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Portfolio Optimization of Flexible Ship Options

15 November 2017

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Abstract

This proposed research has the explicit goal of proposing a reusable, extensible, adaptable, and comprehensive advanced analytical modeling process to help the U.S. Navy in quantifying, modeling, valuing, and optimizing a set of ship design options to create a business case for making strategic decisions under uncertainty. Specifically, we look at a portfolio of options onboard multiple ships across different classes, both at the Program Executive Office Ships (PEO-SHIPS) and extensible to the Navy Fleet. This portfolio of options approach will provide tools to allow decision-makers to decide on the optimal flexible options to implement and allocate in different types of ships subject to budget constraints across multiple types of ships. The office of Chief of Naval Operations (CNO) is also interested in applying portfolio optimization to choose among various programs across the various departments and divisions in the Navy, and applications within the CNO community will be addressed further in a follow-on research article.

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List of Acronyms

AAW	Anti-Aircraft Warfare
ACB	Advanced Concept Build
ASUW	Anti-Surface Warfare
AWS	Anti-Submarine Warfare
CBO	Congressional Budget Office
CNO	Chief of Naval Operations
CSBA	Center for Strategic and Budgetary Assessments
CUO	Common Units of Output
DDG	Arleigh Burke Class of Guided Missile Destroyers
DOD	U.S. Department of Defense
FASO	Flexible and Adaptable Ship Options
FSC	Future Surface Combatants
IRM	Integrated Risk Management
IRR	Internal Rate of Return
KVA	Knowledge Value Added
LCS	Littoral Combat Ship
MAS	Modular Adaptable Ships
MIRR	Modified Internal Rate of Return
NAVSEA	Naval Sea Systems Command
NPV	Net Present Value
OFT	Office of Force Transformation
OPNAV	Navy Operations
OSD	Office of the Secretary of Defense
PEO-SHIPS	Program Executive Office, SHIPS
PEO-IWS	Program Executive Office, Integrated Warfare Systems
PG&E	Pacific Gas and Electric
ROI	Return on Investment
ROKI	Return on Knowledge Investment
ROK	Return on Knowledge
ROM	Rough Order Magnitude
ROV	Real Options Valuation
SoS	System of Systems
SME	Subject Matter Expert
VLS	Vertical Launch Systems

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Introduction

This research showcases how portfolio optimization can be applied in the Navy as well as across the Department of Defense (DOD) in general, where multiple competing stakeholders (e.g., Office of the Secretary of Defense, Office of the Chief of Naval Operations, Congress) have 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 subsequent research with more case-specific examples using actual subject matter expert (SME) data from the Office of the Chief of Naval Operations.

The Army Review to Rank 780 Programs by Priority (September 15, 2016), which is a broad strategic review of about 780 Army weapon and equipment programs, is about to get underway to set priorities for the future. The goal of the Strategic Portfolio Analysis and Review, or SPAR, is “very simple,” according to Lieutenant General John M. Murray, the Army’s deputy chief of staff for programs. “We’re going to go through every program we have—780-ish programs in the Army—and model them in a high-end, near-peer scenario with an actual simulation,” he said. “We’re going to try to figure out how to assign some sort of value to that capability based on its contribution to the fight.”

Similarly, 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) present 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, 2012).

Portfolio Optimization

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 decision alternatives that optimally meet agency objectives.

Greiner, McNutt, Shunk, and Fowler (2001) correctly state 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.

Beaujon, Marin, and McDonald (2001) looked at balancing and optimizing a portfolio of R&D projects with a mathematical formulation of an optimization model designed to select projects for inclusion in an R&D portfolio, subject to a wide variety of constraints (e.g., capital, headcount, strategic intent, etc.). There does seem to be general agreement that all of the proposed methods are subject to considerable uncertainty. A systematic way to examine the sensitivity of project selection decisions to variations in the measure of value is developed by the authors.

Real Options Valuation

In order to successfully implement the Surface Navy's Flexible Ships concept, PEO-SHIPS requires a new methodology that assesses the total future value of various combinations of Flexible Ships design features and how they will enable affordable warfighting relevance over the ship's full-service life. Examples of Flexible Ships design features include decoupling payloads from platforms, standardizing platform-to-payload interfaces, allowance for rapid reconfiguration of onboard electronics and weapons systems, preplanned access routes for mission bays and mission decks, and allowance for sufficient growth margins for various distributed systems. This research analyzes the application of strategic Real Options Valuation methodology within the Integrated Risk Management process to assess the total future value of Flexible Ships design features and its use in the Future Surface Combatant Analysis of Alternatives. The explicit goal of the current research is to propose a reusable, extensible, adaptable, and comprehensive advanced analytical modeling process to help the Navy in quantifying, modeling, valuing, and optimizing a set of ship design options to create a business case for making strategic decisions under uncertainty, optimizing various capabilities and requirements for various ship platforms, and selecting the optimal portfolio, sequenced in phases over time, subject to leadership and warfighter needs and requirements within budgetary and personnel constraints.

The Real Options Valuation methodology is a new approach used successfully in various commercial industries to assess the total future value, including benefits and costs, of decisions made when a high degree of uncertainty exists at the time the decisions need to be made. To successfully implement the Surface Navy's Flexible Ships concept, PEO-SHIPS needs a new methodology that assesses the total future value of various combinations of Flexible Ships design features and how they will enable affordable warfighting relevance over the full ship service life. Examples of Flexible Ships design features include the following:

- Decoupling payloads from platforms
- Standard platform-to-payload interfaces
- Rapid reconfiguration
- Preplanned access routes
- Sufficient growth margins for distributed systems

This research analyzes the application of the strategic Real Options Valuation methodology to assess the total future value of Flexible Ships design features, and, if successful, this methodology will be used during the Future Surface Combatant Analysis of Alternatives (AOA).

This research has the explicit goal of proposing a reusable, extensible, adaptable, and comprehensive advanced analytical modeling process to help the U.S. Navy in quantifying, modeling, valuing, and optimizing a set of ship design options to create a business case for making strategic decisions under uncertainty. Specifically, we will look at a portfolio of options onboard multiple ships across different classes, both at the PEO-SHIPS and extensible to the Navy Fleet. This portfolio of options approach will provide tools to allow decision-makers to decide on the optimal flexible options to implement and allocate in different types of ships subject to budget constraints across multiple types of ships. The process will

- create and model multiple objective optimization models based on IRM methodology built on Monte Carlo risk simulation and Real Options Valuation models. These models will identify which Flexible Ship options and Modular Ship Design options have a positive return on investment under uncertainties.
- allow ship design options to be vetted and modeled, where the options will be framed in context.
- optimize the portfolio of options (i.e., given a set of Flexible Ship options and Modular Ship Design options with different costs, benefits, capabilities, and uncertainties, clarify which design options should be chosen given constraints in budget, schedule, and requirements).

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Research Process and Layout of the Paper

The remainder of the current research paper is laid out as follows.

Literature Review

This section provides a review of the existing literature in terms of portfolio optimization approaches and needs within the DOD, specifically within the U.S. Navy, and, for comparison, within the commercial industrial sector.

Portfolio Optimization

This section represents the main crux of the research, where the basics of portfolio optimization are reviewed, and a simple travel cost planner example is used to illustrate how quickly a portfolio optimization can become mathematically intractable. Then a case example within the PEO-IWS and NAVSEA domain is illustrated and shows how standard capital budgeting with economic and financial information as well as noneconomic data and information is used in a portfolio.

Conclusions and Recommendations

This final section details our conclusions and recommendations going forward regarding the proposed analytical process, data requirements, analyst/engineer training, and modeling tools.

Appendices

The theory of real options valuation and associated methods is covered in Appendix A. This appendix is included to provide a more comprehensive and stand-alone research article for the reader's convenience. The recommended decision analytics framework is briefly explained. This framework will structure the ROV models and methodology in a way that relates to the various design implementations and facilitates data collection, data analysis, and recommendations, regardless of the design-type alternatives. In addition, the ROV analytical modeling methods are introduced as part of the Integrated Risk Management (IRM) process, where other advanced decision analytical methodologies such as Monte Carlo risk simulation, Knowledge Value Added (KVA), and Portfolio Optimization approaches will also be used.

A quick refresher on how an optimization model can be set up is included in Appendix B to provide an overview of the standard portfolio model settings and requirements.

Literature Review

Portfolio Modeling in Military Applications

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, 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." 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." 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 (2016) 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."

Flynn and Field (2006) looked at quantitative measures that are 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 current DON portfolio was selected by financial management and acquisition staff with which to test a methodology of portfolio analysis in the areas of Mine Countermeasures, a diverse, representative system of programs. This pilot model is 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, in accordance 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. The companies GAO reviewed have found that effective portfolio management requires a governance structure with committed leadership, clearly aligned roles and responsibilities, portfolio managers who are empowered to make investment decisions, and accountability at all levels of the organization. In contrast, the DOD approves proposed programs with much less consideration of its overall portfolio and commits to them earlier and with less knowledge of cost and feasibility. Although the military services fight together on the battlefield as a joint force, they identify needs and allocate resources separately, using fragmented decision-making processes that do not allow for an integrated, portfolio management approach like that used by successful commercial companies. Consequently, the DOD has less assurance that its investment decisions address the right mix of warfighting needs, and it starts more programs than current and likely future resources can support, a practice that has created a fiscal bow wave. If this trend goes unchecked, Congress will be faced with a difficult choice: pull dollars from other high-priority federal programs to fund DOD acquisitions or accept gaps in warfighting capabilities.

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.

According to Botkin (2007), government agencies and the Department of Defense require decision-support tools when making funding decisions regarding portfolios of programs or projects. Government agencies have had some success in applying Project Portfolio Management (PPM) when choosing among potential programs; however, once programs are underway, financial managers routinely face funding optimization decisions similar to those of private-sector stock market portfolio managers. While private-sector portfolio managers rely on "stock-price" based financial portfolio analysis to aid decision-making, government financial managers lack an equivalent "stock-price" metric for program or project performance. Botkin's (2007) research suggests the government's Earned Value Management System (EVMS) metrics may be used to generate a suitable proxy with which financial portfolio analysis can be conducted. From this analysis, risk and return trade-offs can be quantified and used when making portfolio decisions. An example using representative EVM data is presented in Botkin's work. Recommendations on the possible applicability and limitations of the technique are discussed.

The Office of Naval Research (ONR) is responsible for defining and sponsoring the R&D necessary to support both the current and future requirements of the Navy and Marine Corps. Silberglitt et al. (2004) and Silberglitt and Sherry (2002) note that to accomplish this mission, the ONR must fund a broad spectrum of research, ranging from basic research needed to open up new options for the long-term, to very near-term advanced technology development to support the current fleet. ONR must make its R&D funding decisions in the presence of uncertainty (uncertainty in required capabilities, uncertainty in performance requirements, and uncertainty in the feasibility of a technology or R&D approach). Silberglitt's report described the adaptation of an R&D portfolio management decision framework recently developed by RAND.

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 (PEO) 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.

Jocic and Gee (2013) provided a comparison of space services delivered by multiple systems in a portfolio that allows a normalized valuation of disparate system features and can be visualized via a three-dimensional graph consisting of capability, cost, and schedule axes. Portfolio optimization is attained by being within the efficient performance frontier in the cost-capability plane, staying within the budgetary constraints in the cost-schedule plane, and decreasing the likelihood of a capability gap in the schedule-capability plane. The desired portfolio capability is derived from the conflict scenario outcomes that are generated through military utility analysis.

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'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 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 (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.

Portfolio Applications in Industry

Dunlop (2004) studied how the amount of wind power capacity in Europe and the U.S. was growing rapidly and becoming increasingly attractive to institutional private equity investors. The author applied modern portfolio theory and the capital asset pricing model to wind farms to discover if the model can be successfully adapted to the wind power sector and if geographical diversification would reduce production volatility. By substituting stock return data with wind power production data, he found that beta can be a useful tool in risk measurement for wind farm selection. He also found that up to 30% of production risk can be diversified away in a practical portfolio to smooth cash flow returns.

According to Haq, Gandhi, and Bahl (2012), for many firms, advanced physical portfolio optimization can provide ways to grow earnings and improve overall margins. Energy companies, including producers, suppliers, or merchant traders of gas, power, oil, or chemicals, that are looking to improve revenues should manage their businesses using a systematic market-based approach that treats all assets in the business—physical assets, term contracts, transport or storage leases, and positions—as an integrated portfolio. The key concept in advanced physical portfolio optimization is that the value of a business should be denominated by the value of the portfolio as a whole and by how the portfolio is managed. The major benefit of advanced physical portfolio optimization is that it improves the management of the overall business at the lowest level of granularity. Advanced physical portfolio optimization provides recommended transactions to maximize profit within asset and contractual constraints.

Yang, Lin, Chang, and Chang (2011) discussed the portfolio selection for military investment assets based on semi-variance as a measure of risk. In this paper the researchers propose a new definition of military investment assets for portfolio selection. Based on the new definition, a semi-variance model is provided. In order to give efficient portfolios to the risk model, the heuristic algorithms are proposed to solve the portfolio selection problem which is otherwise hard to solve with the existing algorithms in traditional ways. In addition, a measure of risk including cardinality constraints is provided for the portfolio selection problem. The cardinality constraints intensify the compatibility of the risk model in a portfolio problem. One numerical example of weighted allocations taking different risk values is also given to illustrate the quantitative idea for the decision-maker in military investment assets.

Setter and Tishler (2007) noted that an ever-growing share of defense R&D expenditures is being dedicated to the development and fielding of integrative technologies that enable separate individual systems to work in a coordinated and synergistic fashion as a single system. The researchers explore the optimal defense budget allocation to the development and acquisition of weapon systems and to the development of integrative technologies. They develop a suitable optimization framework, and then use it to derive the optimal budget allocation and analyze its properties. Finally, they use U.S. defense budget data to calibrate the parameters of the model and provide a quantitative measure for the apparent U.S. military supremacy.

Military applications are producing massive amounts of data due to the use of multiple types of sensors on the battlefield. Yang, Yang, Wang, and Huang (2016) investigated the weapon system portfolio problem with the valuable knowledge extracted from these sensor data. The objective of weapon system portfolio optimization is to determine the appropriate assignment of various weapon units, which maximizes the expected damage of all hostile targets, while satisfying a set of constraints. Yang et al. (2016) present a mixed integer nonlinear optimization model for the weapon system portfolio problem. In order to solve this model, an adaptive immune genetic algorithm using crossover and mutation probabilities that are automatically tuned in each generation is proposed. A ground-based air defensive scenario is introduced to illustrate the feasibility and efficiency of their proposed algorithm. In addition, several large-scale instances that are produced by a test-case generator are also considered to demonstrate the scalability of the algorithm. Comparative experiments have shown that their algorithm outperforms its competitors in terms of convergence speed and solution quality, and it is competent for solving weapon system portfolio problems under different scales.

Girotra, Terwiesch, and Ulrich (2007) noted that understanding the value of a product development project is critical to a firm's choice in project portfolio selection. The value of a project to a firm depends not only on its properties but also on the other projects being developed by the firm. This is due to interactions with the other projects that address the same consumer need and require the same development resources. In their study, the authors investigated the structure and significance of these portfolio-level project interactions using a pharmaceutical industry data set. The study exploited the natural experiment of a product development failure to give a measure of the value of a drug development project to a firm. It then explained the variance in the value of projects based on interactions with other projects in the firm's portfolio.

Johannessen (2015) studied the use of real options and portfolio optimization to improve the quality of the information obtained in the decision-making process and to optimize the project selection for wind power portfolios. The model developed in this thesis was applied to TrønderEnergi's investment portfolio. The projects considered were located in Central Norway.

Brown and Anthony (2011) noted how Pacific Gas and Electric (PG&E) was able to triple its innovation success rate by promoting a portfolio mind-set. According to the authors, P&G communicates to both internal and external stakeholders that it is building a varied portfolio of innovation approaches, ranging from sustaining to disruptive ones. PG&E also deploys portfolio-optimization tools that help managers identify and kill the least-promising programs and nurture the best bets. These tools create projections for every active idea, including estimates of the financial potential and the human and capital investments that will be required. Some ideas are evaluated with classic net-present-value calculations, others with a risk-adjusted, real options approach, and still others with more qualitative criteria. Although the tools assemble a rank-ordered list of projects, P&G's portfolio management isn't, at its core, a mechanical exercise; it's a dialogue about resource allocation and business growth building blocks. Numerical input informs but doesn't dictate decisions.

According to a paper by Gurgur and Morley (2008), Dennis Garegnani, Director of FO&S, Lockheed Martin Space Systems, writes: “The optimization model developed for our team has made substantial contributions to the long-term effectiveness of our organization. Up until now, capital allocation decisions had been made largely based on qualitative, tacit knowledge held by various decision-makers within the department and through a painstaking and argumentative review process. Adding this quantitative aspect to our investment strategy has undoubtedly benefited the department over the long term and in some immediate ways as well.” Garegnani further adds that “having the model at Lockheed Martin’s disposal has added another level of credibility to the department among its peers. Organization of past financial performance data to predict and control future financial performance has long been needed and the model has addressed this issue as well. Watching the correction and evolution of the model to match our needs has been extraordinarily constructive for the entire department. Simply put, the optimization model has been a huge success and directly affects our productivity and ability to deliver positive results. It has already been recognized as a best practice” (Gurgur & Morley, 2008).

As further testimony to the usefulness of portfolio optimization, in ExxonMobil’s 2015 Summary Annual Report, the company states that “capturing the highest value for our products combined with our relentless focus on operational excellence, disciplined cost management, selective investments, and portfolio optimization generates superior shareholder returns.”

Another example of the application of portfolio optimization in industry is provided by Kellogg’s Global CMO, Mark Baynes, in his statement that portfolio optimization “really [provides] the ability to prioritize brands in our investments against ensuring that our portfolio spending remains relative and competitive against each of the markets where we're investing” (Lazar, Bryant, Baynes, & Dissinger, 2011). Additionally, Zacks Equity Research (2015) attributed DuPont's higher earnings in the fourth quarter of 2014 to the company’s focus on executing strategic actions including portfolio optimization, disciplined capital allocation, and cost control.

Portfolio Optimization

What Is 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), as shown in Figure 1.

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.

What Is Optimization?

An approach used to find the combination of inputs to achieve the best possible output subject to satisfying certain prespecified constraints and conditions. Examples of applications include:

- What stocks to pick in a portfolio, as well as the weights of each stock as a percent of total budget
- Optimal staffing needs for a production line
- Project strategy selection and prioritization
- Inventory optimization
- Optimal pricing and royalty rates
- Utilization of employees for workforce planning
- Configuration of machines for production scheduling
- Location of facilities for distribution
- Tolerances in manufacturing design
- Treatment policies in waste management

Figure 1: What Is Optimization?

The Travel Cost Planner

A very simple example is in order. Figure 2 illustrates the traveling financial planner problem. Suppose the traveling financial planner has to make three sales trips: to New York, to Chicago, and to Seattle. Further suppose that the order of arrival at each city is irrelevant. All that is important in this simple example is to find the lowest total cost possible to cover all three cities. Figure 2 also lists the flight costs between these different cities.

The problem here is cost minimization, suitable for optimization. One basic approach to solving this problem is through an ad hoc or brute force method. That is, an individual could manually list all six possible permutations, as seen in Figure 3.

Clearly the cheapest itinerary is going from the east coast to the west coast, going from New York to Chicago and finally on to Seattle. Here, the problem is simple and can be calculated manually, as there were three cities and, hence, six possible itineraries. However, add two more cities and the total number of possible itineraries jumps to 120. Performing an ad hoc calculation will be fairly intimidating and time consuming. On a larger scale, suppose there are 100 cities on the salesman's list; the possible itineraries will be as many as 9.3×10^{157}. The problem will take many years to calculate manually, which is where optimization software steps in, automating the search for the optimal itinerary.

Travel Cost Planning Problem

You have to travel and visit clients in New York, Chicago, and Seattle. You may start from any city, and you will stay at your final city (i.e., you will need to purchase three airline tickets). Your goal is to travel as cheaply as possible given these rates:

- Seattle to Chicago: $325
- Chicago to Seattle: $225
- New York to Seattle: $350
- Seattle to New York: $375
- Chicago to New York: $325
- New York to Chicago: $325

How do you solve the problem?

- Ad-hoc approach: start trying different combinations
- Enumeration: look at all possible alternatives

Figure 2: The Travel Cost Planner

Multiple Combinations

- o Seattle–Chicago–New York: $325 + $325 = $650
- o Seattle–New York–Chicago: $375 + $325 = $700
- o Chicago–Seattle–New York: $225 + $375 = $600
- o Chicago–New York–Seattle: $325 + $350 = $675
- o New York–Seattle–Chicago: $350 + $325 = $675
- o New York–Chicago–Seattle: $325 + $225 = $550

Additionally, say you want to include San Antonio and Denver. For the five cities, you now have 5! = 5×4×3×2×1 = 120 combinations

- What about 100 different cities? You would have 100! = 100×99×98×…×1 = 93,326,215,443,944,200,000,000,000,...,000 = 9.3×10^{157} combinations!

Figure 3: Multiple Combinations of the Travel Cost Problem

The example illustrated to this point is a deterministic optimization problem, that is, the airline ticket prices are known ahead of time and are assumed to be constant. Now suppose the ticket prices are not constant but are uncertain, following some distribution (e.g., a ticket from Chicago to Seattle averages $325, but is never cheaper than $300 and usually never exceeds $500). The same uncertainty applies to tickets for the other cities. The problem now becomes an optimization under uncertainty. Ad hoc and brute force approaches simply do not work under uncertainty. Software such as ROV Risk Simulator can take over this optimization problem and automate the entire process seamlessly. The next section discusses the terms required in an optimization under uncertainty.

Figure 4 illustrates the *Portfolio Optimization's Optimization Settings* 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*.

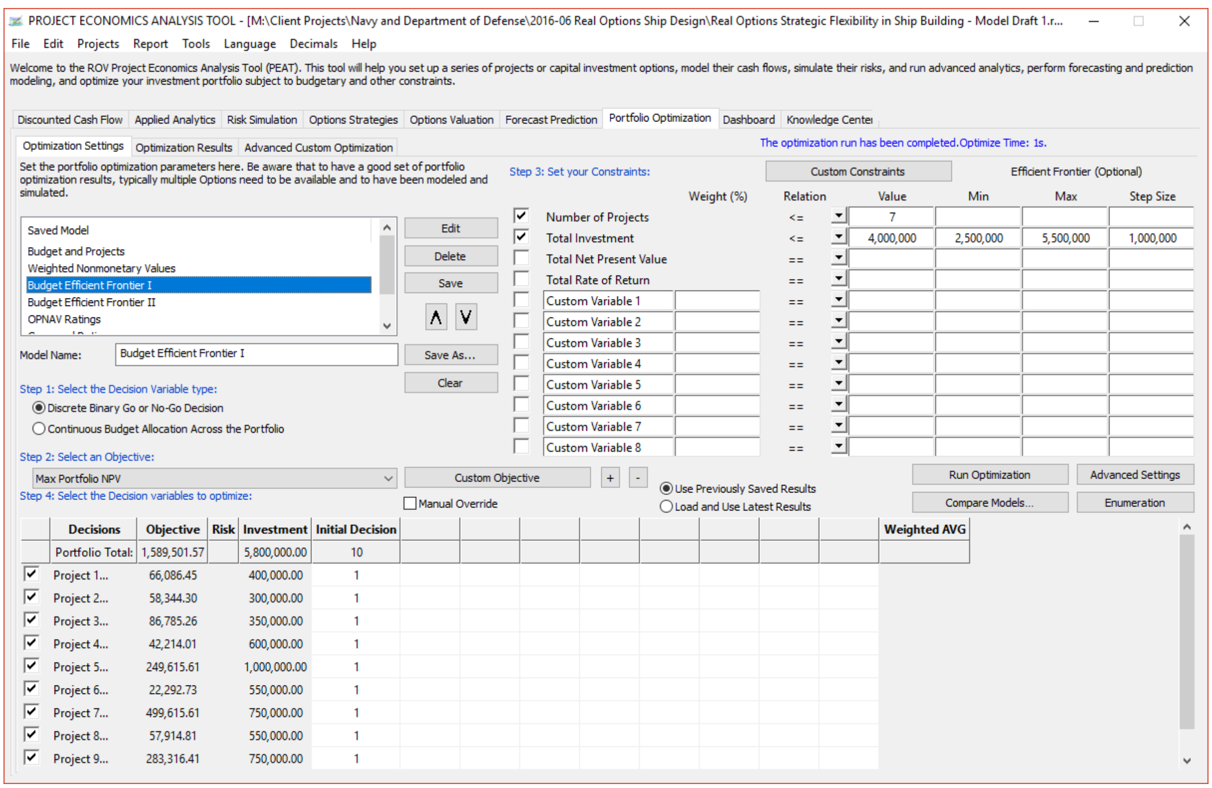


Figure 4: Portfolio Optimization Settings

Figure 5 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 5 and 6 are critical results for decision-makers as they allow decision-makers flexibility in designing their own portfolio of options. For instance, Figure 5 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 5 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 $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 5 shows the efficient frontier where the constraints such as number of options allowed and budget were varied to determine the efficient portfolio selection, Figure 6 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 OPNAV (Naval Operations) 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 us 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.

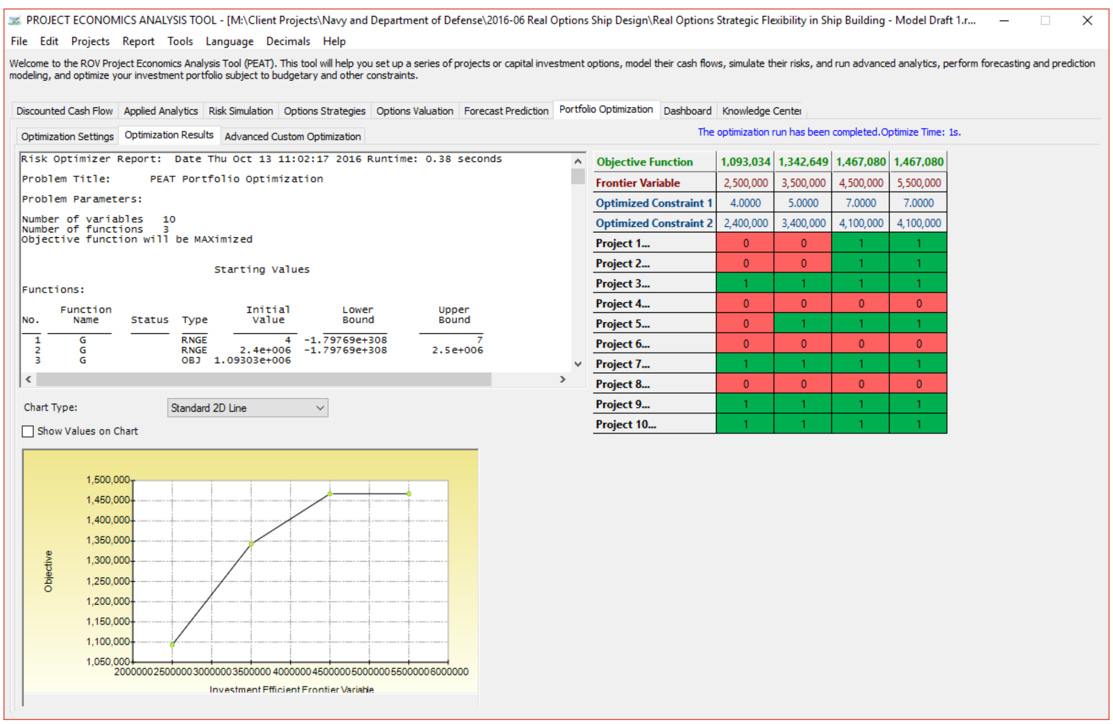


Figure 5: Portfolio Optimization Results

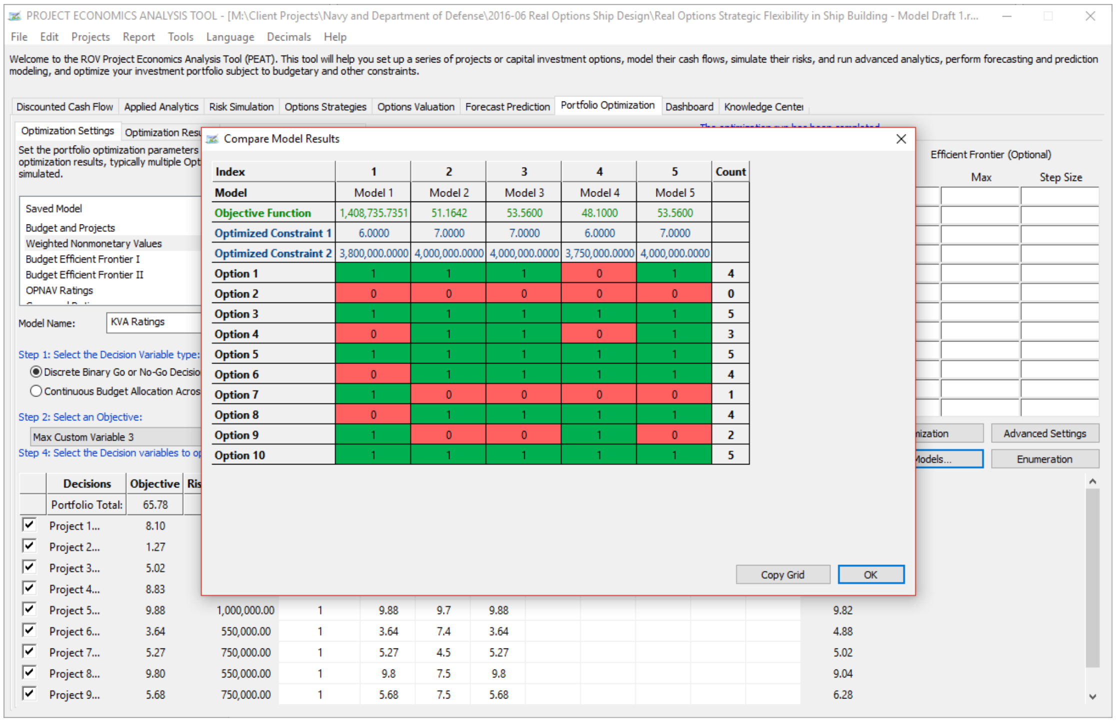


Figure 6: Multi-Criteria Portfolio Optimization Results

As a side note and for the purposes of being comprehensive and inclusive, we point out that multiple types of algorithms have been developed over the years to find the solutions of an optimization problem, from basic linear optimization using the simplex model and solving first partial differential equations. However, when more and more complex real-life problems are assumed, these basic methods tend to break down and more advanced algorithms are required. In solving our efficient frontier problem, we utilized a combination of genetic algorithm, Lagrange multipliers, and taboo-based reduced gradient search methodologies.

Simplistically, the Lagrange multiplier solution assumes some nonlinear problem of

$$\min or \max f(x)$$

$$s.t. \quad g_i(x) = \; b_i \;\; \forall \; i = 1, \ldots, m$$

where the equality is often replaced by some inequality values indicating a ceiling or floor constraint.

From this functional form, we first derive the Lagrange multiplier *v* for all *i* values:

$$L(x,v) \triangleq f(x) + \sum_{i=1}^{m} v_i[b_i - g_i(x)]$$

$$s.t. constraints\ g_i(x) = b_1, \dots, g_m(x) = b_m$$

The solution (*x**, *v**) is a set of points along the Lagrange function *L(x,v)* if it satisfies the condition:

$$\sum_i \nabla g_i(x^*)v^* = f(x^*)\ which\ requires\ \sum_i \frac{\partial g_i}{\partial x_j} v_i = \frac{\partial f}{\partial x_j} \forall j\ and\ \ g_i(x^*) = b_i$$

This approach is simple and elegant but limited to linear and quasi-linear, as well as some simple nonlinear functional forms of *f(x)*. In order to be able to extend the functional form to generalized nonlinear applications, we need to add conditions to the solution set and apply some search algorithms to cover a large (and often unlimited) set of optimal allocations. One limitation is the requirement that the Kuhn-Tucker condition is satisfied where the nonlinear problems have a differentiable general form:

$$\min or \max f(x)$$

$$s.t. \quad g_i(x) \geq\ b_i\ \ \forall\ i \in Feasible\ Set$$

$$g_i(x) \leq\ b_i\ \ \forall\ i \in Feasible\ Set$$

$$g_i(x) =\ b_i\ \ \forall\ i \in Feasible\ Set$$

and the inequality constraints will need to be active at a local optimum or when the Lagrange variable is set to null:

$$v_i[b_i - g_i(x)] = 0$$

In addition, mathematical algorithms will have to be developed to perform both ad-hoc and systematic searches of the optimal solution set. Using an enumeration method will take even a supercomputer close to an infinite number of years to delineate all possible permutations. Therefore, search algorithms are typically used in generating an efficient frontier using optimization. One simple approach is the use of a reduced gradient search method. To summarize the approach, we assume

$$\nabla f(x) \cdot \Delta x$$

where the functional form *f(x)* is the objective function and is divided into two parts, a basic (*B*) and nonbasic portion (*N*) that is multiplied by the change in vector direction *x*. Using a Taylor expansion, we obtain:

$$\begin{aligned} \nabla f(x) \cdot \Delta x &= \nabla f(x)^B \cdot \Delta x^B + \nabla f(x)^N \cdot \Delta x^N \\ &= \nabla f(x)^B \cdot (-B^{-1} N \Delta x^N) + \nabla f(x)^N \cdot \Delta x^N \\ &= (\nabla f(x)^N - \nabla f(x)^B B^{-1} N) \Delta x^N \end{aligned}$$

The reduced gradient with respect to the solution matrix *B* is

$$r \triangleq (r^B, r^N)$$

where

$$r^B \triangleq 0$$
$$r^N \triangleq \nabla f(x)^N - \nabla f(x)^B B^{-1} N$$

Solving for this solution set is manually possible when the number of decision variables is small (typically fewer than four or five), but once the number of decision variables is large, as in most real-life situations, the manual solution is intractable and computer search algorithms have to be employed. The general method employed includes taking the following steps:

1. Estimate starting point and obtain the basis matrix set.
2. Compute sample test points and obtain the reduced gradient vector direction.
3. Test for constraint feasibilities at the limits.
4. Solve for the Lagrange optimal set.
5. Start on a new set of points.
6. Change the basis set if a better set of points is obtained, or stop optimization.
7. Repeat iteration and advance or stop when tolerance level is achieved.

The Lingo of Optimization

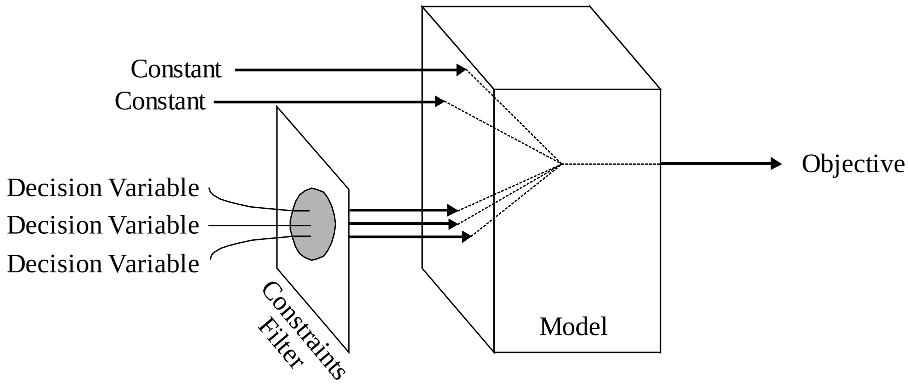
Before embarking on solving an optimization problem, it is vital to understand the terminology of optimization—the terms used to describe certain attributes of the optimization process. These words include *decision variables, constraints,* and *objectives*.

Decision variables are quantities over which you have control; for example, the amount of a product to make, the number of dollars to allocate among different investments, or which projects to select from among a limited set. As an example, portfolio optimization analysis includes a go or no-go decision on particular projects. In addition, the dollar or percentage of budget allocation across multiple projects can also be structured as decision variables.

Constraints describe relationships among decision variables that restrict the values of the decision variables. For example, a constraint might ensure that the total amount of money allocated among various investments cannot exceed a specified amount or, at most, that one project from a certain group can be selected. Other constraints might concern budget, timing, minimum returns, or risk tolerance levels.

Objectives give a mathematical representation of the model's desired outcome, such as maximizing profit or minimizing cost, in terms of the decision variables. In financial analysis, for example, the objective may be to maximize returns while minimizing risks (maximizing the Sharpe's ratio or returns-to-risk ratio).

Conceptually, then, an optimization model might look like Figure 7.



Deterministic Optimization Model

Figure 7: Visualizing the Optimization Process

The solution to an optimization model provides a set of values for the decision variables that optimizes (maximizes or minimizes) the associated objective. If the real business conditions were simple and if the future were predictable, all data in an optimization model would be constant, making the model deterministic.

In many cases, however, a deterministic optimization model cannot capture all the relevant intricacies of a practical decision-making environment. When a model's data are uncertain and can only be described probabilistically, the objective will have some probability distribution for any chosen set of decision variables. You can find this probability distribution by simulating the model using Risk Simulator. An optimization model under uncertainty has several additional elements, including *assumptions* and *forecasts*.

Assumptions capture the uncertainty of model data using probability distributions, whereas forecasts are the frequency distributions of possible results for the model. Forecast statistics are summary values of a forecast distribution, such as the mean, standard deviation, and variance. With uncertainty, the optimization process (Figure 8) controls the optimization by maximizing or minimizing the objective.

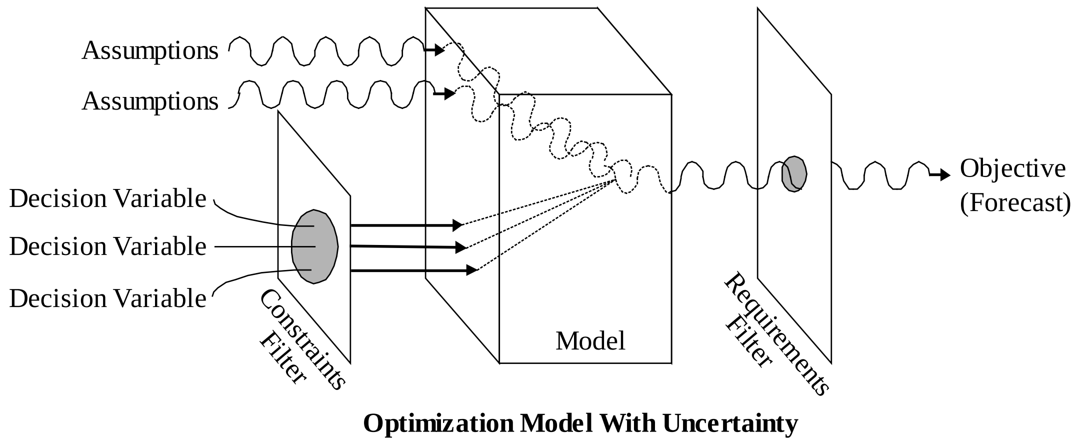


Figure 8: Optimization With Uncertainties and Risk

Each optimization model has one objective, a variable that mathematically represents the model's objective in terms of the assumption and decision variables. Optimization's job is to find the optimal (minimum or maximum) value of the objective by selecting and improving different values for the decision variables. When model data are uncertain and can only be described using probability distributions, the objective itself will have some probability distribution for any set of decision variables.

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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 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 U.S. Department of Defense has 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 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, we 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:

- Model and compare each of these ACB capabilities 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 noneconomic 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.
- The following table shows the remaining relevant information needed to run the models. All monetary values are in thousands of dollars ($000).

Capability Acronym	Savings Now	Short-Term Benefits	Maintenance 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

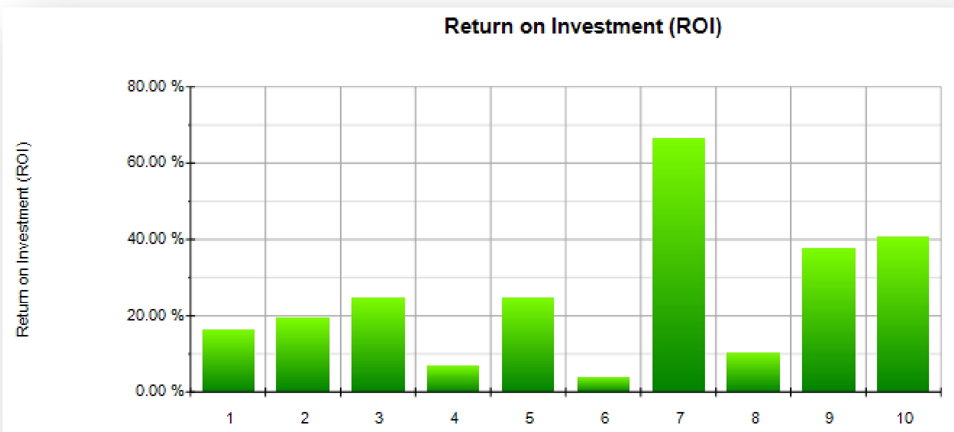
- “Savings Now” is the immediate monetary cost savings benefits obtained by implementing the new upgraded system (e.g., lower overhead requirements, reduced parts and labor requirements). This amount is applied in the first year of the cash flow stream only (Year 1 or 2018) as its effects are deemed 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 below.

- 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 are 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, noneconomic 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 9 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



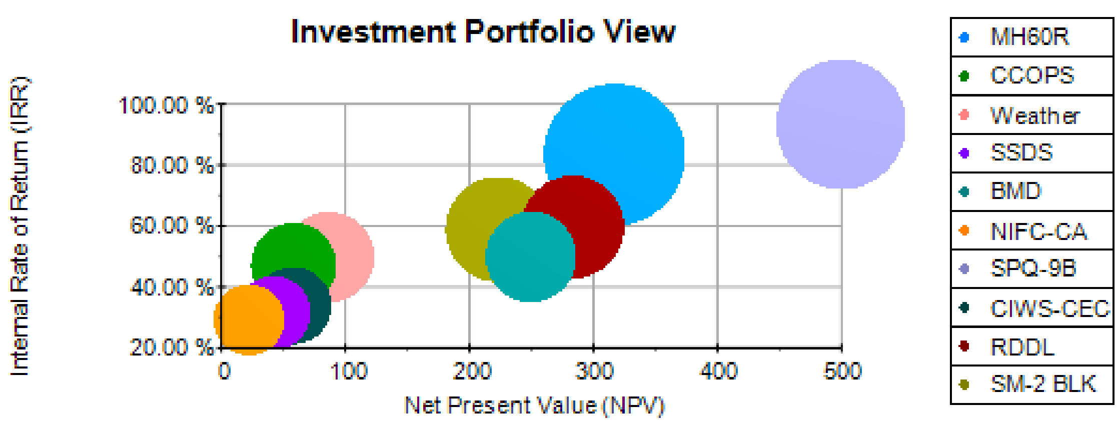


Figure 9: Capital Budgeting Results Comparison

Based on the analysis, the top five recommended ACB capabilities based on Static Portfolio Analysis are SPQ-9B, SM-2 BLK, MH60R, BMD, and RDDL. Figure 10 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.

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 10: Program Rankings

Figures 11 and 12 show 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.

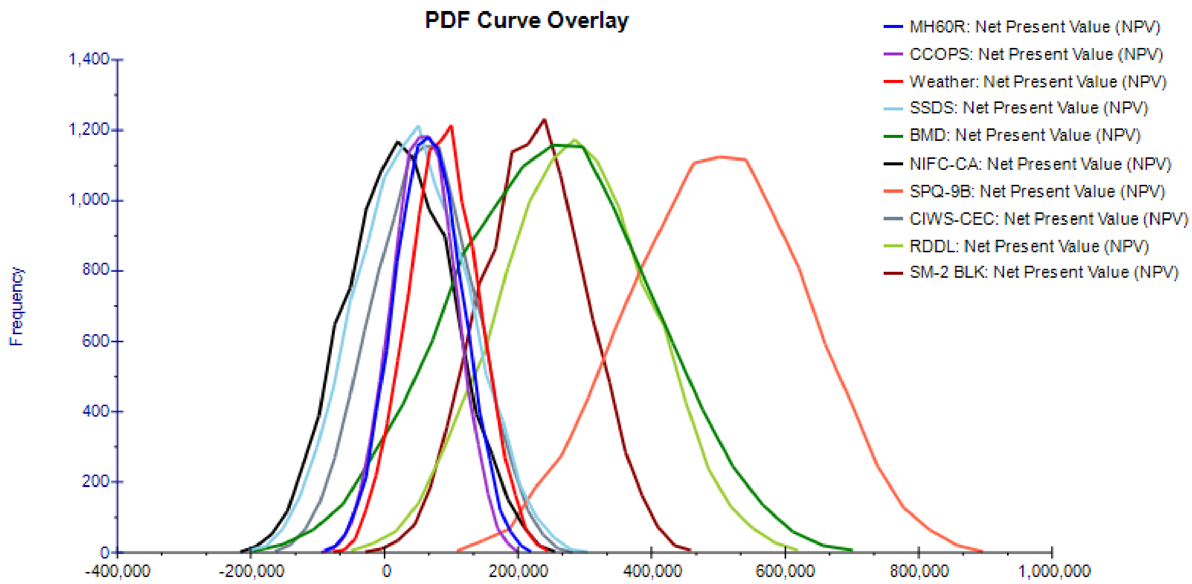


Figure 11: Comparison of Simulated NPV Probability Distributions

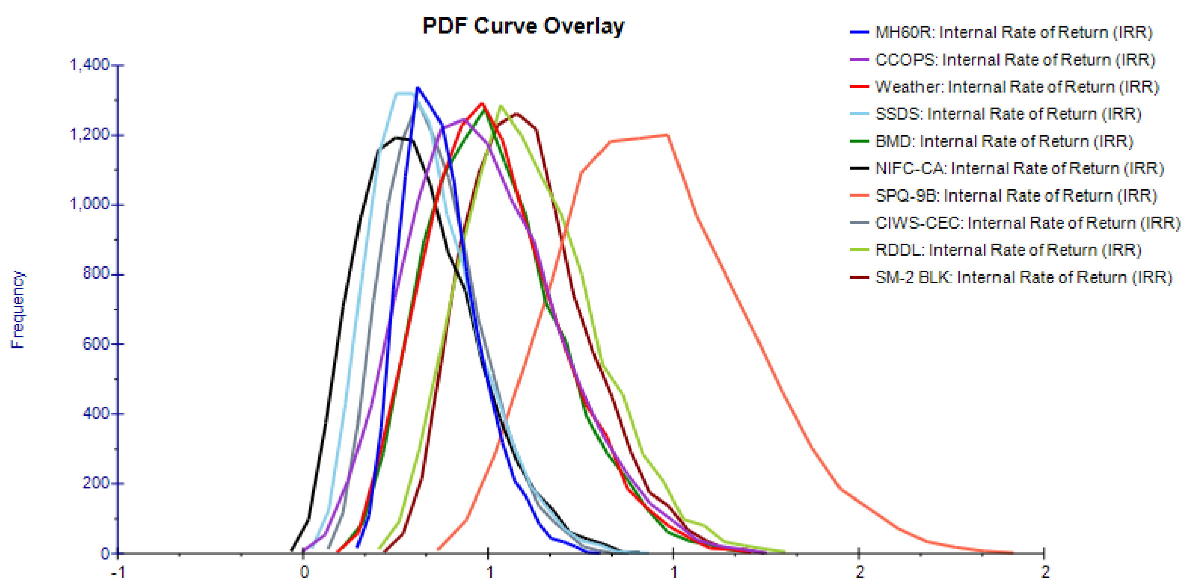


Figure 12: Comparison of Simulated IRR Probability Distributions

Figure 13 shows the probability of success of each program. These are currently based on using NPV but can be applied to any noneconomic 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 13: Economic Probability of Success

OPTIONS	MH60R	CCOPS	Weather	SSDS	BMD	NIFC-CA	SPQ-9B	CIWS-CEC	RDDL	SM-2 BLK
Mean	317.21	58.42	87.10	42.33	248.70	22.28	498.49	57.66	282.98	223.17
Median	317.31	58.35	87.63	42.90	250.47	23.11	499.38	57.25	283.64	223.09
Stdev	59.57	46.25	51.65	81.11	146.28	77.60	130.78	72.07	110.25	78.04
Variance	354844.00 %	213880.00 %	266758.00 %	657813.00 %	2139483.00 %	602136.00 %	1710160.00 %	519395.00 %	1215348.00 %	608908.00 %
CV	0.19	0.79	0.59	1.92	0.59	3.48	0.26	1.25	0.39	0.35
Skew	0.00	0.01	-0.01	0.03	-0.02	0.01	-0.01	0.02	-0.01	0.04
Kurtosis	-0.23	-0.32	-0.35	-0.29	-0.27	-0.33	-0.32	-0.30	-0.28	-0.29
Minimum	127.43	-87.07	-78.97	-205.15	-225.25	-207.74	100.99	-171.61	-66.15	-11.77
Maximum	503.47	204.99	250.12	290.42	712.88	259.07	901.46	282.05	641.59	470.56
Range	376.04	292.06	329.08	495.56	938.13	466.80	800.47	453.67	707.74	482.33
0% Percentile	127.43	-87.07	-78.97	-205.15	-225.25	-207.74	100.99	-171.61	-66.15	-11.77
5% Percentile	218.54	-17.82	2.37	-90.85	7.38	-105.39	282.21	-59.93	101.31	96.07
10% Percentile	239.84	-2.17	19.40	-63.85	57.60	-79.60	327.89	-36.20	138.79	122.09
20% Percentile	266.33	18.17	41.25	-27.64	120.72	-45.72	384.27	-4.97	187.35	156.49
30% Percentile	285.37	32.77	58.91	-2.14	168.93	-19.62	427.24	18.18	223.54	180.21
40% Percentile	301.55	46.62	73.88	20.79	212.29	1.55	463.47	37.98	253.99	202.20
50% Percentile	317.31	58.35	87.63	42.90	250.47	23.11	499.38	57.25	283.64	223.09
60% Percentile	332.44	70.30	101.47	63.17	289.02	42.68	534.83	76.59	312.47	242.37
70% Percentile	348.96	83.76	115.53	85.41	327.04	63.99	570.09	96.37	342.66	264.09
80% Percentile	368.00	98.38	132.05	112.12	376.07	90.00	611.81	120.01	379.21	290.71
90% Percentile	395.51	119.17	154.54	148.05	436.89	123.49	669.22	151.79	426.15	326.86
95% Percentile	416.59	134.65	171.79	177.52	491.10	151.19	713.57	178.17	464.05	355.49
100% Percentile	503.47	204.99	250.12	290.42	712.88	259.07	901.46	282.05	641.59	470.56

Low Risk/ High Expected Return

High Risk/ Low Expected Return

Figure 14: Comparison of Options Decision Risk Profile

Figure 15 shows the results of Portfolio 1, which assumes a budget of $4.0 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.

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 15: Portfolio Optimization 1

Figure 16 shows Portfolio Optimization 2, which runs an Investment Efficient Frontier. It assumes a budgetary range of $2.5–$5.0 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	1,093,034	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

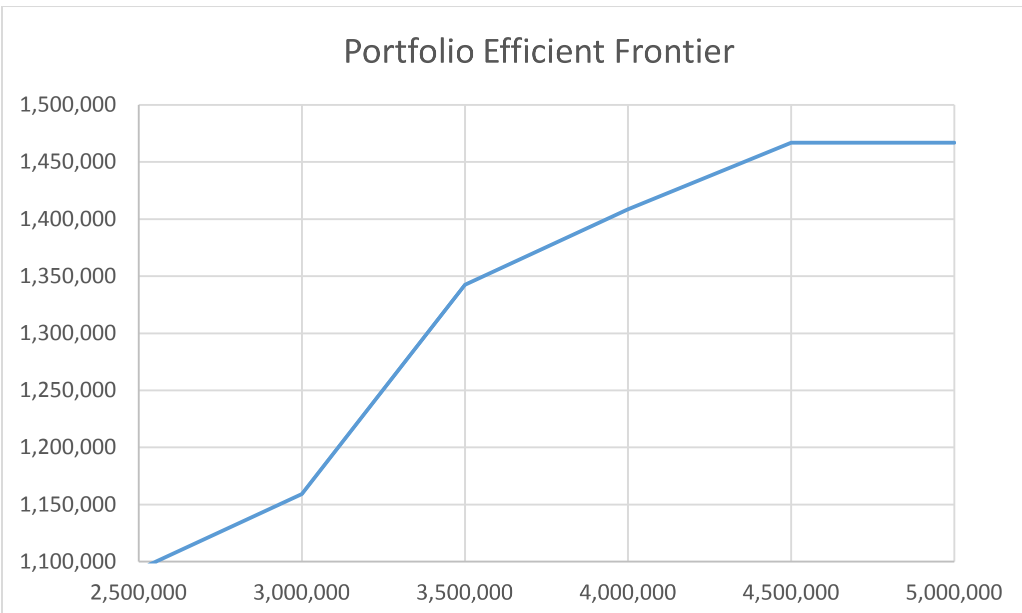


Figure 16: Portfolio Optimization 2

Figure 17 shows the results for OPNAV, Figure 18 for COMMAND, and Figure 19 for KVA. 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 17: Portfolio Optimization 3 (OPNAV)

Objective Function	33.50	40.60	43.20	48.10	52.60	55.10	59.60
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	2,500,000	3,000,000	3,500,000	3,750,000	4,350,000	4,800,000	5,400,000
MH60R	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CCOPS	1.00	0.00	1.00	0.00	0.00	1.00	1.00
Weather	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SSDS	0.00	0.00	0.00	0.00	1.00	0.00	1.00
BMD	0.00	1.00	1.00	1.00	1.00	1.00	1.00
NIFC-CA	0.00	1.00	0.00	1.00	1.00	1.00	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	1.00	0.00	1.00	1.00	1.00	1.00	1.00
SM-2BLK	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Figure 18: Portfolio Optimization 4 (COMMAND)

Objective Function	31.46	35.80	39.64	43.98	47.59	50.69	55.03
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 19: Portfolio Optimization 5 (KVA)

Figure 20 illustrates the portfolio optimization results of the Weighted Average Nonmonetary Values. This objective variable is calculated based on 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. Instead of looking at one variable at a time, this is a cumulative variable where each value is weighted based on the decision-makers' preferences (e.g., Capability may be awarded a 30% weight compared to 10% for Health of Execution). The Efficient Frontier results are shown in Figure 20.

Objective Function	33.55	38.66	42.79	47.91	51.08	54.15	59.24
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	4,750,000	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	1.00	1.00
SPQ-9B	0.00	0.00	0.00	0.00	0.00	0.00	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 20: Portfolio Optimization 6 (Weighted Average)

Figure 21 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 $4,000,000 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 21, these 5 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 21: Portfolio Optimization 7 (Combined View)

Conclusions and Recommendations

The analytical methods illustrated in this 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 noneconomic 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 subject matter 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 we want or expect 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, assign critical value metrics to these events and programs, and use these as guideposts for generating future subject matter expert (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.

- Analytical hierarchical processes, multi-objective optimization, and other algorithms need to be evaluated and the results compared.
- Using risk-based simulations, risks of cost and budget overruns as well as delivery delays can be modeled and accounted for in the portfolio.

To summarize, based on the research performed thus far, we conclude 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 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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Appendix A: The Theory of Strategic Real Options, Knowledge Value Added, and Integrated Risk Management

In the past, corporate investment decisions were cut and dried. Buy a new machine that is more efficient, make more products costing a certain amount, and if the benefits outweigh the costs, execute the investment. Hire a larger pool of sales associates, expand the current geographical area, and if the marginal increase in forecast sales revenues exceeds the additional salary and implementation costs, start hiring. Need a new manufacturing plant? Show that the construction costs can be recouped quickly and easily by the increase in revenues the plant will generate through new and improved products, and the initiative is approved.

However, real-life business conditions are a lot more complicated. Your firm decides to go with an e-commerce strategy, but multiple strategic paths exist. Which path do you choose? What are the options you have? If you choose the wrong path, how do you get back on the right track? How do you value and prioritize the paths that exist? You are a venture capitalist firm with multiple business plans to consider. How do you value a start-up firm with no proven track record? How do you structure a mutually beneficial investment deal? What is the optimal timing for a second or third round of financing?

Real options are useful not only in valuing a firm through its strategic business options, but also as a strategic business tool in capital investment decisions. For instance, should a firm invest millions in a new facility expansion initiative? How does a firm choose among several seemingly cashless, costly, and unprofitable information-technology infrastructure projects? Should a firm indulge its billions in a risky research and development initiative? The consequences of a wrong decision can be disastrous or even terminal for certain firms. In a traditional discounted cash flow model, these questions cannot be answered with any certainty. In fact, some of the answers generated through the use of the traditional discounted cash flow model are flawed because the model assumes a static, one-time decision-making process, whereas the real options approach takes into consideration the strategic managerial options that certain projects create under uncertainty and management's flexibility in exercising or abandoning these options at different points in time, when the level of uncertainty has decreased or has become known over time.

The Real Options Valuation (ROV) approach incorporates a learning model, such that management makes better and more informed strategic decisions when some levels of uncertainty are resolved through the passage of time, actions, and events. Traditional discounted cash flow analysis assumes a static investment decision and assumes that strategic decisions are made initially with no recourse to choose other pathways or options in the future. To create a good analogy of real options, visualize it as a strategic road map of long and winding roads with multiple perilous turns and branches along the way. Imagine the intrinsic and extrinsic value of having such a road map or global positioning system when navigating through unfamiliar territory, as well as having road signs at every turn to guide you in making the best and most informed driving decisions. Such a strategic map is the essence of real options.

The answer to evaluating such projects lies in real options analysis, which can be used in a variety of settings, including pharmaceutical drug development, oil and gas exploration and production, manufacturing, start-up valuation, venture capital investment, information technology infrastructure, research and development, mergers and acquisitions, e-commerce and e-business, intellectual capital development, technology development, facility expansion, business project prioritization, enterprise risk management, business unit capital budgeting, licenses, contracts, intangible asset valuation, and the like.

The Real Options Solution in a Nutshell

Simply defined, the real options method is a systematic approach and integrated solution using financial theory, economic analysis, management science, decision sciences, statistics, and econometric modeling in applying options theory in valuing real physical assets, as opposed to financial assets, in a dynamic and uncertain business environment where business decisions are flexible in the context of strategic capital investment decision-making, valuing investment opportunities, and project capital expenditures. Real options are crucial in

- Identifying different acquisition or investment decision pathways or projects that management can navigate given highly uncertain business conditions
- Valuing each of the strategic decision pathways and what they represent in terms of financial viability and feasibility
- Prioritizing these pathways or projects based on a series of qualitative and quantitative metrics
- Optimizing the value of strategic investment decisions by evaluating different decision paths under certain conditions or using a different sequence of pathways that can lead to the optimal strategy
- Timing the effective execution of investments and finding the optimal trigger values and cost or revenue drivers
- Managing existing or developing new optionalities and strategic decision pathways for future opportunities

ROV is useful for valuing a project, alternative path, implementation option, or ship design through its strategic options especially in capital-intensive investment decisions under uncertainty. In a traditional cost-benefit and cash flow model, the ROI or cost-benefit question cannot be answered with any certainty. In fact, some of the answers generated using traditional cash flow models are flawed because the model assumes a static, one-time decision-making process with no recourse to choose other pathways or options in the future. In contrast, the real options approach takes into consideration the strategic managerial options certain projects create under uncertainty and the decision-makers' flexibility in exercising or abandoning these options at different points in time, when the level of uncertainty has decreased or has become known over time.

Industry Leaders Embracing Strategic Real Options

The first industries to use real options as a tool for strategic decision were oil and gas and mining companies; its use later expanded into utilities, biotechnology, and pharmaceuticals; and now into telecommunications, high-tech, and across all industries. The following examples relate how real options have been or should be used in various kinds of companies.

Automobile and Manufacturing Industry

In automobile and manufacturing, General Motors (GM) applies real options to create *switching options* in producing its new series of autos. This option is essentially to use a cheaper resource over a given period. GM holds excess raw materials and has multiple global vendors for similar materials with excess contractual obligations above what it projects as necessary. The excess contractual cost is outweighed by the significant savings of switching vendors when a certain raw material becomes too expensive in a particular region of the world. By spending the additional money in contracting with vendors and meeting their minimum purchase requirements, GM has essentially paid the premium on purchasing an *option to switch,* which is important especially when the price of raw materials fluctuates significantly in different regions around the world. Having an option here provides the holder a hedging vehicle against pricing risks.

Computer Industry

In the computer industry, HP–Compaq used to forecast sales in foreign countries months in advance. It then configured, assembled, and shipped the highly specific configuration printers to these countries. However, given that demand changes rapidly and forecast figures are seldom correct, the preconfigured printers usually suffer the higher inventory holding cost or the cost of technological obsolescence. HP–Compaq can create an *option to wait* and defer making any decisions too early through building assembly plants in these foreign countries. Parts can then be shipped and assembled in specific configurations when demand is known, possibly weeks in advance rather than months in advance. These parts can be shipped anywhere in the world and assembled in any configuration necessary, while excess parts are interchangeable across different countries. The premium paid on this option is building the assembly plants, and the upside potential is the savings in making wrong demand forecasts.

Airline Industry

In the airline industry, Boeing spends billions of dollars and takes several years to decide if a certain aircraft model should even be built. If the wrong model is tested in this elaborate strategy, Boeing's competitors may gain a competitive advantage relatively quickly. Because so many technical, engineering, market, and financial uncertainties are involved in the decision-making process, Boeing can conceivably create an *option to choose* through parallel development of multiple plane designs simultaneously, knowing well the increasing cost of developing multiple designs simultaneously with the sole purpose of eliminating all but one in the near future. The added cost is the premium paid on the option. However, Boeing will be able to decide which model to abandon or continue when these uncertainties and risks become known over time. Eventually, all the models will be eliminated save one. This way, the company can hedge itself against making the wrong initial decision and benefit from the knowledge gained through parallel development initiatives.

Oil and Gas Industry

In the oil and gas industry, companies spend millions of dollars to refurbish their refineries and add new technology to create an *option to switch* their mix of outputs among heating oil, diesel, and other petrochemicals as a final product, using real options as a means of making capital and investment decisions. This option allows the refinery to switch its final output to one that is more profitable based on prevailing market prices, to capture the demand and price cyclicality in the market.

Telecommunications Industry

In the past, telecommunications companies like Sprint and AT&T installed more fiber-optic cable and other telecommunications infrastructure than any other company to create a *growth option* in the future by providing a secure and extensive network and to create a high barrier to entry, providing a first-to-market advantage. Imagine having to justify to the board of directors the need to spend billions of dollars on infrastructure that will not be used for years to come. Without the use of real options, this decision would have been impossible to justify.

Real Estate Industry

In the real estate arena, leaving land undeveloped creates an option to develop later at a more lucrative profit level. However, what is the *optimal wait time* or the *optimal trigger price* to maximize returns? In theory, one can wait for an infinite amount of time, and real options provide the solution for the optimal timing and optimal price trigger value.

Utilities Industry

In the utilities industry, firms have created an *option to execute* and an *option to expand* by installing cheap-to-build inefficient energy generator *peaker* plants to be used only when electricity prices are high and to shut down when prices are low. The price of electricity tends to remain constant until it hits a certain capacity utilization trigger level, when prices shoot up significantly. Although this occurs infrequently, the possibility still exists, and by having a cheap standby plant, the firm has created the option to turn on the expanded capacity generation whenever it becomes necessary, to capture this upside price fluctuation.

Pharmaceutical Research and Development Industry

In pharmaceutical or research and development initiatives, real options can be used to justify the large investments in what seems to be cashless and unprofitable under the discounted cash flow method but actually creates *sequential compound options* in the future. Under the myopic lenses of a traditional discounted cash flow analysis, the high initial investment of, say, a billion dollars in research and development may return a highly uncertain projected few million dollars over the next few years. Management will conclude under a net present value analysis that the project is not financially feasible. However, a cursory look at the industry indicates that research and development is performed everywhere. Hence, management must see an intrinsic strategic value in research and development. How is this intrinsic strategic value quantified? The real options valuation approach would optimally time and spread the billion-dollar initial investment into a multiple-stage investment structure. At each stage, management has an *option to wait* and see what happens as well as the *option to abandon* or the *option to expand* into the subsequent stages. The ability to defer cost and proceed only if situations are permissible creates value for the investment.

High-Tech and e-Business Industry

In e-business strategies, real options can be used to prioritize different e-commerce initiatives and to justify those large initial investments that have an uncertain future. Real options can be used in e-commerce to create incremental investment stages compared to a large one-time investment (invest a little now, wait and see before investing more) as well as create *options to abandon* and other future growth options.

Mergers and Acquisitions

In valuing a firm for acquisition, you should consider not only the revenues and cash flows generated from the firm's operations but also the strategic options that come with the firm. For instance, if the acquired firm does not operate up to expectations, an *abandonment option* can be executed where it can be sold for its intellectual property and other tangible assets. If the firm is highly successful, it can be spun off into other industries and verticals or new products and services can be eventually developed through the execution of an *expansion option*. In fact, in mergers and acquisition, several strategic options exist. For instance, a firm acquires other entities to enlarge its existing portfolio of products or geographic location or to obtain new technology (*expansion option*); or to divide the acquisition into many smaller pieces and sell them off as in the case of a corporate raider (*abandonment option*); or it merges to form a larger organization due to certain synergies and immediately lays off many of its employees (*contraction option*). If the seller does not value its real options, it may be leaving money on the negotiation table. If the buyer does not value these strategic options, it is undervaluing a potentially highly lucrative acquisition target.

Knowledge Value Added (KVA)

In the U.S. military context, the Knowledge Value Added (KVA) methodology is a new way of approaching the problems of estimating the productivity (in terms of ROI) for military capabilities embedded in processes that are impacted by technology. KVA addresses the requirements of the many DOD policies and directives by providing a means to generate comparable value or benefit estimates for various processes and the technologies and people that execute them. It does this by providing a common and relatively objective means for estimating the value of new technologies as required by the following:

- Clinger-Cohen Act of 1996 that mandates the assessment of the cost benefits for information technology investments.
- Government Accountability Office's (formerly the General Accounting Office) Assessing Risks and Returns: A Guide for Evaluating Federal Agencies' IT Investment Decision-Making," which requires that IT investments apply ROI measures.
- DOD Directive 8115.01, which mandates the use of performance metrics based on outputs, with ROI analysis required for all current and planned IT investments.
- The DOD's *Risk Management Guidance Defense Acquisition Guidebook* that requires alternatives to the traditional cost estimation be considered because legacy cost models tend not to adequately address costs associated with information systems or the risks associated with them.

KVA is a methodology that describes all organizational outputs in common units, thus providing a means to compare the outputs of all assets (human, machine, information technology) regardless of the aggregated outputs produced. It monetizes the outputs of all assets, including intangible knowledge assets. Thus, the KVA approach can provide insights about the productivity level of processes, people, and systems in terms of a ratio of common units of output (CUO). CUO produced by each asset (a measure of benefits) is divided by the cost to produce the output. By capturing the value of knowledge embedded in an organization's core processes, employees, and technology, KVA identifies the actual cost and value of people, systems, or processes. Because KVA identifies every process required to produce an output and the historical costs of those processes, unit costs and unit values of outputs, processes, functions, or services are calculated. An output is defined as the result of an organization's operations; it can be a product or service, as shown in Figure 22.

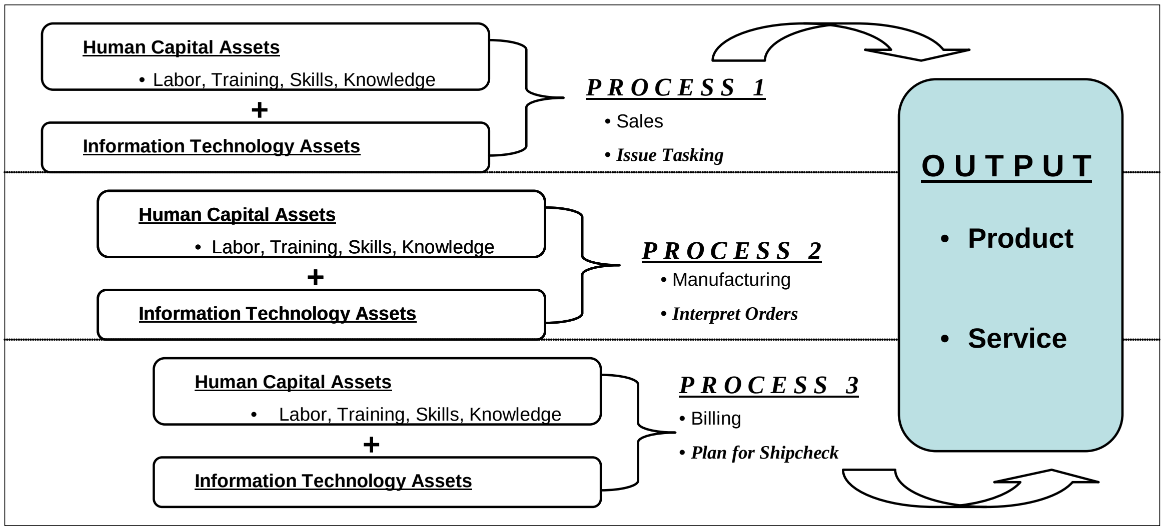


Figure 22: Measuring Output

For the purpose of this study, KVA was used to measure the value added by the human capital assets (i.e., military personnel executing the processes) and the system assets (e.g., new sensor) by analyzing the performances of the processes. By capturing the value of knowledge embedded in systems and used by operators of the processes, KVA identified the productivity of the system-process alternatives. Because KVA identifies every process output required to produce the final aggregated output, the common unit costs and the common unit values were estimated.

The KVA methodology has been applied in over 80 projects within the DOD, from flight scheduling applications to ship maintenance and modernization. In general, the KVA methodology was used for this study because it could

- Compare alternative approaches in terms of their relative productivity
- Allocate value and costs to common units of output

- Measure value added by the system alternatives based on the outputs each produced
- Relate outputs to cost of producing those outputs in common units

KVA quantifies value in two key productivity metrics: Return on Knowledge (ROK) and Return on Knowledge Investment (ROI). Calculations of these key metrics are shown in Figure 23.

Metric	Description	Type	Calculation
Return on Knowledge (ROK)	Basic productivity, cash-flow ratio	Function or process level performance ratio	Benefits in common units or cost to produce the output
Return on Investment (ROI)	Same as ROI at the sub-corporate or process level	Traditional investment finance ratio	[Revenue – Investment Cost] / [Investment Cost]

Figure 23: KVA Metrics

Although ROI is the traditional financial ratio, ROK identifies how a specific process converts existing knowledge into producing outputs so decision-makers can quantify costs and measure value derived from investments in human capital assets. A higher ROK signifies better utilization of knowledge assets. If IT investments do not improve the ROK value of a given process, steps must be taken to improve that process's function and performance (see Figure 24).

Traditional Accounting (Explains What Was Spent)		KVA Process Costing (Explains How It Was Spent)	
Compensation	5,000	Review Task	1,000
Benefits/OT	1,000	Determine OP	1,000
Supplies/Materials	2,000	Input Search Function	2,500
Rent/Leases	1,000	Search/Collection	1,000
Depreciation	1,500	Target Data Acquisition	1,000
Admin & Others	900	Target Data Processing	2,000
Total	$11,400	Format Report	600
		Quality Control Report	700
		Transmit Report	1,600
		Total	$11,400

Figure 24: Comparison of Traditional Accounting Versus Process-Based Costing

Based on the tenets of complexity theory, KVA assumes that humans and technology in organizations add value by taking inputs and changing them (measured in common units of complexity) into outputs through core processes. The amount of change within a process an asset produces can be described as a measure of value or benefit. The additional assumptions in KVA include the following:

- Describing all process outputs in common units (e.g., using a knowledge metaphor for the descriptive language in terms of the time it takes an average employee to learn how to produce the outputs) allows historical value and cost data to be assigned to those processes historically.
- All outputs can be described in terms of the time required for a single point of reference learner to learn to produce them.
- Learning Time, a surrogate for procedural knowledge required to produce process outputs, is measured in common units of time. Consequently, units of learning time are proportional to common units of output.
- Common units of output make it possible to compare all outputs in terms of cost per unit as well as value (e.g., price) per unit, because value (e.g., revenue) can now be assigned at the suborganizational level.
- Once cost and revenue streams have been assigned to suborganizational outputs, normal accounting, financial performance, and profitability metrics can be applied.

Describing processes in common units also permits, but does not require, market comparable data to be generated, particularly important for nonprofits such as the U.S. military. Using a market comparables approach, data from the commercial sector can be used to estimate price per common unit, allowing for revenue estimates of process outputs for nonprofits. This approach also provides a common-unit basis to define benefit streams regardless of the process analyzed.

KVA differs from other nonprofit ROI models because it can allow for revenue estimates, enabling the use of traditional accounting, financial performance, and profitability measures at the suborganizational level. KVA can rank processes or process alternatives by their relative ROIs. This ranking assists decision-makers in identifying how much various processes or process alternatives add value.

In KVA, value is quantified in two key metrics: Return on Knowledge (ROK: revenue/cost) and ROI (revenue-investment cost/investment cost). The raw data from a KVA analysis can become the input into the ROI models and various forecasting techniques such as real options analysis, portfolio optimization, and Monte Carlo simulation.

Integrated Risk Management (IRM)

Integrated Risk Management (IRM) is an eight-step, quantitative software-based modeling approach for the objective quantification of risk (cost, schedule, technical), flexibility, strategy, and decision analysis (see Figure 26). The method can be applied to program management, resource portfolio allocation, return on investment to the military (maximizing expected military value and objective value quantification of nonrevenue government projects), analysis of alternatives or strategic flexibility options, capability analysis, prediction modeling, and general decision analytics. The method and toolset provide the ability to consider hundreds of alternatives with budget and schedule uncertainty, and provide ways to help the decision-maker maximize capability and readiness at the lowest cost. This methodology is particularly amenable to resource reallocation and has been taught and applied by the authors for the past 10 years at over 100 multinational corporations and over 30 projects at the DOD.

IRM provides a structured approach that will yield a rapid, credible, repeatable, scalable, and defensible analysis of cost savings and total cost of ownership while ensuring that vital capabilities are not lost in the process. The IRM + KVA methods do this by estimating the value of a system or process in a common and objective way across various alternatives and providing the return on investment (ROI) of each in ways that are both comparable and rigorous. These ROI estimates across the portfolio of alternatives provide the inputs necessary to predict the value of various options. IRM incorporates risks, uncertainties, budget constraints, implementation, life-cycle costs, reallocation options, and total ownership costs in providing a defensible analysis describing management options for the path forward. This approach identifies risky projects and programs, while projecting immediate and future cost savings, total life-cycle costs, flexible alternatives, critical success factors, strategic options for optimal implementation paths/decisions, and portfolio optimization. Its employment presents ways for identifying the potential for cost overruns and schedule delays and enables proactive measures to mitigate those risks. IRM provides an optimized portfolio of capability or implementation options while maintaining the value of strategic flexibility.

In the current case, IRM provides a way to differentiate among various alternatives for implementation of Flexible and Adaptable Ship Options (FASO)/Modular Adaptable Ships (MAS) with respect to options in ship design, and to postulate where the greatest benefit could be achieved for the available investment from within the portfolio of alternatives. As a strategy is formed and a plan developed for its implementation, the toolset provides for inclusion of important risk factors, such as schedule and technical uncertainty, and allows for continuous updating and evaluation by the program manager to understand where these risks come into play and to make informed decisions accordingly.

Using Monte Carlo risk simulation, the resulting stochastic KVA ROK model yielded a distribution of values rather than a point solution. Thus, simulation models analyze and quantify the various risks and uncertainties of each program. The result is a distribution of the ROKs and a representation of the project's volatility.

In real options, the analyst assumes that the underlying variable is the future benefit minus the cost of the project. An implied volatility can be calculated through the results of a Monte Carlo risk simulation. The results for the IRM analysis will be built on the quantitative estimates provided by the KVA analysis. The IRM will provide defensible quantitative risk analytics and portfolio optimization suggesting the best way to allocate limited resources to ensure the highest possible value over time.

The first step in real options is to generate a strategic map through the process of framing the problem. Based on the overall problem identification occurring during the initial qualitative management screening process, certain strategic options would become apparent for each project. The strategic options could include, among other things, the option to wait, expand, contract, abandon, switch, stage-gate, and choose.

Risk analysis and real options analysis assume that the future is uncertain, and that decision-makers can make midcourse corrections when these uncertainties become resolved or risk distributions become known. The analysis is usually done ahead of time and, thus, ahead of such uncertainty and risks. Therefore, when these risks become known, the analysis should be revisited to incorporate the information in decision-making or to revise any input assumptions. Sometimes, for long-horizon projects, several iterations of the real options analysis should be performed, where future iterations are updated with the latest data and assumptions. Understanding the steps required to undertake an IRM analysis is important because the methodology provides insight not only into the methodology itself but also into how IRM evolves from traditional analyses, showing where the traditional approach ends and where the new analytics start.

The risk simulation step required in the IRM provides us with the probability distributions and confidence intervals of the KVA methodology's resulting ROI and ROK results. Further, one of the outputs from this risk simulation is volatility, a measure of risk and uncertainty, which is a required input into the real options valuation computations. In order to assign input probabilistic parameters and distributions into the simulation models, we relied on the *Air Force Cost Analysis Agency Handbook (AFCAA Handbook)*, as seen in Figure 25. In the handbook, the three main distributions recommended are the triangular, normal, and uniform distributions. We chose the triangular distribution because the limits (minimum and maximum) are known, and its shape resembles the normal distribution, with the most likely values having the highest probability of occurrence and the extreme ends (minimum and maximum values) having considerably lower probabilities of occurrence. Also, the triangular distribution was chosen instead of the normal distribution because the latter's tail ends extend toward positive and negative infinities, making it less applicable in the model we are developing. Finally, the *AFCAA Handbook* also provides options for left skew, right skew, and symmetrical distributions. In our analysis, we do not have sufficient historical or comparable data to make the proper assessment of skew and, hence, revert to the default of a symmetrical triangular distribution.

Figure 26 shows the steps required in a comprehensive IRM process.

AFCAA Cost Risk Analysis Handbook

Table 2-5 Default Bounds for Subjective Distributions

Distribution	Point Estimate Interpretation	Point Estimate and Probability	Mean	15%	85%
Triangle Low Left	Mode	1.0 (75%)	0.878	0.695	1.041
Triangle Low	Mode	1.0 (50%)	1.000	0.834	1.166
Triangle Low Right	Mode	1.0 (25%)	1.122	0.959	1.305
Triangle Med Left	Mode	1.0 (75%)	0.796	0.492	1.069
Triangle Med	Mode	1.0 (50%)	1.000	0.723	1.277
Triangle Med Right	Mode	1.0 (25%)	1.204	0.931	1.508
Triangle High Left*	Mode	1.0 (75%)	0.745	0.347	1.103
Triangle High	Mode	1.0 (50%)	1.000	0.612	1.388
Triangle High Right	Mode	1.0 (25%)	1.286	0.903	1.711
Triangle EHigh Left*	Mode	1.0 (75%)	0.745	0.300	1.130
Triangle EHigh	Mode	1.0 (50%)	1.004	0.509	1.500
Triangle EHigh Right	Mode	1.0 (25%)	1.367	0.876	1.914

Figure 25: U.S. Probability Risk Distribution Spreads

(Source: *Air Force Cost Analysis Agency Handbook*)

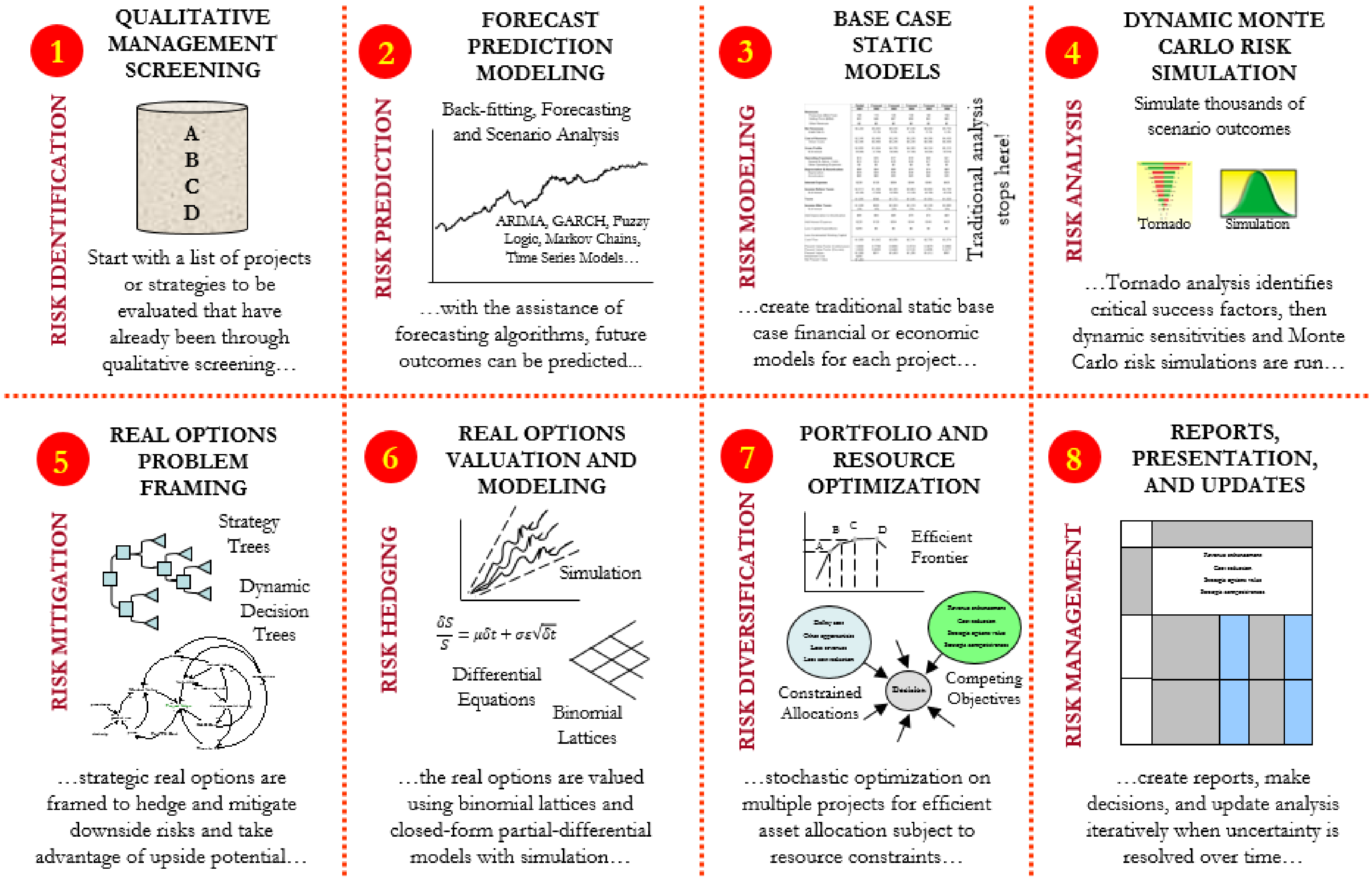


Figure 26: Integrated Risk Management Process

Appendix B: A Refresher on Portfolio Optimization

Many algorithms exist to run optimization and many different procedures exist when optimization is coupled with Monte Carlo simulation. In Risk Simulator, there are three distinct optimization procedures and optimization types as well as different decision variable types. For instance, Risk Simulator can handle *Continuous Decision Variables* (1.2535, 0.2215, and so forth), *Integer Decision Variables* (e.g., 1, 2, 3, 4 or 1.5, 2.5, 3.5, and so forth), *Binary Decision Variables* (1 and 0 for go and no-go decisions), and *Mixed Decision Variables* (both integers and continuous variables). On top of that, Risk Simulator can handle *Linear Optimization* (i.e., when both the objective and constraints are all linear equations and functions) and *Nonlinear Optimizations* (i.e., when the objective and constraints are a mixture of linear and nonlinear functions and equations).

As far as the optimization process is concerned, Risk Simulator can be used to run a *Discrete Optimization*, that is, an optimization that is run on a discrete or static model, where no simulations are run. In other words, all the inputs in the model are static and unchanging. This optimization type is applicable when the model is assumed to be known and no uncertainties exist. Also, a discrete optimization can first be run to determine the optimal portfolio and its corresponding optimal allocation of decision variables before more advanced optimization procedures are applied. For instance, before running a stochastic optimization problem, a discrete optimization is first run to determine if solutions to the optimization problem exist before a more protracted analysis is performed.

Next, *Dynamic Optimization* is applied when Monte Carlo simulation is used together with optimization. Another name for such a procedure is *Simulation-Optimization*. That is, a simulation is run first, then the results of the simulation are applied in the Excel model, and an optimization is applied to the simulated values. In other words, a simulation is run for *N* trials, and then an optimization process is run for *M* iterations until the optimal results are obtained or an infeasible set is found. Using Risk Simulator's optimization module, you can choose which forecast and assumption statistics to use and replace in the model after the simulation is run.

Then, these forecast statistics can be applied in the optimization process. This approach is useful when you have a large model with many interacting assumptions and forecasts, and when some of the forecast statistics are required in the optimization. For example, if the standard deviation of an assumption or forecast is required in the optimization model (e.g., computing the Sharpe Ratio in asset allocation and optimization problems where we have mean divided by standard deviation of the portfolio), then this approach should be used.

The *Stochastic Optimization* process, in contrast, is similar to the dynamic optimization procedure with the exception that the entire dynamic optimization process is repeated *T* times. That is, a simulation with *N* trials is run, and then an optimization is run with *M* iterations to obtain the optimal results. Then the process is replicated *T* times. The results will be a forecast chart of each decision variable with *T* values. In other words, a simulation is run and the forecast or assumption statistics are used in the optimization model to find the optimal allocation of decision variables. Then, another simulation is run, generating different forecast statistics, and these new updated values are then optimized, and so forth. Hence, the final decision variables will each have their own forecast chart, indicating the range of the optimal decision variables. For instance, instead of obtaining single-point estimates in the dynamic optimization procedure, you can now obtain a distribution of the decision variables, hence, a range of optimal values for each decision variable, also known as a stochastic optimization.

Finally, an Efficient Frontier optimization procedure applies the concepts of marginal increments and shadow pricing in optimization. That is, what would happen to the results of the optimization if one of the constraints were relaxed slightly? Say, for instance, the budget constraint is set at $1 million. What would happen to the portfolio’s outcome and optimal decisions if the constraint were now $1.5 million, or $2 million, and so forth. This is the concept of the Markowitz efficient frontier in investment finance, where if the portfolio standard deviation is allowed to increase slightly, what additional returns will the portfolio generate? This process is similar to the dynamic optimization process with the exception that *one* of the constraints is allowed to change, and with each change, the simulation and optimization process is run, a process best applied manually using Risk Simulator. This process can be run either manually (rerunning the optimization several times) or automatically (using Risk Simulator's changing constraint and efficient frontier functionality). For example, the manual process is: Run a dynamic or stochastic optimization, then rerun another optimization with a new constraint, and repeat that procedure several times. This manual process is important, as by changing the constraint, the analyst can determine if the results are similar or different, and, hence, whether it is worthy of any additional analysis, or to determine how far a marginal increase in the constraint should be to obtain a significant change in the objective and decision variables. This is done by comparing the forecast distribution of each decision variable after running a stochastic optimization. Alternatively, the automated efficient frontier approach will be shown later in the chapter.

One item is worthy of consideration. Other software products exist that supposedly perform stochastic optimization, but, in fact, they do not. For instance, after a simulation is run, then *one* iteration of the optimization process is generated, and then another simulation is run, then the *second* optimization iteration is generated and so forth. This process is simply a waste of time and resources; that is, in optimization, the model is put through a rigorous set of algorithms, where multiple iterations (ranging from several to thousands of iterations) are required to obtain the optimal results. Hence, generating *one* iteration at a time is a waste of time and resources. The same portfolio can be solved using Risk Simulator in under a minute as compared to multiple hours using such a backward approach. Also, such a simulation-optimization approach will typically yield bad results and is not a stochastic optimization approach. Be extremely careful of such methodologies when applying optimization to your models.

The following are two examples of optimization problems. One uses continuous decision variables while the other uses discrete integer decision variables. In either model, you can apply discrete optimization, dynamic optimization, or stochastic optimization, or even manually generate efficient frontiers with shadow pricing. Any of these approaches can be used for these two examples. Therefore, for simplicity, only the model setup is illustrated, and it is up to the user to decide which optimization process to run. Also, the continuous decision variable example uses the nonlinear optimization approach (because the portfolio risk computed is a nonlinear function, and the objective is a nonlinear function of portfolio returns divided by portfolio risks), while the second example of an integer optimization is an example of a linear optimization model (its objective and all of its constraints are linear). Therefore, these two examples encapsulate all of the procedures aforementioned.

Discrete Integer Optimization

Sometimes, the decision variables are not continuous but discrete integers (e.g., 1, 2, 3) or binary (e.g., 0 and 1). We can use such binary decision variables as on-off switches or go/no-go decisions. Figure 27 illustrates a project selection model where there are 12 projects listed. Each project, like before, has its own returns (ENPV and NPV for expanded net present value and net present value—the ENPV is simply the NPV plus any strategic real options values), costs of implementation, risks, and so forth. If required, this model can be modified to include required full-time equivalences (FTE) and other resources of various functions, and additional constraints can be set on these additional resources. The inputs into this model are typically linked from other spreadsheet models. For instance, each project will have its own discounted cash flow or returns on investment model. The application here is to maximize the portfolio's Sharpe Ratio subject to some budget allocation. Many other versions of this model can be created, for instance, maximizing the portfolio returns, or minimizing the risks, or adding constraints where the total number of projects chosen cannot exceed 6, and so forth and so on. All of these items can be run using this existing model.

Projects	ENPV	Cost	Risk $	Risk %	Return to Risk Ratio	Profitability Index	Selection
Project 1	$458.00	$1,732.44	$54.96	12.00%	8.33	1.26	1.0000
Project 2	$1,954.00	$859.00	$1,914.92	98.00%	1.02	3.27	1.0000
Project 3	$1,599.00	$1,845.00	$1,551.03	97.00%	1.03	1.87	1.0000
Project 4	$2,251.00	$1,645.00	$1,012.95	45.00%	2.22	2.37	1.0000
Project 5	$849.00	$458.00	$925.41	109.00%	0.92	2.85	1.0000
Project 6	$758.00	$52.00	$560.92	74.00%	1.35	15.58	1.0000
Project 7	$2,845.00	$758.00	$5,633.10	198.00%	0.51	4.75	1.0000
Project 8	$1,235.00	$115.00	$926.25	75.00%	1.33	11.74	1.0000
Project 9	$1,945.00	$125.00	$2,100.60	108.00%	0.93	16.56	1.0000
Project 10	$2,250.00	$458.00	$1,912.50	85.00%	1.18	5.91	1.0000
Project 11	$549.00	$45.00	$263.52	48.00%	2.08	13.20	1.0000
Project 12	$525.00	$105.00	$309.75	59.00%	1.69	6.00	1.0000
Total	$17,218.00	$8,197.44	$7,007	40.70%			12.00
Goal:	MAX	< =$5000					<=6
Sharpe Ratio	2.4573						

ENPV is the expected NPV of each investment or project, while Cost can be the total cost of investment, and Risk is the Coefficient of Variation of the project's ENPV.

Figure 27: Discrete Go and No-Go Decision for Project and Program Selection

Results Interpretation

Figure 29 shows a sample optimal selection of projects that maximizes the Sharpe Ratio. In contrast, one can always maximize total revenues, but this process is trivial and simply involves choosing the highest returning project and going down the list until you run out of money or exceed the budget constraint. Doing so will yield theoretically undesirable projects as the highest yielding projects typically hold higher risks. Now, if desired, you can replicate the optimization using a stochastic or dynamic optimization by adding in assumptions in the ENPV and Risk values.

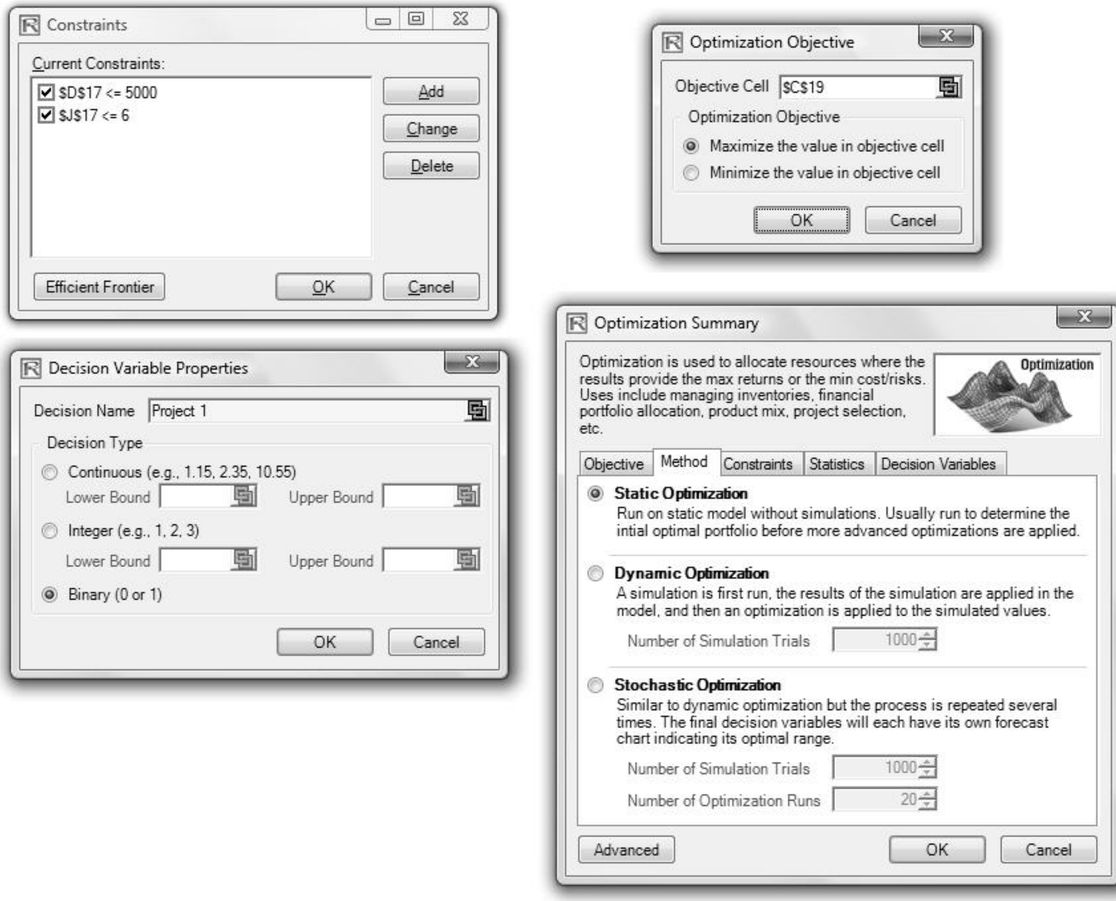


Figure 28: Portfolio Optimization Model Settings

	ENPV	Cost	Risk $	Risk %	Return to Risk Ratio	Profitability Index	Selection
Project 1	$458.00	$1,732.44	$54.96	12.00%	8.33	1.26	1.0000
Project 2	$1,954.00	$859.00	$1,914.92	98.00%	1.02	3.27	0.0000
Project 3	$1,599.00	$1,845.00	$1,551.03	97.00%	1.03	1.87	0.0000
Project 4	$2,251.00	$1,645.00	$1,012.95	45.00%	2.22	2.37	1.0000
Project 5	$849.00	$458.00	$925.41	109.00%	0.92	2.85	0.0000
Project 6	$758.00	$52.00	$560.92	74.00%	1.35	15.58	1.0000
Project 7	$2,845.00	$758.00	$5,633.10	198.00%	0.51	4.75	0.0000
Project 8	$1,235.00	$115.00	$926.25	75.00%	1.33	11.74	1.0000
Project 9	$1,945.00	$125.00	$2,100.60	108.00%	0.93	16.56	0.0000
Project 10	$2,250.00	$458.00	$1,912.50	85.00%	1.18	5.91	0.0000
Project 11	$549.00	$45.00	$263.52	48.00%	2.08	13.20	1.0000
Project 12	$525.00	$105.00	$309.75	59.00%	1.69	6.00	1.0000
Total	$5,776.00	$3,694.44	$1,539	26.64%			6.00
Goal:	MAX	< =$5000					<=6
Sharpe Ratio	3.7543						

ENPV is the expected NPV of each credit line or project, while Cost can be the total cost of administration as well as required capital holdings to cover the credit line, and Risk is the Coefficient of Variation of the credit line's ENPV.

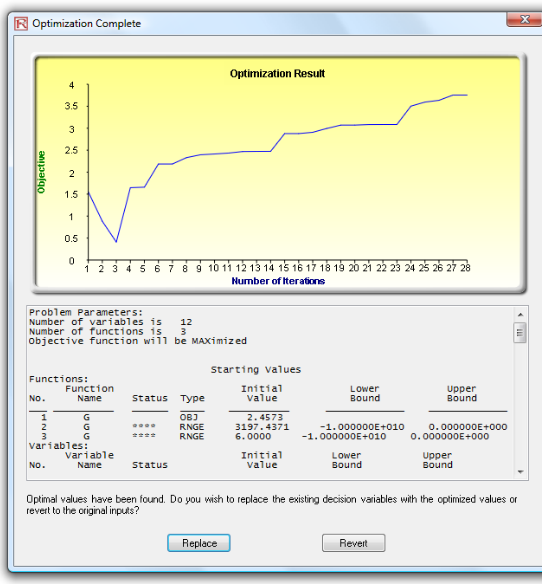


Figure 29: Optimal Selection of Projects Maximizing Sharpe Ratio

Efficient Frontier and Advanced Optimization

Figure 30 shows the efficient frontier constraints for optimization. You can get to this interface using Risk Simulator software by going to the *Efficient Frontier* button *after* you have set some constraints. You can now make these constraints changing. That is, each of the constraints can be created to step through between some minimum and maximum value. As an example, the constraint in cell J17 <= 6 can be set to run between 4 and 8 (Figure 30). That is, five optimizations will be run, each with the following constraints: J17 <= 4, J17 <= 5, J17 <= 6, J17 <= 7, and J17 <= 8. The optimal results will then be plotted as an efficient frontier and the report will be generated (Figure 31).

Specifically, following are the steps required to create a changing constraint:

- In an optimization model (i.e., a model with Objective, Decision Variables, and Constraints already set up), click on *Risk Simulator* | *Optimization* | *Constraints,* and then click on *Efficient Frontier*.
- Select the constraint you want to change or step (e.g., J17), enter the parameters for Min, Max, and Step Size (Figure 30), and click *ADD*, then *OK*, and *OK* again. You should *deselect* the D17 <= 5000 constraint before running.
- Run Optimization as usual. You can choose static, dynamic, or stochastic. To get started, select the *Static Optimization* to run.
- The results will be shown as a user interface (Figure 31). Click on *Create Report* to generate a report worksheet with all the details of the optimization runs.

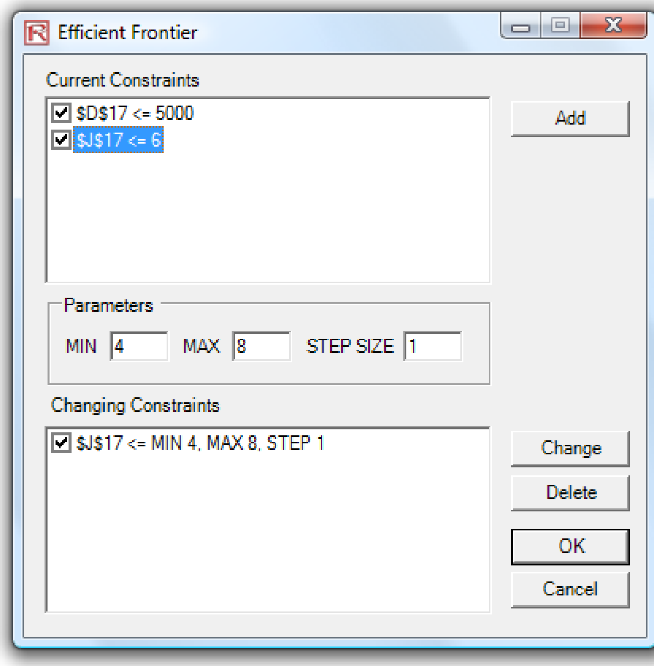
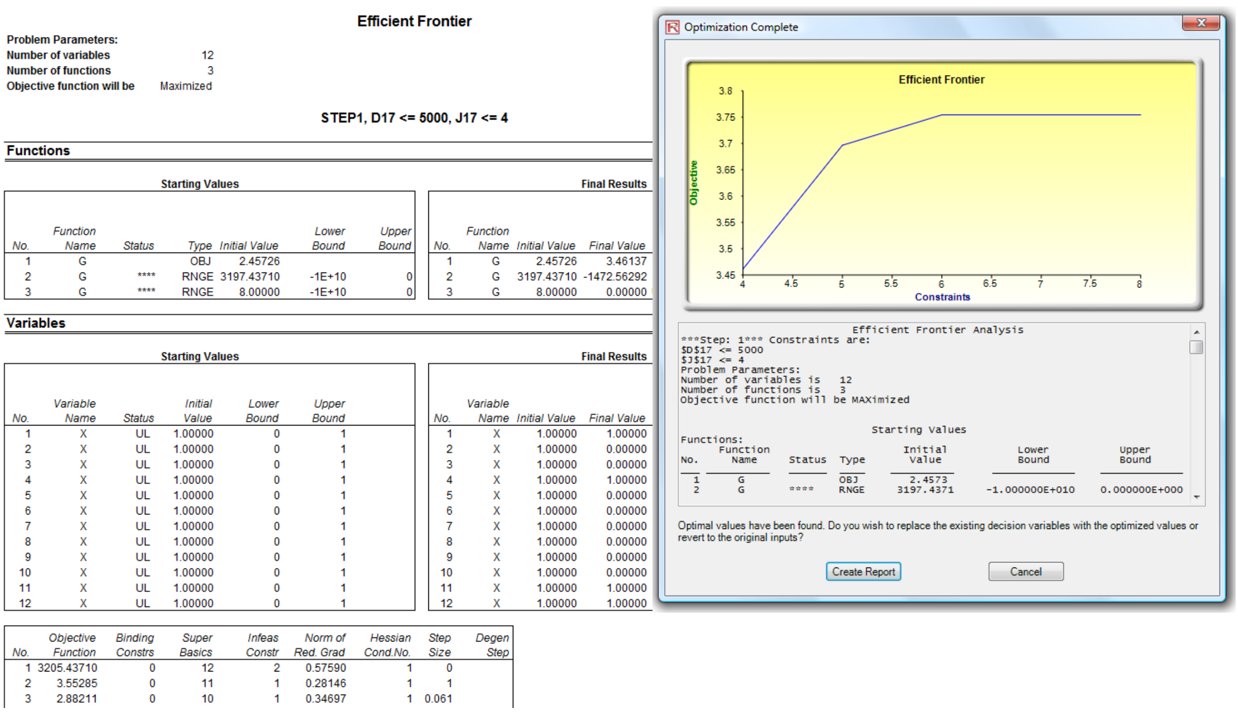


Figure 30: Generating Changing Constraints in an Efficient Frontier



No.	Function Name	Status	Type	Initial Value	Lower Bound	Upper Bound
1	G		OBJ	2.45726		
2	G	****	RNGE	3197.43710	-1E+10	0
3	G	****	RNGE	8.00000	-1E+10	0

No.	Function Name	Initial Value	Final Value
1	G	2.45726	3.46137
2	G	3197.43710	-1472.56292
3	G	8.00000	0.00000

No.	Variable Name	Status	Initial Value	Lower Bound	Upper Bound
1	X	UL	1.00000	0	1
2	X	UL	1.00000	0	1
3	X	UL	1.00000	0	1
4	X	UL	1.00000	0	1
5	X	UL	1.00000	0	1
6	X	UL	1.00000	0	1
7	X	UL	1.00000	0	1
8	X	UL	1.00000	0	1
9	X	UL	1.00000	0	1
10	X	UL	1.00000	0	1
11	X	UL	1.00000	0	1
12	X	UL	1.00000	0	1

No.	Variable Name	Initial Value	Final Value
1	X	1.00000	1.00000
2	X	1.00000	0.00000
3	X	1.00000	0.00000
4	X	1.00000	1.00000
5	X	1.00000	0.00000
6	X	1.00000	0.00000
7	X	1.00000	0.00000
8	X	1.00000	0.00000
9	X	1.00000	0.00000
10	X	1.00000	0.00000
11	X	1.00000	1.00000
12	X	1.00000	1.00000

No.	Objective Function	Binding Constrs	Super Basics	Infeas Constr	Norm of Red. Grad	Hessian Cond.No.	Step Size	Degen Step
1	3205.43710	0	12	2	0.57590	1	0	
2	3.55285	0	11	1	0.28146	1	1	
3	2.88211	0	10	1	0.34697	1	0.061	

Figure 31: Efficient Frontier Results

Biographies

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EDUCATION

Lehigh University, Doctor of Philosophy

Finance and Economics, 1998

Nova Southeastern University, Master of Business Administration

Business Management, 1995 (Summa Cum Laude)

University of Miami, Bachelor of Science

Biology and Physics, 1994 (Magna Cum Laude)

EXPERIENCE

2005–Present: Research Professor, Naval Postgraduate School,

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2005–Present: Chairman and CEO, Real Options Valuation, Inc., Dublin, California

2001–2010: Visiting Professor, University of Applied Sciences and

Swiss School of Management, Switzerland

2001–2004: Vice President of Analytics, Decisioneering-Oracle, Denver, Colorado

1999–2001: Senior Manager and Economist, KPMG Consulting, California

1998–2001: Adjunct Professor, Golden Gate Univ. and St. Mary’s College, California

1998–1999: Manager, Viking, Inc. (FDX Corporation), California

PUBLISHED BOOKS

- *Modeling Risk: Applying Monte Carlo Risk Simulation, Strategic Real Options Analysis, Stochastic Forecasting, and Portfolio Optimization,* Third Edition, Thomson-Shore (2015).
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- Academic Program Director, University of Southern California, Marshall School of Business, 8/98–8/01.
- Director (Vice President), Consumer Behavior Research in Telematics and Informatics, Centro Studies, Salvador (Telecom Italia), 1/94–8/95.
- Chief Business Process Engineer, Strategic Information Systems Division, Pacific Bell, 10/92–1/94.
- Director, Business Development and Domain Engineering, Strategic Information Systems Division, Pacific Bell, 8/91–10/92.

- Assistant Professor of Business Communication (clinical), University of Southern California, School of Business Administration, 1982–1991.
- Associate Director, Center for Operations Management Education and Research, University of Southern California, 1987–1991.
- Associate Director, Center for Telecommunications Management, University of Southern California, 1984–1985.
- Assistant Professor, University of Kentucky, College of Communications, 1977–1982.

PUBLICATIONS

- Rodgers, Waymond, and Housel, Thomas J. (2009). “Problems and Resolutions to Future Knowledge-Based Assets Reporting,” *Journal of Intellectual Capital,* Vol. 10, No. 4.
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