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

30 September 2018

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

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Table of Contents

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List of Acronyms

AA	Achieved Availability
AAW	Anti-Aircraft Warfare
ACB	Advanced Concept Build
AHP	Analytical Hierarchy Process
APMS	Army Portfolio Management Solution
AQ	Aggregate Quality
ASUW	Anti-Surface Warfare
ASW	Anti-Submarine Warfare
BCR	Base-Case Rank
BMD	Ballistic Missile Defense
CAPM	Capital Asset-Pricing Model
CBO	Congressional Budget Office
CCOPS	Carry-On Cryptologic Programs
CEC	Cost Estimating Categories
CES	Cost Element Structures
CF	Cash Flow
CM	Capability Measures
CNO	Chief of Naval Operations
COTS	Commercial Off-the-Shelf
CSBA	Center for Strategic and Budgetary Assessments
CUO	Common Units of Output
DC	Domain Capabilities
DCF	Discounted Cash Flow

DDG	Arleigh Burke–Class of Guided Missile Destroyers
DOD	U.S. Department of Defense
DON	Department of the Navy
DPS	Dividends Per Share
EA	Effective Availability
EMV	Expected Military Value
ELECTRE	Elimination et Choix Traduisant la Realité [Elimination and Choice Expressing Reality]
ENPV	Expanded Net Present Value
EPS	Earnings Per Share
EVMS	Earned Value Management System
FASO	Flexible and Adaptable Ship Options
FCF	Free Cash Flow
FSC	Future Surface Combatants
FTE	Full-Time Equivalences
FY	Fiscal Year
GAAP	Generally Accepted Accounting Principles
GDP	Gross Domestic Product
GGM	Gordon Growth Model
IA	Inherent Availability
IDA	Institute for Defense Analyses
IR	Inherent Reliability
IRM	Integrated Risk Management
IRR	Internal Rate of Return

KVA	Knowledge Value Added
LCS	Littoral Combat Ship
LDT	Logistics Delay Time
LPOM	Local Partial Order Model
LPOMext	Extended Local Partial Order Model
MA	Mission Availability
MAPT	Multiple Asset-Pricing Theory
MAS	Modular Adaptable Ships
MCA	Multicriteria Analysis
MDT	Mean Down Time
MIRR	Modified Internal Rate of Return
MMT	Mean Maintenance Time
MR	Mission Reliability
NAVSEA	Naval Sea Systems Command
NPS	Naval Postgraduate School
NPV	Net Present Value
OA	Operational Availability
OD	Operational Dependability
OFT	Office of Force Transformation
ONR	Office of Naval Research
OPNAV	Navy Operations
ORR	Operational Ready Rate
OSD	Office of the Secretary of Defense
PA	Portfolio Analysis

PDF	Probability Distribution Function
PDSA	Principal DOD Space Advisor
PE	Price-to-Earnings [ratio]
PEO-SHIPS	Program Executive Office Ships
PEO-IWS	Program Executive Office Integrated Warfare Systems
PG&E	Pacific Gas and Electric
PMA	Portfolio Management Analysis
PPM	Project Portfolio Management
PRM	Partitioned Multiobjective Risk Method
PR	Payout Ratio
PROMETHEE	Preference Ranking Organization Methods for Enrichment Evaluations
PV	Performance Value
RI	Relative Importance
RO	Real Options
ROI	Return on Investment
ROK	Return on Knowledge
ROKI	Return on Knowledge Investment
ROM	Rough Order Magnitude
ROV	Real Options Valuation
SME	Subject Matter Expert
SoS	System of Systems
SPR	Strategic Portfolio Review
TBD	To Be Determined

TLC	Total Lifecycle Cost
TOC	Total Ownership Cost
VaR	Value at Risk
VLS	Vertical Launch Systems
WACC	Weighted Average Cost of Capital
WBS	Work Breakout Structures

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List of Figures

Introduction

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

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

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

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

Capital Budgeting

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

Portfolio Optimization

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

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

Such decisions might involve thousands or millions of potential alternatives. Considering and evaluating each of them would be impractical or even impossible.

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

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

Relevance of Proposed Effort to Research Area

The research is expected to reveal the important critical success factors for developing a strategic real options valuation methodology and model to more accurately identify various ship design flexibilities and to value each design option path to determine the best course of action. In addition, the research will make recommendations for implementation of these new methods. These recommendations will provide a platform for discussion, decision making, and action toward adoption.

Research Questions and Objectives

The proposed research attempts to answer the following research questions:

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

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

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

The Army Review to Rank 780 Programs by Priority (Association of the United States Army, 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) presented a model developed for the Boeing Company in Seattle to optimize a portfolio of product development improvement projects. The authors illustrate how a dependency matrix (modeling of interdependencies among projects) is applied in a nonlinear integer programming methodology to optimize project selection. The model also balances risk, overall objectives, and the cost and benefit of the entire portfolio. Once the optimum strategy is identified, the model enables the team to quickly quantify and evaluate small changes to the portfolio.

In the U.S. military context, risk analysis, real options analysis, and portfolio optimization techniques enable a new way of approaching the problems of estimating return on investment (ROI) and the risk value of various strategic real options. There are many DOD requirements for using more advanced analytical techniques. For instance, the Clinger-Cohen Act of 1996 mandates the use of portfolio management for all federal agencies. The GAO's 1997 report entitled *Assessing Risks and Returns: A Guide for Evaluating Federal Agencies' IT Investment Decision-Making* requires that IT investments apply ROI measures. DOD Directive (DODD) 8115.01 (DOD, 2005) mandates the use of performance metrics based on outputs, with ROI analysis required for all current and planned IT investments. DODD 8115.bb (2006) implements policy and assigns responsibilities for the management of DOD IT investments as portfolios within the DOD enterprise where it defines a portfolio to include outcome performance measures and an expected return on investment. The DOD's *Risk Management Guidance Defense*

Acquisition Guidebook requires that alternatives to the traditional cost estimation need to be considered because legacy cost models tend not to adequately address costs associated with information systems or the risks associated with them (see Mun, Ford, & Housel, 2012).

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.

Capital Budgeting and the Value Concept

This section reviews the concepts of capital budgeting in industry and best practices relating to financial and economic capital budgeting, including the applications of market approach, income approach, and cost approach.

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 Program Executive Office Integrated Warfare Systems (PEO IWS) and Naval Sea Systems Command (NAVSEA) domain is presented to show how standard capital budgeting with economic and financial information as well as non-economic data and information are used in a portfolio.

Alternative Analytical Approaches

This next section looks at alternative methods to optimization, such as a lexicographic average rank approach, as well as other risk metrics methods.

Optimization Application at PEO-IWS and NAVSEA

An example application using notional values is performed utilizing illustrations from PEO-IWS and NAVSEA. Multiple capabilities are combined into a portfolio to run capital budgeting and optimization.

Conclusions and Recommendations

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

Appendices

The theory behind corporate capital budgeting methods, discounting conventions, and real options valuation and associated methods is covered in the appendices. These appendices are included to provide a more comprehensive and stand-alone research for the reader's convenience. In Appendix A, some basic financial statement analysis concepts used in applying real options are covered. As an overview of the standard portfolio model settings and requirements, Appendix B is a quick refresher on how an optimization model can be set up. Finally, the recommended decision analytics framework is briefly explained in Appendix C. This framework structures 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 are also used.

Literature Review

Portfolio Modeling in Military Applications

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

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

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 was developed by the authors.

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

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

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

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

The GAO (1997, 2007) emphasized the approach of optimizing a portfolio mix to manage risk and maximize the rate of return. Although the DOD produces superior weapons, the GAO reported that the department has failed to deliver weapon systems on time, within budget, and with desired capabilities. While recent changes to the DOD's acquisition policy held the potential to improve outcomes, programs continue to experience significant cost and schedule overruns. The GAO was asked to examine how the DOD's processes for determining needs and allocating resources can better support weapon system program stability. To do this, according to the report, the GAO compared the DOD's processes for investing in weapon systems to the best practices that successful commercial companies use to achieve a balanced mix of new products, including companies such as Caterpillar, Eli Lilly, IBM, Motorola, and Procter and Gamble. Based on the reports, the GAO found that to achieve a balanced mix of executable development programs and ensure a good return on their investments, the successful commercial companies the GAO reviewed take an integrated, portfolio management approach to product development. Through this approach, companies assess product investments collectively from an enterprise level, rather than as independent and unrelated initiatives. These commercial entities weigh the relative costs, benefits, and risks of proposed products using established criteria and methods and select those products that can exploit promising market opportunities within resource constraints and move the company toward meeting its strategic goals and objectives. In these firms, investment decisions are frequently revisited, and if a product falls short of expectations, companies make tough go/no-go decisions over time. The companies the GAO reviewed 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 DOD 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 financial portfolio analysis based on “stock price” 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) notes 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. The 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 (2004) 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 (PEOs) today often focus on executing a dozen similar but independent programs. In contrast, large commercial businesses manage integrated product lines for items ranging from automobiles and electronics to software and health services. The DOD could leverage this model as a basis for constructing portfolios of similar programs that deliver enhanced capabilities in shorter timeframes.

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 that can be visualized via a three-dimensional graph illustrating 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 et al.'s paper discussed research that builds on prior work that explored system design trade-spaces for affordability under uncertainty, extending it to the program and portfolio level. Time-varying exogenous factors, such as resource availability, stakeholder needs, or production delays, may influence the potential for value contribution by constituent systems over the life cycle of a portfolio and make an initially attractive design less attractive over time. Vascik et al. (2015) introduced a method to conduct portfolio design for affordability by augmenting Epoch-Era Analysis with aspects of Modern Portfolio Theory. The method is demonstrated through the design of a carrier strike group portfolio involving the integration of multiple legacy systems with the acquisition of new vessels.

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

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. To give efficient portfolios to the risk model, the heuristic algorithms are proposed to solve the portfolio selection problem that 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 individual systems to work in a coordinated and synergistic fashion as a single system. The researchers explored the optimal defense budget allocation to the development and acquisition of weapon systems and to the development of integrative technologies. They developed a suitable optimization framework and then used it to derive the optimal budget allocation and analyze its properties. Finally, they used 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. The authors presented 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, PG&E 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, PG&E's portfolio management is not, at its core, a mechanical exercise; it's a dialogue about resource allocation and business growth building blocks. Numerical input informs but does not 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.

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Capital Budgeting and the Value Concept

The Traditional Views

Value is defined as the single time-value discounted number that is representative of all future net profitability. In contrast, the market price of an asset may or may not be identical to its value (“assets,” “projects,” and “strategies” are used interchangeably). For instance, when an asset is sold at a significant bargain, its price may be somewhat lower than its value, and one would surmise that the purchaser has obtained a significant amount of value. The idea of valuation in creating a fair market value is to determine the price that closely resembles the true value of an asset. This true value comes from the physical aspects of the asset as well as its nonphysical, intrinsic, or intangible aspects. Both aspects have the capability to generate extrinsic monetary value or intrinsic strategic value. Traditionally, there are three mainstream methodologies to valuation, namely, the market approach, the income approach, and the cost approach (see Mun, Hernandez, & Rocco, 2016, for more details).

Market Approach

The market approach looks at comparable assets in the marketplace and their corresponding prices and assumes that market forces will tend to move the market price to an equilibrium level. It is further assumed that the market price is also the fair market value after adjusting for transaction costs and risk differentials. Sometimes a market-, industry- or firm-specific adjustment is warranted to bring the comparables closer to the operating structure of the firm whose asset is being valued. These could include common-sizing the comparable firms by performing quantitative screening using criteria that closely resemble the firm’s industry, operations, size, revenues, functions, profitability levels, operational efficiency, competition, market, and risks.

Income Approach

The income approach looks at the future potential profit or free-cash-flow-generating potential of the asset and attempts to quantify, forecast, and discount these net free cash flows to a present value. The cost of implementation, acquisition, and development of the asset is then deducted from this present value of cash flows to generate a net present value. Often, the cash flow stream is discounted at a firm-specified hurdle rate, at the weighted average cost of capital, or at a risk-adjusted discount rate based on the perceived project-specific risk, historical firm risk, or overall business risk.

Cost Approach

The cost approach looks at the cost a firm would incur if it were to replace or reproduce the asset's future profitability potential, including the cost of its strategic intangibles, if the asset were to be created from the ground up. Although the financial theories underlying these approaches are sound in the more traditional deterministic view, they cannot be reasonably used in isolation when analyzing the true strategic flexibility value of a firm, project, or asset.

Other Approaches

Other approaches used in valuation, more appropriately applied to the valuation of intangibles, rely on quantifying the economic viability and economic gains the asset brings to the firm. There are several well-known methodologies for intangible-asset valuation, particularly in valuing trademarks and brand names. These methodologies apply the combination of the market, income, and cost approaches just described.

The first method compares pricing strategies and assumes that by having some dominant market position by virtue of a strong trademark or brand recognition––for instance, Coca-Cola––the firm can charge a premium price for its product. Hence, if we can find market comparables producing similar products, in similar markets, performing similar functions, facing similar market uncertainties and risks, the price differential would then pertain exclusively to the brand name. These comparables are generally adjusted to account for the different conditions under which the firms operate. This price premium per unit is then multiplied by the projected quantity of sales, and the outcome after performing a discounted cash flow (DCF) analysis will be the residual profits allocated to the intangible. A similar argument can be set forth in using operating profit margin in lieu of price per unit. Operating profit before taxes is used instead of net profit after taxes because it avoids the problems of comparables having different capital structure policies or carry-forward net operating losses and other tax-shield implications.

Another method uses a common-size analysis of the profit and loss statements between the firm holding the asset and market comparables. This method takes into account any advantage from economies of scale and economies of scope. The idea here is to convert the income statement items as a percentage of sales and balance sheet items as a percentage of total assets. In addition, in order to increase comparability, the ratio of operating profit to sales of the comparable firm is then multiplied by the asset-holding firm's projected revenue structure, thereby eliminating the potential problem of having to account for differences in economies of scale and scope. This approach uses a percentage of sales, return on investment, or return on asset ratio as the common-size variable.

Practical Issues Using Traditional Valuation Methodologies

The traditional valuation methodology relying on a discounted cash flow series does not get at some of the intrinsic attributes of the asset or investment opportunity. Traditional methods assume that the investment is an all-or-nothing strategy, and they do not account for managerial flexibility that exists such that management can alter the course of an investment over time when certain aspects of the project's uncertainty become known. One of the value-added components of using real options is that it takes into account management's ability to create, execute, and abandon strategic and flexible options.

There are several potential problem areas in using a traditional discounted cash flow calculation on strategic optionalities. These problems include undervaluing an asset that currently produces little or no cash flow, the nonconstant nature of the weighted average cost of capital discount rate through time, the estimation of an asset's economic life, forecast errors in creating the future cash flows, and insufficient tests for plausibility of the final results. Real options, when applied using an options theoretical framework, can mitigate some of these problematic areas. Otherwise, financial profit level metrics, such as NPV, or internal rate of return (IRR), will be skewed and not provide a comprehensive view of the entire investment value.

DCF: Synopsis of Advantages and Disadvantages

While there are concerns about using only traditional discounted cash flow analysis, the discounted cash flow model does have its merits (Mun, 2016):

- Clear, consistent decision criteria for all projects
- Same results regardless of risk preferences of investors
- Quantitative, decent level of precision and economically rational
- Not as vulnerable to accounting conventions (depreciation, inventory valuation, etc.)
- Factors in the time value of money and risk structures
- Relatively simple, widely taught, and widely accepted
- Simple to explain to management: "If benefits outweigh the costs, do it!"

In reality, however, an analyst should be aware of several issues prior to using discounted cash flow models, as shown in Table 1. The most important aspects include the business reality that risks and uncertainty abound when decisions have to be made and that management has the strategic flexibility to make and change decisions as these uncertainties become known over time. In such a stochastic world, using deterministic models such as the discounted cash flow may potentially grossly underestimate the value of a particular project. A deterministic discounted cash flow model assumes at the outset that all future outcomes are fixed. If this is the case, then the discounted cash flow model is correctly specified as there would be no fluctuations in business conditions that would change the value of a particular project. In essence, there would be no value in flexibility. However, the actual business environment is highly fluid, and if management has the flexibility to make appropriate changes when conditions differ, then there is indeed value in flexibility, a value that will be grossly underestimated using a discounted cash flow model.

DCF Assumptions	*Realities*
Decisions are made now, and cash flow streams are fixed for the future.	Uncertainty and variability in future outcomes. Not all decisions are made today as some may be deferred to the future, when uncertainty becomes resolved.
Projects are “mini firms,” and they are interchangeable with whole firms.	With the inclusion of network effects, diversification, interdependencies, and synergy, firms are portfolios of projects and their resulting cash flows. Sometimes projects cannot be evaluated as stand-alone cash flows.
Once launched, all projects are passively managed.	Projects are usually actively managed through project life cycle, including checkpoints, decision options, budget constraints, etc.
Future free cash flow streams are all highly predictable and deterministic.	It may be difficult to estimate future cash flows as they are usually stochastic and risky in nature.
Project discount rate used is the opportunity cost of capital, which is proportional to nondiversifiable risk.	There are multiple sources of business risks with different characteristics, and some are diversifiable across projects or time.
All risks are completely accounted for by the discount rate.	Firm and project risk can change during the course of a project.
All factors that could affect the outcome of the project and value to the investors are reflected in the DCF model through the NPV or IRR.	Because of project complexity and so-called externalities, it may be difficult or impossible to quantify all factors in terms of incremental cash flows. Distributed, unplanned outcomes (e.g., strategic vision and entrepreneurial activity) can be significant and strategically important.
Unknown, intangible, or immeasurable factors are valued at zero.	Many of the important benefits are intangible assets or qualitative strategic positions.

DCF Analysis Versus Advanced Analytics

Figure 1 shows a simple example of applying discounted cash flow analysis. Assume that there is a project costing $1,000 to implement at Year 0 that will bring in the following projected positive cash flows in the subsequent five years: $500, $600, $700, $800, and $900. These projected values are simply subjective best-guess forecasts on the part of the analyst. As can be seen in Figure 1, the time line shows all the pertinent cash flows and their respective discounted present values.

Assuming the analyst decides that the project should be discounted at a 20% risk-adjusted discount rate using a weighted average cost of capital (WACC), we calculate the NPV to be $985.92 and a corresponding IRR of 54.97%. (The NPV is simply the sum of the present values of future cash flows less the implementation cost. The IRR is the implicit discount rate that forces the NPV to be zero. Both calculations can be easily performed in Excel using its "NPV()" and "IRR()" functions.) Furthermore, the analyst assumes that the project will have an infinite economic life and assumes a long-term growth rate of cash flows of 5%. Using the Gordon constant growth model, the analyst calculates the terminal value of the project's cash flow at Year 5 to be $6,300. Discounting this figure for five years at the risk-adjusted discount rate and adding it to the original NPV yields a total NPV with terminal value of $3,517.75. The calculations can all be seen in Figure 1, where *w* is defined as the weights, *d* for debt, *ce* for common equity and *ps* for preferred stocks, *FCF* as the free cash flows, *tax* as the corporate tax rate, *g* as the long-term growth rate of cash flows, and rf as the risk-free rate.

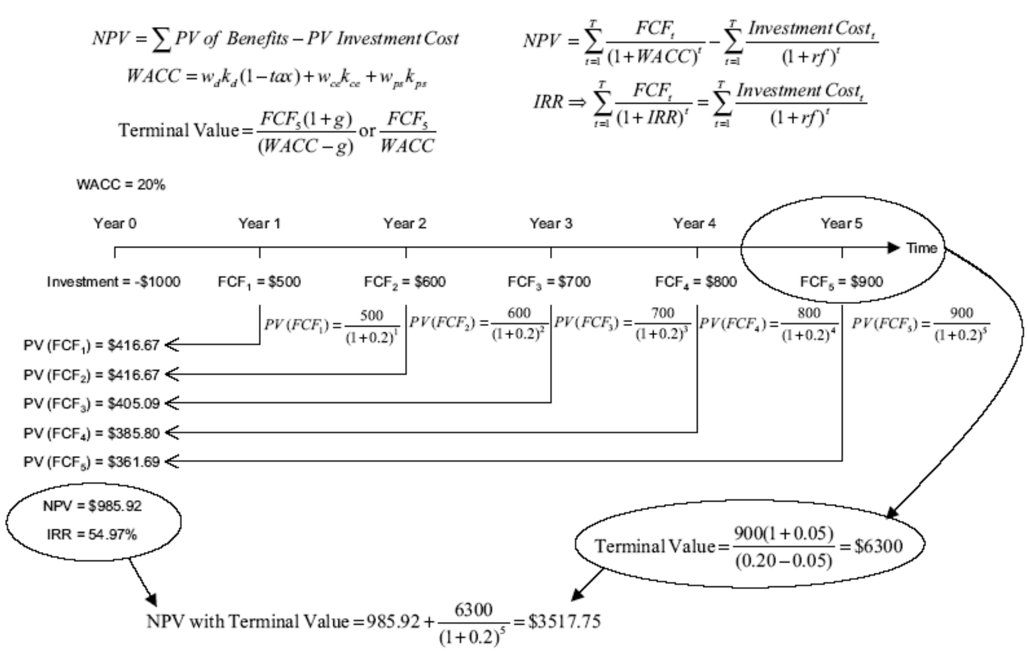

Figure 1: Applying Discounted Cash Flow Analysis

Even with a simplistic discounted cash flow model like this, one can see the many shortcomings of using a discounted cash flow model that are worthy of mention. Figure 2 lists some of the more notable issues. For instance, the NPV is calculated as the present value of future net free cash flows (benefits) less the present value of implementation costs (investment costs). However, in many instances, analysts tend to discount both benefits and investment costs at a single identical market risk-adjusted discount rate, usually the WACC. This approach, of course, is flawed (Mun, 2016).

The benefits should be discounted at a market risk-adjusted discount rate like the WACC, but the investment cost should be discounted at a reinvestment rate similar to the risk-free rate. Cash flows that have market risks should be discounted at the market risk-adjusted rate, while cash flows that have private risks should be discounted at the risk-free rate because the market will only compensate the firm for taking on the market risks but not private risks. It is usually assumed that the benefits are subject to market risks (because benefit free cash flows depend on market demand, market prices, and other exogenous market factors) while investment costs depend on internal private risks (such as the firm's ability to complete building a project in a timely fashion or the costs and inefficiencies incurred beyond what is projected). On occasion, these implementation costs may also be discounted at a rate slightly higher than a risk-free rate, such as a money-market rate, or at the opportunity cost of being able to invest the sum in another project yielding a particular interest rate. Suffice it to say that benefits and investment costs should be discounted at different rates if they are subject to different risks. Otherwise, discounting the costs at a much higher market risk-adjusted rate will reduce the costs significantly, making the project look as though it were more valuable than it actually is.

The chosen discount rate is typically calculated from a WACC, Capital Asset-Pricing Model (CAPM), Multiple Asset-Pricing Theory (MAPT), or Arbitrage Pricing Theory (APT), and set by management as a requirement for the firm or as a hurdle rate for specific projects. In most circumstances, if we were to perform a simple discounted cash flow model, the most sensitive variable is usually the discount rate.

It is also the most difficult variable to correctly quantify. Hence, this leaves the discount rate open to potential abuse and subjective manipulation. A target NPV value can be obtained by simply massaging the discount rate to a suitable level.

In addition, certain input assumptions required to calculate the discount rate are also subject to question. For instance, in the WACC, the input for the cost of common equity is usually derived using some form of the CAPM. In the CAPM, the infamous beta (β) is extremely difficult to calculate. For financial assets, we can obtain beta through a simple calculation of the covariance between a firm's stock prices and the market portfolio, divided by the variance of the market portfolio. Beta is then a sensitivity factor measuring the co-movements of a firm's equity prices with respect to the market. The problem is that equity prices change every few minutes! Depending on the time frame used for the calculation, beta may fluctuate wildly. In addition, for nontraded physical assets, we cannot reasonably calculate beta this way. Using a firm's tradable financial assets' beta as a proxy for the beta on a project within a firm that has many other projects is ill advised. Mun (2015) introduced a method of obtaining discount rates through the use of internal comparables, Monte Carlo simulation, and real options volatility estimates. This approach, discussed in the risk versus uncertainty section (Mun, 2015), provides a more robust discount rate estimate than the CAPM with external market comparables.

There are risk and return diversification effects among projects as well as investor psychology and overreaction in the market that are not accounted for. There are also other more robust asset-pricing models that can be used to estimate a project's discount rate, but they require great care. For instance, the APT models are built on the CAPM and have additional risk factors that may drive the value of the discount rate. These risk factors include maturity risk, default risk, inflation risk, country risk, size risk, nonmarketable risk, control risk, minority shareholder risk, and others. Even the firm's CEO's golf score can be a risk hazard (e.g., rash decisions may be made after a bad game, or bad projects may be approved after a hole-in-one, believing in a lucky streak). The issue arises when one has to decide which risks to include and which not to include. This is definitely a difficult task, to say the least. A multiple regression or principal component analysis can be performed but probably with only limited success for physical assets as opposed to financial assets, because there are usually very little historical data available for such analyses.

One other widely used method is that of comparability analysis. By gathering publicly available data on the trading of financial assets by stripped-down entities with similar functions, markets, risks, and geographical location, analysts can then estimate the beta (a measure of systematic risk) or even a relevant discount rate from these comparable firms. For instance, an analyst who is trying to gather information on a research and development effort for a particular type of drug can conceivably gather market data on pharmaceutical firms performing only research and development on similar drugs, existing in the same market, and having the same risks. The median or average beta value can then be used as a market proxy for the project currently under evaluation. Obviously, there is no silver bullet, but if an analyst were diligent enough, he or she could obtain estimates from these different sources and create a better estimate. Monte Carlo simulation is most preferred in situations like these. The analyst can define the relevant simulation inputs using the range obtained from the comparable firms and simulate the discounted cash flow model to obtain the range of relevant variables (typically the NPV and IRR).

Now that a relevant discount rate is obtained, the free cash flow stream should then be discounted appropriately. Herein lies another problem: forecasting the relevant free cash flows and deciding if they should be discounted on a continuous basis or a discrete basis, versus using end-of-year or midyear conventions. Free cash flows should be net of taxes, with the relevant noncash expenses added back. Because free cash flows are generally calculated starting with revenues and proceeding through direct cost of goods sold, operating expenses, depreciation expenses, interest payments, taxes, and so forth, there is certainly room for mistakes to compound over time.

Forecasting cash flows several years into the future is oftentimes very difficult and may require the use of fancy econometric regression modeling techniques, time-series analysis, management hunches, and experience. A recommended method is not to create single-point estimates of cash flows at certain time periods but to use Monte Carlo simulation and assess the relevant probabilities of cash flow events. In addition, because cash flows in the distant future are certainly riskier than in the near future, the relevant discount rate should also change to reflect this condition. Instead of using a single discount rate for all future cash flow events, the discount rate should incorporate the changing risk structure of cash flows over time. This can be done by either weighing the cash flow streams' probabilistic risks (standard deviations of forecast distributions) or using a stepwise technique of adding the maturity risk premium inherent in U.S. Treasury securities at different maturity periods. This bootstrapping approach allows the analyst to incorporate what the market experts predict the future market risk structure looks like. That is, discount the cash flows twice: once for time value of money and once for risk. This way, changes in risk structure and risk-free rate can be adjusted accordingly over time.

Finally, the issue of terminal value is of major concern for anyone using a discounted cash flow model. Several methods of calculating terminal values exist, such as the Gordon constant growth model (GGM), zero growth perpetuity consul, and the supernormal growth models. The GGM is the most widely used, where at the end of a series of forecast cash flows, the GGM assumes that cash flow growth will be constant through perpetuity. The GGM is calculated as the free cash flow at the end of the forecast period multiplied by a relative growth rate, divided by the discount rate less the long-term growth rate. Shown in Figure 2, we see that the GGM breaks down when the long-term growth rate exceeds the discount rate. This growth rate is also assumed to be fixed, and the entire terminal value is highly sensitive to this growth rate assumption. In the end, the value calculated is highly suspect because a small difference in growth rates will mean a significant fluctuation in value. Perhaps a better method is to assume some type of growth curve in the free cash flow series. These growth curves can be obtained through some basic time-series analysis as well as using more advanced assumptions in stochastic modeling. Nonetheless, we see that even a well-known, generally accepted and applied discounted cash flow model has major analytical restrictions and problems. These problems are rather significant and can compound over time, creating misleading results. Great care should be taken when performing such analyses. While Mun (2015) introduced the concepts of Monte Carlo simulation, real options, and portfolio optimization, all of which do address some of the issues discussed previously, it should be stressed that these analytics do not provide a silver bullet for valuation and decision-making. They provide value-added insights, and the magnitude of insights and value obtained from these methods depend solely on the type and characteristic of the project under evaluation.

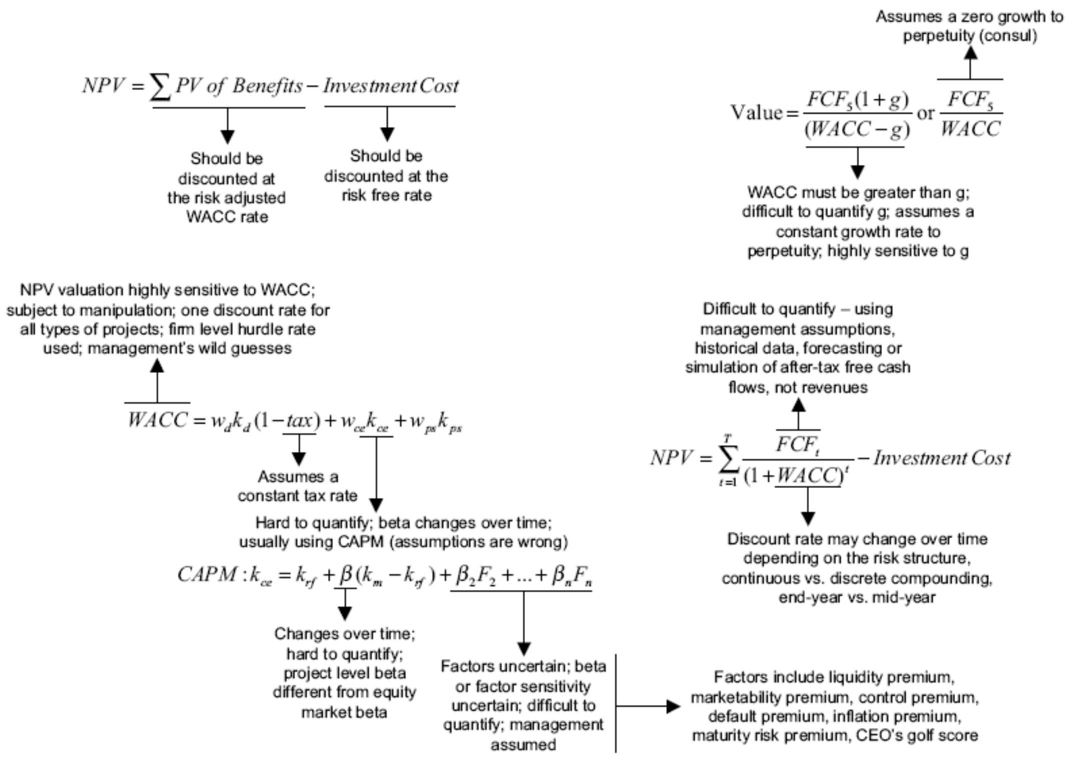

Figure 2: Shortcomings of Discounted Cash Flow Analysis

The applicability of traditional analysis versus the advanced analytics across a time horizon is depicted in Figure 3. During the shorter time period, holding everything else constant, the ability for the analyst to predict the near future is greater than when the period extends beyond the historical and forecast periods.

This is because the longer the horizon, the harder it is to fully predict all the unknowns, and, hence, management can create value by being able to successfully initiate and execute strategic options.

The traditional and new analytics can also be viewed as a matrix of approaches as seen in Figure 4, where the analytics are segregated by their analytical perspective and type. With regard to perspective, the analytical approach can be either a top-down or a bottom-up approach. A top-down approach implies a higher focus on macro variables than on micro variables. The level of granularity from the macro to micro levels include starting from the global perspective and working through market or economic conditions, impact on a specific industry, and, more specifically, the firm's competitive options. At the firm level, the analyst may be concerned with a single project and the portfolio of projects from a risk management perspective. At the project level, detail focus will be on the variables impacting the value of the project.

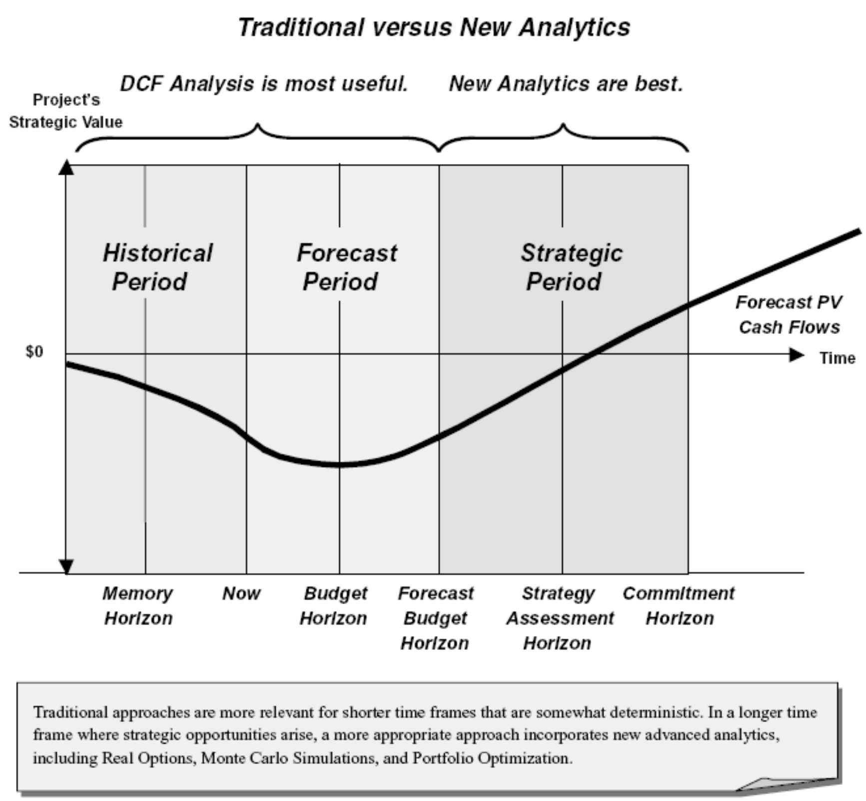

Figure 3: Using the Appropriate Analysis

Traditional analyses, such as those that utilize the discounted cash flow model, are fraught with problems. They underestimate the flexibility value of a project and assume that all outcomes are static and all decisions made are irrevocable. In reality, business decisions are made in a highly fluid environment where uncertainties abound, and management is always vigilant in making changes in decisions when the circumstances require a change. To value such decisions in a deterministic view may potentially grossly underestimate the true intrinsic value of a project. New sets of rules and methodology are required in light of these managerial flexibilities. It should be emphasized that real options analysis builds on traditional discounted cash flow analysis, providing value-added insights to decision making. In the appendices, it will be shown that discounted cash flow analysis is a special case of real options analysis when there is no uncertainty in the project.

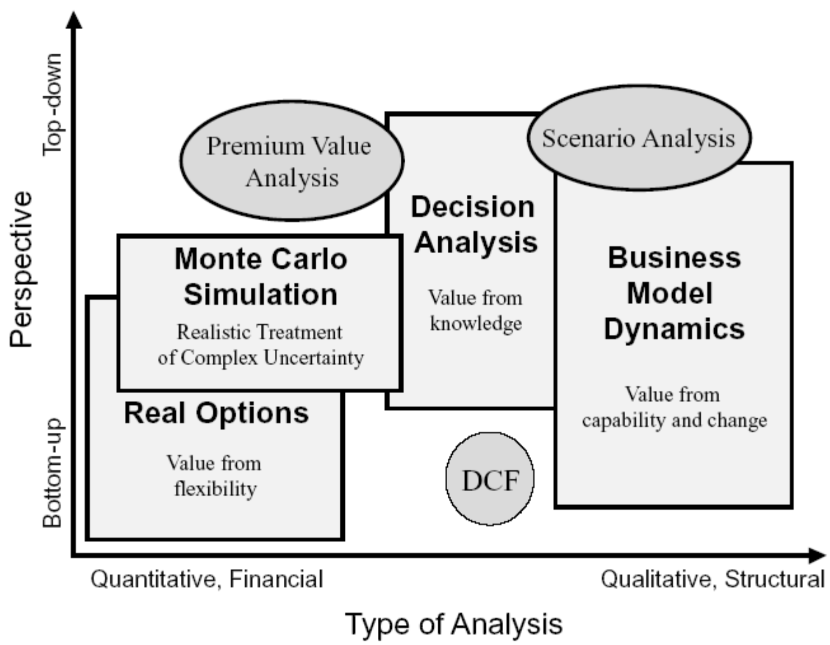

Figure 4: An Analytical Perspective

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 5.

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

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

However, instead of two decision variables, consider six, then consider that trying all combinations requires 1,000,000 iterations (106 alternatives). It is easily possible for complete enumeration to take weeks, months, or even years to carry out (Mun, 2015).

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 5: What Is Optimization?

The Travel Cost Planner

A very simple example is in order. Figure 6 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 6 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 7.

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 6: The Travel Cost Planner

Multiple Combinations

- Seattle–Chicago–New York: \$325 + \$325 = \$650
- Seattle–New York–Chicago: \$375 + \$325 = \$700
- Chicago–Seattle–New York: \$225 + \$375 = \$600
- Chicago–New York–Seattle: \$325 + \$350 = \$675
- New York–Seattle–Chicago: \$350 + \$325 = \$675
- 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 7: 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 (Mun, 2015).

Figure 8 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*.

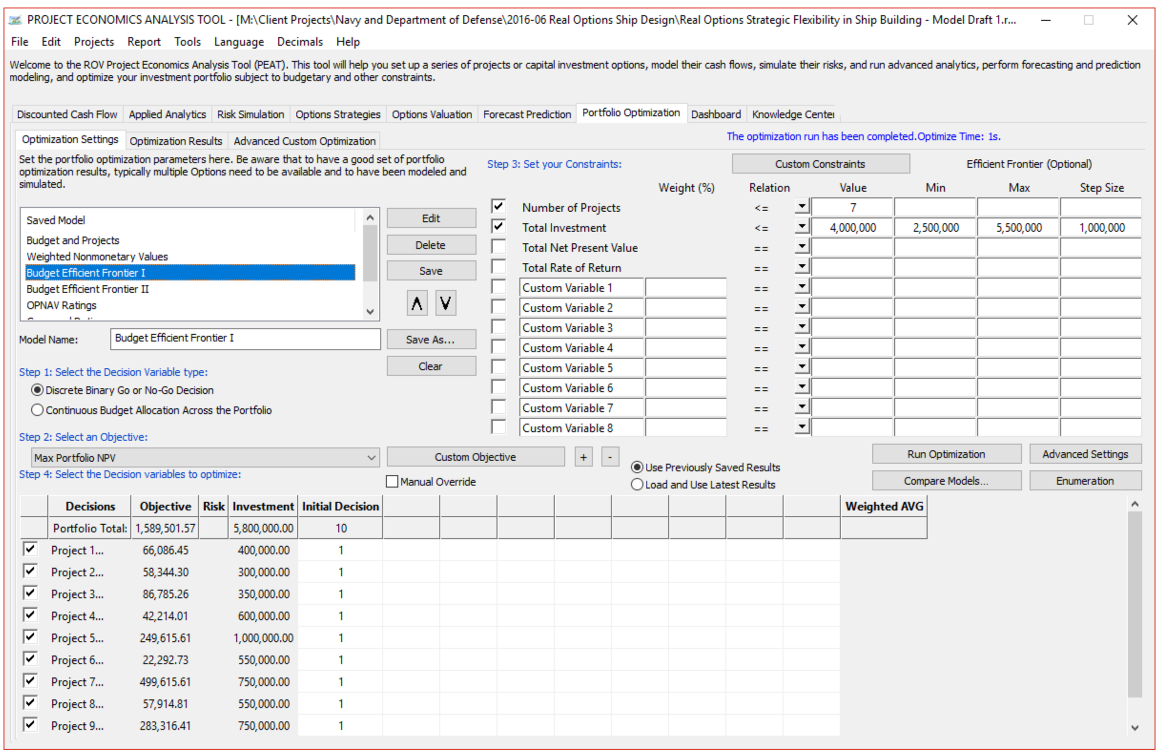

Figure 8: Portfolio Optimization Settings

Figure 9 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 9 and 10 are critical results for decision makers as they allow decision makers flexibility in designing their own portfolio of options. For instance, Figure 9 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 9 show the various combinations of budget limits and maximum number of options allowed. For instance, if a program office in the Navy only allocates $2.5 million (see the Frontier Variable located on the second row) and no more than four options per ship, then only options 3, 7, 9, and 10 are feasible, and this portfolio combination would generate the biggest bang for the buck while simultaneously satisfying the budgetary and number of options constraints. If the constraints were relaxed to, say, five options and a $3.5 million budget, then option 5 is added to the mix. Finally, at $4.5 million and no more than seven options per ship, options 1 and 2 should be added to the mix. Interestingly, even with a higher budget of $5.5 million, the same portfolio of options is selected. In fact, the Optimized Constraint 2 shows that only $4.1 million is used. Therefore, as a decision-making tool for the budget-setting officials, the maximum budget that should be set for this portfolio of options should be $4.1 million. Similarly, the decision maker can move backwards, where, say, if the original budget of $4.5 million was slashed by Congress to $3.5 million, then the options that should be eliminated would be options 1 and 2.

While Figure 9 shows the efficient frontier where the constraints such as number of options allowed and budget were varied to determine the efficient portfolio selection, Figure 10 shows multiple portfolios with different objectives. For instance, the five models shown were to maximize the financial bang for the buck (minimizing cost and maximizing value while simultaneously minimizing risk), maximizing Naval Operations (OPNAV) value, maximizing KVA value, maximizing Command value, and maximizing a Weighted Average of all objectives. This capability is important because depending on who is doing the analysis, their objectives and decisions will differ based on different perspectives. Using a multiple criteria optimization approach allows one to see the scoring from all perspectives. The option with the highest count (e.g., option 5) would receive the highest priority in the final portfolio, as it satisfies all stakeholders' perspectives and would hence be considered first, followed by options with counts of 4, 3, 2, and 1.

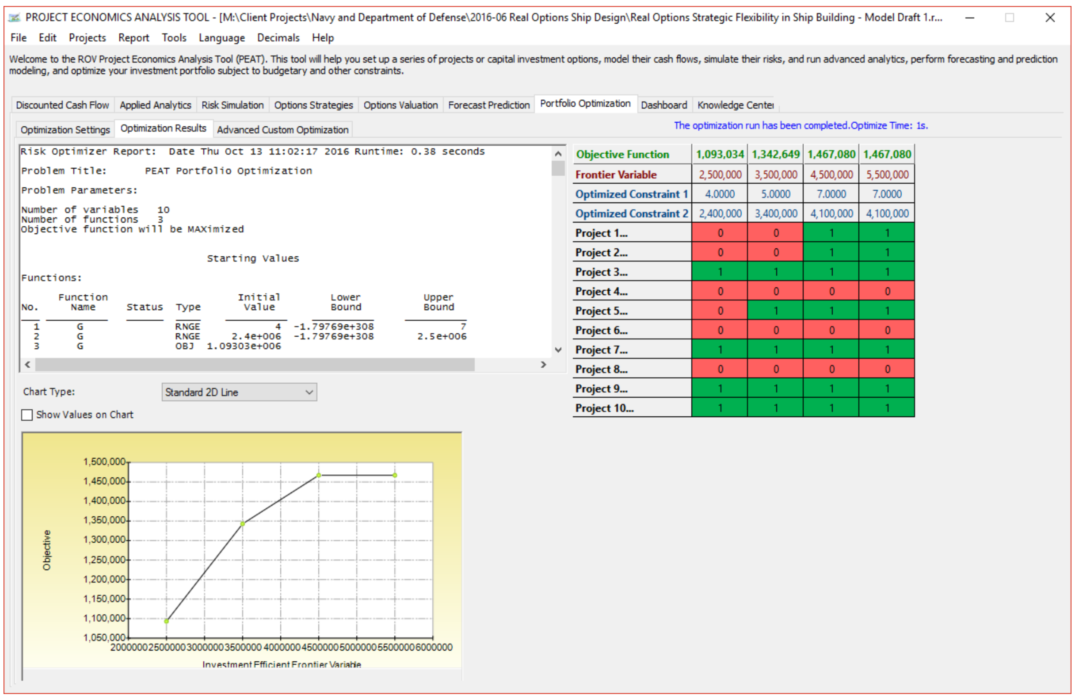

Figure 9: Portfolio Optimization Results

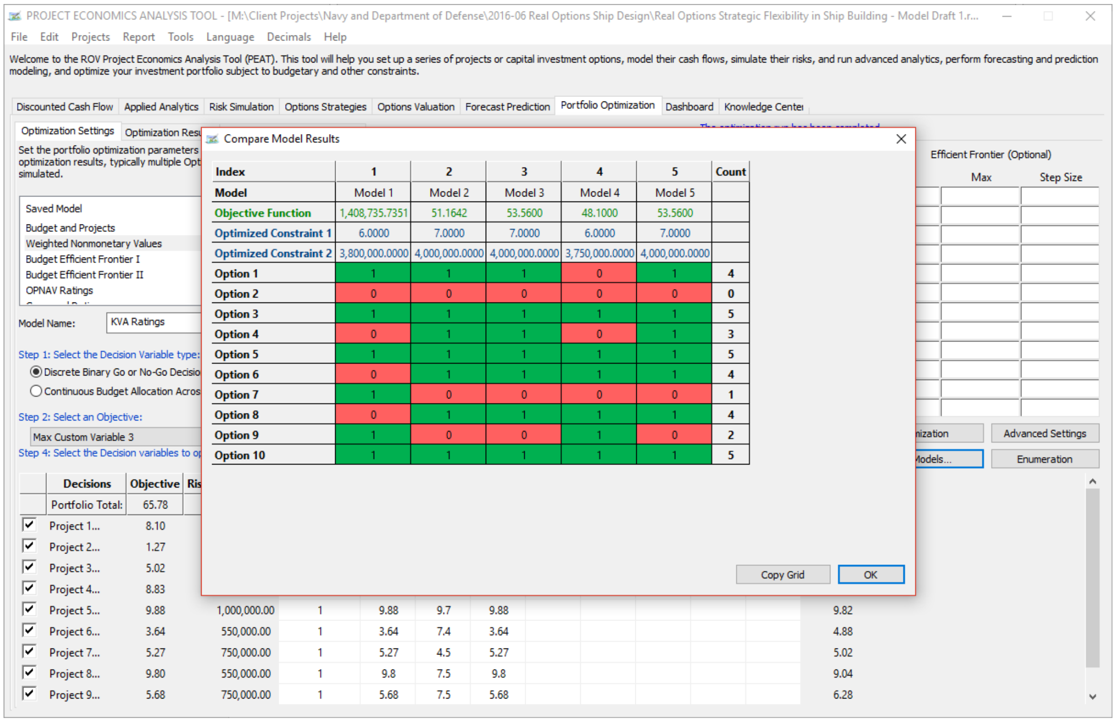

Figure 10: Multi-Criteria Portfolio Optimization Results

As a side note and for the purposes of being comprehensive and inclusive, it is essential to 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 to 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 (Mun, 2015).

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

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

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

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 11.

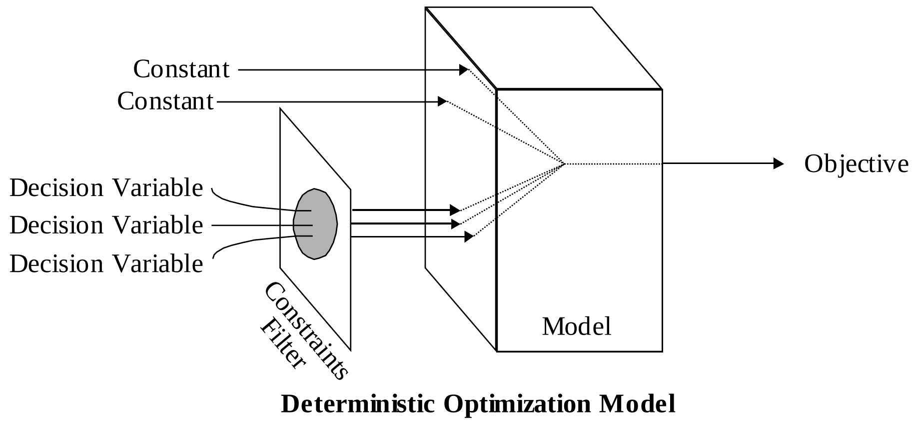

Figure 11: Visualizing the Optimization Process

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 (Mun, 2015).

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 12) controls the optimization by maximizing or minimizing the objective.

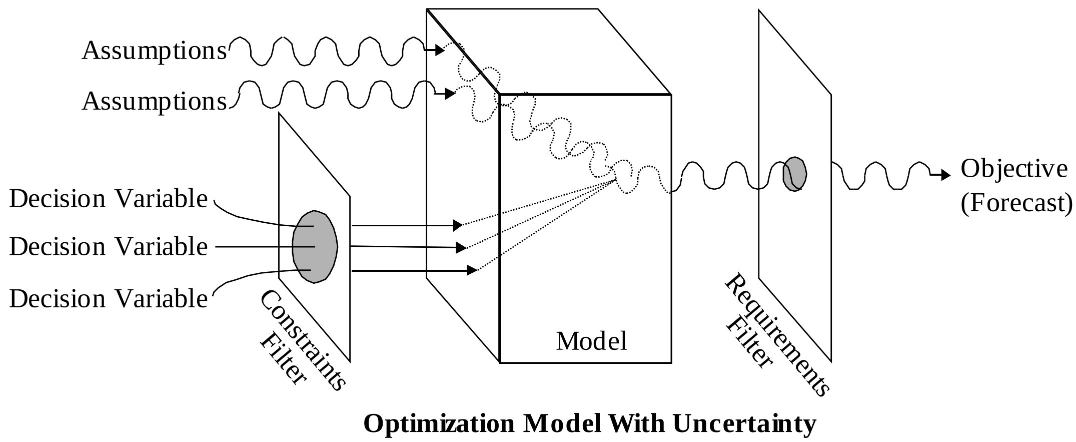

Figure 12: Optimization With Uncertainties and Risk

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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Alternative Analytical Approaches

A Combined Lexicographic Average Rank Approach for Evaluating Uncertain Multi-Indicator Matrices with Risk Metrics

In many situations, projects are characterized by several criteria or attributes that can be assessed from multiple perspectives (financial, economic, etc.). Each criterion is quantified via performance values (PV), which can either be numerical or categorical. This information is typically structured in a multi-indicator matrix **Q**. A typical problem faced by a decision maker is to define an aggregate quality (AQ) able to synthesize the global characteristics of each project and then derive the rankings from the best to the worst base-case ranking (Mun et al., 2016).

Ranking techniques can be classified as parametric and nonparametric. A parametric technique requires information about decision-maker preferences (e.g., criterion weights). According to Dorini, Kapelan, and Azapagic (2011), some examples of parametric techniques include the ELECTRE methods (Roy, 1968) and PROMETHEE—Preference Ranking Organization Methods for Enrichment Evaluations (Brans & Vincke, 1985). Nonparametric techniques, such as Partial Order Ranking (Bruggemann, Bücherl, Pudenz, & Steinberg, 1999) and Copeland Scores (Al-Sharrah, 2010), do not require information from the decision maker. In general, all of these techniques are able to produce a ranking of the alternatives from the best to the worst.

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

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

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

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

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

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

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

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

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

Average Rank Approach

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

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

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

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

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

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

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

Then, the following average rank indexes are defined:

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

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

where *n* is the number of objects,

$|V|$ defines the cardinality of the set *V,*
$p_y^< = |O(x) \cap U(y)|$, $p_y^> = |F(x) \cap U(y)|$, and $y \in U(x)$

Lexicographic Approach

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

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

Risk Metrics and Compliance

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

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

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

Zanoli, Gambelli, Solfanelli, and Padel (2014) analyze impacts of risk factors on noncompliance in UK farming.

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

PROMETHEE and ELECTRE

In addition to uncertainty and flexibility, another complexity appears when decision makers need to introduce potentially conflicting decision criteria (quantitative or qualitative, monetary and nonmonetary) into project management, such as legal (taxes, compliance, social responsibility, etc.), environmental (level of pollution, noise, watershed issues, etc.), economic (level of economic growth, national income, inflation, unemployment, etc.), and social (number of employees, value to society, safety and security, community development), among others. Furthermore, those criteria might have different relative importance (RI) or weights. For example, in BP's (2015) sustainability report, the statements that business "has to earn and maintain the support of society" and "has to take action to help safeguard the environment for future generations" may indicate that some decision makers would prefer profitability over social responsibility, or vice versa. Hence, it is important to consider those differences in the decision-making process (Mun et al., 2017).

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

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

PROMETHEE methods are suitable because of their theoretical and practical advantages. For instance, they can associate to each project an AQ index that maximizes the available information in terms of decision-makers' preferences over the criteria selected, as well as the preferences' intensities among alternatives and the nature of each criteria (Bouyssou et al., 2006). PROMETHEE methods have been applied in many energy-related studies, for example, sustainable energy planning (Pohekar & Ramachandran, 2004; Cavallaro, 2005); renewable energy alternatives (Georgopoulou, Lalas, & Papagiannakis, 1997); heating system options (Ghafghazi et al., 2010); and oil and gas pipeline planning (Tavana et al., 2013); among other applications (Behzadian et al., 2010).

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

Although some studies have tried to integrate real options (RO) into MCA (Cavallaro, 2005; Angelou & Economides, 2008; Tolga & Kahraman, 2008; Zandi & Tavana, 2010; Tolga, 2011, 2012), there is little evidence of an integrated RO-MCA methodology for ranking a portfolio of projects in state-owned energy companies, characterized also by pursuing nonfinancial objectives.

The author claims that while RO value and assess flexibility and uncertainty for PM, MCA allows considering additional criteria such as gross domestic product (GDP) and employment in their strategic plans criteria to obtain an AQ for selecting the best projects.

Operational and Logistics

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

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

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

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

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

$$MR = ORR * IR$$

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

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

- **Mean Down Time** (MDT), **Mean Maintenance Time** (MMT), **Logistics Delay Time** (LDT), and their combinations.

- **Achieved Availability** (AA), **Operational Availability** (OA), **Mission Availability** (MA)

Financial and Economic

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

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

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

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

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

Strategic and Capability

Multiple value metrics can be determined from **Subject Matter Experts** (SME):

Expected Military Value

Strategic Value

Future Weapon Strategy

Capability Measures (CM). Difficult to quantify and needs SME judgment:

Innovation Index, Conversion Capability, Ability to Meet Future Threats

Force Structure (size/units), Modernization (technical sophistication), Combat Readiness, Sustainability

Future Readiness (ability to meet evolving threats, ability to integrate future weapons systems)

Domain Capabilities (DC)

Portfolios are divided into different domains, and each domain is optimized separately and then combined into the enterprise level and re-optimized; example domains include Coastal Defense, Anti-Air Surface Warfare, Anti-Surface Warfare, Anti-Submarine Warfare, Naval Strike, Multi-Mission Air Control, Sea Control, Deep Strike, Missile Defense, and so on.

Constraints can be added whereby each domain needs to have a minimum amount of capability or systems, and within each domain, different “value” parameters can be utilized.

Optimization Application at PEO-IWS and NAVSEA

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

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

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

To summarize, this case illustration requires the following assumptions:

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

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

- For all models, we assumed a 10-year time horizon for the cost savings (all future savings past Year 10 after discounting will be assumed to be negligible). The discounting base year is 2017 (Year 0 and Capital Investment is required in 2017), whereas immediate savings and short-term benefits and maintenance savings start in Year 1 (2018). This means Year 10 is 2027.
- Table 2 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

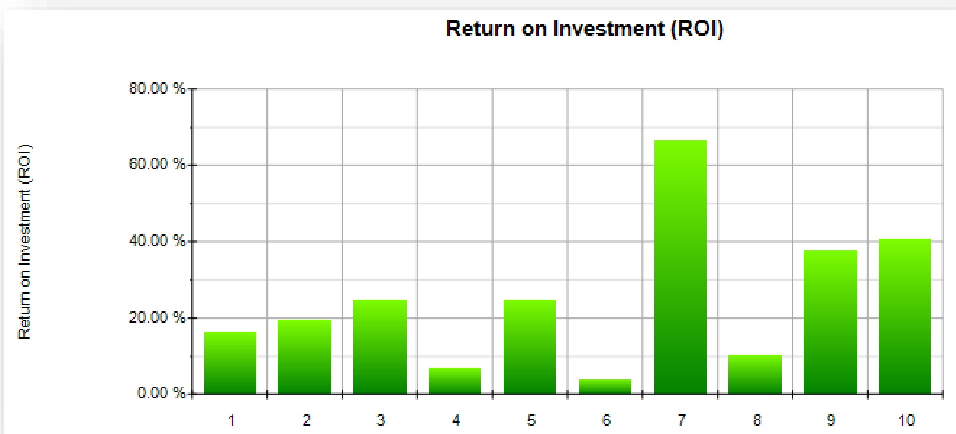
- "Savings Now" is the immediate monetary cost savings benefits obtained by implementing the new upgraded system (e.g., lower overhead requirements, reduced parts and labor requirements). This amount is applied in the first year of the cash flow stream only (Year 1 or 2018) as its effects are deemed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

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

Figure 13 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



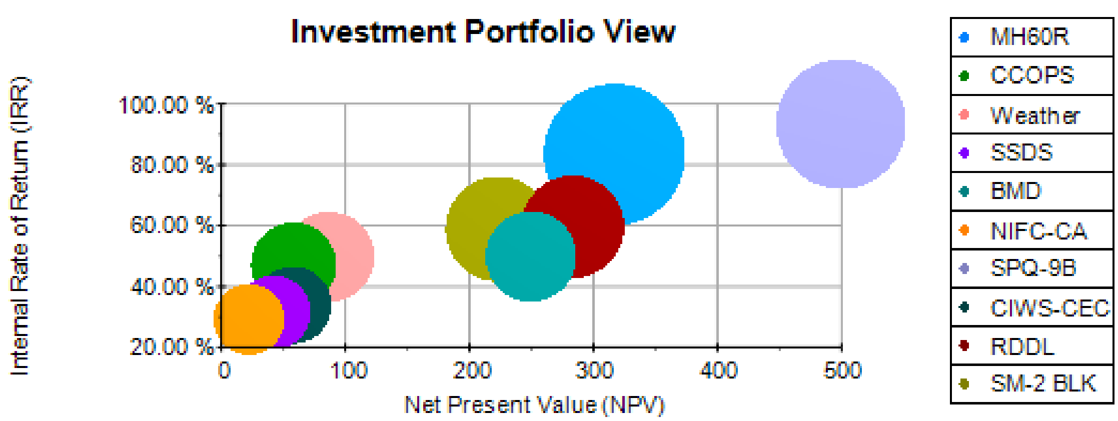


Figure 13: Capital Budgeting Results Comparison

According to the analysis, the top five recommended ACB capabilities based on Static Portfolio Analysis are SPQ-9B, SM-2 BLK, MH60R, BMD, and RDDL. Figure 14 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		ROI		PP	
Rank	Project	Rank	Project	Rank	Project
1	SPQ-9B	1	SPQ-9B	1	SPQ-9B
2	RDDL	2	SM-2 BLK	2	CCOPS
3	BMD	3	RDDL	3	RDDL
4	SM-2 BLK	4	BMD	4	BMD
5	Weather	5	Weather	5	Weather
6	MH60R	6	CCOPS	6	SM-2 BLK
7	CCOPS	7	MH60R	7	NIFC-CA
8	CIWS-CEC	8	CIWS-CEC	8	SSDS
9	SSDS	9	SSDS	9	CIWS-CEC
10	NIFC-CA	10	NIFC-CA	10	MH60R

Figure 14: Program Rankings

Figures 15 and 16 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.

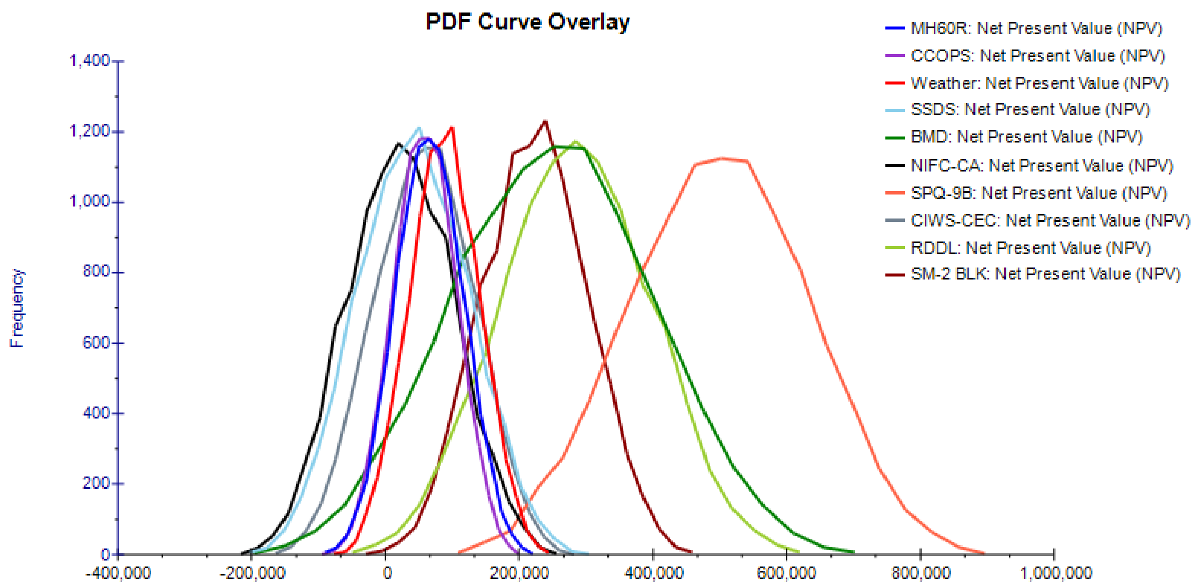


Figure 15: Comparison of Simulated NPV Probability Distributions

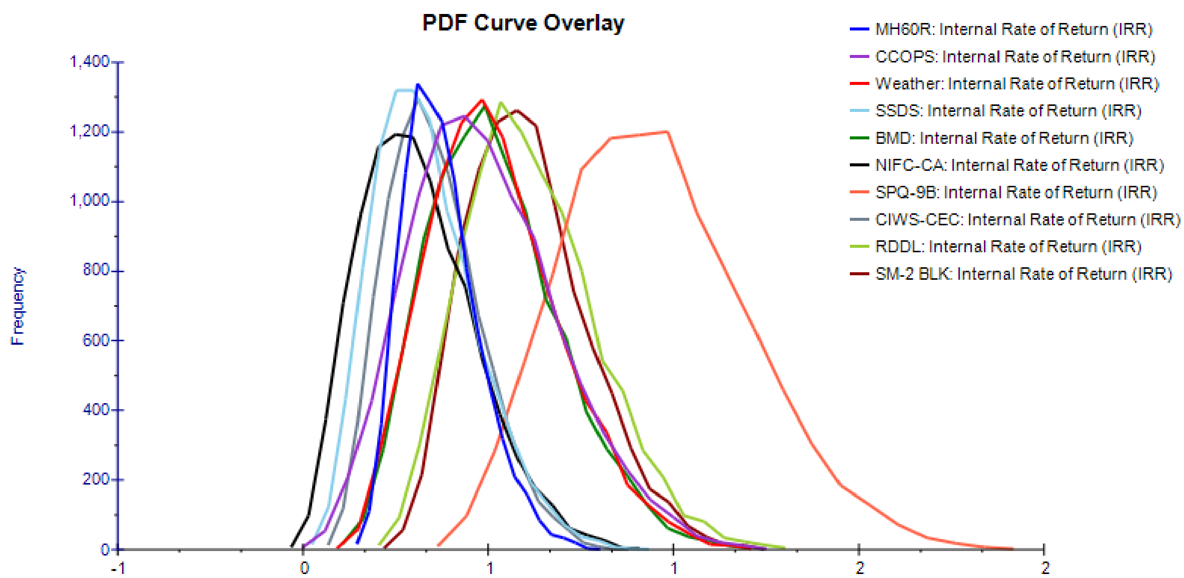


Figure 16: Comparison of Simulated IRR Probability Distributions

Figure 17 shows the probability of success of each program. These are currently based on using NPV but can be applied to any non-economic variable. The definition used here is the probability (PROB) of NPV > 0. Based on the values below, (1 – PROB)%, is the probability of failure.

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

Figure 17: 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 18: Comparison of Options Decision Risk Profile

Figure 19 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 19: Portfolio Optimization 1

Figure 20 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

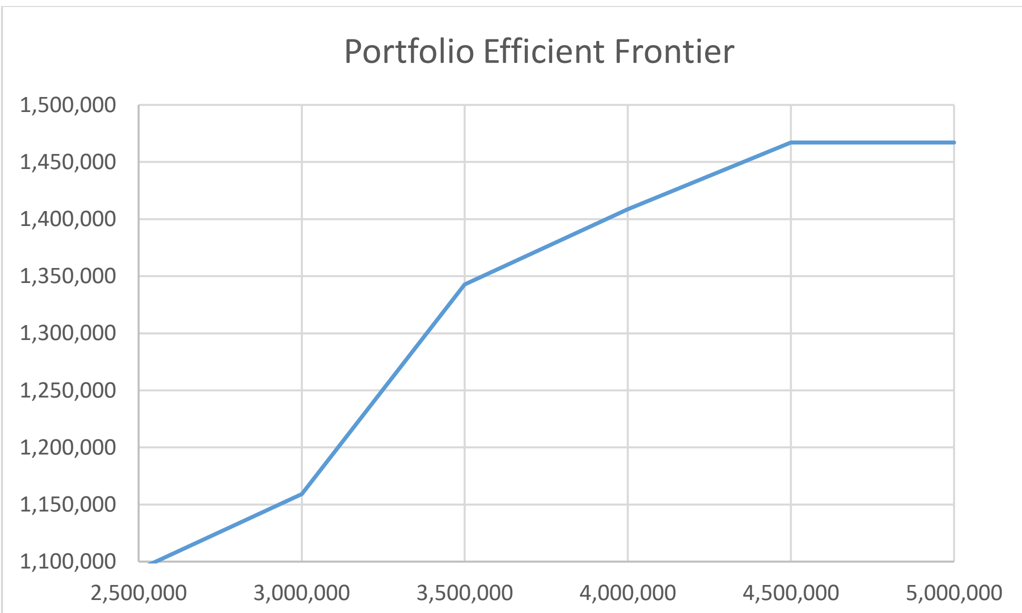


Figure 20: Portfolio Optimization 2

Figure 21 shows the results for OPNAV; Figure 22, for COMMAND; and Figure 23, 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 21: 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 22: 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 23: Portfolio Optimization 5 (KVA)

Figure 24 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 24.

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 24: Portfolio Optimization 6 (Weighted Average)

Figure 25 shows a combined view where multiple optimizations were run and compared against one another. Additional constraints can be added as needed, but the case illustration applies a $4 million budget, and no more than seven programs can be chosen at a time. In other words, the following monetary and nonmonetary portfolios were optimized:

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

As seen in Figure 25, these five portfolios are combined into a matrix that shows the count of GO decisions. Clearly, for a decision maker, the lowest-hanging fruits would be to execute the programs starting with the highest count. For instance, Weather, BMD, and SM-2BLK would be considered the highest priority, as regardless of the point of view and stakeholder under consideration, these programs have always been chosen.

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

Figure 25: Portfolio Optimization 7 (Combined View)

Conclusions and Recommendations

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

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

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

considered. These competing objectives need to be reconciled to determine a Pareto optimal portfolio.

- Evaluate analytical hierarchical processes, multi-objective optimization, and other algorithms and compare the results.
- Within the portfolio, model and account for risks of cost and budget overruns as well as delivery delays using risk-based simulations.

To summarize, based on the research performed thus far, the researcher concludes that the methodology has significant merits and is worthy of more detailed follow-on analysis. It is therefore recommended that the portfolio optimization methodology outlined in this research be applied on a real case study facing the U.S. Navy, using actual data and tracking the project's outcomes over time. The approach described does not necessarily have to be performed in lieu of existing methods, but in conjunction with them. After all, if the Navy and 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.

Appendix A: Financial Statement Analysis

This appendix provides some basic financial statement analysis concepts used in applying real options. The focus is on calculating the free cash flows used under different scenarios, including making appropriate adjustments under levered and unlevered operating conditions. Although many versions of free cash flows exist, these calculations are examples of more generic free cash flows applicable under most circumstances. An adjustment for inflation and the calculation of terminal cash flows are also presented here. Finally, a market multiple approach that uses price-to-earnings ratios is also briefly discussed.

Free Cash Flow Calculations

The following is a list of some generic financial statement definitions used to generate free cash flows based on generally accepted accounting principles (GAAP):

- Gross Profits = Revenues – Cost of Goods Sold
- Earnings Before Interest and Taxes = Gross Profits – Selling Expenses – General and Administrative Costs – Depreciation – Amortization
- Earnings Before Taxes = Earnings Before Interest and Taxes – Interest
- Net Income = Earnings Before Taxes – Taxes
- Free Cash Flow to Equity = Net Income + Depreciation + Amortization – Capital Expenditures ± Change in Net Working Capital – Principal Repayments + New Debt Proceeds – Preferred Dividends – Interest (1 – Tax Rate)
- Free Cash Flow to the Firm = Earnings Before Interest and Taxes (1 – Tax Rate) + Depreciation + Amortization – Capital Expenditures ± Change in Net Working Capital = Free Cash Flow to Equity + Principal Repayment – New Debt Proceeds + Preferred Dividends + Interest (1 – Tax Rate)

Free Cash Flow to a Firm

An alternative version of the free cash flow for an unlevered firm can be defined as

Free Cash Flow = Earnings Before Interest and Taxes [1 – Effective Tax Rate] + Depreciation + Amortization – Capital Expenditures ± Change in Net Working Capital

Levered Free Cash Flow

For a levered firm, the free cash flow becomes

- Free Cash Flow = Net Income + α [Depreciation + Amortization] ± α [Change in Net Working Capital] – α [Capital Expenditures] – Principal Repayments + New Debt Proceeds – Preferred Debt Dividends

where α is the equity-to-total-capital ratio and (1 – α) is the debt ratio.

Inflation Adjustment

The following adjustments show an inflationary adjustment for free cash flows and discount rates from nominal to real conditions:

- $\text{Real } CF = \dfrac{\text{Nominal } CF}{(1+\text{E}[\pi])}$
- $\text{Real } \rho = \dfrac{1+\text{Nominal } \rho}{(1+\text{E}[\pi])} - 1$

where

CF is the cash flow series;

π is the inflation rate;

$E[\pi]$ is the expected inflation rate; and

ρ is the discount rate.

Terminal Value

The following are commonly accepted ways of getting terminal free cash flows under zero growth, constant growth, and supernormal growth assumptions:

- Zero Growth Perpetuity: $\sum_{t=1}^{\infty} \dfrac{FCF_t}{[1+WACC]^t} = \dfrac{FCF_T}{WACC}$
- Constant Growth: $\sum_{t=1}^{\infty} \dfrac{FCF_{t-1}(1+g_t)}{[1+WACC]^t} = \dfrac{FCF_{T-1}(1+g_T)}{WACC-g_T} = \dfrac{FCF_T}{WACC-g_T}$

- Punctuated Supernormal Growth: $\sum_{t=1}^{N} \frac{FCF_t}{[1+WACC]^t} + \frac{\left[\frac{FCF_N(1+g_N)}{[WACC-g_N]}\right]}{[1+WACC]^N}$

where

$WACC = \omega_d k_d (1-\tau) + \omega_{pe} k_{pe} + \omega_e k_e$ is the weighted average cost of capital;

FCF is the free cash flow series;

g is the growth rate of free cash flows;

t is the individual time periods;

T is the terminal time at which a forecast is available;

N is the time when a punctuated growth rate occurs;

ω is the respective weights on each capital component;

k_e is the cost of common equity;

k_d is the cost of debt;

k_{pe} is the cost of preferred equity; and

τ is the effective tax rate.

Price-to-Earnings Multiples Approach

Related concepts in valuation are the uses of market multiples. An example is using the price-to-earnings multiple, which is a simple derivation of the constant growth model shown above, breaking it down into dividends per share (DPS) and earnings per share (EPS) components.

The derivation starts with the constant growth model:

$$P_0 = \frac{DPS_0(1+g_n)}{k_e - g_n} = \frac{DPS_1}{k_e - g_n}$$

Then, using the fact that the dividend per share next period (DPS_1) is the earnings per share current period multiplied by the payout ratio (PR), defined as the ratio of dividends per share to earnings per share, which is assumed to be constant, multiplied by one plus the growth rate (1+ g) of earnings:

$$DPS_1 = EPS_0[PR](1+g_n)$$

Similarly, the earnings per share the following period is the same as the earnings per share this period multiplied by one plus the growth rate:

$$EPS_1 = EPS_0(1+g_n)$$

Substituting the earnings per share model for the dividends per share in the constant growth model, we get the pricing relationship:

$$P_0 = \frac{EPS_0[PR](1+g_n)}{k_e - g_n}$$

Because we are using price-to-earnings ratios, we can divide the pricing relationship by earnings per share to obtain an approximation of the price-to-earnings ratio (PE):

$$\frac{P_0}{EPS_1} = \frac{[PR]}{k_e - g_n} \approx PE_1$$

Assuming that the PE and EPS ratios are fairly stable over time, one can estimate the current pricing structure through forecasting the next term EPS. We obtain

$$P_0 = \tilde{EPS}_1[PE_1]$$

Issues of using PE ratios include the fact that PE ratios change across different markets. If a firm serves multiple markets, it is difficult to find an adequate weighted average PE ratio. PE ratios may not be stable through time and are most certainly not stable across firms. If more efficient firms are added to less efficiently run firms, the average PE ratio may be skewed. In addition, market overreaction and speculation, particularly among high-growth firms, provide an overinflated PE ratio. Furthermore, not all firms are publicly held, some firms may not have a PE ratio, and if valuation of individual projects is required, PE ratios may not be adequate because it is difficult to isolate a specific investment’s profitability and its corresponding PE ratio. Similar approaches include using other proxy multiples including Business Enterprise Value to Earnings, Price to Book, Price to Sales, and so forth, with similar methods and applications.

Discounting Conventions

In using discounted cash flow analysis, several conventions require consideration: continuous versus discrete discounting, midyear versus end-of-year convention, and beginning versus end-of-period discounting.

Continuous Versus Periodic Discrete Discounting

The discounting convention is important when performing a discounted cash flow analysis. Using the same compounding period principle, future cash flows can be discounted using the effective annualized discount rate. For instance, suppose an annualized discount rate of 30% is used on a $100 cash flow. Depending on the compounding periodicity, the calculated present value and future value differ, as shown in the list below.

Periodicity	*Periods/ Year*	*Interest Factor*	*Future Value*	*Present Value*
Annual	1	30.00%	$130.00	$76.92
Quarterly	4	33.55%	$133.55	$74.88
Monthly	12	34.49%	$134.49	$74.36
Daily	365	34.97%	$134.97	$74.09
Continuous	∞	34.99%	$134.99	$74.08

To illustrate this point further, a $100 deposit in a 30% interest-bearing account will yield $130 at the end of one year if the interest compounds once a year. However, if interest is compounded quarterly, the deposit value increases to $133.55 due to the additional interest-on-interest compounding effects. For instance,

Value at the end of the first quarter = $\$100.00\ [1 + 0.30/4]^1 = \$107.50$

Value at the end of the second quarter = $\$107.50\ [1 + 0.30/4]^1 = \$115.56$

Value at the end of the third quarter = \$115.56 $[1 + 0.30/4]^1$ = \$124.23

Value at the end of the fourth quarter = \$124.23 $[1 + 0.30/4]^1$ = \$133.55

That is, the annualized discount rate for different compounding periods is its effective annualized rate, calculated as $\left(1+\frac{\text{discount}}{\text{periods}}\right)^{\text{periods}} - 1$. For the quarterly compounding interest rate, the effective annualized rate is $\left(1+\frac{30\%}{4}\right)^{4} - 1 = 33.55\%$. Applying this rate for the year, we have \$100(1 + 0.3355) = \$133.55.

This analysis can be extended for monthly, daily, or any other periodicities. In addition, if the interest rate is assumed to be continuously compounding, the continuous effective annualized rate should be used, where $\lim_{n\to\infty}\left(1+\frac{\text{discount}}{\text{periods}}\right)^{\text{periods}} - 1$. For instance, the 30% interest rate compounded continuously yields $e^{0.3} - 1$ = 34.99%. Notice that as the number of compounding periods increases, the effective interest rate increases until it approaches the limit of continuous compounding.

The annual, quarterly, monthly, and daily compounding is termed *discrete periodic compounding*, as compared to the continuous compounding approach using the exponential function. In summary, the higher the number of compounding periods, the higher the future value and the lower the present value of a cash flow payment. When applied to discounted cash flow analysis, if the discount rate calculated using a weighted average cost of capital is continuously compounding (e.g., interest payments and cost of capital are continuously compounding), then the net present value calculated may be overoptimistic if discounted discretely.

Full-Year Versus Midyear Convention

In the conventional discounted cash flow approach, cash flows occurring in the future are discounted back to the present value and summed, to obtain the net present value of a project. These cash flows are usually attached to a particular period in the future, typically measured in years, quarters, or months. The following time line illustrates a sample series of cash flows over the next five years, with an assumed 20% discount rate. Because the cash flows are attached to an annual time line, they are usually assumed to occur at the end of each year. That is, $500 will be recognized at the end of the first full year, $600 at the end of the second year, and so forth. This is termed the *full-year discounting* convention.

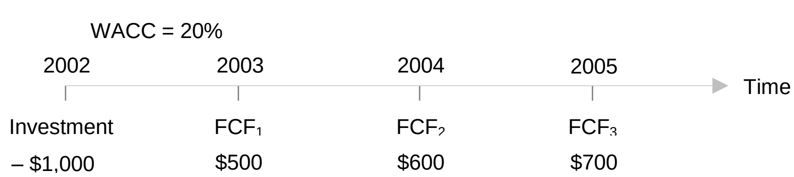
$$NPV = -\$1{,}000 + \frac{\$500}{(1+0.2)^{1}} + \frac{\$600}{(1+0.2)^{2}} + \frac{\$700}{(1+0.2)^{3}} + \frac{\$800}{(1+0.2)^{4}} + \frac{\$900}{(1+0.2)^{5}} = \$985$$

$$NPV = -\$1{,}000 + \frac{\$500}{(1+0.2)^{0.5}} + \frac{\$600}{(1+0.2)^{1.5}} + \frac{\$700}{(1+0.2)^{2.5}} + \frac{\$800}{(1+0.2)^{3.5}} + \frac{\$900}{(1+0.2)^{4.5}} = \$1{,}175$$

However, under normal business conditions, cash flows tend to accrue throughout the entire year and do not arrive in a single lump sum at the end of the year. Instead, the midyear convention may be applied. That is, the $500 cash flow gets accrued over the entire first year and should be discounted at 0.5 years, rather than 1.0 years. Using this midpoint supposes that the $500 cash flow comes in equally over the entire year.

End-of-Period versus Beginning-of-Period Discounting

Another key issue in discounting involves the use of end-of-period versus beginning-of-period discounting. Suppose the cash flow series are generated on a time line such as the following:



Further suppose that the valuation date is January 1, 2002. The $500 cash flow can occur either at the beginning of the first year (January 1, 2003) or at the end of the first year (December 31, 2003). The former requires the discounting of one year, and the latter, the discounting of two years. If the cash flows are assumed to roll in equally over the year—that is, from January 1, 2002 to January 1, 2003—the discounting should only be for 0.5 years. In retrospect, suppose that the valuation date is December 31, 2002, and the cash flow series occurs at January 1, 2003, or December 31, 2003. The former requires no discounting, while the latter requires a one-year discounting using an end-of-year discounting convention. In the midyear convention, the cash flow occurring on December 31, 2003, should be discounted at 0.5 years.

Discount Rate Versus Risk-Free Rate

Generally, the weighted average cost of capital (WACC) would be used as the discount rate for the cash flow series. The only mitigating circumstance is when the firm wishes to use a hurdle rate that exceeds the WACC to compensate for the additional uncertainty, risks, and opportunity costs the firm believes it will face by investing in a particular project. As we will see, the use of a WACC is problematic, and in the real options world, the input is, instead, a U.S. Treasury spot rate of return with its maturity corresponding to the economic life of the project under scrutiny.

In general, the WACC is the weighted average of the cost components of issuing debt, preferred stock, and common equity: WACC = $\omega_d k_d (1-\tau) + \omega_p k_p + \omega_e k_e$, where ω represents the respective weights, τ is the corporate effective tax rate, and the k are the costs corresponding to debt,[1] *d*; preferred stocks,[2] *p;* and common equity,[3] *e*.

[1] Use the after-tax cost of debt because interest paid on debt is tax deductible. We need to include this tax shield. Therefore, Cost of Debt = Interest Paid – Taxes Saved. Similarly, we have Cost of Debt = $K_d - TK_d = K_d (1-T)$.

However, multiple other factors affect the cost of capital that need to be considered, including

1. The company's capital structure used to calculate the relevant WACC discount rate may be inadequate because project-specific risks are usually not the same as the overall company's risk structure.
2. The current and future general interest rates in the economy may be higher or lower, thus bond coupon rates may change in order to raise the capital based on fluctuations in the general interest rate. Therefore, an interest-rate-bootstrapping methodology should be applied to infer the future spot interest rates using forward interest rates.
3. Tax law changes over time may affect the tax shield enjoyed by debt repayments. Furthermore, different tax jurisdictions in different countries have different tax law applications of tax shields.
4. The firm's capital structure policy may have specific long-term targets and weights that do not agree with the current structure, and the firm may find itself moving toward that optimal structure over time.
5. Payout versus retention rate policy may change the dividend yield and thereby change the projected dividend growth rate necessary to calculate the cost of equity.
6. Investment policy of the firm, including minimum required rate of return and risk profile.
7. Dynamic considerations in the economy and industry both *ex post* and *ex ante*.

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[2] The cost of preferred stock is $K_{ps} = D_{ps} \div P_{net}$, where D is the dividend paid (assumed to be a perpetuity) and P is the net or clean price paid on the preferred stock after taking into account any accrued interest and carrying costs.

[3] There are generally three accepted methods to calculating the cost of equity: (a) The CAPM Approach uses $K_s = K_{rf} + \beta_i(K_m - K_{rf})$, where β is the beta-risk coefficient of the company's equity; K_m is the equity market portfolio rate of return; and K_{rf} is the corresponding maturity's risk-free Treasury rate. (b) The Discounted Cash Flow (Gordon Growth Model) assumes $K_s = [D_1 \div P_0(1-F)] + g$, where g = Retention Rate x Return on Equity and F is the floatation cost. (c) The Risk Premium over Bond Yield approach assumes that K_s = Bond Yield + Risk Premium, corresponding to the appropriate risk structure.

8. Measurement problems on specific security cost structure.
9. Small business problems making it difficult to measure costs correctly.
10. Depreciation-generated funds and off-balance-sheet items are generally not included.
11. Geometric averages and not simple arithmetic averages should be used for intra-year WACC rates.[4]
12. Selection of market value versus book value weightings[5] in calculating the WACC.
13. The Capital Asset-Pricing Model (CAPM) is flawed.

The CAPM Versus the Multiple Asset-Pricing Model

The CAPM model states that under some simplifying assumptions, the rate of return on any asset may be expected to be equal to the rate of return on a riskless asset plus a premium that is proportional to the asset's risk relative to the market.

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[4] Suppose you have an asset that costs \$100 and increases to \$110 in the first period but reverts back to \$100 the second period. The return in period one is 10%, and the return in period two is –9.09%. Hence, the arithmetic average of both periods' returns is 0.455%, but it is illogical because you ended up with what you started off with. The geometric average is calculated as $\sqrt[2]{\frac{110}{100}\times\frac{100}{110}}-1=0\%$, which seems more logical.

[5] Book value is generally used because it captures the value of the security when it was issued. However, critics have argued that the market value more closely reflects the current situation the firm faces when operating in its current condition. Furthermore, market values tend to be forward-looking, and book values tend to be backward-looking. Because the valuation analysis looks at forecast values, we can argue for the use of market value weightings. The problem with that logic is magnified when there is significant volatility in the equity and debt market due to speculation.

The CAPM is developed in a theoretical and hypothetical world with multiple assumptions[6] that do not hold true in reality, and, therefore, it is flawed by design.[7]

The alternative is to use a multifactor model that adequately captures the systematic risks experienced by the firm. Other researchers have tested the CAPM and found that a single factor, beta, does not sufficiently explain expected returns. Their empirical research finds support for the inclusion of both size (measured using market value) and leverage variables. The two leverage variables found to be significant were the book-to-market ratio and the price-to-earnings ratio. However, when used together, the book-to-market ratio and size variable absorb the effects of

[6] The assumptions for the CAPM include the following: investors are risk-averse individuals who maximize their expected utility of their end-of-period wealth; investors are price-takers and have homogeneous beliefs and expectations about asset returns; there exists a risk-free asset, and investors may borrow or lend unlimited amounts at the risk-free rate; the quantities of assets are fixed, and all assets are marketable and perfectly divisible; asset markets are frictionless, and information is costless and available to all investors; and there are no market imperfections like taxes, regulations, or restrictions on short sales.

[7] The CAPM requires that the market portfolio be efficient in equilibrium. It must lie on the upper half of the minimum variance opportunity set where the marginal rate of substitution equals the marginal rate of transformation *(MRS = MRT)*. The efficiency can be established based on homogeneous expectation assumptions. Given this, they will all perceive the same minimum variance opportunity set. The market portfolio must, hence, be efficient because the market is simply the sum of all holdings, and all individual holdings are efficient. Given market efficiency, the market portfolio *M* where all assets are held according to their market value weights by simple algebraic manipulation (i.e., equating the slope of the capital market line with the slope of the opportunity set), we can derive the following expression: $E(R_i) = R_f + [E(R_m) - R_f](\sigma_{i,m}/\sigma^2_m)$. This CAPM model can also be derived using the *MRT = MRS* convention, where a linear programming method is used to solve for the minimum variance opportunity set and the maximum expected return efficiency set.

the price-to-earnings ratio. With empirical support that beta alone is insufficient to capture risk, their model relies on the addition of the natural logarithm of both the book-to-market ratio and the size of the firm's market equity as

$$E[R_{i,t}] - R_{f,t} = \beta_{i,t}\left(E[R_{m,t}] - R_{f,t}\right) + \delta_{i,t}\ \ln\left(BME_{i,t}\right) + \gamma_{i,t}\ \ln\left(ME_{i,t}\right)$$

where $R_{i,t}$, $R_{m,t}$, and $R_{f,t}$ are the individual expected return for firm *i,* the expected market return, and the risk-free rate of return at time *t,* respectively. $BME_{i,t}$ and $ME_{i,t}$ are the book-to-market ratio and the size of the total market equity value for firm *i* at time *t,* respectively.

Other researchers have confirmed these findings that a three-factor model better predicts expected returns than the single-factor CAPM. Their main conjecture is that asset-pricing is rational and conforms to a three-factor model that does not reduce to the standard single-factor CAPM. One of the major problems with the single-factor CAPM is that of determining a good proxy for the market, which should truly represent all traded securities. In addition, the expected return on the market proxy typically relies on *ex post* returns and does not truly capture expectations. Therefore, the multifactor model is an attempt to recover the expected CAPM results without all the single-factor model shortcomings. A variation of the three-factor model is shown as

$$E[R_{i,t}] - R_{f,t} = \beta_{i,t}\left(E[R_{m,t}] - R_{f,t}\right) + \xi_{i,t}\ \ln\left(SMB_{i,t}\right) + \psi_{i,t}\ \ln\left(HML_{i,t}\right)$$

where $SMB_{i,t}$ is the time series of differences in average returns from the smallest and largest capitalization stocks. $HML_{i,t}$ is the time series of differences in average returns from the highest to the lowest book-to-market ratios, after ranking the market portfolios into differing quartiles.

We can adapt this multifactor model to accommodate any market and any industry. The factors in the foregoing model can be sector- or industry-specific. The macroeconomic variables used will have to be highly correlated to historical returns of the firm. If sufficient data are available, a multifactor regression model can be generated, and variables found to be statistically significant can then be used.

Obviously, there is potential for abuse and misuse of the model.[8] If used correctly, the model will provide a wealth of information on the potential risks that the project or asset holds. However, in the end, the jury is still out on what constitutes a good discount rate model.

[8] For instance, multicollinearity, autocorrelation, random walk (nonstationarity), seasonality, and heteroskedasticity pose a problem in macroeconomic time series. The model should be developed carefully.

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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 several 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, etc.), *Integer Decision Variables* (e.g., 1, 2, 3, 4 or 1.5, 2.5, 3.5, etc.), *Binary Decision Variables* (1 and 0 for go and no-go decisions), and *Mixed Decision Variables* (both integers and continuous variables). In addition, Risk Simulator can handle *Linear Optimization* (i.e., when both the objective and constraints are all linear equations and functions) and *Nonlinear Optimization* (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, prior to 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, one 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.

One point 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) 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. 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 26 illustrates a project selection model where there are 12 projects listed. Each project 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 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 26**: Discrete Go and No-Go Decision for Project and Program Selection**

Results Interpretation

Figure 28 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.

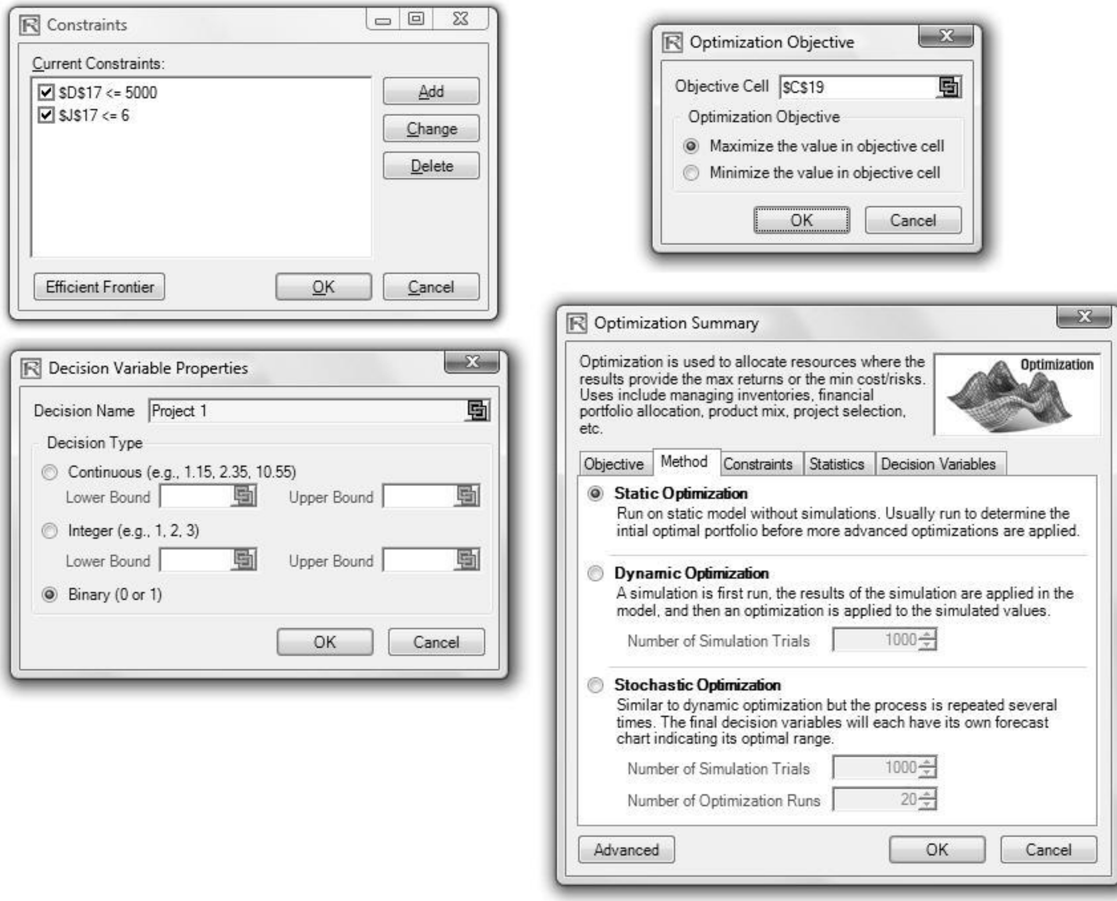


Figure 27: Portfolio Optimization Model Settings

	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.

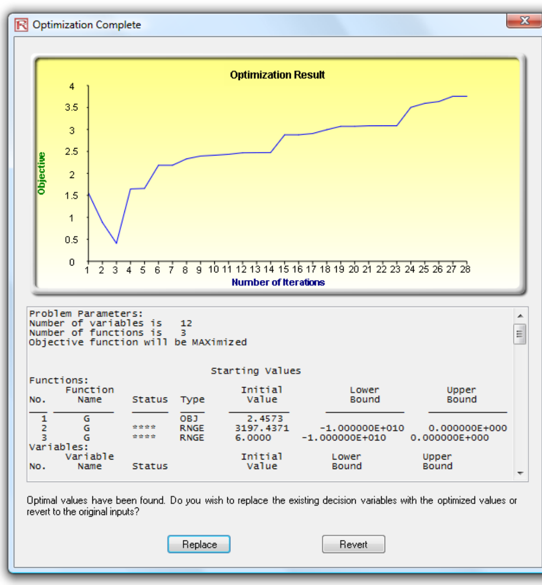


Figure 28: Optimal Selection of Projects Maximizing Sharpe Ratio

Efficient Frontier and Advanced Optimization

Figure 29 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 29). 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 30).

Specifically, the 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 29), 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 30). Click on *Create Report* to generate a report worksheet with all the details of the optimization runs.

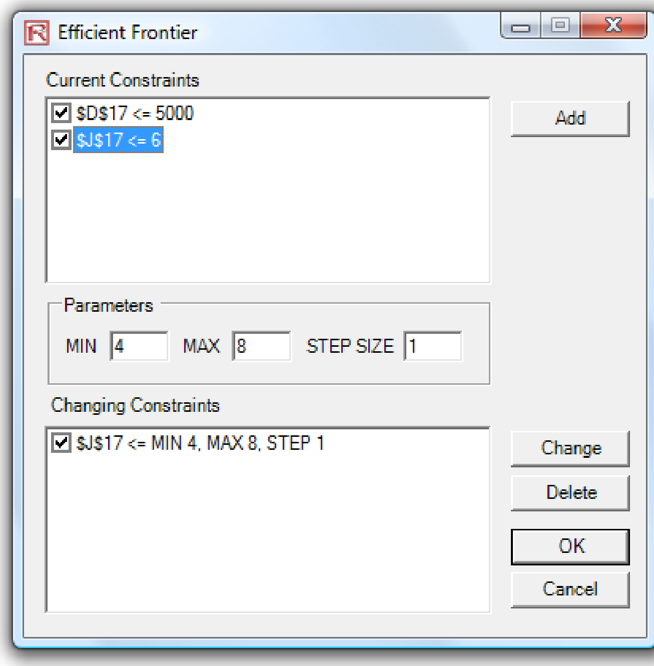
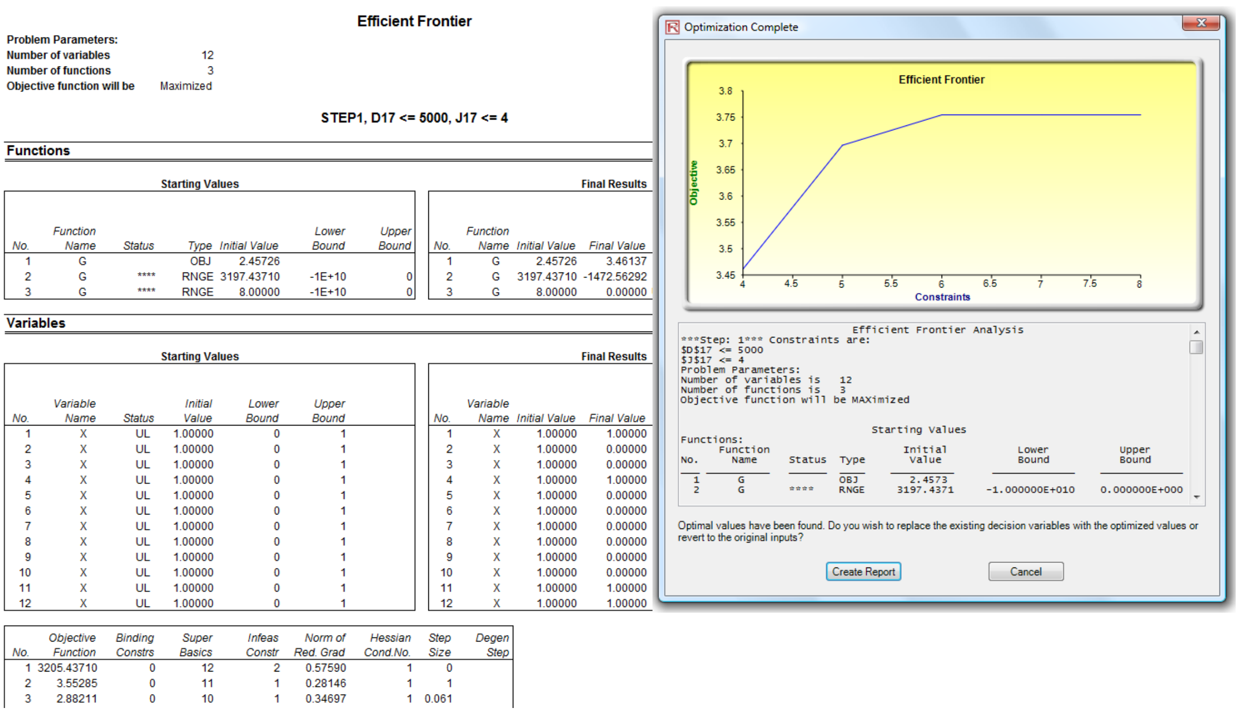


Figure 29: Generating Changing Constraints in an Efficient Frontier



Efficient Frontier

Problem Parameters:

Number of variables	12
Number of functions	3
Objective function will be	Maximized

STEP1, D17 <= 5000, J17 <= 4

Functions

Starting Values

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

Final Results

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

Variables

Starting Values

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

Final Results

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 30: Efficient Frontier Results

Appendix C: 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 making 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 be 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, thereby capturing this upside price fluctuation.

Pharmaceutical Research and Development Industry

In pharmaceutical research and development initiatives, real options can be used to justify the large investments in what seem to be cashless and unprofitable projects under the discounted cash flow method but actually create *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

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, which mandates the assessment of the cost benefits for information technology investments
- The 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*, which 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 31.

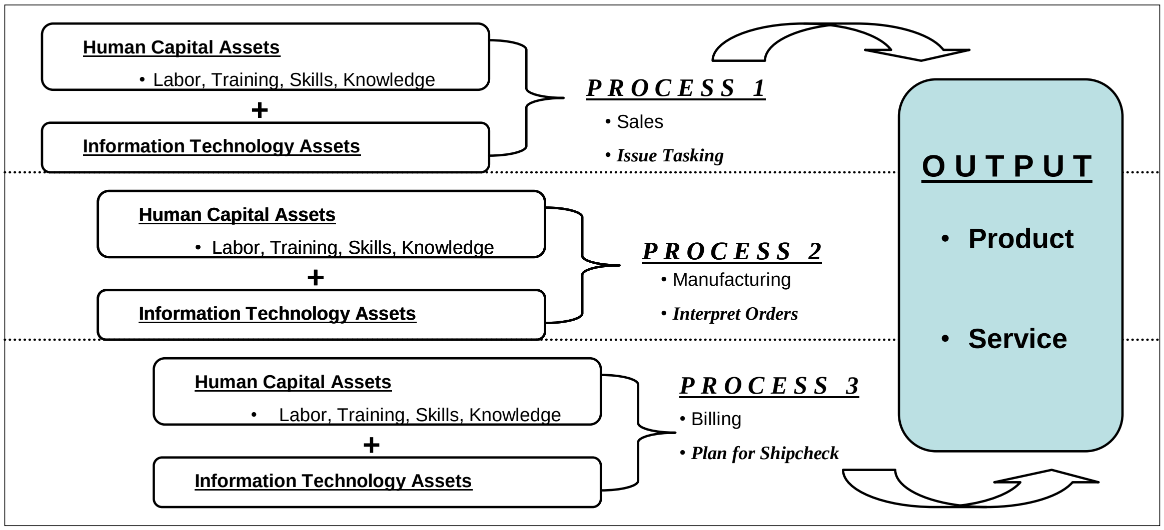


Figure 31: Measuring Output

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 (ROKI). Calculations of these key metrics are shown in Figure 32.

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 32: 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 33).

Explains What Was Spent

Traditional Accounting		KVA Process Costing	
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

Explains How It Was Spent

Figure 33: 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 system 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

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 35). 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 author 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 one 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 (AFCAA) Handbook*, as seen in Figure 34. 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 35 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 34: U.S. Probability Risk Distribution Spreads.

Source: *Air Force Cost Analysis Agency Handbook*

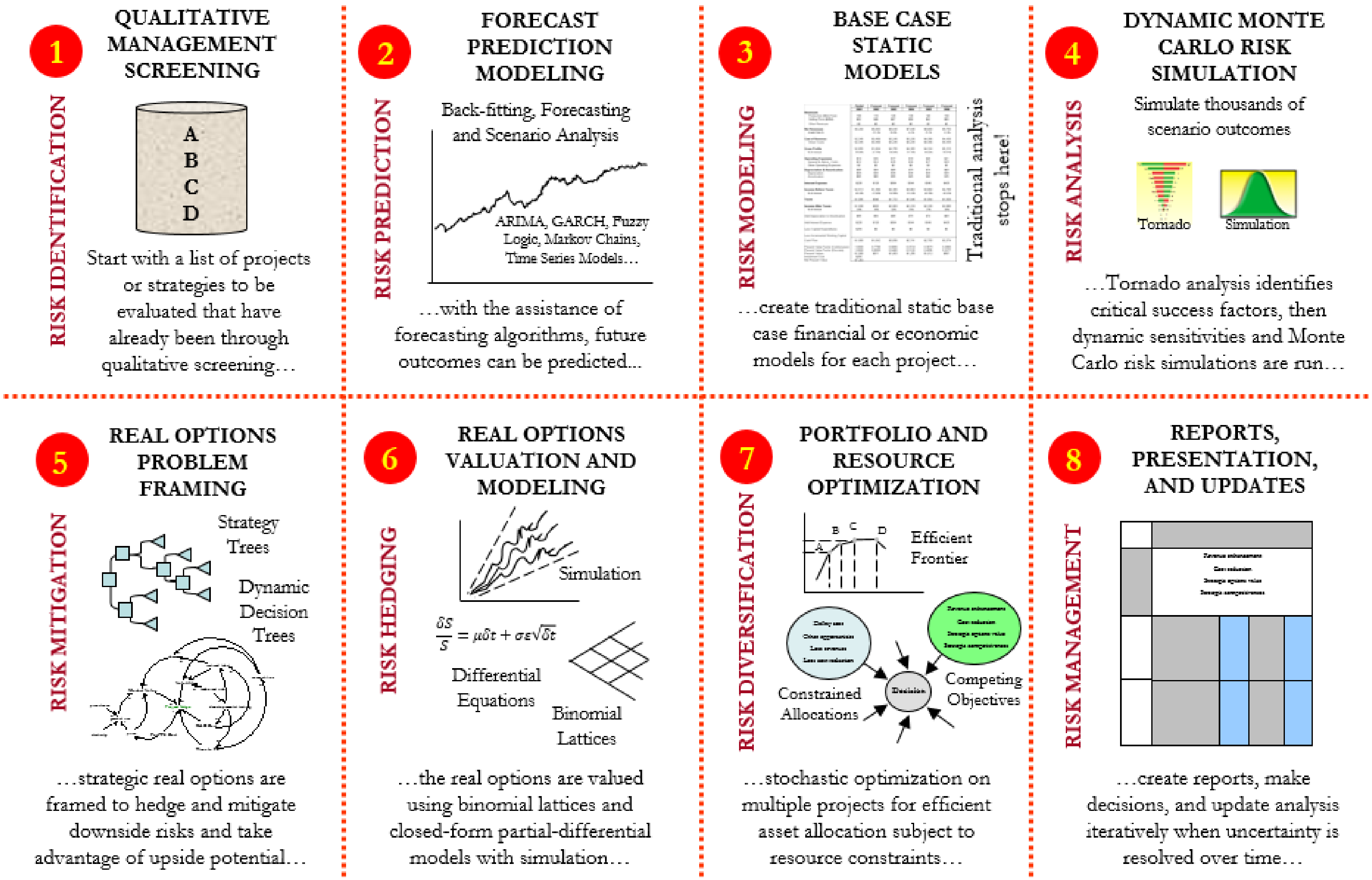


Figure 35: Integrated Risk Management Process

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