Strategic Technology Investment Analysis: an Integrated System Approach

V. Adumitroaie and C. R. Weisbin
Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Dr.
Pasadena, CA 91109
818-393-7038
Virgil.Adumitroaie@jpl.nasa.gov

Abstract—Complex technology investment decisions within NASA are increasingly difficult to make such that the end results are satisfying the technical objectives and all the organizational constraints. Due to a restricted science budget environment and numerous required technology developments, the investment decisions need to take into account not only the functional impact on the program goals, but also development uncertainties and cost variations along with maintaining a healthy workforce. This paper[1,2] describes an approach for optimizing and qualifying technology investment portfolios from the perspective of an integrated system model. The methodology encompasses multi-attribute decision theory elements and sensitivity analysis. The evaluation of the degree of robustness of the recommended portfolio provides the decision-maker with an array of viable selection alternatives, which take into account input uncertainties and possibly satisfy non-technical constraints. The methodology is presented in the context of assessing capability development portfolios for NASA technology programs.

Keywords: decision support, technology investment

TABLE OF CONTENTS

1. OVERVIEW 1
2. APPROACH 2
3. APPLICATIONS 3
4. CONCLUSIONS 7
5. ACKNOWLEDGMENTS 7
REFERENCES 8
BIOGRAPHY 9

1. OVERVIEW

In response to the need for consistent, transparent and auditable decision-making processes and tools [1], we employ a systematized approach to assessing optimal portfolios of capabilities and technologies. Project investments are selected through optimization of net mission value as a function of capability level achieved, subject to cost and time constraints. The investment selection is generated using the optimization module included in our own decision-support system START (STrategic Assessment of Risk and Technology) [2, 3, 4].

The underlying data set, which quantitatively characterizes requirements (performance, cost, schedule, risk) and proposed technological solutions (achievable capabilities, resource requirements, degree of maturity, schedule), is replete with uncertainty. This inherent uncertainty of the input data must be combined into a global confidence range, which provides the decision maker with an overall sense of quality and likelihood of success of the investment strategy.

We use two complementary methods to take a first step in evaluating the degree of confidence about the standard optimal investment portfolio and determining how the choice of capabilities is affected by variations in the information provided by the capability developers: parametric sensitivity analysis and k-best sets analysis.

The parametric sensitivity analysis reveals whether a given uncertainty in a cost or expected utility might lead to a portfolio recommendation differing from the initial portfolio, and ultimately allows to categorize capabilities as "robustly chosen", "robustly rejected", or "trade candidates" (i.e., capabilities that were chosen or rejected with significant uncertainty). In addition to the parametric screening, a k-best analysis is performed to identify competitive portfolios and their common set of capabilities. This common set is in turn compared to the set of robustly chosen capabilities, while the k-best portfolios are presented as options to the optimal recommendation.

The application of the sensitivity analysis presented here originates from a study conducted for NASA's Aeronautics Research Mission Directorate (ARMD). The United States has set a goal of enabling a Next Generation Air Transportation System [5] by the year 2025 to provide for substantially increased capacity while improving or keeping constant any harmful effects on the environment (emissions, noise), safety, and security. The Joint Program Development Office facilitates the multi-agency support of this effort. NASA contributes primarily as an R&D provider of enhanced capabilities, and its Aeronautics Research Mission Directorate (ARMD) has initiated an activity to formulate and assess the return on investment (ROI) for candidate

1

[1] 978-1-4244-3888-4/10/$25.00 ©2010 IEEE.
[2] IEEEAC Paper #1523 Version 4, Updated January 04, 2010

capability-development tasks deemed necessary for the realization of the new system.

Three scenarios were identified as potential elements of an overall architecture to address the country's air transportation needs during the next several decades: (1) Linear extrapolation of today's capabilities; (2) More large regional airports with more large airplanes using them; (3) A highly decentralized system in which considerable traffic is handled by small planes travelling directly point-to-point.

Comparing the relative merits of these three approaches was not among the study's objectives; our analysis included recommendations for capability investments (consistent with the data made available) for each of the three scenarios. Candidate capability areas were derived from programs in vehicle systems development, airspace control, safety, and security. A total of 38 capabilities were specified and quantified in terms of state-of-the-art vs. required performance and maturity; system-level importance; estimated cost; time required for development; and uncertainties in meeting the technical performance objective (assuming full funding) and associated acceptance. The portfolio analysis targeted identifying the best set of capabilities that would support the implementation of desirable future scenarios that contribute to the high-level Joint Planning and Development Office (JPDO) goals, subject to performance requirements, and budget and development time constraints. Further details of this study are found in [3, 6].

During the past 5 years, the START methodology and its expression as a decision support system has been applied extensively in the assessment and prioritization of investment portfolios for technologies and capabilities across several NASA programs and directorates. START is currently being employed to prioritize investments for NASA's Exploration Systems Mission Directorate (ESMD) [7], and has been an approach under consideration for PA&E. It has been used in technology portfolio analysis for Mars missions under the Science Mission Directorate (SMD) [8, 9], capability portfolio planning for the Aeronautics Research Mission Directorate (ARMD) [6, 10, 11], the Space Operations Directorate (SLEP Program), and technology planning for JPL's Office of the Chief Technologist (CTO) [12, 13].

2. APPROACH

Ideally, a R&D investment selection process should be based on a fine-grained characterization of the contending solutions to the extent that all major discriminators are taken into account. For large programs, this often leads to substantial inflows of data, which are difficult to process without specialized decision support systems. To this effect, START is a comprehensive methodology for capability and technology portfolio assessment and planning, which can support large programs [14, 15]. It allows decision-makers to see explicitly the information and the assumptions that go into the analysis process, to guide the decision process through the establishment of institutional constraints and priorities, and to conduct "what-if" experiments with

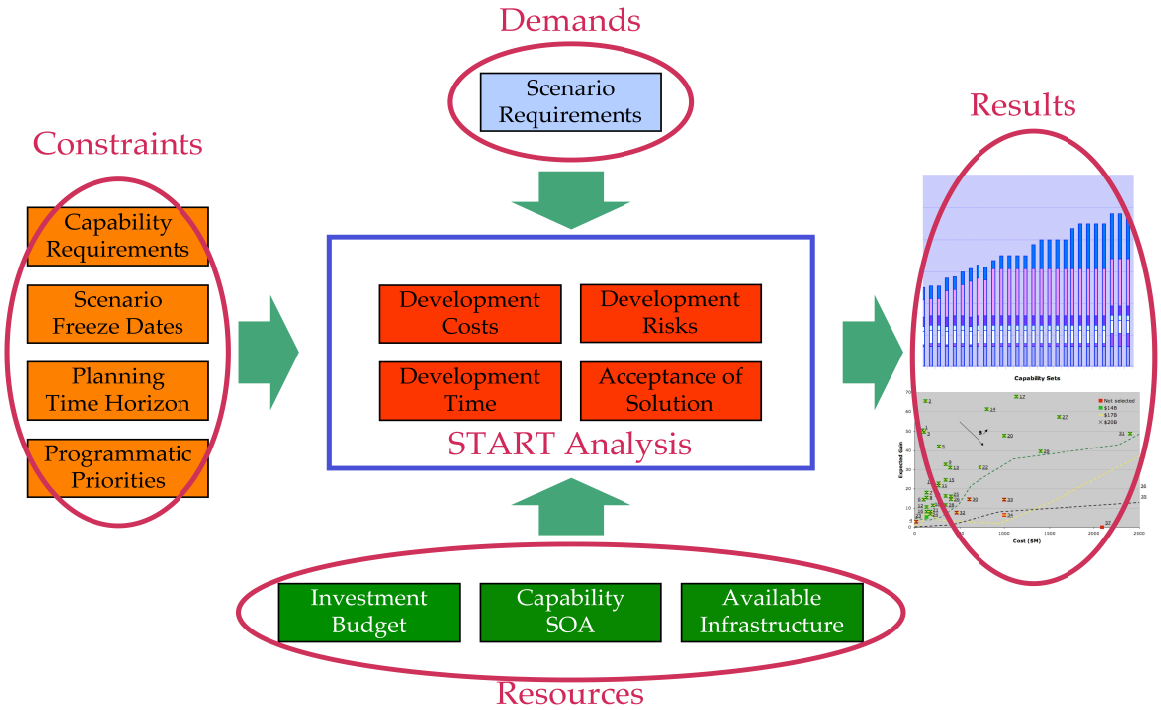

Figure 1: START system view

different scenarios and assumptions. The results of the analyses are presented to the decision-maker in tabular and graphical forms, allowing large amounts of information to be conveyed rapidly and accurately. START is composed of both an operational sequence of steps, and an analytical decision framework.

The operational sequence of steps in the application of the START methodology is listed below:

1. Develop a clear, complete statement of the decision problem to be studied. This includes eliciting the pertinent policy, schedule, and budget constraints, as well as all relevant assumptions.

2. Identify the goals and priorities of the decision-maker, and the associated metrics. This includes relative priorities or range of relative priorities among multiple goals.

3. Identify the scenarios, programs or mission architectures that are to be fulfilled.

4. Identify the capabilities and/or technologies required by the scenarios, programs or missions.

5. Characterize the capabilities and/or technologies using a variety of metrics, including the state of the art (SOA), desired performance levels, development cost and risk, influence on goal(s), etc., and validate the data collected.

6. Capture the perceived importance and risk of the required performance domain through a corresponding utility range. This step benefits greatly from functional models of the systems/architectures to which the proposed technologies will contribute. The functional models should be used to evaluate the sensitivity of the system/architecture overall value to performance variations in the underlying technologies. The sensitivity coefficients can then be translated/mapped to importance levels.

7. Compute optimal portfolios in the limits of investment budgets and timelines that are of interest to the decision-maker.

8. Validate the results, both through consistency checks of the data and through automated sensitivity analysis of the results. This allows the decision-maker to have confidence metrics associated with the results.

The analytical framework used for START is based primarily on decision-theoretical methods [16, 17]. The data used to characterize the requirements is used to assess the expected utility of different capabilities or technologies, again based on their quantitative and qualitative description. Capabilities or technologies are "matched" against the requirements using concepts from multi-objective decision theory [18] to compute this expected utility. This information, together with the associated development costs, is used as input to an integer optimization algorithm to compute the best portfolio possible under the given available investment budget, and taking into account the various constraints associated with the problem [2].

START's analysis capabilities (Figure 1) are the result of the available functional features which include improved modeling of uncertainties, dependencies and utilities, analytical modules for temporal analysis, modeling of enabling vs. enhancing technologies, partial funding of tasks, dealing with non-technical constraints, etc.

3. APPLICATIONS

The starting point in this analysis is the optimal portfolio for a given investment budget level. For each capability, the capability utility, probability of development success, and the probability of acceptance are combined to compute an overall expected utility of the capability [4]. The expected utility, together with the development cost of the capability, are the key quantities used in computing an optimal portfolio. The optimal portfolio selection problem is to determine the set of capabilities that provide the maximum composite value while fitting within the available budget. In the START decision support system the solution is obtained by employing a knapsack algorithm [19].

Given the preponderance of input uncertainties and political constraints the optimal solution in itself is not very useful without other qualifying information. Generally, the decision maker needs to know about the robustness of the optimal solution and if there are alternative selections close to the optimal point (perhaps satisfying a non-technical preference).

Parametric Screening Method. Having obtained an optimal portfolio, we employed two approaches to examine the robustness of our results. First, we changed incrementally the cost and utility, one at a time, for each capability until a change in the resulting portfolio was observed with respect to the nominal solution. This approach yielded the range within which the portfolio selections would be indifferent to a change in the specific value of a particular cost or utility. In other words, it revealed whether a given uncertainty in a cost or utility might lead to a portfolio different from the one computed as optimal.

If the expected utility for a selected capability were reduced below the lowest value in the range, the capability would be rejected, possibly making room in the budget for the selection of one of the currently unselected capabilities represented by a red bar. Similarly, if the expected utility of an unselected capability is increased beyond the limits of its indifference range it would become selected, possibly knocking one or more of the previously selected capabilities out of the portfolio. Changes in cost can be even more

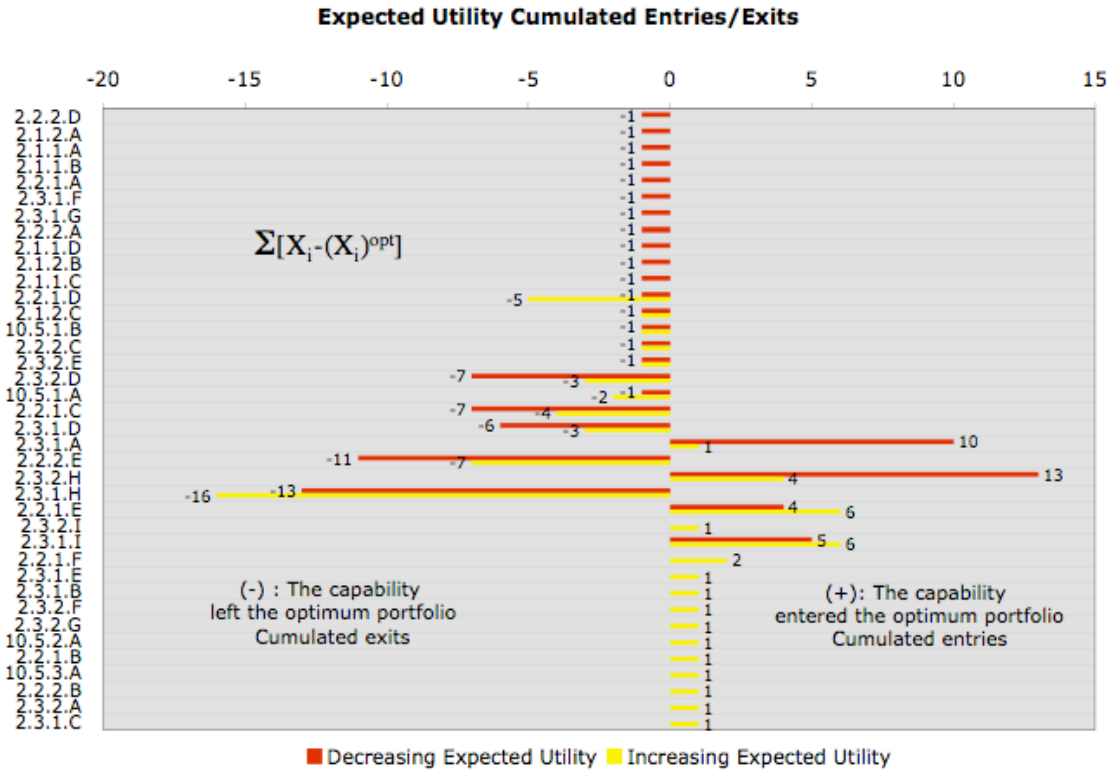

Figure 2. Portfolio movement tallies during the parametric sweep. The red/yellow bars denote the cumulated moves while decreasing/increasing the expected utility, respectively.

unpredictable. For example, raising the cost of a selected capability beyond the limits of its range could cause it to become unselected—or it could be retained at the sacrifice of a different, less-valuable capability.

The above-mentioned procedure not only produces the indifference ranges for each capability, but also their individual tendencies to remain, enter or exit the portfolio. This information is the result of tracking and cumulating the observed changes in the portfolio at the edge of the indifference range. Figure 2 depicts the cumulated tendencies for each capability during the parametric screening on the expected utility. The negative numbers represent exits from the original portfolio composition, while the positive numbers reflect entries.

Note that the wider bars represent capabilities that entered or exited the portfolio more frequently in this study. Such behavior characterizes the marginal groups, whose performance-cost ratios made them expendable or marginally acceptable, subject to the vagaries of their own cost and performance expectations and those of the other capability groups. Although a univariate analysis such as this represents an "ideal case" in which only one parameter is uncertain, it does provide the decision maker with essential information regarding their technology portfolio. For example, some capabilities would require at least a doubling of their expected utility to get selected and consequently are definitely not a contender.

Monte Carlo Analysis. In addition to this procedure, which dealt with the effect on a portfolio of only one variation in only one capability group at a time, we also performed a Monte Carlo simulation in which variations were applied to all capability groups simultaneously. In this study, the portfolio optimizations were run 1000 times with the cost and expected utility of each capability group varied randomly each time up to a 10% increase or decrease relative to its initially assigned value. Then an additional 1000 runs were performed with variations up to 25%.

The status (in or out) of each capability is accumulated from each run such that a selection frequency is computed from this stage of the parametric screening. Figure 3 shows the selection frequency chart for the Monte Carlo runs with +/- 25% variations (with capabilities sorted alphabetically).

The results from the two parametric approaches are mutually calibrated in order to issue a common categorization of the projects sets as "robustly selected", "robustly rejected", and "trade candidates". For example, we found that in this study that "robust selection" translates into "less than 10 exits for a selected capability" in the deterministic analysis and "greater than 85% selection record" in the Monte Carlo analysis. Illustrative results of this procedure applied to the NGATS 2004 system are shown in Table 1.

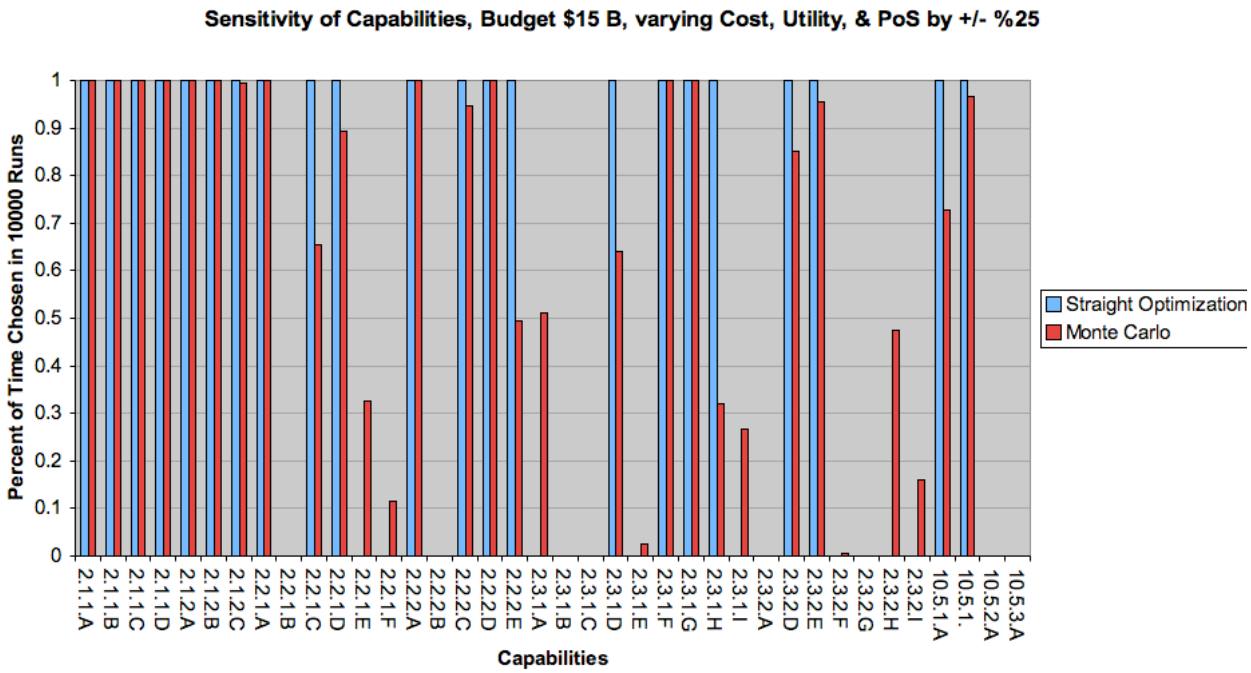

Figure 3. Selection frequency in the Monte Carlo analysis. The red bars indicate the percentage selection under varying parameters. The blue bars represent the nominal optimization.

Robust Selection	Not Recommended
Less than 10 exits for a selected capability in the deterministic analysis. *Greater than 85% selection record for a selected capability in the Monte Carlo.*	Less than 10 entries for a non-selected capability in the deterministic analysis. *Less than 15% selection record for a non-selected capability in the Monte Carlo*
2.1.1.A Protect/Prevent Abnormal Operations & System Failures 2.1.1.B Detect & Mitigate Natural Hazards 2.1.1.C Prevent Breakdown of Human/Machine Interface 2.1.1.D Integrity & Efficiency of Accepting Advanced Software Systems 2.1.2.A Detect & Inform Potential System Vulnerabilities 2.1.2.B Mitigate Consequences from Intentional Attack 2.1.2.C Detect & Contain Diseases & Bio/Chem Agents 2.2.1.A Low emission subsonic vehicles 2.2.1.D Low emission personal air vehicles 2.2.2.A Low noise subsonic vehicles 2.2.2.C Low noise ESTOL vehicles 2.2.2.D Low noise personal air vehicles 2.3.1.F Increase Arrival/Landing Rates at Commercial Airports 2.3.1.G Commercial Operations from Small/Underused Airport 2.3.2.E Efficient all-weather rotorcraft 10.5.1.B Conduct Routine UAV in NAS	2.2.1.B Low emission supersonic vehicles 2.2.1.F Low emission UAVs 2.2.2.B Low noise supersonic vehicles 2.3.1.B General Aviation During Peak Demand 2.3.1.C Public Service Aircraft During Peak Demand 2.3.1.E Globally Harmonized Equipage & Operations 2.3.2.A Efficient subsonic vehicles 2.3.2.F Complete Decision Information to All in NAS 2.3.2.G Low Cost Vehicles for Bulk Cargo 2.3.2.I Minimum Impediments of Mode Change 10.5.2.A Extended Autonomous Flight in Mars Atmosphere 10.5.3.A Incorporating Hypersonic Air-Breathing Propulsion
	Trade Candidate
	2.2.1.C Low emission ESTOL vehicles 2.2.1.E Low emission rotorcraft 2.2.2.E Low noise rotorcraft 2.3.1.A Capacity En-Route Commercial Operations in NAS 2.3.1.D Minimize System-Wide Disruptions 2.3.1.H Commercial Operations with short/no Runways 2.3.1.I Incorporate Full Spectrum of Aircraft to NAS 2.3.2.D Efficient easy-to-operate personal air vehicles 2.3.2.H Increased Speed & Range for Pedestrian Travel 10.5.1.A Autonomous high altitude long-endurance flight

Table 1: Recommended Portfolio Composition for the Next Generation Air Transportation System at a budget level of $15B.

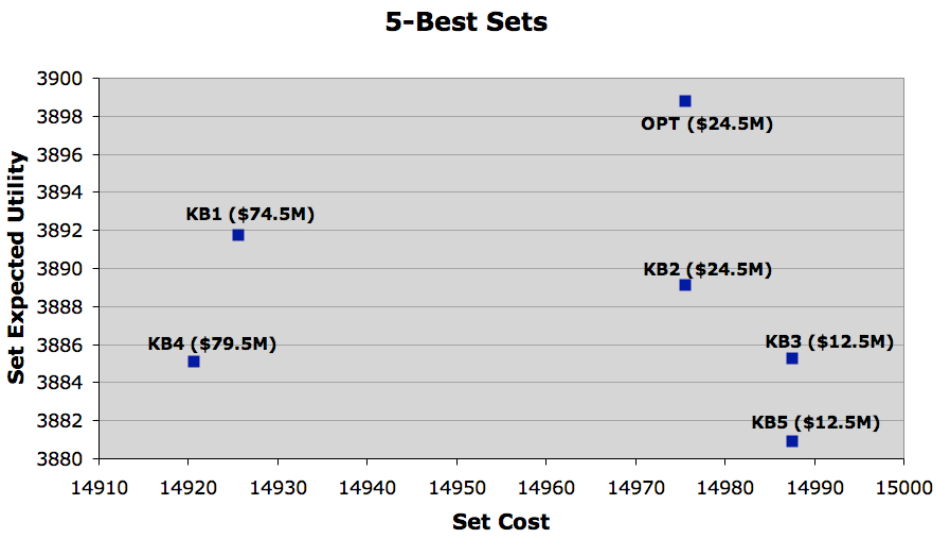

Figure 4. "5-best" portfolios mapping in the aggregated expected utility/ total cost. The figures in parenthesis denote the budget slack.

K-best Analysis. The k-best sets analysis [20] offers the "k" suboptimal portfolios closest to the optimal recommendation for a given budget level. Based on the k-best sets the decision-maker can take into account aspects of the problem that are not easily modeled quantitatively, as well as additional constraints important to the decision.

When finding the k-best sets with the base case input parameters and then comparing the values of these sets over the entire range of possible values for the input parameters, competitor portfolios can be proposed. The intersection of the k-best portfolios with the optimal portfolio produces a set of project selections deemed as "persistent."

Figure 4 shows the relative positioning of the five closest competitive portfolios with respect to the optimal recommendation in an aggregated expected utility/total cost mapping. From the placement and composition of the suboptimal portfolios the decision-maker can fulfill supplementary requirements. For example, if the extra constraint is to spend most of the available budget, KB3 is the close to the optimal portfolio, but in addition it minimizes the budget slack.

Table 2 identifies the actual 5-best portfolios and the categorization of the capabilities by their overall percent presence in the suboptimal portfolios (including the "persistent" set displayed in green color). The coloring convention is similar to the one utilized in the parametric screening analysis. The color green denotes the stable set, while the orange cells represent the trade candidates. One final observation can be made at this point: the parametric sensitivity analysis and the k-best analysis generate consistent choices of "robust" and "persistent" recommendations. With two exceptions the robust recommendations from the sensitivity analysis are the same as the ones suggested by the k-best analysis. This

Table 2: Identification of the common set of capabilities in the "5-best" portfolios and their percent overall presence

Capability	Opt	KB1	KB2	KB3	KB4	KB5	Overall
2.2.2.D	1	1	1	1	1	1	100.00%
2.1.2.A	1	1	1	1	1	1	100.00%
2.1.1.A	1	1	1	1	1	1	100.00%
2.1.1.B	1	1	1	1	1	1	100.00%
2.2.1.A	1	1	1	1	1	1	100.00%
2.3.1.F	1	1	1	1	1	1	100.00%
2.3.1.G	1	1	1	1	1	1	100.00%
2.2.2.A	1	1	1	1	1	1	100.00%
2.1.1.D	1	1	1	1	1	1	100.00%
2.1.2.B	1	1	1	1	1	1	100.00%
2.1.1.C	1	1	1	1	1	1	100.00%
2.2.1.D	1	1	1	1	0	1	83.33%
2.1.2.C	1	1	1	1	1	1	100.00%
10.5.1.B	1	1	1	1	1	1	100.00%
2.2.2.C	1	1	1	1	1	1	100.00%
2.3.2.E	1	1	1	1	1	1	100.00%
2.3.2.D	1	1	1	0	1	0	66.67%
10.5.1.A	1	1	1	1	1	1	100.00%
2.2.1.C	1	1	1	1	1	0	83.33%
2.3.1.D	1	1	1	1	1	0	83.33%
2.3.1.A	0	0	0	0	0	1	16.67%
2.2.2.E	1	1	0	1	1	0	66.67%
2.3.2.H	0	0	0	1	0	0	16.67%
2.3.1.H	1	0	1	1	1	0	66.67%
2.2.1.E	0	1	1	0	0	0	33.33%
2.3.2.I	0	0	0	0	0	0	0.00%
2.3.1.I	0	1	0	0	0	1	33.33%
2.2.1.F	0	0	0	0	0	0	0.00%
2.3.1.E	0	0	0	0	0	0	0.00%
2.3.1.B	0	0	0	0	0	0	0.00%
2.3.2.F	0	0	0	0	0	0	0.00%
2.3.2.G	0	0	0	0	0	0	0.00%
10.5.2.A	0	0	0	0	0	0	0.00%
2.2.1.B	0	0	0	0	0	0	0.00%
10.5.3.A	0	0	0	0	0	0	0.00%
2.2.2.B	0	0	0	0	0	0	0.00%
2.3.2.A	0	0	0	0	0	0	0.00%
2.3.1.C	0	0	0	0	0	0	0.00%

information can be used to increase the level of confidence in the decision-making process and to provide valuable insights and choices to the results of the optimality analysis.

4. CONCLUSIONS

We describe an approach for optimizing and qualifying technology investment portfolios from the perspective of an integrated system model. The methodology includes multi-attribute decision theory elements and sensitivity analysis. The evaluation of the degree of robustness of the recommended portfolio provides the decision-maker with an array of viable selection alternatives, which take into account input uncertainties and possibly satisfy non-technical constraints. Two complementary methods - parametric sensitivity analysis and k-best sets analysis, for qualifying optimal technology portfolios were employed. The parametric sensitivity analysis relies on two types of evaluation procedures: deterministic and statistical (Monte Carlo simulation).

The deterministic sampling yields the range within which the portfolio selections are invariant to changing cost or for the given budget. The statistical sampling expands the search domain with consideration of joint variation in capability input parameters. The change events are recorded and accumulated over the two parametric samplings. By performing a mutual calibration between the accumulated activities, the sets of projects "robustly selected", "robustly rejected", and "trade candidates" are identified.

The k-best sets analysis offers the "k" suboptimal portfolios closest to the optimal recommendation for a given budget level. The intersection of the k-best portfolios with the optimal portfolio produces a set of project selections deemed as "persistent." Although the two above approaches are complementary, their results are consistent, in that the "persistent" set is similar in composition to the "robust" set.

The goal of the sensitivity study is to enhance and improve the decision-making process by providing additional qualifications and substitutes to the optimal solution. The methodology is illustrated in the context of NASA technology project selections. The results highlight the importance and the usefulness of the sensitivity analysis in providing a higher level of confidence to the technology portfolio recommendations under uncertainty.

5. ACKNOWLEDGMENTS

The research described here was conducted at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration and would not have been possible without the encouragement of a number of outstanding and technically knowledgeable sponsors. We want to thank those particularly involved in the case studies presented in this paper, including Douglas A. Craig, Directorate Integration Office, NASA HQ; Jay Falker, Technology Assessment Lead, Office of Program Analysis and Evaluation, NASA HQ; Yuri O. Gawdiak, Program Integration Manager, Aeronautics Research Mission Directorate, NASA HQ; Terrence J. Hertz, Director, Aeronautics Technology, Aeronautics Research Mission Directorate, NASA HQ; and George Price, Special Assistant, Aeronautics Research Mission Directorate, NASA HQ. We would also like to express our appreciation for the support of our Program Office led by Stephen L. Prusha, Program Manager, Strategic Systems Technology Program Office, JPL/ California Institute of Technology. Copyright 2010 California Institute of Technology. Government sponsorship acknowledged.

REFERENCES

[1] Silberglitt, R. and Sherry, L.,"A Decision Framework for Prioritizing Industrial Materials Research and Development," RAND Monograph Report MR-1558-NREL, 2002.

[2] Weisbin, C.R., Rodriguez, G., Elfes, A. and Smith, J.H., "Toward a Systematic Approach for Selection of NASA Technology Portfolios," Systems Engineering Journal, Vol. 7, No. 4, pp. 285-302, 2004.

[3] Weisbin, C.R., Manvi, R., Shelton, K., Adumitroaie, V., Derleth, J.E. and Elfes, A., "Capability-Development Return on Investment for the NASA Aeronautics Program", 16th International Conference on Systems Engineering (ICSEng 2005), August 16-18, 2005, Las Vegas, NV.

[4] A. Elfes, C. R. Weisbin, R. Manvi, V. Adumitroaie, W. P. Lincoln, K. Shelton, "Extending the START Framework: Computation of Optimal Capability Development Portfolios Using a Decision Theory Approach", Systems Engineering Journal, Vol 9, Number 4, Winter 2006, pgs 331-357.

[5] NGATS 2004, "Next Generation Air Transportation System", Joint Program Development Office, December 2004. http://www.jpdo.aero.

[6] Manvi, R., Weisbin, C.R., Elfes, A. and Rodriguez, G., "Risk-Driven Interdependent Task Analysis Applied to a NASA R&D Program", IEA/AIE 2005 18th International Conference on Industrial & Engineering Applications (IEA) of Artificial Intelligence & Expert Systems (AIE), Bari, Italy, June 22-25, 2005. Published in the Springer-Verlag Lecture Notes on Artificial Intelligence series, Vol. 3533, 2005.

[7] W. Lincoln, J. Mrozinski, H. Hua, S. Merida, K. Shelton, V. Adumitroaie, C. R. Weisbin, J. Derleth, "START Analysis for ESAS Capability Needs Prioritization", INCOSE 2006, Orlando, Florida.

[8] J.H. Smith, B. Dolgin, and C. Weisbin. "Reaching Mars: Multi-Criteria R&D Portfolio Selection for Mars Exploration Technology Planning," Proceedings of the 32nd Annual Meeting of the Western Decision Sciences Institute, Marriott Resort and Beach Club, Lihue, Hawaii, April 15-19, 2003.

[9] J. H. Smith, J. Wertz, and C. Weisbin. "Building a Pathway to Mars: Technology Investment for Science Return", Journal of Space Mission Architecture (JSMA), Issue 3, page 101, September 2003. Also available as JPL Publication No. 03-15, Jet Propulsion Laboratory, Pasadena, CA.

[10] R. Manvi, C. Weisbin, and A. Elfes. "Portfolio Optimization of a NASA R&D Program Including Dependencies & Partial Funding", CSER/INCOSE 2006 Conference, Los Angeles, CA, April 7-8, 2006.

[11] V. Adumitroaie, K. Shelton, A. Elfes and C.R. Weisbin, "Postoptimality Analysis in the Selection of Technology Portfolios". CSER/INCOSE 2006 Conference, Los Angeles, CA, April 7-8, 2006.

[12] W. Lincoln and C. R. Weisbin, V. Adumitroaie, S. Merida, "Capability Investment Strategy to Enable JPL Future Space Missions", Earth and Space 2006 Conference, Houston, Texas, March 8-12, 2006.

[13] W. Lincoln, H. Hua, and C.R. Weisbin, "Temporal Investment Strategy to Enable JPL Future Space Missions". Second International Conference on Space Mission Challenges for Information Technology (SMC-IT 2006), Pasadena, CA, July 17—21, 2006.

[14] J. Derleth, C.R. Weisbin, and G. Rodriguez. "A Structured Approach to Strategic Decision Making for NASA's Technology Development", 3rd Annual Conference on Systems Engineering Research (CSER), Hoboken, New Jersey, March 23-25, 2005.

[15] K.E. Shelton, G. Rodriguez, and C.R. Weisbin. "Evaluating Expected Return from NASA's Proposed Missions in Terms of the Agency High Level Goals", 2005 INCOSE International Symposium - Systems Engineering: Bridging Industry, Government, and Academia, Rochester, NY, July 10-15, 2005.

[16] J. O. Berger. "Statistical Decision Theory and Bayesian Analysis". Springer-Verlag, Berlin 1985. 2nd edition.

[17] J. W. Pratt, H. Raiffa and R. Schlaifer. "Introduction to Statistical Decision Theory", MIT Press, Cambrigde, MA, 1995.

[18] R.L. Keeney and H. Raiffa. "Decisions With Multiple Objectives", Wiley, NY, 1976.

[19] Martello, S. and Toth, P., Knapsack Problems - Algorithms and Computer Implementations, Wiley, 1990.

[20] Guikema, S. D. and Milke, M. W., "Sensitivity Analysis for Multi-Attribute Project Selection Problems," Civil Engineering and Environmental Systems, Vol. 20, No. 3, pp. 143-162, 2003.

BIOGRAPHY

Virgil Adumitroaie *received his Ph.D. degree in Mechanical Engineering from the State University of New York at Buffalo in 1997, where he performed research in simulation and modeling of high-speed turbulent reacting flows. He served for six years as a Senior Engineer at the CFD Research Corporation, Huntsville, AL prior to joining the Jet Propulsion Laboratory as a Senior Member of Technical Staff in 2004. He has published papers and technical reports on advanced modeling of compressible flows, direct numerical simulations and large eddy simulations (LES) of chemically reacting flows, and magnetohydrodynamics. During his career he has been involved in turbulent combustion modeling, data dimension reduction, neural networks, signaling pathways and scientific software development. Currently, his work in optimization methods and uncertainty analysis applied to decision problems supports tasks from the JPL's Strategic Technologies Program Office.*

Charles R. Weisbin, *Eng. Sc. D. 1969 Columbia University. currently serves as Deputy Program Manager for the System Modeling and Analysis Program Office, reporting to the Jet Propulsion Laboratory Associate Director for Strategic Planning and Project Formulation. Prior to this, at JPL, he led the Surface Systems Thrust Area, within the NASA Cross-Enterprise Technology Development Program. He was Program Manager for Robotics and Mars Exploration Technology Programs and before this, Section Manager for Robotic Systems and Advanced Computer Technology. At the Oak Ridge National Laboratory, he was Director of the Robotics and Intelligent Systems Program and Director for the Center for Engineering Systems Advanced Research. Dr. Weisbin was Associate Professor of Computer Science, teaching artificial intelligence at the University of Tennessee. He was the co-chairman of the NASA Telerobotics Intercenter Working Group for seven years and received the 1993 NASA Exceptional Service Medal for formulation and development of the NASA Telerobotics Program. He is a recipient of the 1998 Thomas O Paine Award for Advancement of Human Exploration to Mars and an IEEE Computer Society Golden Core Member award. He also received the 1999 NASA Exceptional Service Medal for development and infusion of robotics from basic research into NASA flight missions and missions of other agencies. He received the award for Outstanding Leadership in Surface Robotics for the year 2000, the Decadal Planning Team achievement award in 2001, and the NASA Group Achievement Award in 2001, a Lifetime Achievement Award from the World Automation Congress in 2004, and the award for Best Paper published in the System Engineering Journal in 2004.*