of employees, value to society, safety and security, community development). Furthermore, those criteria might have different relative importance (RI) or weights.

To address this concern, multicriteria analysis (MCA) has become a powerful mechanism to handle multidimensional problems and to obtain an Aggregate Quality (AQ) supporting the final decision (Bouyssou et al., 2006; Brito, de Almeida, & Mota, 2010). MCA refers to a set of methods, techniques, and tools that help people with their decision problems (description, clustering, ranking, and selection) by simultaneously considering more than one objective or criterion (Roy, 1996; Ghafghazi et al., 2010; Kaya & Kahraman, 2011; Afsordegan et al., 2016).

The Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE; Goumas & Lygerou, 2000; Brans & Mareschal, 2005; Behzadian et al., 2010; Tavana et al., 2013) has been proposed as a proper MCA technique. PROMETHEE methods are based on outranking the relationship *S*. This concept does not determine if the relationship among two alternatives *a* and *b* is a strong preference (*a P b*), weak preference (*a Q b*), or indifference (*a I b*), but instead it establishes if "the alternative *a* is at least as good as the alternative *b*" (Brans & Mareschal, 2005).

PROMETHEE methods are suitable because of their theoretical and practical advantages. For instance, they can associate to each project an AQ index that maximizes the available information in terms of decision-makers' preferences over the criteria selected, as well as the preferences' intensities among alternatives and the nature of each criteria (Bouyssou et al., 2006).

Other methods could also be allowed to handle this multicriteria approach, for example, the ELECTRE methods (Bouyssou et al., 2006), AHP—Analytical Hierarchy Process (Desai, Bidanda, & Lovell, 2012; Saaty, 2013), MACBETH (Cliville, Berrah, & Mauris, 2007; Costa, De Corte, & Vansnick, 2012), and TOPSIS (Kaya & Kahraman, 2011; Sakthivel et al., 2013), to name some. However, these other methods do not clearly state the advantages aforementioned, and the AQ is difficult to interpret.

Capital Budgeting and Portfolio Optimization in the DoD

Operational and Logistics

- **Inherent Availability** (IA). Measures operational percentage in an ideal support environment per design specifications.

  $$IA = \frac{MTBF}{MTBF+MTTR}$$

- **Effective Availability** (EA). Probability a ship's system is available at any instant during the maximum operational period, accounting for all critical failures, reparable and nonrepairable at sea, and preventive maintenance.

  $$EA = 1 - \frac{MTTR}{MTBF+MTTR} - \frac{MDT}{MT} - 0.5\frac{MT}{MTTF}$$

- **Mission Reliability** (MR). Operational Ready Rate (ORR) at the start of a mission compared to its Inherent Reliability (IR).

  $$MR = ORR * IR$$

- **Operational Dependability** (OD). Probability a system can be used to perform a specified mission when desired.

  $$OD = \frac{MTTF}{MTBF}$$

- **Mean Down Time** (MDT), **Mean Maintenance Time** (MMT), **Logistics Delay Time** (LDT), and their combinations.
- **Achieved Availability** (AA), **Operational Availability** (OA), **Mission Availability** (MA)

Financial and Economic

Cost Deterrence and Avoidance. Soft or shadow-revenue (cost savings) over the economic and operational life of the program or system. Milestone A, B, C.

Traditional Financial Metrics. Net Present Value (NPV), **Internal Rate of Return** (IRR), **Return on Investment** (ROI), and other metrics, as long as there are financial and monetary values.

Budget Constraint. FY Budget limitations and probabilities of budgetary overruns.

Total Ownership Cost (TOC) and **Total Lifecycle Cost** (TLC). Accounting for the cost of developing, producing, deploying, maintaining, operating, and disposing of a system over its entire lifespan. Uses **Work Breakout Structures** (WBS), **Cost Estimating Categories** (CEC), and **Cost Element Structures** (CES).

Knowledge Value Added (KVA). **Monetizing Learning Time**, **Number of Times Executed**, **Automation**, **Training Time**, and **Knowledge Content**.

Strategic and Capability

Multiple value metrics can be determined from Subject Matter Experts (SME): Expected Military Value and Strategic Value

Future Weapon Strategy

Capability Measures (CM). Difficult to quantify and needs SME judgment: Innovation Index, Conversion Capability, Ability to Meet Future Threats; Force Structure (size/units), Modernization (technical sophistication), Combat Readiness, Sustainability; Future Readiness (ability to meet evolving threats, ability to integrate future weapons systems)

Domain Capabilities (DC). Portfolios are divided into different domains, and each domain is optimized separately and then combined into the enterprise level and re-optimized; example domains include Coastal Defense, Anti-Air Surface Warfare, Anti-Surface Warfare, Anti-Submarine Warfare, Naval Strike, Multi-Mission Air Control, Sea Control, Deep Strike, Missile Defense, and so on. Constraints can be added whereby each domain needs to have a minimum amount of capability or systems, and within each domain, different “value” parameters can be utilized.

Optimization Application at PEO-IWS and NAVSEA

The following is a case illustration of portfolio optimization. The values and variables shown are nominal and used for illustration only; they should not be, and have not been, used for making any actual decisions. Nonetheless, all that has to be done in any future real-life applications is to change the names of these options and the values. The analytical process and portfolio methodology remain the same.

The Program Executive Office—Integrated Warfare Systems (PEO-IWS) at the DoD engaged a graduate student team from the Naval Postgraduate School (NPS) to conduct a study to apply the Integrated Risk Management (IRM) method to estimate the value stream and cost savings in its Advanced Concept Build (ACB) for Navy ships, and to provide a set of solid recommendations to its multiple stakeholders going forward. Every few years, Navy destroyers will receive ACB updates to the Aegis ship defense system. These updates include basic hardware enhancement but are mostly software patches and updates for their various capabilities (e.g., ballistic missile defense systems, or BMD 5.X; carry-on cryptologic programs, or CCOPS; weather sensor algorithm updates, or Weather NOW; and many others). The issue is that there are more ACB capabilities than there is budget available for them. The cost to implement new ACB updates can be rather high, and sometimes there are several implementation paths or strategic options to consider in each ACB capability. The task is to model each of these approaches and provide an assessment and recommendation of the best path forward, model each capability, and recommend the best combinatorial portfolio that maximizes the utility to the Navy, both monetary (cost savings, KVA analysis, benefits) and nonmonetary (OPNAV leadership requirements, force readiness, systems integration, obsolescence, etc.).

One of the modeling problems is that the DoD is not in the business of selling its products and services, and, consequently, obtaining a solid set of revenues would prove to be difficult. In such situations, one can resort to using KVA analysis or cost savings approaches. KVA allows us to generate market comparables as proxy variables to determine a shadow price and provide comparable *revenues*. Alternatively, cost savings, or the amount of money that would not have to be spent, can similarly be used as proxy for benefits or revenues in a discounted cash flow model. In addition, there might be competing stakeholders and requirements. For instance, BMD 5.X is very expensive, provides low cost savings (monetary benefits), and is not used often (sometimes not used at all between ACB cycles), but OPNAV and the office of the CNO may want this update to maintain readiness for the fleet and see this upgrade as critical. These considerations need to be modeled.

To summarize, this case illustration requires the following assumptions:

- Each of these ACB capabilities was modeled and compared as a portfolio of static NPV, IRR, ROI, and so forth.
- Using the ROV PEAT software, Monte Carlo risk simulations were run on the main inputs based on the *Air Force Cost Analysis Agency Handbook* (*AFCAA Handbook*) and used to interpret the dynamic results.
- Portfolio optimization algorithms were run using budgetary and project constraints, and efficient frontier analyses based on changing budgets were then executed. Finally, OPNAV requirements, KVA valuation, and other non-economic military values were used to run multi-criteria portfolio optimizations.

The following are the parameters of the ACB program under consideration:

- For all models, we assumed a 10-year time horizon for the cost savings (all future savings past Year 10 after discounting will be assumed to be negligible). The discounting base year is 2017 (Year 0 and Capital Investment is required in 2017), whereas immediate savings and short-term benefits and maintenance savings start in Year 1 (2018). This means Year 10 is 2027.
- Table 1 shows the remaining relevant information needed to run the models. All monetary values are in thousands of dollars.

Table 1. Information Needed to Run the Models

Capability Acronym	Savings Now	Short-Term Benefits	Mainten-ance Savings	Capital Cost	Fixed Cost	Operating Cost	OPNAV Value	Command Value	KVA Value
MH60R	$550	$30	$60	$400	$3	$2	8.1	1.2	9.11
CCOPS	$650	$5	$10	$300	$3	$2	1.27	2.5	1.43
Weather	$700	$35	$10	$350	$3	$2	5.02	7.5	5.65
SSDS	$1,000	$50	$20	$600	$3	$2	8.83	4.5	9.93
BMD	$2,000	$100	$20	$1,000	$3	$2	9.88	9.7	11.11
NIFC-CA	$1,000	$10	$20	$550	$3	$2	3.64	7.4	4.09
SPQ-9B	$2,000	$100	$20	$750	$3	$2	5.27	4.5	5.93
CIWS-CEC	$850	$75	$20	$550	$3	$2	9.8	7.5	11.02
RDDL	$1,500	$125	$20	$750	$3	$2	5.68	7.5	6.39
SM-2 BLK	$1,000	$125	$20	$550	$3	$2	8.29	8.5	9.33

- “Savings Now” is the immediate monetary cost savings benefits obtained by implementing the new upgraded system (e.g., lower overhead requirements, reduced parts and labor requirements). This amount is applied in the first year of the cash flow stream only (Year 1 or 2018) as its effects are deemed to be immediate.
- “Short-Term Benefits” is the savings per year for the first 5 years, stemming from reduction in staffing requirements, but these savings are deemed to be reabsorbed later on. Savings apply from 2018 to 2022.
- “Maintenance Savings” is the savings each year for all 10 years starting in 2018 where system maintenance cost is reduced and saved.
- “Capital Cost” is applied in Year 0 or 2017 as a one-time capital expenditure.
- Assume a “Fixed [Direct] Cost” and constant “[Indirect] Operating Cost” per year for all 10 years starting in 2018. The new equipment upgrades will require some fixed overhead cost and operating expenses to maintain. The idea is that these will be less than the total sum of benefits obtained by implementing the capability.
- Value metrics on Innovation, Capability, Time to Intercept, Warfighting Impact, Health, and Execution were compiled with the help of subject matter experts, and these values are weighted and summarized as “OPNAV” (Innovation, Capability, and Execution Health) and “Command” (Time to Intercept and Warfighting Impact) variables. These are weighted average values of multiple subject matter experts’ estimates of the criticality (1–10, with 10 being the highest) of each capability. “KVA” is unit equivalence (this can be multiplied by any market price comparable such

as $1 million per unit or used as-is in the optimization model). These will be used later in the optimization section that follows.

- Tornado analysis was run using ROV PEAT.
- The *AFCAA Handbook* recommendations for uncertainty and risk distributions were used, with the following parameters for simulation:
    - Savings Now and Capital Investment inputs were set using Triangular distributions based on the risk and uncertainty levels perceived by the subject matter experts, or they can be based on a fitting of historical data.
    - Run 10,000 to 1,000,000 simulation trials.
    - The multiple simulated distributions' results were compared using Overlay Charts and Analysis of Alternatives.
- Finally, multiple portfolio optimization models were run in this case illustration using the following parameters:
    - Constraints for the portfolio optimization were a $4,000,000 budget and less than or equal to 7 Opportunities. The portfolio's NPV was maximized.
    - Investment Efficient Frontier was run between $2,500,000 and $5,500,000 with a step of $1,000,000 and no more than 7 Opportunities. The portfolio's NPV was maximized.
    - Another Investment Efficient Frontier was run between $2,500,000 and $5,000,000 with a step of $500,000 and no more than 7 Opportunities. The portfolio's NPV was maximized.
    - Finally, a series of portfolios using the nonmonetary, non-economic military OPNAV, COMMAND, and KVA estimates were applied in the portfolio model but using budgetary constraints. The relevant custom military values and their weighted average values for the portfolio were maximized.

Figure 3 shows the results of a capital budgeting analysis. The 10 programs under consideration were evaluated based on their financial and economic viability. The standard economic metrics such as NPV, IRR, MIRR, ROI, and others are shown. The bar chart provides a visual representation of one of the metrics, whereas the bubble chart shows multiple result metrics at once (e.g., the NPV on the x-axis and the IRR on the y-axis, and size represents NPV with Terminal Value). In this chart, the large-ball programs on the top far right of the chart would be better ranked than smaller-ball projects on the bottom left.

	Economic Results	MH60R	CCOPS	Weather	SSDS	BMD	NIFC-CA	SPQ-9B	CIWS-CEC	RDDL	SM-2 BLK
☑	Net Present Value (NPV)	66,086.45	58,344.30	86,785.26	42,214.01	249,615.61	22,292.73	499,615.61	57,914.81	283,316.41	223,316.41
☑	Net Present Value (NPV) with Terminal Value	83,109.93	59,891.88	88,332.84	46,856.77	254,258.37	26,935.49	504,258.37	62,557.57	287,959.17	227,959.17
☑	Internal Rate of Return (IRR)	36.02%	47.04%	49.72%	31.53%	49.84%	29.20%	93.31%	33.94%	59.65%	58.85%
☑	Modified Internal Rate of Return (MIRR)	26.93%	27.24%	27.80%	25.85%	27.82%	25.50%	31.55%	26.26%	29.07%	29.33%
☑	Profitability Index (PI)	1.17	1.19	1.25	1.07	1.25	1.04	1.67	1.11	1.38	1.41
☑	Return on Investment (ROI)	16.52%	19.45%	24.80%	7.04%	24.96%	4.05%	66.62%	10.53%	37.78%	40.60%
☑	Payback Period (PP)	0.9691	0.6993	0.7277	0.8667	0.7274	0.8255	0.5456	0.9002	0.7036	0.7422
☑	Discounted Payback Period (DPP)	3.2718	0.8741	0.9096	2.8857	0.9093	2.7933	0.6819	2.7933	0.8795	0.9278

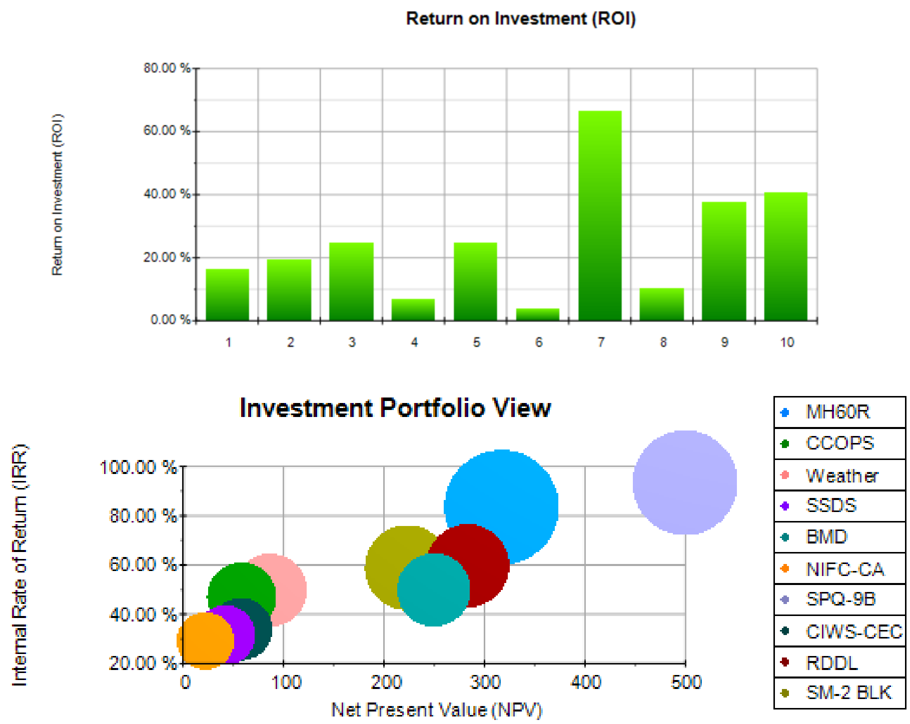

Figure 3. Capital Budgeting Results Comparison

NPV	
Rank	Project
1	SPQ-9B
2	RDDL
3	BMD
4	SM-2 BLK
5	Weather
6	MH60R
7	CCOPS
8	CIWS-CEC
9	SSDS
10	NIFC-CA

ROI	
Rank	Project
1	SPQ-9B
2	SM-2 BLK
3	RDDL
4	BMD
5	Weather
6	CCOPS
7	MH60R
8	CIWS-CEC
9	SSDS
10	NIFC-CA

PP	
Rank	Project
1	SPQ-9B
2	CCOPS
3	RDDL
4	BMD
5	Weather
6	SM-2 BLK
7	NIFC-CA
8	SSDS
9	CIWS-CEC
10	MH60R

Figure 4. Program Rankings

According to the analysis, the top five recommended ACB capabilities based on Static Portfolio Analysis are SPQ-9B, SM-2 BLK, MH60R, BMD, and RDDL. Figure 4 shows a summary of the ranking. Three main distinctions include the following:

- The highest NPV belongs to SPQ-9B.
- Middle range NPVs belong to BMD, RDDL, and SM-2 BLK.
- The lowest range of NPVs belong to MH-60R, CCOPS, Weather, SSDS, NIFC-CA, and CIWS-CEC.

This distinction is generally true for all other metrics. Data from all metrics are compared to create a numerical ranking from key figures. Although not black and white, this linear ranking helps in decision-making comparative analysis. Figure 5 shows the PDF Curve Overlay where all the programs' simulation results are overlaid on top of each other. Only the SPQ-9B has a positive NPV across all trials. This finding is consistent with the results of the ACB Capability Comparison.

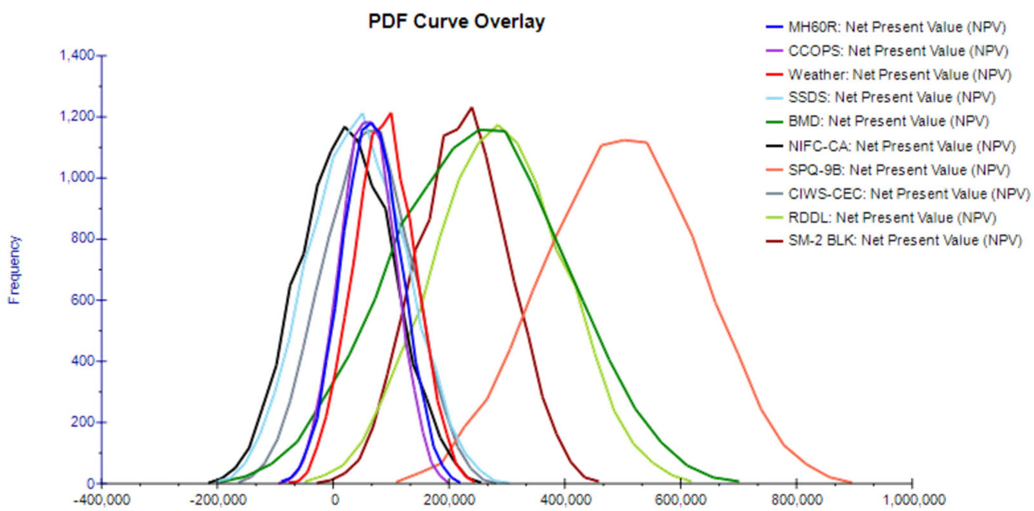

Figure 5. Comparison of Simulated NPV Probability Distributions

Figure 6 shows the probability of success of each program. These are currently based on using NPV but can be applied to any non-economic variable. The definition used here is the probability (PROB) of NPV > 0. Based on the values below, (1 – PROB)%, is the probability of failure.

PEAT NPV Probabilities	
100.00%	**SPQ-9B**
99.94%	**SM-2 BLK**
99.62%	**RDDL**
97.61%	**Weather**
95.41%	**BMD**
89.90%	**MH60R**
89.37%	**CCOPS**
77.58%	**CIWS-CEC**
70.11%	**SSDS**
61.34%	**NIFC-CA**

Figure 6. Economic Probability of Success

Figure 7 shows the results of Portfolio Optimization 1, which assumes a budget of $4 million, Portfolio Size: ≤7, and the goal of Maximizing Portfolio NPV. In this simple optimization, the model recommends excluding CCOPS, SSDS, NIFC-CA, and CIWS-CEC from the portfolio. Figure 8 shows Portfolio Optimization 2, which runs an Investment Efficient Frontier. It assumes a budgetary range of $2.5–$5 million with a step size of $500,000. It also assumes a Portfolio Size ≤7 and the explicit goal of Maximizing Portfolio NPV. Weather, SPQ-9B, RDDL, and SM-2 BLK were consistently in the optimal portfolio. Based on budget, other capabilities were recommended. Above $4.5 million, there is no change to the portfolio.

Objective Function	1,408,736
Optimized Constraint 1	7.0000
Optimized Constraint 2	3,800,000
MH60R	1.00
CCOPS	0.00
Weather	1.00
SSDS	0.00
BMD	1.00
NIFC-CA	0.00
SPQ-9B	1.00
CIWS-CEC	0.00
RDDL	1.00
SM-2BLK	1.00

Figure 7. Portfolio Optimization 1

Objective Function	1,093,034	1,159,120	1,342,649	1,408,736	1,467,080	1,467,080
Frontier Variable	2,500,000	3,000,000	3,500,000	4,000,000	4,500,000	5,000,000
Optimized Constraint	2,400,000	2,800,000	3,400,000	3,800,000	4,100,000	4,100,000
MH60R	0.00	1.00	0.00	1.00	1.00	1.00
CCOPS	0.00	0.00	0.00	0.00	1.00	1.00
Weather	1.00	1.00	1.00	1.00	1.00	1.00
SSDS	0.00	0.00	0.00	0.00	0.00	0.00
BMD	0.00	0.00	1.00	1.00	1.00	1.00
NIFC-CA	0.00	0.00	0.00	0.00	0.00	0.00
SPQ-9B	1.00	1.00	1.00	1.00	1.00	1.00
CIWS-CEC	0.00	0.00	0.00	0.00	0.00	0.00
RDDL	1.00	1.00	1.00	1.00	1.00	1.00
SM-2BLK	1.00	1.00	1.00	1.00	1.00	1.00

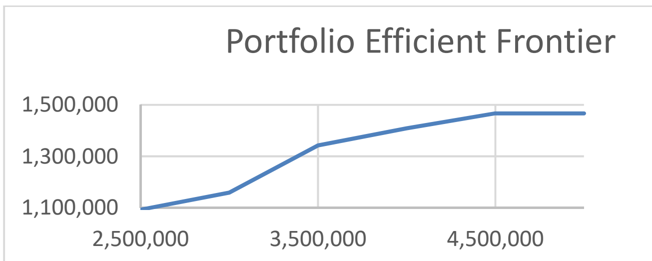

Figure 8. Portfolio Optimization 2

Figure 9 shows the results for OPNAV. Similar results were run on COMMAND and KVA objectives. OPNAV Value is a combination of subject matter experts' assessments of Innovation, Capability, and Execution Health metrics. Command Value is the subject matter experts' assessments of Time to Intercept and Warfighting Impact.

Objective Function	40.04	43.68	49.92	53.56	56.87	60.87	64.51
Frontier Variable	2,500,000	3,000,000	3,500,000	4,000,000	4,500,000	5,000,000	5,500,000
Optimized Constraint	2,450,000	3,000,000	3,450,000	4,000,000	4,500,000	4,950,000	5,500,000
MH60R	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CCOPS	0.00	0.00	0.00	0.00	1.00	0.00	0.00
Weather	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SSDS	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BMD	0.00	0.00	1.00	1.00	1.00	1.00	1.00
NIFC-CA	0.00	1.00	0.00	1.00	0.00	0.00	1.00
SPQ-9B	0.00	0.00	0.00	0.00	0.00	1.00	1.00
CIWS-CEC	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RDDL	0.00	0.00	0.00	0.00	1.00	1.00	1.00
SM-2BLK	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Figure 9. Portfolio Optimization 3 (OPNAV)

Figure 10 shows a combined view where multiple optimizations were run and compared against one another. Additional constraints can be added as needed, but the case illustration applies a $4 million budget, and no more than seven programs can be chosen at a time. In other words, the following monetary and nonmonetary portfolios were optimized:

- Model 1—Maximize Monetary Values (NPV)
- Model 2—Maximize OPNAV Value (i.e., subject matter experts' assessments of Innovation, Capability, and Execution Health)
- Model 3—Maximize All Weighted Average Nonmonetary Values (this is a percentage weighted average of all nonmonetary military values that are part of the OPNAV and COMMAND variables, as well as any other variables of interest to senior leadership)
- Model 4—Maximize Military Command Value (i.e., subject matter experts' assessments of Time to Intercept and Warfighting Impact)
- Model 5—Maximize KVA Value

As seen in Figure 10, these five portfolios are combined into a matrix that shows the count of GO decisions. Clearly, for a decision maker, the lowest-hanging fruits would be to execute the programs starting with the highest count. For instance, Weather, BMD, and SM-2BLK would be considered the highest priority, as, regardless of the point of view and stakeholder under consideration, these programs have always been chosen.

Model	1. NPV	2. OPNAV	3. W/AVG	4. COMMAND	5. KVA	Count
Objective	1,408,735.73	51.16	53.56	48.10	53.56	
Budget Constraint	3,800,000	4,000,000	4,000,000	3,750,000	4,000,000	
Program Constraint	6	7	7	6	7	
MH60R	1.00	1.00	1.00	0.00	1.00	4
CCOPS	0.00	0.00	0.00	0.00	0.00	0
Weather	1.00	1.00	1.00	1.00	1.00	5
SSDS	0.00	1.00	1.00	0.00	1.00	3
BMD	1.00	1.00	1.00	1.00	1.00	5
NIFC-CA	0.00	1.00	1.00	1.00	1.00	4
SPQ-9B	1.00	0.00	0.00	0.00	0.00	1
CIWS-CEC	0.00	1.00	1.00	1.00	1.00	4
RDDL	1.00	0.00	0.00	1.00	0.00	2
SM-2BLK	1.00	1.00	1.00	1.00	1.00	5

Figure 10. Portfolio Optimization 7 (Combined View)

Conclusions and Recommendations

The analytical methods illustrated in the case study apply stochastic risk-based Monte Carlo simulations to generate tens of thousands to millions of scenarios and algorithmic portfolio optimization by applying economic and non-economic military values. The methods are objective, verifiable, replicable, and extensible and can be easily modified to incorporate additional constraints and limitations (e.g., manpower, force mix, minimum capability requirements, domain-specific requirements, cross-domain needs, etc.).

It is recommended that any follow-on research incorporate the following items:

- Apply the methods to actual programs with real-life data and assumptions, with SME estimates.
    - Create new or evaluate existing concepts of military value. These will incorporate
        - Data validity tests using applied statistical tests (from basic linear and nonlinear correlations to econometric models and nonparametric hypothesis tests). These are applied over time to identify if the collected data are valid and actually describe what the researcher wants or expects the data to describe. In other words, are the data collected valid, accurate, and precise?
        - Big data analysis—trying to find patterns and analytical relationships in large data sets.
        - Historical data to perform backcasting (back testing historical data to known historical events).
        - Tweaking and creating lighthouse events and programs in the past, assigning critical value metrics to these events and programs, and using these as guideposts for generating future SME estimates.
        - Creating more exact definitions and methods for SME assumptions that allow for collecting a more objective and defensible data set.
- Utilize multi-objective optimization. Interdependencies and competing stakeholder needs (e.g., Congress versus Office of the Secretary of Defense [OSD] and other external stakeholders) need to be considered. These competing objectives need to be reconciled to determine a Pareto optimal portfolio.
- Evaluate analytical hierarchical processes, multi-objective optimization, and other algorithms and compare the results.
- Within the portfolio, model and account for risks of cost and budget overruns as well as delivery delays using risk-based simulations.

To summarize, based on the research performed thus far, the researcher concludes that the methodology has significant merits and is worthy of more detailed follow-on analysis. It is therefore recommended that the portfolio optimization methodology outlined in this research be applied on a real case study facing the U.S. Navy, using actual data and tracking the project’s outcomes over time. The approach described does not necessarily have to be performed in lieu of existing methods, but in conjunction with them. After all, if the Navy and the DoD are spending hundreds of billions of dollars on capability upgrades, the least that can be done is to have another point of view, an analytically robust and verifiable way of looking at the decision portfolios. The more information decision makers have, the better informed they will be and the better their decision outcomes will be.

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