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CAPTURING RISK IN CAPITAL BUDGETING

by

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Capturing Risk in Capital Budgeting

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This research has the goal of proposing a novel, reusable, extensible, adaptable, and comprehensive advanced analytical process and Integrated Risk Management to help the (DOD) with risk-based capital budgeting, Monte Carlo risk-simulation, predictive analytics, and stochastic optimization of 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. Stochastic portfolio optimization with dynamic simulations and efficient investment frontiers will be run 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. The results include actionable intelligence developed from an analytically robust case study that senior leadership at the DOD may utilize to make optimal decisions. The main deliverables will be a detailed written research report and presentation brief on the approach to capturing risk and uncertainty in capital budgeting analysis. The report will detail the proposed methodology and applications, as well as a summary case study and examples of how the methodology can be applied.

I. INTRODUCTION

Optimizing the Navy budget requires characterization of risk in cost, schedule, and performance. Recent NRP developed stochastic optimization. This effort conducts deep dives on risk in cost, schedule, and performance. This research has the goal of proposing a novel, reusable, extensible, adaptable, and comprehensive advanced analytical process and Integrated Risk Management to help the (DOD) with risk-based capital budgeting, Monte Carlo risk-simulation, predictive analytics, and stochastic optimization of 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. Stochastic portfolio optimization with dynamic simulations and efficient investment frontiers will be run for the purposes of selecting the best combination of programs and capabilities also addressed, as are other alternative methods such as average ranking, risk metrics, lexicographic methods, PROMETHEE, ELECTRE, and others. The results include actionable intelligence developed from an analytically robust case study that senior leadership at the DOD may utilize to make optimal decisions. The main deliverables will be a detailed written research report and presentation brief on the approach to capturing risk and uncertainty in capital budgeting analysis. The report will detail the proposed methodology and applications, as well as a summary case study and examples of how the methodology can be applied.

Research Objectives and Questions

The proposed research will apply multiple novel approaches to enhance its success in generating a credible and defensible ROI using risk-based stochastic capital budgeting techniques within the Department of Defense (DOD). The success criteria will be to determine a defensible ROI from multiple points of view and approaches, to triangulate to a valid and reliable ROI value, in order to provide guidance and intelligence to DOD decision-makers with respect to the optimal program selection and portfolio allocation of resources. The methods will be within the constructs of a correlated portfolio of decision options that can be stochastically optimized (Markowitz efficient frontiers). Other portfolio- and program-selection approaches such as Preference Ranking Organization Methods for Enrichment Evaluations (PROMETHEE), Elimination and Choice Expressing the Reality (ELECTRE), Multi-Criteria Analysis (MCA), and Hierarchical Scoring-Ranking (HSR) methods will be applied.

Research Methodology

The proposed methodologies may or may not include the following methodologies, depending on the availability of data and the sponsor's requirements: Theoretical Constructs by using a systems-dynamics approach to utilization (closed-form partial differential equation); Convolution methods to determine the frequency and quantity of use; an Analytical Framework; Empirical Impact analysis; Work-Lifecycle Total Ownership Cost with Analysis of Alternatives (cradle-to-grave lifecycle acquisitions) approach; and all of which will be combined with Integrated Risk Management methodologies to run Monte Carlo simulations, advanced data analytical approaches (artificial intelligence and data science methods), strategic flexibility real options, and stochastic optimization. We will be using both economic data (total lifecycle cost, total ownership cost, acquisition cost, cost deferred, schedule, risk), logistics data (e.g., inherent availability, effective availability, mission reliability, operational dependability, mean downtime, mean maintenance time, logistics delay time, achieved availability, operational availability, mission availability, fielded capabilities, Likert levels of creative and novel technology, as well as other metrics), qualitative subject matter expert estimates (strategic value, value to society, command priorities, legal and regulatory impact scores, etc.), and market comparables to operationalize various elements of DOD benefit.

II. LITERATURE REVIEW

Portfolio Modeling in Military Applications

Optimization is a long-standing and legendary subject that involves using data and information to assist decision-making in order to achieve an optimal or near-optimal result. Despite the fact that they collect more data than ever before, “government agencies have been significantly slower to apply these approaches to boost efficiency and mission effectiveness” (Bennett, 2017). Optimization solutions for these government agencies can make use of enormous volumes of data from many sources to give decision-makers alternative options that best match agency goals.

Standard economic indicators such as the internal rate of return (IRR), net present value (NPV), and return on investment (ROI) are often employed in evaluating commercial-based R&D projects to find optimal alternatives, as Greiner, McNutt, Shunk, and Fowler (2001) accurately stated. However, in their commercial form, such economic criteria are of little utility in appraising weapon system development efforts. As a result, this study looks at the difficulties the Department of Defense has in estimating the value of weapon systems during the R&D portfolio selection process.

Beaujon, Marin, and McDonald (2001) used a mathematical formulation of an optimization model to choose projects for inclusion in an R&D portfolio, subject to a range of constraints, to balance and optimize a portfolio of R&D projects (e.g., capital, headcount, strategic intent, etc.). There does appear to be widespread consensus that all of the recommended methods are fraught with risk. The authors devised a method for examining the sensitivity of project selection decisions to changes in the measure of value.

Burk and Parnell (2011) looked at how portfolio decision analysis is used in military applications such as weapon systems, force types, installations, and military R&D initiatives. They began by contrasting military and commercial portfolio challenges in general, as well as outlining the military decision environment's distinctive characteristics: aggressive and adaptive opponents, a public decision process with various stakeholders, and high system complexity. The authors concluded that the "most widely prominent element of these applications is the rigorous modeling of value from numerous objectives" based on their research (Burk & Parnell, 2011). "Quantitative approaches of evaluating and valuing risk are surprisingly infrequent, given the high level of uncertainty in the military environment," they discovered (Burk & Parnell, 2011). Their investigation focused on how military analysts model portfolio values, weight evaluations, restrictions and dependencies, and uncertainty and risk in portfolio applications.

Davendralingam and DeLaurentis (2015) used a system of systems (SoS) technique to analyze military capabilities. According to the authors, this technique poses major technical, operational, and programmatic obstacles in terms of development. There aren't any tools for deciding how to construct and evolve SoS that takes performance and risk into account. To aid decision making within SoS, they used methods from financial engineering and operations research perspectives in portfolio optimization. To address intrinsic real-world challenges of data ambiguity, inter-nodal performance, and developmental risk, the authors suggested using more robust portfolio algorithms. The paper used a naval battle scenario to demonstrate scenario applications for finding system portfolios from a candidate list of accessible systems. Their findings reveal that by allowing the optimization problem to handle the mathematically intensive components of the decision-making process, the optimization framework effectively minimizes the combinatorial complexity of trade-space exploration. As a result, the authors argued that human decision-makers should be entrusted with selecting suitable risk aversion weights rather than the portfolio's mathematical constructions when making final decisions.

A portfolio management analysis was conducted by Sidiropoulos, Sidiropoulou, and Lalagas (2014) with the goal of identifying and evaluating current commercial off-the-shelf (COTS) Portfolio Analysis (PA) software tools and solutions. Portfolio models were created using the Risk Simulator software. These models were filled with pertinent data before being run through a sufficient number of simulation iterations to evaluate candidate projects in terms of risk and expected military value (EMV). Portfolio Management Analysis (PMA) is discussed in this paper through examples and models at various levels of project management and systems engineering. The PMA aim is achieved after the full project design infrastructure is in place and the end users' instruments are ready to use. The authors wanted to find "approaches and tools to incorporate PMA net-centric strategies to meet warfighter and business operations requirements while maintaining current levels of service, ensuring manpower conservation, and meeting infrastructure resource requirements" according to the authors (Sidiropoulos, Sidiropoulou, & Lalagas, 2014).

Flynn and Field (2006) examined quantitative metrics in the works to assess the Department of the Navy's (DON) procurement portfolio in order to improve business operations through better analytical tools and models. The authors discovered that the DON's time would be better spent if it shifted its focus away from individual acquisition projects (which have now been well examined) and toward a portfolio of systems as a whole. This strategy is similar to the methodology used in the commercial sector as a best practice. According to the study, this high-level view offers senior military officials useful metrics for assessing cost, capability, and requirement risks and uncertainties. Senior leaders can make better decisions from a set of plausible portfolios armed with these indicators in order to meet the Navy's national security objectives. To complement their research, financial management and acquisition staff picked a portion of the then-current DON portfolio to test a portfolio analysis approach in the field of Mine Countermeasures, a diverse, representative system of projects. 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 with subject matter experts to determine how well current and future systems match capabilities to requirements and developing a way to display results so decision-makers can examine risk-reward analysis and trade-offs. The researchers' ultimate goal was to use portfolio analysis to evaluate military investments.

The GAO (1997, 2007) stressed the importance of adjusting a portfolio mix in order to reduce risk and maximize returns. Despite the fact that the Department of Defense creates superior weapons, the GAO found that it has failed to deploy weapon systems on time, on budget, and with the intended capabilities. While recent changes to the Department of Defense's acquisition policy have the potential to improve outcomes, major cost and schedule overruns continue to plague programs. The GAO was tasked with looking into how the Department of Defense's mechanisms for determining needs and allocating funding could be improved to better support weapon system program stability. According to the report, the GAO compared the DOD's policies for investing in weapon systems to the best practices used by successful commercial organizations such as Caterpillar, Eli Lilly, IBM, Motorola, and Procter and Gamble to produce a balanced mix of new products. According to the studies, successful commercial enterprises that the GAO studied employ an integrated portfolio management approach to product development in order to establish a balanced mix of executable development programs and ensure a favorable return on their investments. Companies evaluate product investments collectively from an enterprise level other than as separate and unrelated activities using this method. These commercial entities use established criteria and methods to weigh the relative costs, benefits, and risks of proposed products and select those that can exploit promising market opportunities while staying within resource constraints and moving the company toward its strategic goals and objectives. Investment decisions are regularly reconsidered in these enterprises, and if a product fails to meet expectations, companies make difficult go/no-go judgments over time. Effective portfolio management necessitates 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, according to the companies examined by the GAO. The Department of Defense, on the other hand, authorizes new initiatives with far less regard for the broader portfolio and commits to them sooner and with less knowledge of cost and feasibility. Despite fighting as a joint force on the battlefield, the military services define needs and allocate resources individually, utilizing fragmented decision-making processes that do not allow for an integrated portfolio management approach like that utilized by successful commercial firms. As a result, the Department of Defense might be less certain that its investment decisions meet the correct mix of warfighting demands, and it begins more programs than current and likely future resources can support, resulting in a fiscal tsunami. If this pattern continues, Congress will be forced to choose between diverting funds from other high-priority federal programs to pay DOD acquisitions or accepting gaps in warfighting capability.

The Army has adopted the Army Portfolio Management Solution (APMS) to enable the collection and analysis of information needed to prioritize the thousands of IT investments in its portfolio, according to Wismeth (2012). Warfighter, Business, and Enterprise Information Environment Mission Areas, each of which is overseen by a three- or four-star general officer or senior executive, are the three mission areas that IT investments serve.

Government agencies and the Department of Defense, according to Botkin (2007), require decision-support systems when making funding decisions for portfolios of programs or projects. When it comes to selecting potential programs, government agencies have had some success with Project Portfolio Management (PPM); however, once programs are up and running, financial managers are faced with funding optimization decisions that are similar to those faced by private-sector stock market portfolio managers. Government finance managers lack an analogous "stock-price" metric for program or project performance, whereas private-sector portfolio managers rely on financial portfolio analysis based on "stock price" to guide decision making. According to Botkin's (2007) research, the government's Earned Value Management System (EVMS) indicators can be utilized to provide a good proxy for financial portfolio analysis. Risk and return trade-offs can be quantified and used to make portfolio decisions based on the results of this study. Botkin's study includes an example utilizing representative EVM data. Recommendations on the technique's potential usefulness and limits are presented.

The Office of Naval Research (ONR) is in charge of establishing and sponsoring the R&D required to support the Navy and Marine Corps current and future requirements. According to Silberglitt et al. (2004), the ONR must fund a broad range of research to achieve this purpose, ranging from basic research to open up new long-term choices to extremely near-term advanced technology development to support the current fleet. In the face of uncertainty, the ONR must make R&D funding decisions (uncertainty in required capabilities, uncertainty in performance requirements, and uncertainty in the feasibility of a technology or R&D approach). The application of a RAND R&D portfolio management decision framework was presented in Silberglitt's (2004) study.

The DOD should support dynamic and innovative solutions for tomorrow's warfighter by building acquisition portfolios that deliver an integrated suite of capabilities, according to Janiga and Modigliani (2014). Today's program executive officers (PEOs) are sometimes tasked with executing a dozen or more identical but separate programs. Large commercial businesses, on the other hand, oversee integrated product lines that include everything from autos and electronics to software and health services. The Department of Defense might use this technique to build portfolios of similar initiatives that yield improved capabilities in shorter timeframes.

Jocic and Gee (2013) developed a method for comparing space services given by several systems in a portfolio that allows for a normalized value of diverse system properties and can be displayed using a three-dimensional graph with capability, cost, and scheduling axes. Portfolio optimization is achieved by remaining within the cost-capability plane's efficient performance frontier, maintaining the cost-schedule plane's budgetary restrictions, and reducing the likelihood of a capability gap in the schedule-capability plane. The required portfolio capability is obtained from the military utility analysis-generated combat scenario outcomes.

Under an assignment headed "Portfolio Optimization Feasibility Study," the Institute for Defense Analyses (IDA) prepared a document for the Office of the Director, Acquisition

Resources and Analysis (Weber et al., 2003). The goal was to see if it was possible to use optimization technology to improve long-term defense acquisition strategy. The model provided in this document is an example of optimization techniques that can estimate and optimize Acquisition Category I program production schedules over an 18-year period.

The modern warfighter, according to Vascik, Ross, and Rhodes (2015), operates in an environment that has substantially evolved in sophistication and interconnection over the last half-century. With each passing year, acquisition officers have more challenges in making decisions about potential joint capability programs due to the infusion of ever more complicated technology and integrated systems. Furthermore, despite efforts since 2010 to ensure system affordability, large cost overruns in recent acquisition programs demonstrate that more work is needed to develop improved methodologies and methods. Vascik et al. presented research that expands on previous work that looked at system design trade-spaces for affordability under uncertainty and applied it to programs and portfolios. Exogenous factors that change over time, such as resource availability, stakeholder needs, or production delays, can affect the potential for value contribution by constituent systems throughout the course of a portfolio's life cycle, making an initially appealing design less appealing. By combining features of Epoch-Era Analysis with aspects of Modern Portfolio Theory, Vascik et al. (2015) presented a method for conducting portfolio design for affordability. The process is demonstrated through the creation of a carrier strike group portfolio that includes the integration of different legacy systems as well as the purchase of new vessels.

The DOD Space Assessment (PDSA) analyzes and oversees the performance of the whole DOD space portfolio, according to DODD 5100.96 (DOD, 2017). The PDSA advises senior DOD leadership and suggests NSS enterprise-level adjustments when reviewing space-related risks, requirements, architectures, programs, and their synchronization. When directed, it conducts an annual strategic assessment, or Space Strategic Portfolio Review (SPR), with assistance from the DSC and DCAPE, to address space posture and enterprise-level issues, and it reports the findings to the DMAG and the secretary and deputy secretary of defense, which could include prioritized programmatic choices for space capabilities.

Portfolio Applications in Industry

Dunlop (2004) looked at how wind power capacity in Europe and the United States was fast expanding and becoming more appealing to institutional private equity investors. The author tested whether the current portfolio theory and the capital asset pricing model could be successfully applied to wind farms and whether geographical diversification could reduce production volatility. He discovered that beta could be a valuable tool in risk measurement for wind farm selection by substituting stock return data with wind power production data. He also discovered that in a practical portfolio, up to 30% of production risk could be spread away to smooth cash flow returns.

Advanced physical portfolio optimization, according to Haq, Gandhi, and Bahl (2012), can help many businesses enhance earnings and improve overall margins. Energy companies looking to increase revenues, such as producers, suppliers, or merchant traders of gas, power, oil, or chemicals, should use a systematic market-based approach that treats all assets in the business as an integrated portfolio, including physical assets, term contracts, transport or storage leases, and positions. The value of a firm should be denominated by the value of the portfolio as a whole and how the portfolio is managed, according to advanced physical portfolio optimization. The main advantage of advanced physical portfolio optimization is that it improves overall business management at the granular level. Advanced physical portfolio optimization suggests transactions that optimize profit while staying within asset and contractual limits.

The portfolio selection for military investment assets based on semi-variance as a risk metric was studied by Yang, Lin, Chang, and Chang (2011). The authors suggest a new definition of military investment assets for portfolio selection in this paper. A semi-variance model is developed based on the new definition. Heuristic algorithms are proposed to tackle the portfolio selection problem that is otherwise difficult to solve with existing algorithms in traditional ways in order to provide efficient portfolios to the risk model. In addition, for the portfolio selection problem, a risk measure with cardinality limits is offered. The cardinality requirements increase the risk model's compatibility in a portfolio situation. In order to explain the quantitative idea for the decision maker in military investment assets, a numerical example of weighted allocations with varying risk values is also offered.

According to Setter and Tishler (2007), a growing portion of defense R&D spending is going toward developing and fielding integrative technologies that allow multiple systems to work together in a coordinated and synergistic manner as a single system. The researchers looked into the best defense budget allocation for weapon system development and acquisition, as well as integrative technology development. They created a suitable optimization framework, which they then used to derive and analyze the optimal budget allocation. Finally, they used data from the US defense budget to calibrate the model's parameters and produce a quantitative measure of the US military's apparent superiority.

Due to the usage of many types of sensors on the battlefield, military applications generate large amounts of data. Yang, Yang, Wang, and Huang (2016) used the important knowledge derived from this sensor data to analyze the weapon system portfolio problem. The goal of weapon system portfolio optimization is to find the best combination of weapon units to maximize predicted damage to all hostile targets while staying within a set of constraints. For the weapon system portfolio problem, the authors presented a mixed-integer nonlinear optimization model. An adaptive immune genetic algorithm based on crossover and mutation probabilities that are automatically modified in each generation is proposed to solve this scenario. To demonstrate the viability and efficiency of their proposed algorithm, they present a ground-based air defense scenario. In addition, multiple large-scale cases generated by a test-case generator are taken into account to demonstrate the algorithm's scalability. Comparative tests have revealed that its algorithm surpasses its competitors in terms of convergence speed and solution quality, as well as its ability to solve weapon system portfolio problems at various scales.

Understanding the value of a product development project is crucial to a firm's project portfolio selection, according to Girotra, Terwiesch, and Ulrich (2007). The worth of a project to a company is determined not just by its features but also by the company's other projects. Because of interactions with other projects that serve the same consumer need and require the same development resources, this is the case. The authors used a pharmaceutical sector data set to analyze the nature and significance of these portfolio-level project linkages. The study used the natural experiment of a failed product development project to determine the worth of a medication development project to a company. It then demonstrated how the value of projects varied depending on how they interacted with other projects in the firm's portfolio.

Johannessen (2015) investigated the use of real choices and portfolio optimization to improve the quality of information gained during decision-making and to optimize project selection for wind power portfolios. TrnderEnergi's investment portfolio was subjected to the model established in this thesis. The projects that were considered were in central Norway.

Pacific Gas and Electric (PG&E) was able to triple its innovation success rate by encouraging a portfolio mindset, according to Brown and Anthony (2011). The authors claim that PG&E informs both internal and external stakeholders that it is developing a diverse portfolio of innovative approaches, ranging from sustainable to disruptive. PG&E also uses portfolio-optimization tools to help management identify and terminate the programs that aren't working and nurture the ones that are. These tools generate estimations for every active idea, including potential financial estimates as well as human and capital inputs. Some concepts are assessed using traditional net-present-value calculations, while others are assessed using a risk-adjusted, real-options method, and yet others are assessed using qualitative criteria. Although the tools generate a rank-ordered list of projects, PG&E's portfolio management is more of a conversation about resource allocation and business growth building blocks than a mechanical exercise. Numerical data can help you make better judgments, but it can't make them for you.

According to Gurgur and Morley (2008), Dennis Garegnani, director of FO&S, Lockheed Martin Space Systems,

> 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 have 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 adds that

> having the model at Lockheed Martin's disposal has added another level of credibility to the department among its peers. The 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)

ExxonMobil's 2015 Summary Annual Report 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," which is further evidence of the value of portfolio optimization.

Mark Baynes, Kellogg's Global CMO, says 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). DuPont's better earnings in the fourth quarter of 2014, according to Zacks Equity Research (2015), were due to the company's focus on implementing strategic activities such as portfolio optimization, disciplined capital allocation, and cost reduction.

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III. CAPITAL BUDGETING AND THE VALUE CONCEPT

The Traditional Views

The single time-value discounted number that represents all future net profitability is defined as *value*. The market price of an asset, on the other hand, may or may not be equal to its worth (the terms "assets," "projects," and "strategies" are interchangeable). For example, when an asset is sold at a considerable discount, its price may be slightly lower than its value, leading one to believe that the buyer has gotten a good deal. The goal of valuation in determining a fair market value is to find a price that closely approximates the asset's genuine value. This genuine worth is derived from both the physical and nonphysical, intrinsic, or intangible qualities of the asset. Extrinsic monetary value or intrinsic strategic value can be generated by both components. The market approach, the income approach, and the cost approach are the three most common approaches to valuing a business (see Mun, Hernandez, & Rocco, 2016, for more details).

Market Approach

The market approach examines comparable assets and their associated prices in the marketplace, assuming that market forces will tend to shift the market price to an equilibrium level. After compensating for transaction costs and risk differentials, it is further assumed that the market price is likewise the fair market value. To bring the comparables closer to the working structure of the firm whose asset is being assessed, a market-, industry-, or firm-specific adjustment may be necessary. These could include quantitative screening utilizing parameters that closely mimic the firm's industry, operations, size, revenues, functions, profitability levels, operational efficiency, competition, market, and hazards, to name a few.

Income Approach

The income approach looks at the potential future 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 considers how much it would cost a company to replace or replicate an asset's future profitability potential, including the cost of its strategic intangibles if it were built from scratch. Although the financial theories that underpin these approaches are sound in the more traditional deterministic view, they cannot be utilized in isolation for assessing a firm's, project's, or asset's genuine strategic flexibility value.

Other Approaches

Other approaches to valuation, which are more applicable for intangibles, rely on quantifying the asset's economic viability and economic gains to the company. There are various well-known approaches for valuing intangible assets, including trademarks and brand names. These strategies combine the previously mentioned market, income, and cost approaches.

The first method examines pricing methods and considers that a corporation can charge a higher price for its product if it has a dominant market position due to a strong trademark or brand recognition—for example, Coca-Cola. As a result, if we can discover market comparables that produce identical items, operate in similar markets, perform similar functions, and face similar market uncertainties and dangers, the price difference will be solely due to the brand name. These comparables are typically updated to account for the various operating environments in which the companies operate. After a discounted cash flow (DCF) analysis, the residual profits allocated to the intangible are calculated by multiplying the price premium per unit by the estimated quantity of sales. Using operating profit margin instead of price per unit makes a similar argument. Because it avoids the concerns of comparables with different capital structure policies, carry-forward net operating losses, and other tax-shield considerations, operating profit before taxes is utilized instead of net profit after taxes.

Another method compares the profit and loss statements of the asset's owner with market comparables using a common-size analysis. This strategy accounts for any cost savings resulting from economies of size and scope. The goal is to convert income statements and balance sheet items to a percentage of total assets. Furthermore, to improve comparability, the comparable firm's operating profit to sales ratio is multiplied by the asset-holding firm's predicted revenue structure, removing the possible difficulty of needing to account for differences in economies of scale and scope. The common-size variable in this method is a percentage of sales, return on investment, or return on asset ratio.

Practical Issues Using Traditional Valuation Methodologies

The standard valuation process, which relies on a discounted cash flow series, misses out on some of the asset's or investment opportunity's fundamental characteristics. Traditional methods believe that an investment is an all-or-nothing proposition, and they ignore managerial flexibility, which allows management to change the direction of an investment over time when new information about the project's uncertainty becomes available. The ability of management to generate, execute, and discard strategic and flexible alternatives is one of the value-added components of using real options.

When it comes to strategic options, adopting the standard discounted cash flow estimate might lead to a number of issues. Undervaluing an asset that currently generates little or no cash flow, the non-constant nature of the weighted average cost of capital discount rate over time, the estimation of an asset's economic life, forecast errors in generating future cash flows, and insufficient tests for the plausibility of the final results are all examples of these issues. When used in conjunction with an options theoretical framework, real options can help to reduce some of these issues. Financial profit level measurements, such as net present value (NPV) or internal rate of return (IRR), may be skewed and will not provide a thorough assessment of the entire investment value if this is not done.

DCF: Synopsis of Advantages and Disadvantages

While employing simply standard discounted cash flow analysis has its drawbacks (Mun, 2016), the discounted cash flow model has its advantages:

- 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 actuality, as indicated in Table 1, an analyst should be aware of various difficulties when employing discounted cash flow models. The business fact that risks and uncertainty abound when decisions must be taken, as well as management's strategic flexibility to make and amend judgments as these uncertainties become apparent over time, are the most significant aspects. Using deterministic models like the discounted cash flow in such a chaotic world could potentially dramatically underestimate the value of a given enterprise. A deterministic discounted cash flow model posits that all future outcomes are predetermined from the start. If this is the case, the discounted cash flow model is appropriately described because there would be no changes in business conditions that would affect the project's value. Flexibility would, in essence, be of little use. However, because the actual company environment is constantly fluid, there is value in flexibility, provided management has the flexibility to make necessary changes when conditions change. This value will be severely 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 a 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.
The 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 its 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 depicts a straightforward use of discounted cash flow analysis. Assume a $1,000 project is implemented in Year 0 and generates the following predicted positive cash flows over the next five years: $500, $600, $700, $800, and $900. These estimated values are only the analyst's best guess projections. As shown in Figure 1, the timeline depicts all relevant cash flows as well as their discounted present values. We compute the NPV to be $985.92 and the IRR to be 54.97 percent assuming the analyst selects to discount the project at a 20% risk-adjusted discount rate using a weighted average cost of capital (WACC). (The NPV is simply the sum of future cash flows' present values minus the implementation cost.) The implicit discount rate (IRR) is the rate at which the NPV is forced to zero. Using Excel's "NPV()" and "IRR()" tools, both computations are simple to do.) In addition, the analyst expects that the project will have an unlimited economic life and a long-term cash flow growth rate of 5%. The analyst assesses the terminal value of the project's cash flow at Year 5 to be \$6,300 using the Gordon constant growth model. When you add this to the initial NPV and discount it for five years at the risk-adjusted discount rate, you get a total NPV of \$3,517.75. Figure 1 shows the computations, where *w* stands for weights, *d* for debt, *ce* for common equity, *ps* for preferred stocks, *FCF* for free cash flows, *tax* for corporate tax rate, *g* for long-term cash flow growth rate, and *rf* for the risk-free rate.

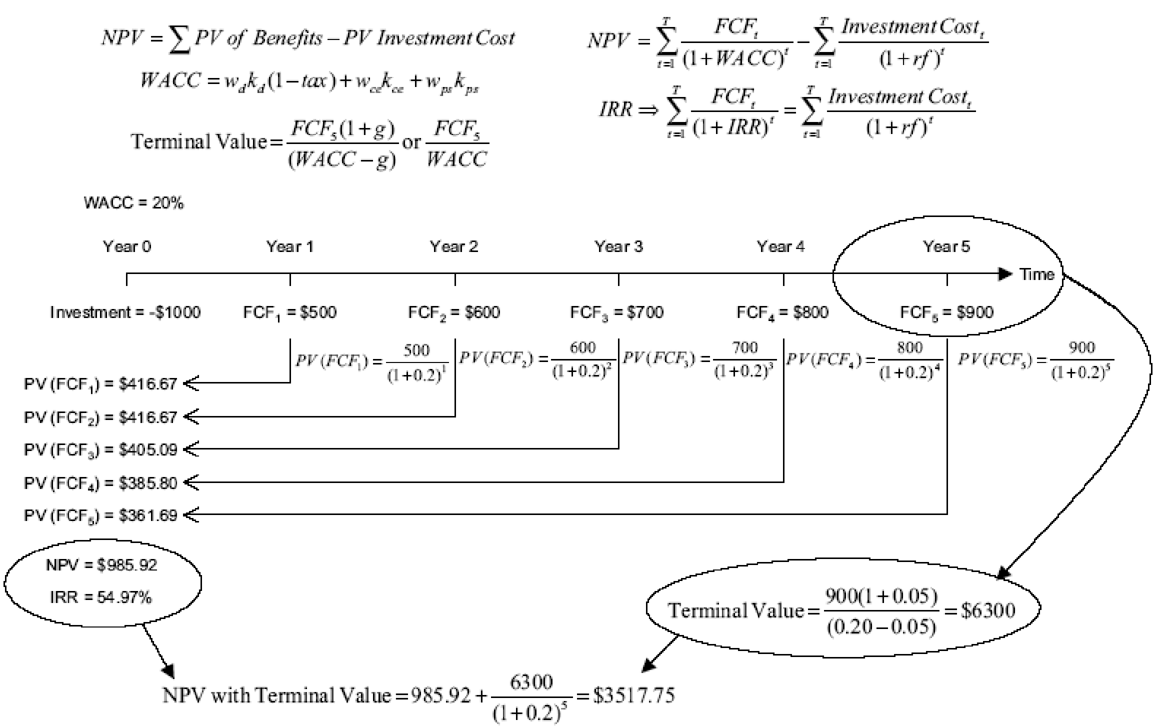

Figure 1: Applying Discounted Cash Flow Analysis

Even with a simple discounted cash flow model like this, there are numerous flaws to be aware of when utilizing a discounted cash flow model. Some of the more noteworthy concerns are listed in Figure 2. For example, the present value of future net free cash flows (benefits) is subtracted from the present value of implementation costs to arrive at the NPV (investment costs). Analysts, on the other hand, frequently discount both benefits and investment costs at the same market risk-adjusted discount rate, usually the WACC. Of course, this strategy is incorrect (Mun, 2016).

The gains should be discounted using a market risk-adjusted discount rate such as the WACC, but the investment cost should be discounted using a risk-free reinvestment rate. Because the market will only reimburse the company for taking on market risks but not private hazards, cash flows with market risks should be discounted at the market risk-adjusted rate, whereas cash flows with private risks should be discounted at the risk-free rate. Benefit-free cash flows are thought to be subject to market risks (because they depend on market demand, market prices, and other exogenous market factors), whereas investment costs are thought to be subject to internal private risks (such as the firm's ability to complete a project on time or the costs and inefficiencies incurred beyond what is projected). These implementation costs may alternatively be discounted at a rate somewhat higher than a risk-free rate, such as a money-market rate, or at the opportunity cost of investing the money in another project paying a specific interest rate. Simply put, if benefits and investment costs are subject to different risks, they should be discounted at different rates. Otherwise, discounting the expenses at a considerably higher market risk-adjusted rate will significantly reduce the costs, making the project appear more valuable than it is.

The chosen discount rate is often determined using a WACC, Capital Asset Pricing Model (CAPM), Multiple Asset Pricing Theory (MAPT), or Arbitrage Pricing Theory (APT), and established by management as a company requirement or a project hurdle rate. In most cases, the discount rate is the most sensitive variable in a simple discounted cash flow model. It's also the hardest characteristic to quantify accurately. As a result, the discount rate is vulnerable to abuse and subjective manipulation. Simply massage the discount rate to a sufficient level to acquire a target NPV value.

Furthermore, several of the input assumptions used to calculate the discount rate have been called into doubt. The input for the cost of common equity in the WACC, for example, is commonly derived using some variant of the CAPM. The famed beta (() in the CAPM is incredibly tough to compute. We may calculate beta for financial assets by dividing the covariance between a firm's stock prices and the market portfolio by the variance of the market portfolio. The co-movements of a firm's equity prices with respect to the market are measured by beta, which is a sensitivity factor. The issue is that stock values fluctuate every few minutes! Beta can vary dramatically depending on the time range chosen to calculate it. Furthermore, we cannot calculate beta in this manner for non-traded physical assets. It's not a good idea to use the beta of a company's marketable financial assets as a proxy for the beta of a project within a company with many other projects. Mun (2015) proposed using internal comparables, Monte Carlo simulation, and real options volatility estimations to calculate discount rates. This approach (Mun, 2015) gives a more robust discount rate estimate than the CAPM with external market comparables, as mentioned in the risk versus uncertainty section.

There are unaccounted-for risk and return diversification effects among projects, as well as investor psychology and market response. Other, more comprehensive asset-pricing models can also be used to estimate a project's discount rate, but they must be utilized with caution. The APT models, for example, are based on the CAPM and include extra risk elements that could influence the discount rate's value. Maturity risk, default risk, inflation risk, nation risk, size risk, nonmarketable risk, control risk, minority shareholder risk, and other risk factors are among them. Even the company's CEO's golf score can be a concern (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). When deciding which risks to include and which to exclude, the problem emerges. To say the least, this is a demanding assignment. Because there is frequently relatively little historical data available for such analyses, a multiple regression or principal component analysis can be undertaken, albeit with limited success, for physical assets as opposed to financial assets.

Comparability analysis is another extensively used technique. Analysts can estimate the beta (a measure of systematic risk) or even a meaningful discount rate from these comparable enterprises by accumulating publicly available data on the trading of financial assets by stripped-down entities with similar functions, markets, hazards, and geographical locations. For example, an analyst looking for information on a research and development effort for a specific type of drug could potentially acquire market data on pharmaceutical companies that exclusively do research and development on similar drugs that are available in the same market and pose the same risks. The median or average beta value for the project under consideration can therefore be utilized as a market proxy. Obviously, there is no silver bullet, but if an analyst is attentive enough, he or she may gather data from several sources and build a more accurate assessment. In instances like these, Monte Carlo simulation is the best option. Using the range gained from comparable firms, the analyst can define the relevant simulation inputs and execute the discounted cash flow model to obtain the range of important variables (typically the NPV and IRR).

The free cash flow stream should now be discounted correctly after obtaining a suitable discount rate. Another issue is projecting the appropriate free cash flows and selecting whether to discount them continuously or discretely rather than utilizing end-of-year or mid-year standards. Taxes should be deducted from free cash flows, and noncash expenses should be brought back in. Because free cash flows are often computed from revenues to direct cost of goods sold, operating expenses, depreciation charges, interest payments, taxes, and so on, there is plenty of space for errors to compound over time.

Forecasting cash flows for multiple years can be difficult, and it may necessitate the application of sophisticated econometric regression modeling tools, time-series analysis, management hunches, and expertise. Instead of making single-point estimates of cash flows over specific time periods, a recommended way is to employ Monte Carlo simulation to determine the relevant probabilities of cash flow occurrences. Furthermore, because cash flows in the far future are likely to be riskier than those in the near future, the applicable discount rate should be adjusted to reflect this. Rather than adopting a single discount rate for all future cash flow events, the discount rate should be adjusted to account for the changing risk structure of cash flows over time. This can be accomplished by evaluating the cash flow streams' probabilistic risks (standard deviations of forecast distributions) or by employing a stepwise method of applying the maturity risk premium inherent in US Treasury securities at various maturity periods. The analyst might use this bootstrapping strategy to include what market experts think the future market risk structure will look like. To put it another way, you should discount the cash flows twice: once for time-value-of-money and again for risk. Changes in risk structure and risk-free rate can be adjusted suitably over time in this manner.

Finally, anyone adopting a discounted cash flow model should be concerned about terminal value. The Gordon constant growth model (GGM), the zero-growth perpetuity consul, and the supernormal growth models are all ways of computing terminal values. The GGM is the most generally used, and it implies that cash flow growth would be constant in perpetuity at the end of a series of predicted cash flows. The GGM is calculated by multiplying the free cash flow at the conclusion of the forecast period by a relative growth rate, then dividing it by the discount rate minus the long-term growth rate. The GGM breaks down when the long-term growth rate surpasses the discount rate, as seen in Figure 2. The growth rate is also expected to be constant, and the entire terminal value is largely dependent on this assumption. Finally, the estimated number is very dubious because a slight variance in growth rates will result in a substantial value fluctuation. Perhaps assuming some kind of growth curve in the free cash flow series is a preferable technique. These growth curves can be produced using both basic time-series analysis and more advanced stochastic modeling assumptions. Nonetheless, even a well-known, widely accepted, and widely used discounted cash flow model has significant analytical limitations and issues. These issues are substantial, and they can accumulate over time, resulting in erroneous outcomes. When conducting such evaluations, extreme caution should be exercised. In contrast, Mun (2015) presented the concepts of Monte Carlo simulation, real options, and portfolio optimization, which all address some of the previously described concerns, it should be noted that these techniques do not give a silver bullet for valuation and decision-making. They provide value-added insights, and the degree of the insights and value derived from these methods is wholly determined by the type and characteristics of the project under consideration.

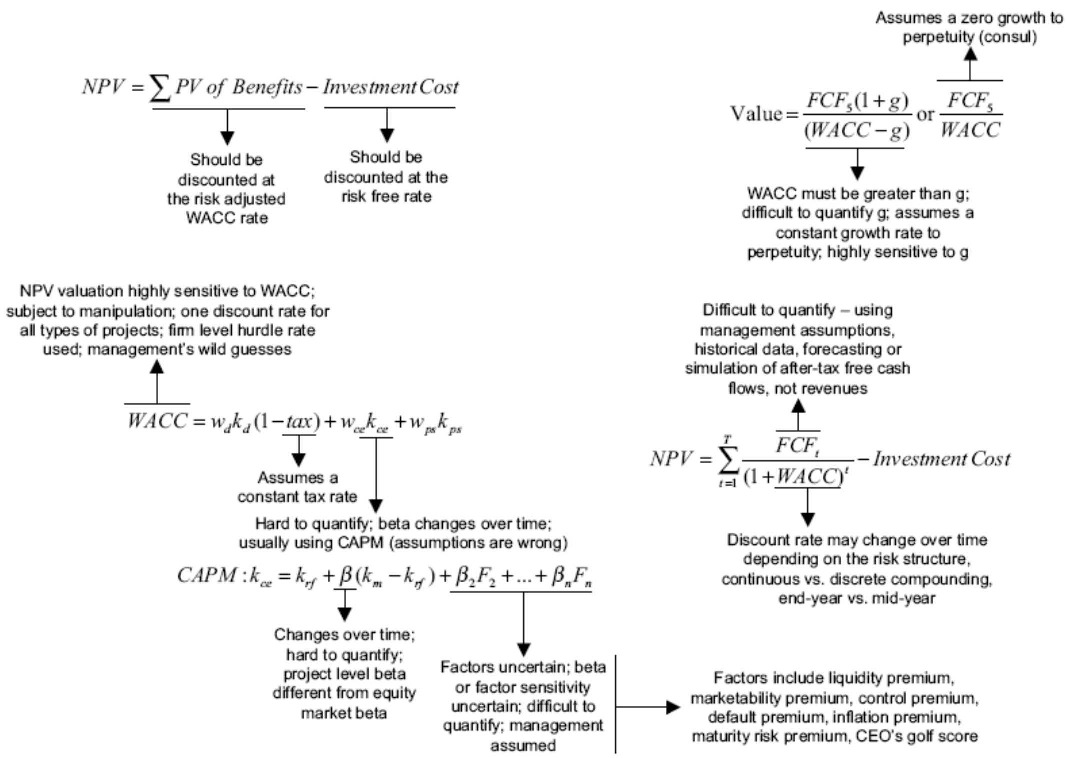

Figure 2: Shortcomings of Discounted Cash Flow Analysis

Figure 3 depicts the applicability of traditional analysis versus advanced analytics over a time horizon. When the time period is shorter and everything else remains constant, the analyst's ability to anticipate the near future is greater than when the timeframe is longer than the historical and prediction periods. This is because the longer the horizon, the more difficult it is to fully foresee all of the unknowns; thus, management can add value by properly initiating and executing strategic options.

Traditional and modern analytics can also be viewed as a matrix of techniques, as shown in Figure 4, in which the analytics are classified according to their analytical perspective and kind. The analytical approach might have a top-down or bottom-up approach in terms of perspective. When using a top-down strategy, macro variables are prioritized over micro variables. Starting with a global perspective and working through the market or economic conditions, impact on a specific industry, and, more specifically, the firm's competitive options, the level of granularity from the macro to micro levels includes starting with a global perspective and working through the market or economic conditions, impact on a specific industry, and, more specifically, the firm's competitive options. From a risk management standpoint, the analyst at the firm level may be concerned with a single project or a portfolio of projects. At the project level, the variables that influence the project's value will be the focus of attention.

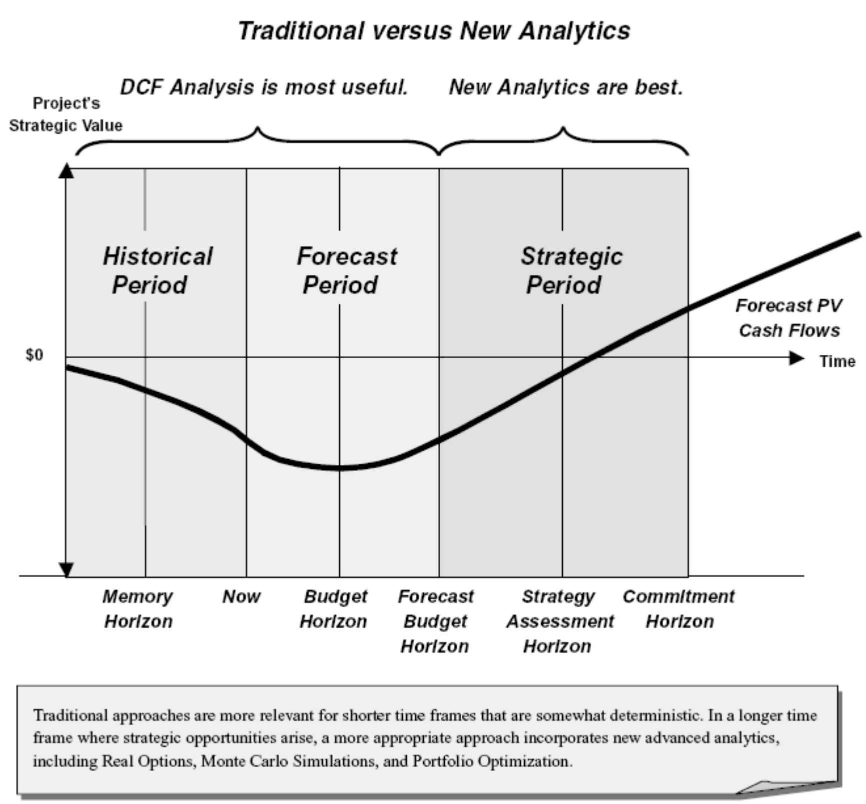

Figure 3: Using the Appropriate Analysis

Traditional studies, such as those based on the discounted cash flow model, have a number of flaws. They undervalue a project's flexibility and presume that all outcomes are set in stone and that all decisions are final. In fact, business decisions are made in a very fluid environment full of uncertainty, and management is continuously on the lookout for opportunities to change course when the situation calls for it. Using a deterministic approach to value such decisions could lead to a huge underestimation of a project's genuine intrinsic value. In light of this management flexibility, new sets of rules and techniques are required. It's worth noting that real options analysis complements standard discounted cash flow analysis by adding value to decision-making. When there is no uncertainty in the project, discounted cash flow analysis is a specific instance of real options analysis, as explained in the appendices.

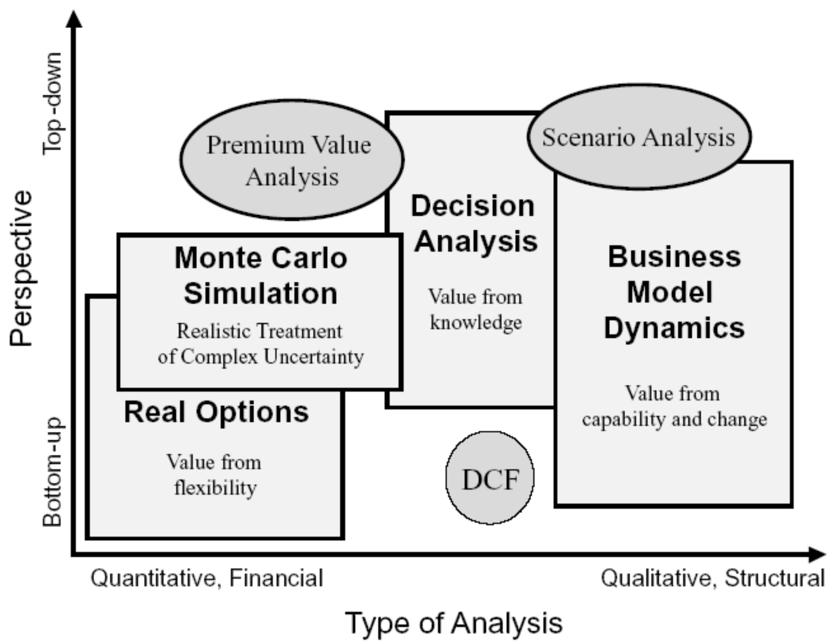

Figure 4: An Analytical Perspective

IV. PORTFOLIO OPTIMIZATION

What Is Portfolio Optimization?

The Department of Defense has many challenging decisions in today's competitive global environment. Allocating financial resources, creating or expanding facilities, managing inventory for maintenance, and selecting force-mix tactics are all examples of these decisions. Thousands or millions of viable options may be considered in such judgments. It would be impracticable, if not impossible, to consider and evaluate each of them individually. When assessing decisions and discovering the best answers, a model can be really useful. Models capture the most significant aspects of a problem and present them in an easy-to-understand format. Models can often reveal things that intuition alone can't. Decision variables, constraints, and an objective are the three major components of an optimization model. In a nutshell, the optimization methodology identifies the best combination or permutation of decision variables (e.g., which products to sell and which projects to execute) that maximizes (e.g., in revenues and net income) or minimizes (e.g., in risk and costs) the objective while still meeting constraints (e.g., budget and resources), as shown in Figure 5.

Obtaining ideal values usually necessitates an iterative or ad hoc search. This procedure entails running one iteration for an initial set of parameters, reviewing the results, altering one or more values, rerunning the model, and continuing the process until a good solution is found. Even for simple models, this procedure can be difficult and time-consuming, and it's not always evident how to alter the numbers from one iteration to the next.

A more rigorous approach lists all available options in a systematic manner. If the model is adequately stated, this approach ensures optimal solutions. Consider an optimization model with only two choice variables. If each variable has ten possible values, there are 100 iterations required to try each combination (102 alternatives). If each repetition is relatively short (e.g., two seconds), the full process could be completed in about three minutes.

Assume six decision variables instead of two, and then consider that trying all combinations will take 1,000,000 iterations (106 alternatives). Complete enumeration can easily take weeks, months, or even years to complete (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

Let's have a look at an easy example. The trip financial planner dilemma is depicted in Figure 6. Assume that the traveling financial advisor has three sales trips planned: New York, Chicago, and Seattle. Assume that the order in which you arrive in each city makes no difference. In this simple example, the only thing that matters is that the overall cost of all three cities is as low as possible. The airline prices between these cities are also shown in Figure 6.

The issue at hand is cost minimization, which is a problem that can be solved by optimization. The use of an ad hoc or brute force strategy to solve this problem is a common approach. That is, as seen in Figure 7, a single person may painstakingly list all six variations. Going from the east to the west coast, from New York to Chicago, and then on to Seattle, is clearly the most cost-effective route. Because there were three cities and hence six possible itineraries, the problem is straightforward and can be solved by hand. When two more cities are added, the total number of feasible routes increases to 120. It will be frightening and time-consuming to perform an ad hoc calculation. Let's say the salesman's list has 100 cities; the number of possible itineraries is 9.3 x 10157. Manually calculating the problem will take many years, which is where optimization software comes in to help, automating the search for the best route.

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 preceding example is a deterministic optimization issue, in which plane ticket prices are known in advance and expected to be constant. Assume that ticket prices are not fixed but fluctuate according to a distribution (for example, a ticket from Chicago to Seattle costs $325 on average but is never less than $300 and seldom surpasses $500). Tickets for the other cities are subject to the same degree of uncertainty. The issue has now changed to one of optimization in the face of uncertainty. In the face of uncertainty, ad hoc and brute-force techniques are ineffective. ROV Risk Simulator, for example, can automate the entire procedure and take care of this optimization challenge (Mun, 2015).

In the ROV PEAT software tool, Figure 8 depicts the Portfolio Optimization settings (courtesy of www.realoptionsvaluation.com). Individual projects can be modeled as a portfolio and optimized in the Portfolio Optimization part of this program to find the portfolio's optimum combination of projects.

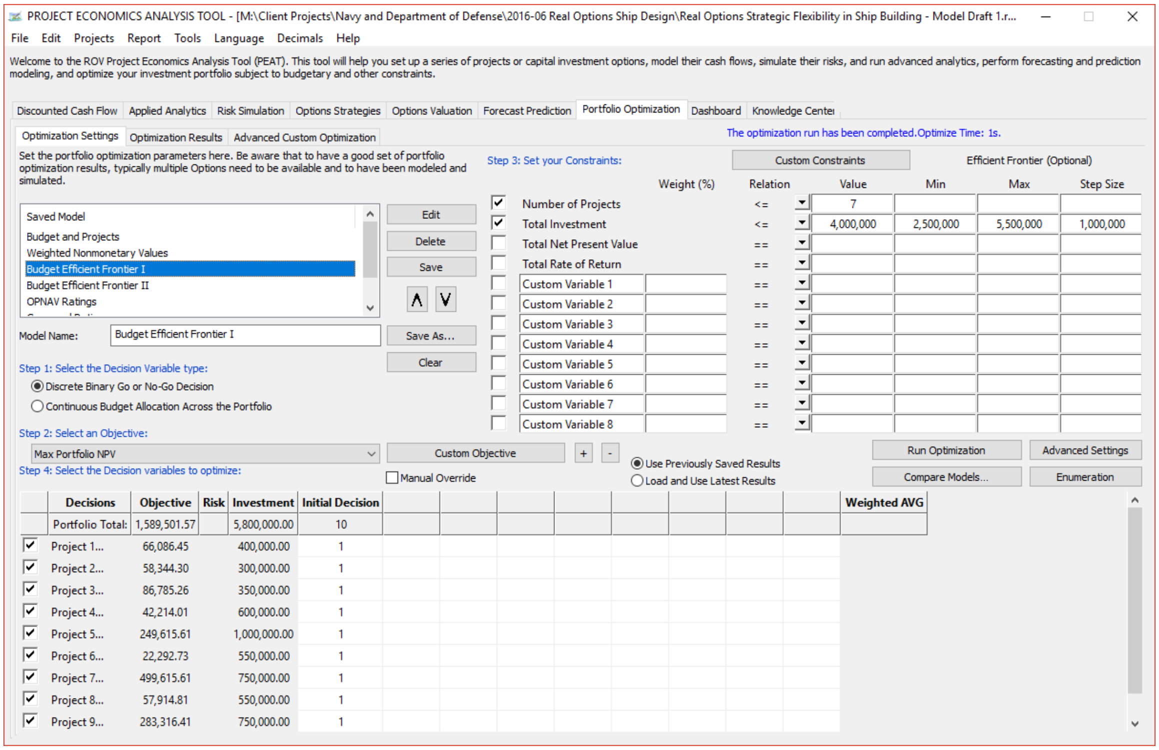

Figure 8: Portfolio Optimization Settings

The Optimization Outcomes, which return the results of the portfolio optimization analysis, are depicted in Figure 9. The data grid displays the major findings, including the final Objective Function results, final Optimized Constraints, and allocation, selection, or optimization across all individual options or projects inside this optimized portfolio. The textual information and results of the optimization algorithms used are displayed in the top left corner of the screen, while the chart depicts the final objective function. For ordinary optimizations, the chart will just display a single point, but if the Efficient Frontier parameters are enabled, it will produce an investment efficient frontier curve (min, max, step size).

Figure 9 and Figure 10 are important outcomes for decision-makers because they give them the freedom to create their own portfolio of alternatives. Figure 9 depicts an efficient portfolio frontier, with each point along the curve representing an optimized portfolio according to a set of constraints. The limits in this scenario were the number of options available on a ship and the overall cost of obtaining these options, which was limited by a budget. In Figure 9, the colored columns on the right represent the various budget restrictions and the maximum number of options that can be selected. For example, if a Navy program office only has $2.5 million (see the Frontier Variable on the second row) and only four options per ship, only options 3, 7, 9, and 10 are viable, and this portfolio combination would provide the best value for money while also meeting the budgetary and the number of options constraints. Option 5 is introduced to the mix if the limits are relaxed to five possibilities and a budget of $3.5 million. Option 1 and 2 should be added to the mix at $4.5 million each and no more than seven options per ship. Surprisingly, the same portfolio of alternatives is chosen even with a bigger budget of $5.5 million. In actuality, just $4.1 million is used according to Optimized Constraint 2. As a result, the maximum budget for this portfolio of alternatives should be set at $4.1 million as a decision-making tool for the budget-setting officials. Option 1 and 2 should be dropped if the original budget of $4.5 million was lowered by Congress to $3.5 million.

Figure 9 depicts the efficient frontier, which was used to identify the most efficient portfolio selection by varying limitations such as the number of alternatives permitted and the budget, whereas Figure 10 depicts numerous portfolios with different objectives. For example, the five models given were to maximize the financial return on investment (minimizing cost and maximizing value while minimizing risk), maximum Naval Operations (OPNAV) value, maximize KVA value, maximize Command value, and maximize a Weighted Average of all objectives. This competence is critical because the analysis' objectives and decisions will alter depending on who is conducting it. When using a multiple criteria optimization strategy, you may observe the scoring from all angles. Option 5 (for example) would have the highest priority in the final portfolio because it satisfies all stakeholders' perspectives and would thus be examined first, followed by alternatives 4, 3, 2, and 1.

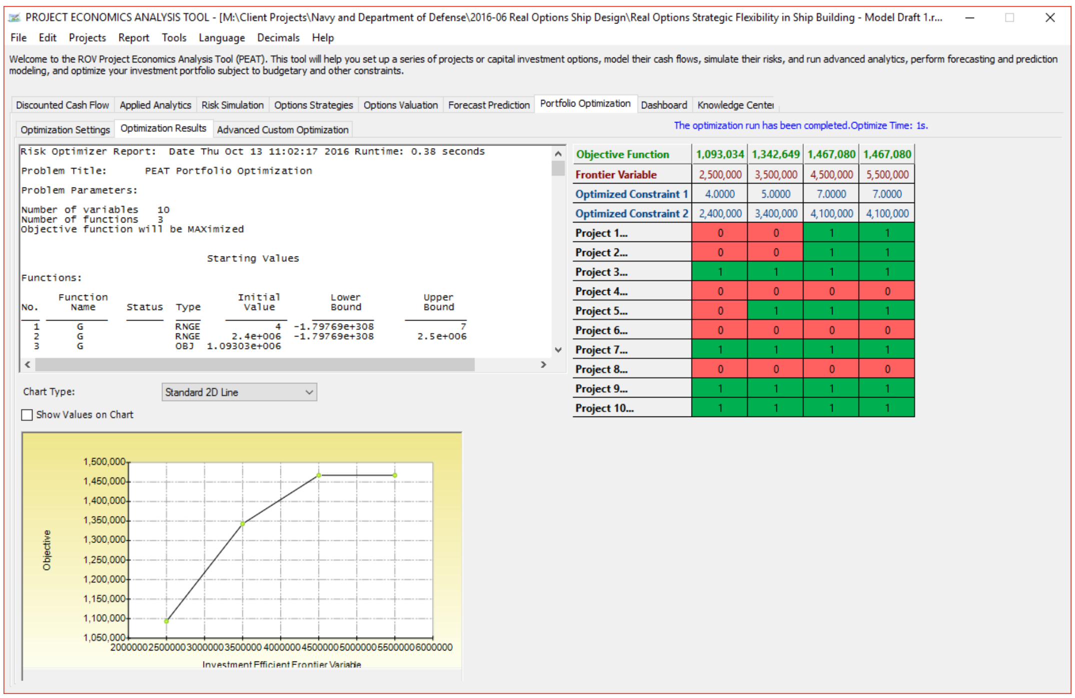

Figure 9: Portfolio Optimization Results

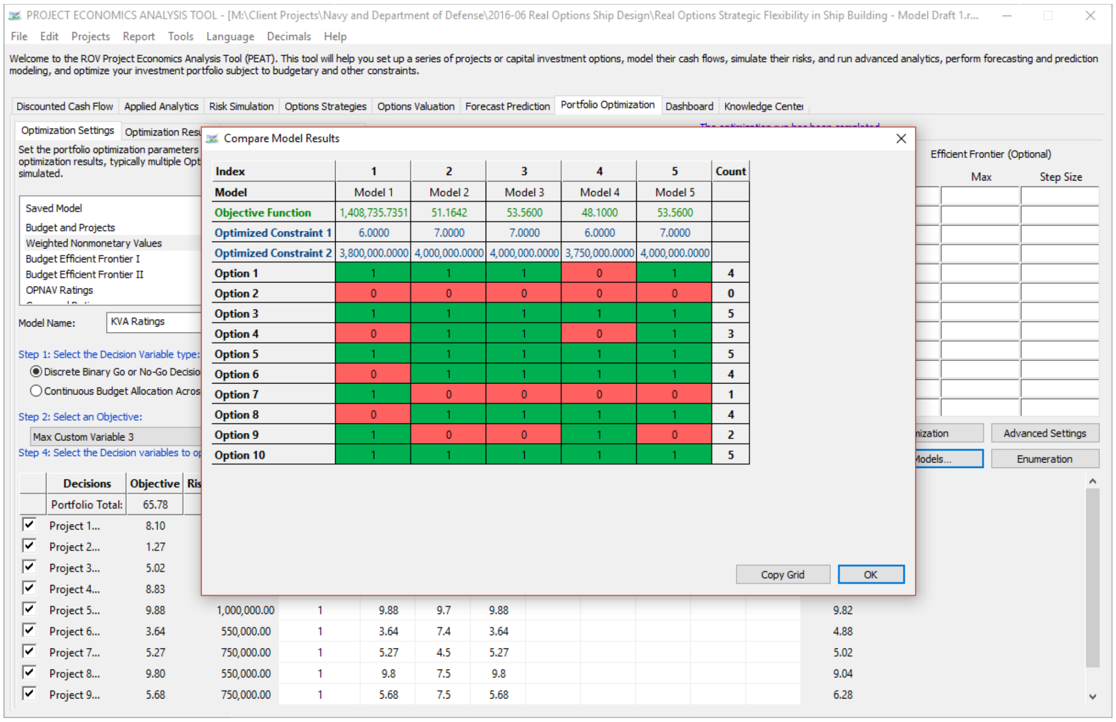

Figure 10: Multi-Criteria Portfolio Optimization Results

As a side note, several types of algorithms have been created throughout the years to find the answers to optimization problems, ranging from basic linear optimization utilizing the simplex model to solving first partial differential equations, in order to be thorough and inclusive. When more complicated real-world situations are imagined, however, these fundamental methods tend to fail, necessitating the use of more powerful algorithms. We used a combination of evolutionary algorithms, Lagrange multipliers, and taboo-based reduced gradient search approaches to solve our efficient frontier problem.

To put it another way, the Lagrange multiplier solution assumes a nonlinear issue of some kind.

$$\min \textit{ or } \max f(x)$$

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

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:

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

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

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

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

This method is straightforward and elegant, but it is confined to linear and quasi-linear functional forms of f, as well as some simple nonlinear functional forms (x). We need to add constraints to the solution set and use search techniques to cover a vast (and frequently infinite) set of optimal allocations in order to expand the functional form to generalized nonlinear applications. One restriction is that where nonlinear problems have a differentiable generic form, the Kuhn-Tucker condition must be satisfied:

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

$$\begin{aligned} s.t.\quad & g_i(x) \geq\ b_i\ \ \forall\ i \in Feasible\ Set \\ & g_i(x) \leq\ b_i\ \ \forall\ i \in Feasible\ Set \\ & g_i(x) =\ b_i\ \ \forall\ i \in Feasible\ Set \end{aligned}$$

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 for both ad-hoc and systematic searches of the optimal solution set will need to be developed. Even a supercomputer would take close to an unlimited number of years to outline all potential permutations using an enumeration method. As a result, search algorithms are frequently used in the optimization of an efficient frontier. The use of a reduced gradient search method is one basic method. To recap our strategy, we suppose

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

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

$$\nabla f(x) \cdot \Delta x = \nabla f(x)^B \cdot \Delta x^B + \nabla f(x)^N \cdot \Delta x^N$$

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

$$= (\nabla f(x)^N - \nabla f(x)^B B^{-1} N) \Delta x^N$$

The reduced gradient with respect to the solution matrix B is

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

where

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

When the number of decision variables is modest (usually less than four or five), manual solution is doable; but, when the number of decision variables is big, as it is in most real-life situations, manual solution is intractable, and computer search algorithms must be used. The following are the stages used in the general method:

1. Estimate a good set of starting points.
2. Continue estimating sample test points and the direction of the reduced gradient vector.

3. Test for feasibilities of constraints at extreme limits.
4. Solve the Lagrange optimal set.
5. Generate a new set of starting 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

It is critical to comprehend the language of optimization—the terminologies used to describe different aspects of the optimization process—before beginning to solve an optimization problem. Decision variables, restrictions, and objectives are examples of these terms.

Decision variables are quantities over which you have control, such as the quantity of a product to produce, the amount of money to invest, or which projects to choose from among a limited range. Portfolio optimization analysis, for example, comprises a go/no-go judgment on certain initiatives. Additionally, decision variables can be represented as the dollar or percentage budget allocation across numerous projects.

Constraints are relationships between decision variables that limit the decision variables' values. A limitation might, for example, ensure that the total amount of money allocated among multiple investments does not exceed a certain amount or that only one project from a given group can be chosen. Budget, timeframe, minimum returns, and risk tolerance limits are examples of other constraints.

In terms of the decision variables, objectives provide a mathematical description of the model's desired outcome, such as maximizing profit or decreasing cost. For example, in financial analysis, the goal can be to maximize profits while avoiding risks (maximizing the Sharpe ratio or returns-to-risk ratio).

As a result, an optimization model can resemble Figure 11.

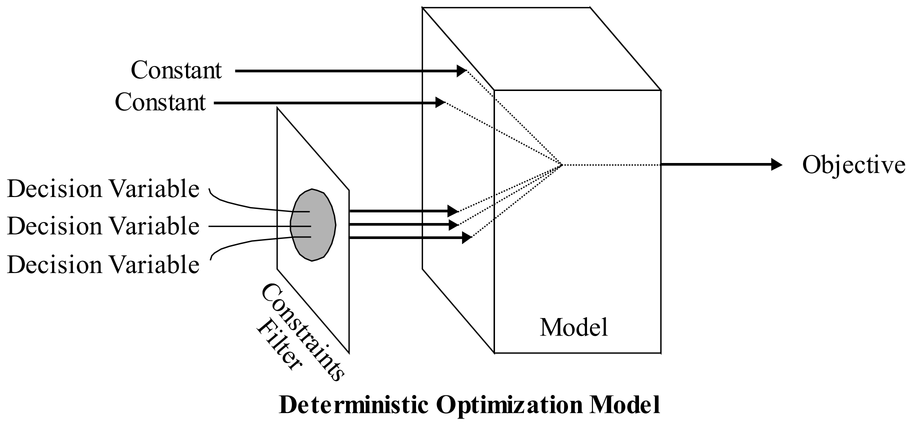

Figure 11: Visualizing the Optimization Process

An optimization model's solution is a collection of values for the decision variables that maximize or reduces the related objective. All data in an optimization model would be constant if the real business conditions were simple and the future was foreseeable, making the model deterministic (Mun, 2015).

A deterministic optimization model, on the other hand, cannot always capture all of the relevant nuances of a practical decision-making environment. When the data in a model is uncertain and can only be characterized probabilistically, the goal will have a probability distribution for any set of decision factors. Risk Simulator can be used to find this probability distribution by running the model. Several extra elements, such as assumptions and forecasts, are included in an optimization model under uncertainty.

Assumptions use probability distributions to describe the uncertainty of model data, whereas predictions are frequency distributions of probable model solutions. Forecast statistics, such as the mean, standard deviation, and variance, are summary values of a forecast distribution. The optimization process (Figure 12) controls the optimization by maximizing or decreasing the objective when there is uncertainty.

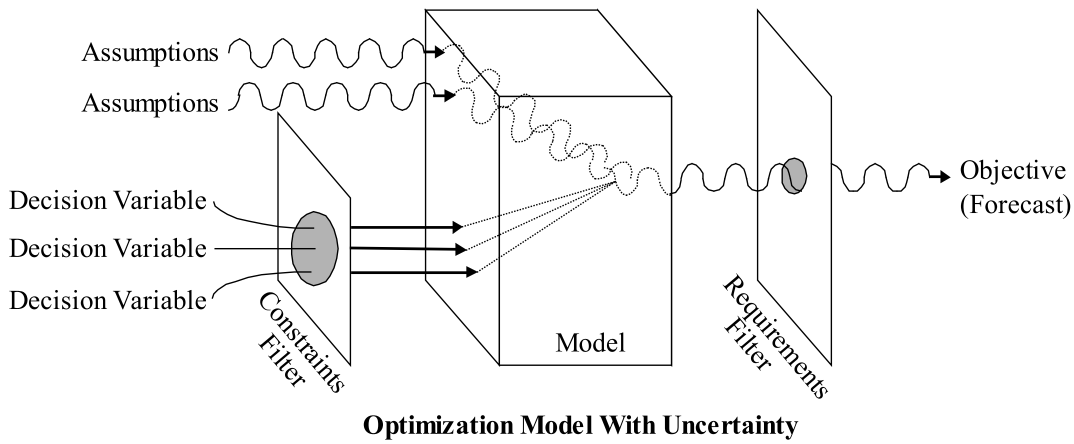

Figure 12: Optimization with Uncertainties and Risk

Every optimization model has a single objective, which is a variable that mathematically expresses the model's goal in terms of the assumptions and decision variables. The goal of optimization is to pick and improve different values for the decision variables in order to discover the optimal (minimum or maximum) value of the objective. When model data is ambiguous and can only be described using probability distributions, any set of choice variables will have some probability distribution.

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V. ALTERNATIVE ANALYTICAL APPROACHES

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

In many cases, projects are defined by a number of criteria or features that can be evaluated from several angles (financial, economic, etc.). Performance values (PV) are used to quantify each criterion, which might be numerical or categorical. This data is usually organized in a Q multi-indicator matrix. A common difficulty that a decision maker has is defining an aggregate quality (AQ) that can synthesize the global characteristics of each project and then create rankings from the best to the worst base-case ranking (Mun et al., 2016).

There are two types of ranking techniques: parametric and nonparametric. A parametric technique necessitates knowledge about the decision maker's preferences (e.g., criterion weights). The ELECTRE methods (Roy, 1968) and PROMETHEE—Preference Ranking Organization Methods for Enrichment Evaluations—are two examples of parametric procedures, according to Dorini, Kapelan, and Azapagic (2011). (Brans & Vincke, 1985). Nonparametric techniques like Partial Order Ranking (Bruggemann, Bücherl, Pudenz, & Steinberg, 1999) and Copeland Scores (Al-Sharrah, 2010) don't require the decision maker to provide any information. All of these strategies, in general, can generate a ranking of the choices from best to worst.

As a result, given a matrix Q, the chosen process produces a ranking, which is known as the base-case rank (BCR). As a result of this evaluation, a specific rank Ri is assigned to each choice, taking into account the multiple viewpoints provided by the decision maker. The set of

Ri corresponds to the global evaluation under the first synthetic attribute, base ranking, which is capable of describing the alternatives in the base case.

In real-life scenarios, however, unpredictable factors may alter each performance figure. Several methods for examining how the uncertainty in the performance values (the input) influences the object ranking has been given (the output; Rocco & Tarantola, 2014; Corrente, Figueira, & Greco, 2014; Hyde, Maier, & Colby, 2004; Hyde & Maier, 2006; Yu, Guikema, Briaud, & Burnett 2012). Each uncertain factor is treated as a random variable with known probability density functions in the approaches based on Monte Carlo simulation. As a result, each alternative’s AQ and, by extension, their rankings become random variables with approximated probability distributions. The decision maker could use probability distribution judgments in these instances. For example, the decision maker could want to know not just what a certain alternative's worst rank is but also its probability and volatility (risk evaluation).

The likelihood of an option being rated as in the BCR is chosen as the synthetic attribute probability capable of characterizing the alternatives under uncertainty in the usual approach.

The stochastic nature of each alternative's AQ should be further evaluated to reflect the risk assessment produced by uncertainty. In this instance, comparing many random variables synthesized by percentiles and statistical moments is required. To this end, several methods have been proposed, including a simple comparison of the expected value and 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

Each alternative is represented by the third synthetic attribute: compliance, in order to consider the risk evaluation produced by uncertainty. This new feature is based on a simultaneous evaluation of multiple risk metrics as well as specific AQ distribution moments (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 viewpoints are then used to create a new multi-indicator matrix Q1 that is linked to projects and synthesized using a ranking method. In some cases, however, decision-makers must select projects sequentially based on their preferred criteria. As a result, a compensation-based aggregation ranking technique is useless.

As a result, the final score is calculated using a mixed approach based on a nonparametric aggregation rule (using the idea of average rank) for attributes 1 and 2, a simple procedure for score assignment for attribute 3, and a lexicographic rule for attribute 3. In addition, a Hasse diagram is used to make a preliminary examination of the possibilities (Bruggemann & Patil, 2011). This form of integrated assessment has not been documented in the literature, to the best of the researcher's knowledge.

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 producing 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 technique enables decision-makers to develop choice rules in which they select more items based on their most important criteria. When two objects have the same influence on the most-preferred criteria, decision-makers prefer the one with the biggest impact on the second most-preferred criteria, and so on, according to Saban and Sethuraman (2014). This lexicographic form simulates situations in which decision-makers have a strong preference for one criterion over another or are in charge of noncompensatory aggregation (Yaman, Walsh, Littman, & Desjardins, 2011; Pulido, Mandow, & de la Cruz, 2014).

Finally, decision-makers can model their strong preferences for the criteria chosen since, after additional investigation of the situation, they are neither indifferent nor uncertain about their preferences for the criteria considered. In other words, they will always favor one criterion over another, regardless of criterion weights.

Risk Metrics and Compliance

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

Risk metrics are used to analyze the volatility or stability of a set of options or a portfolio of alternatives in decision problems, such as financial risk management (Chong, 2004), portfolio risk management (Bodie, Kane, & Marcus, 2009), enterprise risk management (Scarlat, Chirita, & Bradea, 2012), and a variety of other areas (Fabozzi, 2010).

A compliance strategy, or the establishment of a set of rules to guide decision-makers, is used to evaluate how risky an object is and its interaction with other objects (Hopkins, 2011). For assessing compliance, several methodologies have been presented. Barrett and Donald (2003), for example, propose a stochastic dominance analysis to compare probability distributions before establishing a hierarchy; Boucher, Danielsson, Kouontchou, and Maillet (2014) use risk metrics and forecasting to adjust models based on historical performance; and Zanoli, Gambelli, Solfanelli, and Padel (2014) investigate the effects of risk factors on non-compliance in UK agriculture.

Because it permits evaluating whether an item performs according to decision-makers' preferences and overstated risk measures, the compliance approach is more user-friendly for decision-making. The main concept is to divide the risk spectrum into two categories (Hopkins, 2011). As a result, the higher the compliance with a stated risk metric, the closer the decision-makers' preferences are aligned. Scarlat et al, (2012) and Tarantino (2008) examine similar approaches based on important risk indicators.

PROMETHEE and ELECTRE

Another layer of complexity emerges when decision-makers must integrate 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.), and economic (level of economic growth, monetary and nonmonetary). Furthermore, the relative significance (RI) or weights of those criteria may differ. The phrases in BP's (2015) sustainability report that business "must earn and keep society's support" and "must take action to conserve the environment for future generations" may imply that certain decision-makers value profit over social responsibility or vice versa. As a result, it's critical to factor those variances into the decision-making process (Mun et al., 2017).

To solve this issue, multicriteria analysis (MCA) has emerged as an effective tool for dealing with multidimensional problems and obtaining an Aggregate Quality (AQ) that may be used to support a final decision (Bouyssou, Marchant, Pirlot, Tsoukias, & Vincke, 2006; Brito, de Almeida, & Mota, 2010). MCA is a set of strategies, techniques, and tools that aid individuals in solving choice issues (description, grouping, ranking, and selection) by considering multiple objectives or criteria at the same time (Roy, 1996; Ghafghazi et al., 2010; Kaya & Kahraman, 2011; Afsordegan et al., 2016).

The authors propose PROMETHEE (Goumas & Lygerou, 2000; Brans & Mareschal, 2005; Behzadian et al., 2010; Tavana et al., 2013) as an appropriate MCA technique. Outranking the connection S is the basis of PROMETHEE techniques. This notion defines whether "the alternative *a* is at least as good as the alternative *b*," rather than determining whether the relationship between two alternatives a and b is a strong preference (a P b), a weak preference (a Q b), or indifference (a I b) (Brans & Mareschal, 2005).

Because of their theoretical and practical merits, PROMETHEE procedures are appropriate. They can, for example, assign an AQ index to each project that maximizes the available information in terms of decision-makers' preferences for the criteria chosen, as well as the intensity of those preferences among alternatives and the nature of each criterion (Bouyssou et al., 2006). Many energy-related studies have used PROMETHEE methods, including 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); and oil and gas pipeline planning (Tavana (Behzadian et al., 2010).

Other approaches, such as the ELECTRE methodologies (Bouyssou et al., 2006), the AHP—Analytical Hierarchy Process (Desai, Bidanda, & Lovell, 2012; Saaty, 2013), MACBETH (Cliville, Berrah, & Mauris, 2007; Costa, De Corte, & Vansnick, 2012), and TOPSIS (Kaya & Kahrama These alternative approaches, on the other hand, do not clearly describe the aforementioned benefits, and the AQ is harder to read.

Although some studies have attempted to incorporate 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 that pursue nonfinancial objectives.

According to the author, while RO values and assesses flexibility and uncertainty for PM, MCA allows for the inclusion of additional factors such as GDP and employment in strategic planning criteria to produce an AQ for picking the best projects.

VI. CAPITAL BUDGETING AND PORTFOLIO OPTIMIZATION IN THE DEPARTMENT OF DEFENSE

Apart from purely financial and economic values, operational, logistic, and other values can be constructed and used in the prescribed modeling approaches as discussed in this report. The following provides some examples of alternative value metrics. These metrics can be applied in future and subsequent research with actual data collected.

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)

Alternative 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 by Subject Matter Experts (SME) including:
    - **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 at 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.

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VII. APPENDIX: A REFRESHER ON PORTFOLIO OPTIMIZATION

When optimization is combined with Monte Carlo simulation, there are numerous techniques and procedures to choose from. There are various alternative optimization processes and optimization kinds, as well as different decision variable types, in Risk Simulator. Risk Simulator, for example, 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 or no-go decisions), and Mixed Decision Variables (e.g., 1, 2, 3, 4 or 1.5, 2.5, 3.5, etc.), and Mixed Decision Variables (e.g., (both integers and continuous variables). Risk Simulator also supports Linear Optimization (i.e., when the objective and constraints are both linear equations and functions) as well as Nonlinear Optimization (i.e., when the objective and constraints are a mixture of linear and nonlinear functions and equations).

In terms of the optimization process, Risk Simulator can be used to do a Discrete Optimization, which is an optimization that is performed on a discrete or static model without the need for simulations. In other words, the model's inputs are all fixed and unchanging. When the model is presumed to be known, and there are no uncertainties, this optimization type is appropriate. Before using more advanced optimization algorithms, discrete optimization can be used to identify the ideal portfolio and its accompanying optimal allocation of decision variables. For example, before performing a more in-depth analysis on a stochastic optimization problem, a discrete optimization is performed first to see if there are any solutions to the problem.

When Monte Carlo simulation and optimization are combined, Dynamic Optimization is employed. Simulation-Optimization is another term for this approach. That is, a simulation is done first, then the simulation results are implemented in the Excel model, and the simulated values are optimized. In other words, a simulation is conducted for N trials, followed by an optimization procedure for M iterations, until the best results are attained or an infeasible set is discovered. After running the simulation, one can utilize Risk Simulator's optimization module to select which forecast and assumption statistics to use and replace in the model. Then, in the optimization phase, these forecast figures can be used. When you have a large model with numerous interacting assumptions and forecasts, and some of the forecast statistics are necessary for optimization, this approach is useful. This strategy should be utilized, for example, if the standard deviation of an assumption or projection is required in the optimization model (e.g., computing the Sharpe Ratio in asset allocation and optimization problems where the mean is divided by the portfolio's standard deviation).

The Stochastic Optimization procedure, on the other hand, is comparable to the dynamic optimization approach, except that the dynamic optimization procedure is repeated T times. To put it another way, a simulation with N trials is done, and then an optimization with M iterations is run to get the best results. The method is then repeated T times. The end result will be a forecast chart with T values for each decision variable. To put it another way, a simulation is run, and the forecast or assumption statistics are employed in the optimization model to identify the best decision variable allocation. Then another simulation is conducted, this time producing different forecast statistics, which are then optimized, and so on. As a result, each of the final choice variables will have its own forecast chart, reflecting the best decision variables' range. In the dynamic optimization technique, for example, instead of receiving single-point estimates, you can now acquire a distribution of the decision variables, and hence, a range of ideal values for each choice variable, also known as stochastic optimization.

Finally, the notions of marginal increments and shadow pricing are used in an Efficient Frontier optimization technique. That is, what would happen to the optimization results if one of the restrictions was significantly relaxed? For example, let's say the budget limit is established at $1 million. What would happen if the constraint was now $1.5 million, $2 million, and so on, and how would that affect the portfolio's outcome and optimal decisions? What additional returns will the portfolio create if the portfolio standard deviation is permitted to expand slightly? This is the notion of the Markowitz efficient frontier in investment finance. This approach is similar to dynamic optimization with the exception that one of the constraints is permitted to vary, and the simulation and optimization process is conducted with each change, a procedure that is best applied manually using Risk Simulator. This procedure can be carried out manually (by rerunning the optimization numerous times) or automatically (by utilizing Risk Simulator's changing constraint and efficient frontier features). The manual procedure, for example, is as follows: Run a dynamic or stochastic optimization, then restart it with a different constraint and repeat the process numerous times. This manual process is important because it allows the analyst to determine whether the results are similar or different, and thus whether further analysis is warranted or how far a marginal increase in the constraint should be to achieve a significant change in the objective and decision variables. After executing a stochastic optimization, compare the forecast distribution of each choice variable.

One point deserves special attention. There are other software solutions that claim to conduct stochastic optimization but don't. For example, after running a simulation, one optimization iteration is generated, after which another simulation is done, the second optimization iteration is generated, and so on. This is a waste of time and resources; in optimization, the model is put through a rigorous set of procedures, requiring several iterations (varying from dozens to thousands) to achieve the best results. As a result, it is a waste of time and resources to create one iteration at a time. Risk Simulator can solve the identical portfolio in under a minute, as opposed to several hours using a backward technique. Furthermore, such a simulation-optimization method will almost always produce poor results and is not a stochastic optimization method. When applying optimization to your models, be exceedingly cautious about such techniques.

Two instances of optimization problems are given below. You can use discrete optimization, dynamic optimization, stochastic optimization, or even shadow pricing to manually build efficient frontiers in either model. For these two cases, any of these ways can be employed. As a result, only the model setup is shown for clarity, and the user must choose which optimization method to conduct. Also, the continuous decision variable example employs a nonlinear optimization strategy (because the portfolio risk is computed as a nonlinear function, and the objective is a nonlinear function of portfolio returns divided by portfolio risks), whereas the integer optimization example employs a linear optimization strategy (its objective and all of its constraints are linear). As a result, these two instances encompass all of the aforementioned procedures.

Discrete Integer Optimization

The decision variables are sometimes discrete integers (e.g., 1, 2, 3) or binary rather than continuous (e.g., 0 and 1). On-off switches or go/no-go decisions are examples of binary decision variables. Figure 13 depicts a project selection model with a total of 12 projects. Each project has its unique set of returns (ENPV and NPV stand for extended net present value and net present value, respectively—the ENPV is simply the NPV plus any strategic real choices values), implementation costs, and risks, among other things. This model can be updated if necessary to include required full-time equivalences (FTE) and other resources from various functions, as well as extra limitations on these additional resources. This model's inputs are usually linked from other spreadsheet models. For example, each project's discounted cash flow or return on investment model will be unique. The goal is to maximize the Sharpe Ratio of the portfolio while staying under a certain budget. Other variations of this model can be built, such as maximizing portfolio returns or reducing risks, or adding constraints such as limiting the total number of projects picked to six, and so on. This model can be used to run all of these items.

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 13: Discrete Go and No-Go Decision for Project and Program Selection

Figure 14 and Figure 15 depict an example of an optimal project selection that maximizes the Sharpe Ratio. In contrast, total revenues can always be maximized, but this is a simple procedure that entails selecting the highest-returning project and working your way down the list until you run out of money or exceed the budget constraint. As the highest yielding projects often carry higher risks, doing so will result in ventures that are conceptually undesirable. You can now use stochastic or dynamic optimization to duplicate the optimization by adding assumptions to the ENPV and Risk values if desired.

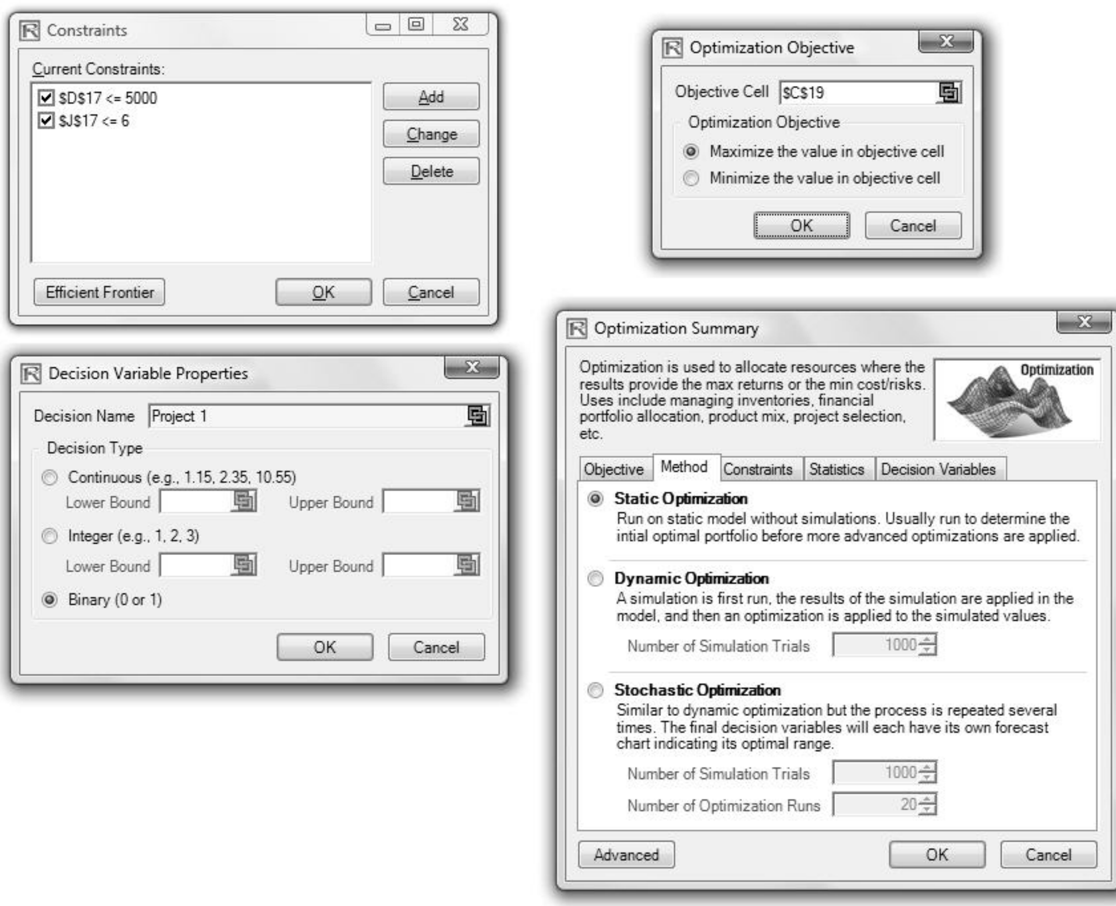

Figure 14: Portfolio Optimization Model Settings

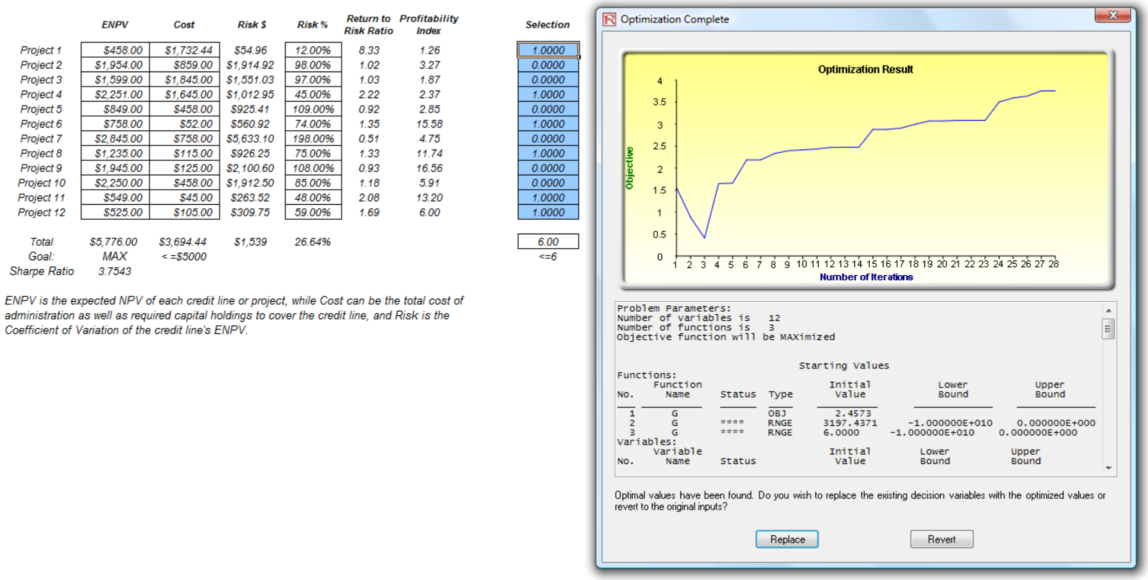

Figure 15: Optimal Selection of Projects Maximizing Sharpe Ratio

Efficient Frontier and Advanced Optimization

The efficient frontier constraints for optimization are shown in Figure 16. After you've set certain limitations, go to the Efficient Frontier button in the Risk Simulator software to go to this interface. These restrictions can now be changed. That is, each constraint can be designed to alternate between a minimum and maximum value. The limitation in cell J17 <= 6 can, for example, be configured to run between 4 and 8 projects (Figure 16). That is, five optimizations will be performed, each with the constraints J17 <= 4, J17 <= 5, J17 <= 6, J17 <= 7, and J17 <= 8. After that, the best findings will be plotted as an efficient frontier, and a report will be produced (Figure 17).

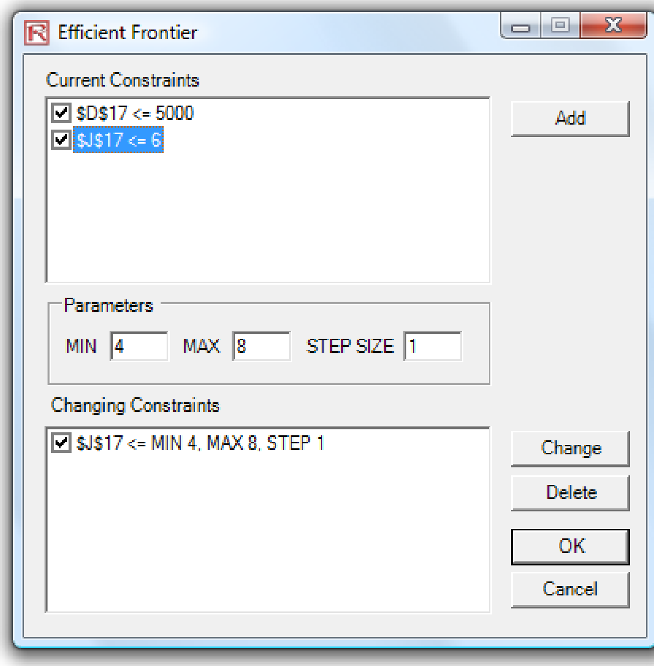

Figure 16: Generating Changing Constraints in an Efficient Frontier

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	

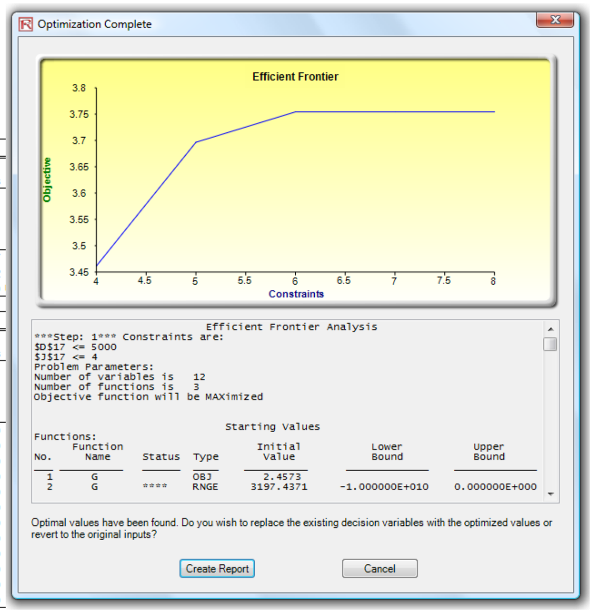

Figure 17: Efficient Frontier Results

VIII. APPENDIX: THE THEORY OF STRATEGIC REAL OPTIONS, KNOWLEDGE VALUE ADDED, AND INTEGRATED RISK MANAGEMENT

Corporate investment decisions used to be straightforward. Purchase more efficient equipment, produce more products at a set price, and if the advantages outweigh the costs, proceed with the investment. Expand the present geographical area, hire a broader pool of sales associates, and start hiring if the marginal gain in expected sales revenues covers the increased compensation and installation costs. Do you require a new manufacturing facility? Demonstrate that the project's construction expenses will be swiftly and easily recouped by increased revenues generated by new and enhanced products, and the initiative will be accepted.

Real-world business situations, on the other hand, are far more intricate. Your company decides to pursue an e-commerce strategy, but there are several strategic options. Which road will you take? What alternatives do you have? How do you get back on the right track if you take the wrong path? How do you value and prioritize the various paths available to you? You work for a venture capital firm, and you have a number of business proposals to explore. What do you put a start-up company with no track record worth? What is the best way to form a mutually beneficial investment agreement? When is the best time to raise money in a second or third round?

Real choices are valuable not just in evaluating a company based on its strategic business possibilities but also in capital investment decisions as a strategic business tool. Should a company, for example, invest millions in a new facility expansion project? How does a company pick between multiple seemingly useless, expensive, and unprofitable IT infrastructure projects? Should a company risk its billions on a high-risk research and development project? For certain businesses, the implications of making the wrong decision can be devastating or even fatal. These questions cannot be answered with certainty in a standard discounted cash flow model. In fact, some of the answers generated using the traditional discounted cash flow model are flawed because the model assumes a static, one-time decision-making process, whereas the real options approach considers the strategic managerial options that certain projects created in the face of uncertainty, as well as management's flexibility in exercising or abandoning these options at different times.

When some degrees of uncertainty are addressed via the passage of time, actions, and events, the Real Options Valuation (ROV) approach adds a learning model, allowing management to make better and more informed strategic decisions. Traditional discounted cash flow analysis assumes a fixed investment decision and that strategic decisions are taken upfront with no flexibility to change paths or options afterward. Visualize it as a strategic road map with lengthy and winding roads with numerous risky bends and branching along the route to produce a decent analogy to real options. Consider the intrinsic and extrinsic advantages of having a road map or GPS system to help you navigate through unknown territory, as well as road signs at every turn to help you make the smartest and most educated driving judgments possible. The core of real alternatives is a strategic map like this.

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, and intellectual capital development, is the answer to evaluating such projects.

The Real Options Solution in a Nutshell

Simply put, the real options method is a systematic approach and integrated solution that applies financial theory, economic analysis, management science, decision sciences, statistics, and econometric modeling to valuing real physical assets, as opposed to financial assets, in a dynamic and uncertain business environment where business decisions are flexible. In this case, having real options is critical.

- Identifying various acquisition or investment decision paths or projects that management can navigate in the face of very uncertain business situations.
- Taking into account the financial viability and feasibility of each of the strategic choice pathways.
- Using a set of qualitative and quantitative indicators to prioritize these pathways or projects.
- Increasing the value of strategic investment decisions by comparing multiple decision paths under different situations or by employing a different sequence of pathways to arrive at the best solution.
- Finding the best trigger values, cost or revenue drivers, and timing the successful implementation of investments
- Managing or expanding existing or new options, as well as strategic decision-making routes for future opportunities

ROV can be used to value a project, alternative path, implementation option, or ship design based on its strategic options, which is especially beneficial when making capital-intensive investment decisions under uncertainty. The ROI or cost-benefit question cannot be answered with any certainty in a typical cost-benefit and cash flow model. In fact, some of the answers given by typical cash flow models are incorrect because the model assumes a static, one-time decision-making process with no future possibilities or pathways. The real options approach, on the other hand, considers the strategic managerial options that certain projects created in the face of uncertainty, as well as decision-makers' flexibility in exercising or abandoning these options at various points in time as the level of uncertainty decreases or becomes known over time.

Industry Leaders Embracing Strategic Real Options

Oil and gas and mining firms were the first to employ real choices as a strategic decision-making tool; it then spread to utilities, biotechnology, and pharmaceuticals, and is today used in telecommunications, high-tech, and across all industries. The examples below show how actual options have been used or should be used in various types of businesses.

Automobile and Manufacturing Industry

General Motors (GM) uses real options to produce switching alternatives in the manufacturing of its new series of automobiles. This option entails using a less expensive resource for a set amount of time. GM has an oversupply of raw resources and several global vendors for similar materials, as well as contractual obligations that are greater than what is projected to be required. When a certain raw material becomes excessively expensive in a certain region of the world, the additional contractual cost is outweighed by the huge savings of switching providers. GM has essentially paid the premium on obtaining an option to switch by spending the extra money on contracting with vendors and achieving their minimum purchase criteria, which is critical, especially when the price of raw materials fluctuates dramatically in different parts of the world. Having an option here gives the holder a way to protect themselves from price risks.

Computer Industry

HP–Compaq used to anticipate sales in overseas nations months in advance in the computer industry. The highly particular configuration printers were then configured, built, and supplied to these countries. Preconfigured printers, on the other hand, frequently bear the higher inventory holding cost or the cost of technology obsolescence because demand fluctuates rapidly, and projection estimates are rarely accurate. By constructing assembly plants in these foreign nations, HP–Compaq can provide an alternative to wait and defer making any judgments too soon. When demand is known, parts can be sent and assembled in specified configurations, sometimes weeks rather than months ahead of time. These pieces can be transported anywhere in the world and assembled in any configuration required, and extra parts can be swapped between countries. The cost of constructing the assembly plants is the premium paid for this choice, and the upside potential is the cost savings from incorrect demand forecasting.

Airline Industry

Boeing spends billions of dollars and years deciding whether or not a certain aircraft model should be constructed in the airline business. If the wrong model is tried in this complex process, Boeing's competitors may soon obtain a competitive advantage. Because there are so many technical, engineering, market, and financial uncertainties in the decision-making process, Boeing could theoretically create an option to choose through parallel development of multiple plane designs simultaneously, knowing the rising cost of doing so with the sole purpose of eliminating all but one in the near future. The premium paid on the choice is the additional cost. When these uncertainties and hazards become clearer, Boeing will be able to decide whether to discard or continue with a particular model. All except one of the models will be eliminated in the end. In this manner, the corporation may protect itself from making a bad first decision while still gaining expertise from parallel development endeavors.

Oil and Gas Industry

Companies in the oil and gas industry spend millions of dollars refurbishing refineries and adding new technology to create the option to switch their output mix between heating oil, diesel, and other petrochemicals as a final product, relying on real options to make capital and investment decisions. This option allows the refinery to transition to a more profitable final output based on current market pricing in order to capture market demand and price cyclicality.

Telecommunications Industry

Telecommunications companies such as Sprint and AT&T have installed more fiber-optic cable and other telecommunications infrastructure than any other company in the past to provide a future growth option by providing a secure and extensive network, as well as to create a high barrier to entry, allowing them to be first to market. Imagine attempting to convince your board of directors that spending billions of dollars on infrastructure that won't be used for years is necessary. This decision would have been impossible to justify without the usage of real options.

Real Estate Industry

In the real estate arena, leaving the 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 utility 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, and *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 acquisitions, 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 context of the US military, the Knowledge Value Added (KVA) technique is a novel approach to measuring the productivity (in terms of ROI) of military capabilities integrated into technology-affected procedures. KVA satisfies the criteria of numerous DOD rules and directives by allowing users to obtain comparable value or benefit estimates for a variety of procedures, as well as the technology and people that carry them out. This is accomplished by providing a standardized and somewhat objective method for determining the value of new technology, 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 for describing all organizational outputs in common units, allowing for the comparison of all assets' outputs (human, machine, and information technology) regardless of the aggregated outputs produced. All assets' outputs, including intangible knowledge assets, are monetized. As a result, the KVA method can reveal information about the productivity of processes, people, and systems in terms of a ratio of common output units

(CUO). The cost to produce the output is divided by the CUO produced by each asset (a measure of benefits). KVA determines the true cost and value of people, systems, and processes by capturing the value of knowledge contained in an organization's fundamental processes, workers, and technology. Unit costs and unit values of outputs, processes, functions, or services are computed because KVA identifies every process required to generate an output as well as the past costs of those processes. As indicated in Figure 18, an output is the result of an organization's operations; it can be a product or a service.

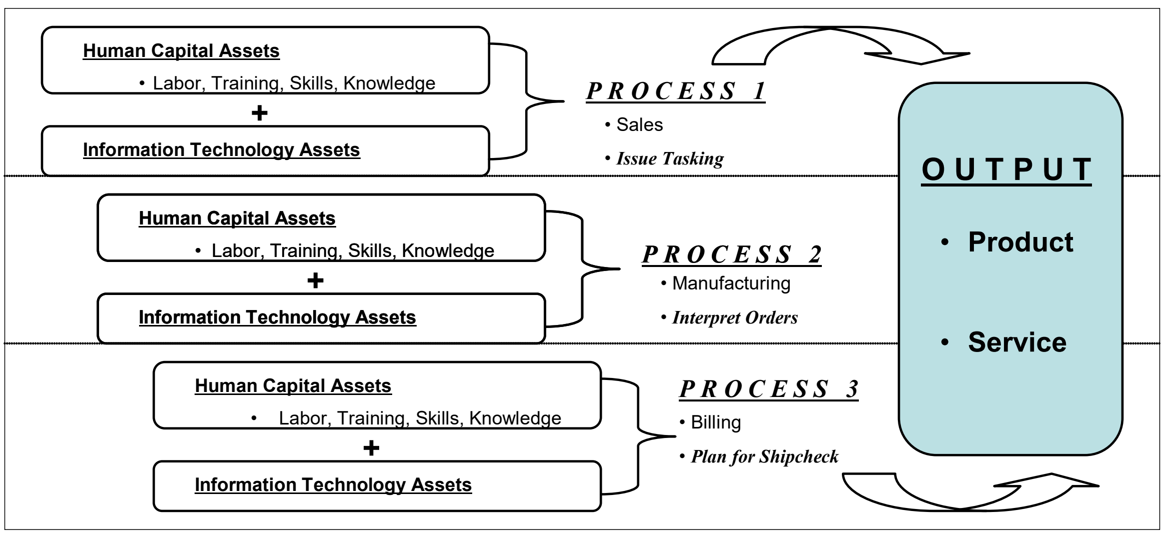

Figure 18: Measuring Output

By examining the performances of the processes, KVA was utilized to measure the value added by human capital assets (i.e., military personnel executing the procedures) and system assets (e.g., new sensor) in this study. KVA determined the productivity of system-process alternatives by quantifying the value of knowledge embodied in systems and utilized by process operators. The common unit costs and values were approximated since KVA identifies every process output required to produce the final aggregated output.

Over 80 DOD projects have used the KVA technique, ranging from flight scheduling apps to ship maintenance and modernization. The KVA approach was utilized for this study in general since it may

- Compare and contrast different techniques in terms of relative productivity.
- Assign value and costs to common output units.
- Calculate the value added by system alternatives based on the outputs they each generated.
- Connect outputs to the cost of producing them 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 19.

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 19: KVA Metrics

ROK identifies how a given process turns existing knowledge into creating outputs so decision-makers may quantify costs and measure value produced from investments in human capital assets, whereas ROI is the typical financial ratio. A higher return on investment (ROI) indicates better knowledge asset usage. If IT investments do not increase a process's ROK value, steps to improve the process's function and performance must be performed (Figure 20).

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

Figure 20: Comparison of Traditional Accounting versus Process-Based Costing

KVA assumes that humans and technology in companies add value by taking inputs and converting them (measured in common units of complexity) into outputs through fundamental processes, based on the concepts of complexity theory. A measure of value or benefit is the amount of change that an asset produces inside a process. The following are some of the additional assumptions in KVA:

- When all process outputs are described in common units (for example, using a knowledge metaphor for the descriptive language in terms of how long it takes an average person to learn how to create the outputs), historical value and cost data can be ascribed to those processes.
- All outputs can be quantified in terms of the amount of time it takes a single point of reference learner to master them.
- Learning Time is a proxy for procedural knowledge needed to produce process outputs, and it is quantified in standard time units. As a result, learning time units are proportional to common output units.

- Because value (e.g., revenue) may now be allocated at the suborganizational level, it is now possible to compare all outputs in terms of cost per unit as well as value (e.g., pricing) per unit.
- Normal accounting, financial performance, and profitability indicators can be applied once cost and revenue streams have been assigned to suborganizational outputs.

Describing processes in common units also allows, but does not require, the generation of market comparable data, which is especially crucial for NGOs like the US military. Data from the commercial sector can be utilized to estimate a price per common unit using a market comparables approach, allowing for revenue projections of process outputs for charities. In addition, regardless of the process being studied, this approach provides a common-unit basis for defining benefit streams.

KVA is different from other nonprofit ROI models in that it can estimate revenue, allowing typical accounting, financial performance, and profitability measurements to be used at the suborganizational level. The relative ROIs of processes or process alternatives can be ranked by KVA. This rating system aids decision-makers in determining the value added by various processes or process alternatives.

Return on Knowledge (ROK, revenue/cost) and ROI (revenue-investment cost/investment cost) are two main measures used by KVA to measure value. The raw data from a KVA study can be used in ROI models and forecasting techniques including real options analysis, portfolio optimization, and Monte Carlo simulation.

Integrated Risk Management

IRM is an eight-step, quantitative software-based modeling approach for the objective measurement of risk (cost, schedule, technical), flexibility, strategy, and decision analysis (see Figure 22). Program management, resource portfolio allocation, return on investment to the military (maximizing expected military value and objective value quantification of non-revenue government projects), analysis of alternatives or strategic flexibility options, capability analysis, prediction modeling, and general decision analytics can all benefit from this method. With budget and schedule uncertainties, the method and toolset allow decision-makers to assess hundreds of options and provide ways to assist them to maximize capability and readiness at the lowest cost. This methodology is particularly well suited to resource reallocation, and the author has taught and used it to over 100 multinational firms and 30 DOD programs over the last ten years.

IRM provides a systematic strategy that will result in speedy, credible, repeatable, scalable, and defensible cost savings and total cost of ownership analysis while ensuring that critical capabilities are not lost in the process. The IRM + KVA methodologies accomplish this by measuring the value of a system or process in a consistent and objective manner across numerous options and delivering a comparable and rigorous return on investment (ROI) for each. These ROI estimates across the portfolio of options provide the information needed to forecast the value of specific options. In order to provide a defensible analysis defining management options for the road forward, IRM combines risks, uncertainties, budget restrictions, implementation, life-cycle costs, reallocation options, and total ownership costs. This method detects high-risk projects and programs while forecasting immediate and long-term cost reductions, total life-cycle costs, flexible options, essential success factors, strategic options for best implementation paths/decisions, and portfolio optimization. Its use allows for the early detection of potential cost overruns and schedule delays, as well as proactive efforts to mitigate those risks. While keeping the benefit of strategic flexibility, IRM provides an optimum portfolio of capability or implementation options.

In this case, IRM is used to distinguish between various alternatives for implementing Flexible and Adaptable Ship Options (FASO)/Modular Adaptable Ships (MAS) in terms of ship design options and to predict where the greatest benefit for the available investment could be found within the portfolio of alternatives. The toolset allows for the inclusion of important risk factors, such as schedule and technical uncertainty, as a strategy is developed and a plan for its implementation is developed and allows for continuous updating and evaluation by the program manager to understand where these risks come into play and make informed decisions accordingly.

The resulting stochastic KVA ROK model generated a spread of values rather than a point answer after Monte Carlo risk simulation. As a result, simulation models examine and quantify each program's numerous risks and uncertainties. As a result, the ROKs are distributed, and the project's volatility is depicted.

The analyst assumes that the underlying variable in real options is the future benefit less the project cost. The results of a Monte Carlo risk simulation can be used to calculate implied volatility. The quantitative estimations supplied by the KVA analysis will be used to build the IRM analysis results. The IRM will give quantifiable risk analytics and portfolio optimization that can be defended. recommending the most efficient use of limited resources to achieve the most possible value over time

The act of defining the problem generates a strategic map, which is the first stage in real possibilities. Certain strategic choices for each project would become obvious based on the overall problem identification that occurred during the initial qualitative management screening phase. Wait, expand, contract, abandon, switch, stage-gate, and choose are some of the strategic alternatives that could be considered.

Risk analysis and real options analysis both presume that the future is unpredictable, and that decision-makers can make mid-course corrections once the uncertainties are resolved, or risk distributions are understood. The analysis is frequently done ahead of time, allowing for such uncertainties and hazards to be avoided. As a result, if these risks are identified, the analysis should be updated to include the new knowledge in decision-making or to revise any input assumptions. Several iterations of the real options analysis should be undertaken for long-horizon projects, with future iterations being updated with the newest data and assumptions. Understanding the stages involved in doing an IRM analysis is critical since the methodology reveals not just the technique itself, but also how IRM differs from traditional analyses, indicating where the traditional approach ends, and the new analytics begin.

The probability distributions and confidence intervals of the KVA-methodology generating ROI and ROK outcomes are provided by the risk simulation step required in the IRM. Furthermore, volatility, a measure of risk and uncertainty, is one of the outputs from this risk simulation, and volatility is an essential input into the real options pricing computations. We used the Air Force Cost Analysis Agency (AFCAA) Handbook to assign input probabilistic parameters and distributions to the simulation models, as shown in Figure 21. The triangular, normal, and uniform distributions are the three main distributions recommended in the manual. The triangular distribution was chosen because its limits (minimum and maximum) are known, and its shape resembles that of a normal distribution, with the most likely values having the highest probability of occurrence and the extreme ends (minimum and maximum values) having much lower probabilities. In addition, the triangular distribution was chosen over the normal distribution since the latter's tail ends extend into positive and negative infinity, making it less applicable in the model we're building. Finally, the AFCAA Handbook includes options for symmetrical, left skew, and right skew distributions. We don't have enough previous or similar data to properly examine skew in our analysis, therefore we resort to the default of a symmetrical triangular distribution.

The processes of a full IRM process are depicted in Figure 22.

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	1.150
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 21: U.S. Probability Risk Distribution Spreads.

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

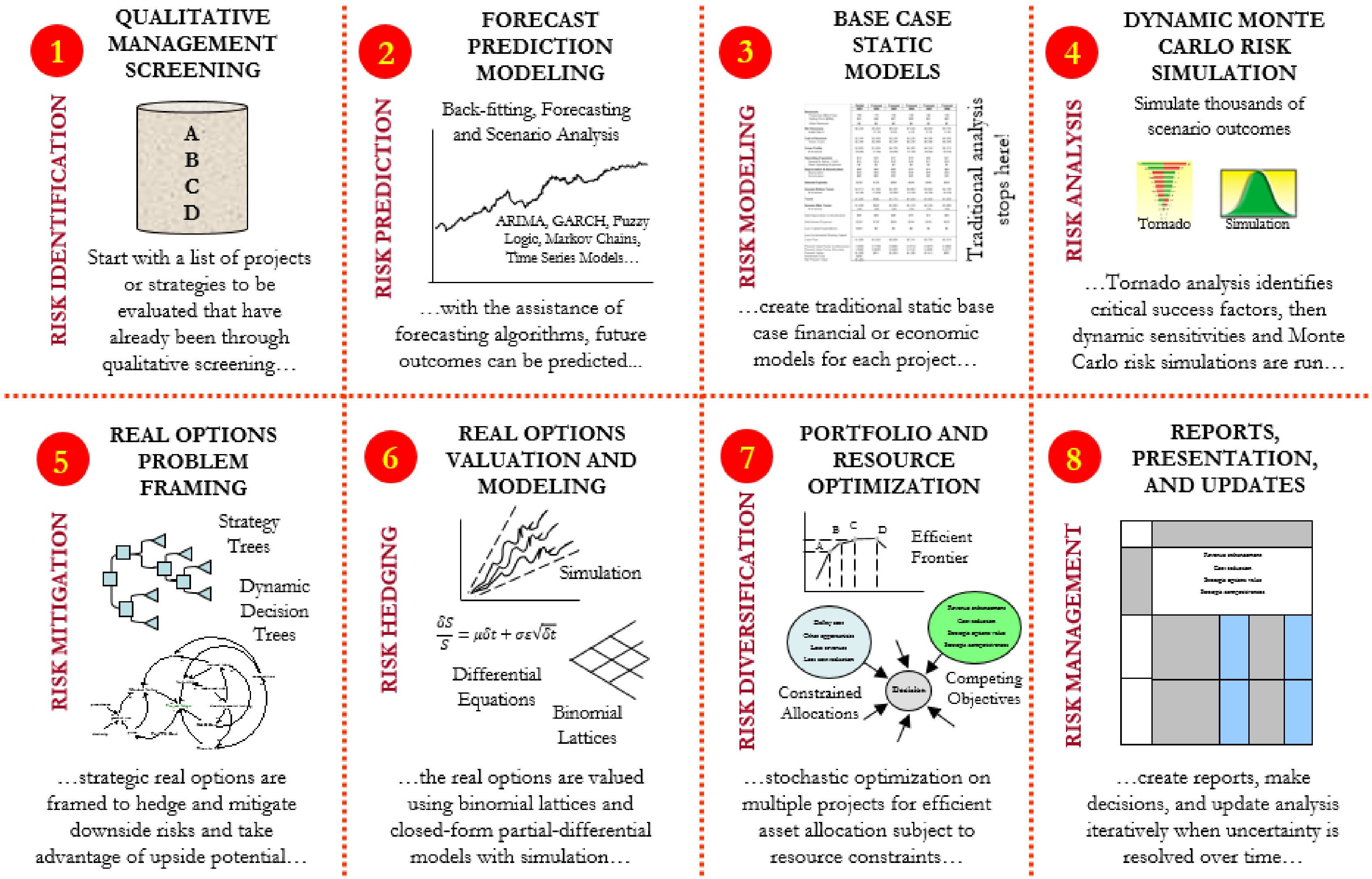

Figure 22: Integrated Risk Management Process

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Dr. Johnathan Mun, the principal investigator of this research, is an expert in modeling uncertainty and risk-based stochastic portfolio optimization decision analytics and strategic real options. He has completed multiple studies and published academic journal articles and technical reports with the Naval Research Program and Naval Acquisitions Research dealing with the ROI on military education and research; total cost ownership and ROI on DARPA's 5G protected waveform; justification of Flexible and Modular Ships for NAVSEA; decision analysis on applying advanced methodologies in using AI and other novel approaches to avoid cost and schedule overruns in the acquisition of IT; carry-on cryptologic programs (CCOPS) intelligence information systems; business case justification of implementing Additive-3D printing technology and ship maintenance technology; business justification and portfolio optimization of implementing modular ships; justification of AI-enabled autonomous vehicles (Lightly Manned Autonomous Combat Capability, LMACC); portfolio optimization and selection of programs in technology insertion (e.g., upgrades to the Aegis weapon system or ballistic missile defense system) on Navy ships using various points of view (OPNAV, SECNAV, and tip of the spear, using non-economic variables such as strategic value and command priorities) for PEO-IWS; the acquisition and development of the Air Force's WeatherNow; and novel ROI approaches to capture non-revenue generating activities in the DOD.

Dr. Johnathan Mun is a Professor of Research at the Naval Postgraduate School in Monterey, California, and is a specialist in advanced decision analytics, quantitative risk modeling, Monte Carlo simulation, strategic flexibility real options, predictive modeling, and portfolio optimization. He has authored over 30 books, holds 22 patents and patents pending, and written over 200 technical reports, white papers, analytical notes, and academic journal articles. His prior positions include being Vice President of Analytics at Oracle/Crystal Ball and a senior manager at KPMG

Consulting. He has developed multiple software applications that run Monte Carlo risk simulations, predictive modeling, portfolio selection and optimization, strategic real options, analysis of alternatives, total ownership cost, and others. Dr. Mun has performed over 100 consulting projects in private industry as well as with the Department of Defense, in areas including decision analytics, return on investment analysis, acquisitions analysis, analysis of alternatives, enterprise risk management, program and project selection and optimization, cost and schedule risk modeling, and others. His latest technical reports with the Naval Research Program and Naval Acquisitions Research Program deals with the return on investment on military education and research, as well as total cost ownership modeling and return on investment on DARPA's 5G protected waveform open-source initiative. He holds a PhD in finance and economics from Lehigh University, with specializations in advanced risk analytics, econometric modeling, financial analytics, decision analysis, and strategic real options. He also holds an MBA in management and a BS in physics and biology, as well as multiple other designations such as the CQRM (Certified in Quantitative Risk Management), FRM (Certified in Financial Risk Management), CFC (Chartered Financial Consultant), among others.