2022

Capturing Risk in Capital Budgeting

Mun, Johnathan C.

Monterey, California: Naval Postgraduate School

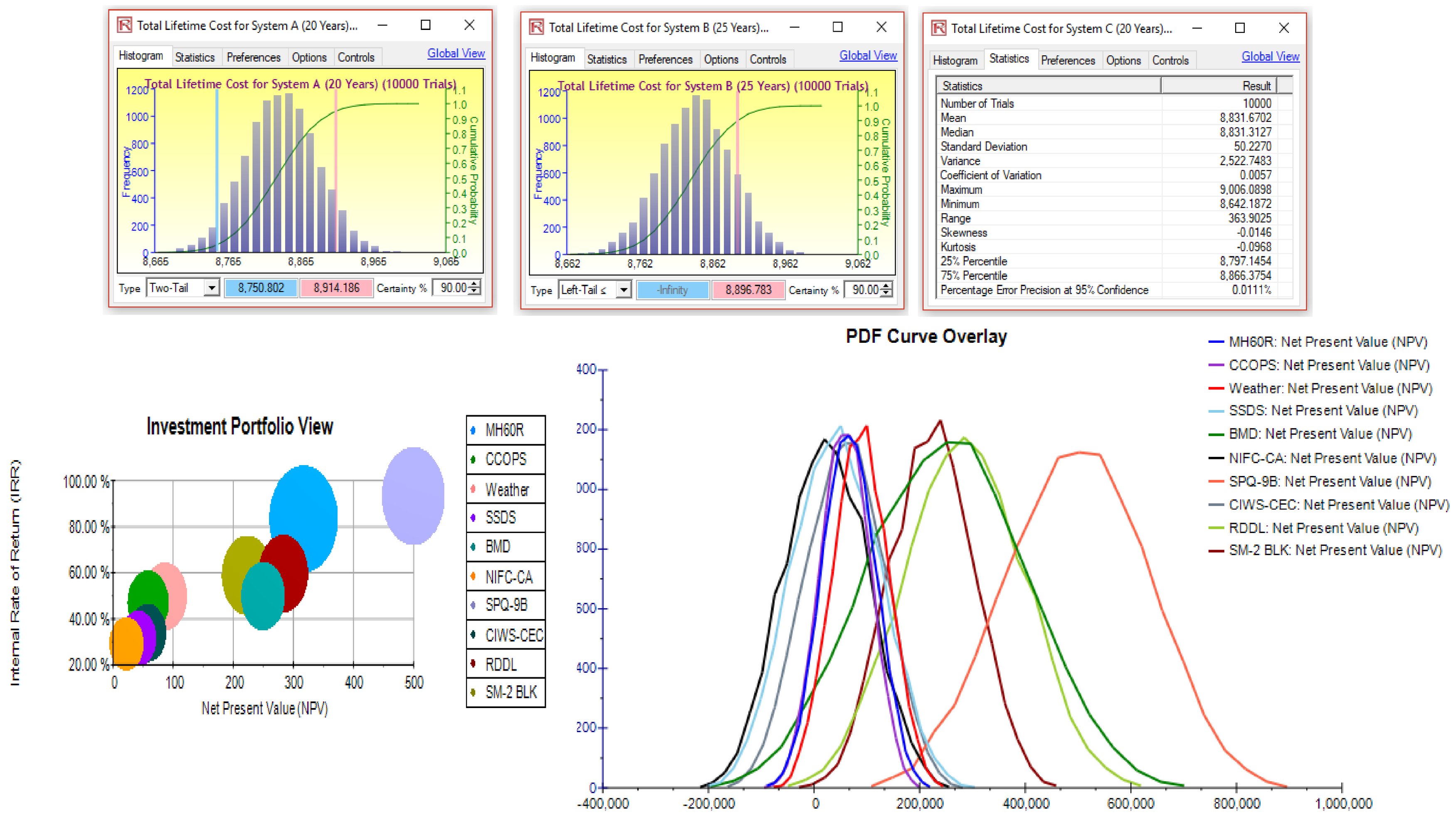
https://hdl.handle.net/10945/71939

Capturing Risk in Capital Budgeting

Naval Postgraduate School

Integrated Risk Management

This research has the goal of proposing novel, reusable, extensible, adaptable, and comprehensive advanced analytical processes 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 investment efficient 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 of 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.



Stochastic Simulation

Average Rank Choice Selection

From the Hasse diagram, several sets can be derived. 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 $y \in U(x)$

Systems Approach with Utilization Metrics

The standard utility model can be adapted to a more modern systems approach with the utilization model specified as: $\delta U = N[(\Phi_T - \Phi_{UT})\Omega\sigma - C]$ where δU is the net monetary value of training; *N* is the number of trained individuals; Φ is the output generated by trained, T, and untrained, UT, individuals; Ω is the duration of the training; C is the cost of the training; and σ is the standard deviation of the performance output of the untrained group. Therefore, $ROI = \frac{\delta U}{C} \times 100\%$.

Frequency and Quantity of Use Approach

To quantify the value of the knowledge learned, the frequency and quantity of use approach looks at both the frequency and quantity of learned knowledge used. Specifically, let *X*, *Y*, and *Z* be real-valued random variables whereby *X* and *Y* are independently distributed with no correlations. Further, we define F_X, F_Y, and F_Z as their corresponding cumulative distribution functions (CDFs), and f_X, f_Y, f_Z as their corresponding probability density functions (PDFs). Next, we assume that *X* is a random variable denoting the *frequency* that a certain type of learned knowledge is triggered or used and is further assumed to have a discrete Poisson distribution computed using the Knowledge Value Added methodology and can be distributed from among a group of continuous distributions (e.g., Fréchet, Gamma, Log Logistic, Lognormal, Pareto, Weibull, etc.). The Total Usage formula yields: $F_Z(t) = P(Z < t) = \sum_k P(XY < t \mid X = k) \times P(X = k)$ where the term with $X = 0$ is treated separately:

$$F_Z(t) = P(0 < t|X = 0) \times P(X = 0) + \sum_{k \neq 0} P\left(Y < \frac{t}{k}\right) \times P(X = k) \text{ and } F_Z(t) = \sum_{k \neq 0} f_X(k) F_Y\left(\frac{t}{k}\right) + P(X = 0)$$

Analytical Framework Approach

An analytical framework approach is used if cross-sectional data can be gathered. Specifically, data on measurable outputs, such as those in a production function $Y = f(\epsilon, \tau, \varphi, \theta, \omega, \ldots, \varepsilon)$ where *Y* is the measurable production output, ϵ is the education and training investment amount, τ is the technology supporting said production, φ is the capital investment, θ is the organizational design structure, ω is the environmental impacts, and ε is the forecast error in the model. Therefore, we can determine $\frac{\partial Y}{\partial \epsilon}$, and this will represent the expected change in average value of production with respect to each unitary change in educational investment, after accounting for all the other variables. In other words, this is the net effect of educational contribution to overall outcomes. Performing some partial differentials, we obtain: $\frac{\partial Y}{\partial \epsilon} = \frac{\partial f}{\partial \tau}\frac{\partial \tau}{\partial \epsilon} + \frac{\partial f}{\partial \varphi}\frac{\partial \varphi}{\partial \epsilon} + \frac{\partial f}{\partial \theta}\frac{\partial \theta}{\partial \epsilon} + \frac{\partial f}{\partial \omega}\frac{\partial \omega}{\partial \epsilon}$. A nonlinear regression can be run on the preceding assuming continuous data variables, or Logit, Probit, and Tobit models can be run on discrete and truncated limited dependent variables.

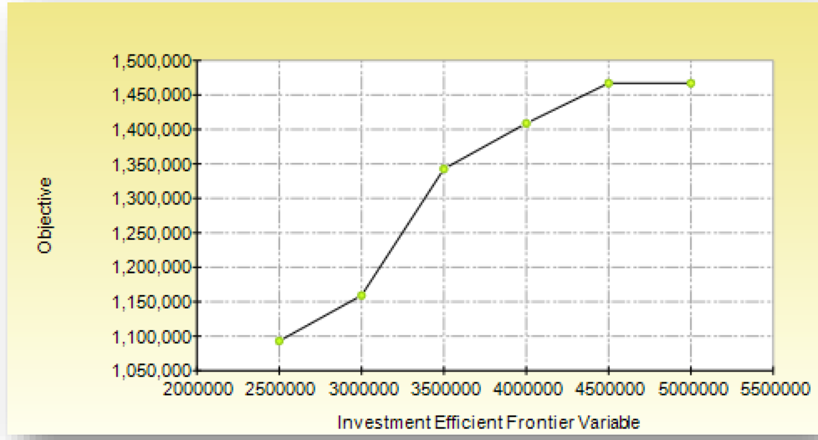
Program Rank Selection and Evaluation

Stochastic Optimization on Budget Allocation

Objective Function	1,093,034	1,159,120	1,342,649	1,408,736	1,467,080	1,467,080
Frontier Variable	2,500,000	3,000,000	3,500,000	4,000,000	4,500,000	5,000,000
Optimized Constraint 1	4.0000	5.0000	5.0000	6.0000	7.0000	7.0000
Optimized Constraint 2	2,400,000	2,800,000	3,400,000	3,800,000	4,100,000	4,100,000
MH60R	0	1	0	1	1	1
CCOPS	0	0	0	0	1	1
Weather	1	1	1	1	1	1
SSDS	0	0	0	0	0	0
BMD	0	0	1	1	1	1
NIFC-CA	0	0	0	0	0	0
SPQ-9B	1	1	1	1	1	1
CIWS-CEC	0	0	0	0	0	0
RDDL	1	1	1	1	1	1
SM-2 BLK	1	1	1	1	1	1

Methodology

- Stochastic Efficient Portfolio Allocation when input assumptions are uncertain, subject to different stakeholders' competing objectives, as well as budgetary, risk, schedule, operational, and strategic constraints.
- Capital budgeting techniques (standard NPV, IRR, ROI as well as non-economic metrics such as expected military value, strategic and tactical value, etc.)
- Monte Carlo simulation to model the uncertainties and stochastic assumptions for probabilistic results
- Project/program selection and portfolio optimization for budget allocation
- Combines hierarchical selection methods (PROMETHEE, Hierarchical Scoring-Ranking, Multicriteria Optimization) with stochastic optimization
- Considers operational, logistic, strategic, and tactical needs as well as optimizing across single or multiple domains or operational units
- Considers and models dynamic sensitivity (inputs that have the highest impact or leverage), strategic flexibility (strategic options for future adaptability), game theory (perfect and imperfect information, limited time or perpetual games, Nash/Bayes updating)



Efficient Frontier

Key Conclusions and Recommendations

Optimizing 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 novel, reusable, extensible, adaptable, and comprehensive advanced analytical processes 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 investment efficient 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.

Researcher: Dr. Johnathan Mun, Professor of Research, Dept. of Information Science, Naval Postgraduate School
Topic Sponsor: N8 - Integration of Capabilities & Resources

NRP Project ID:
NPS-22-N298

This research is supported by funding from the Naval Postgraduate School, Naval Research Program (PE 0605853N/2098). Approved for public release; distribution is unlimited.