Strategic Technology Investment Analysis: an Integrated System Approach

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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 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

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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...
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

![START system view](image)
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.

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.

<table>
<thead>
<tr>
<th>Robust Selection</th>
<th>Not Recommended</th>
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<tbody>
<tr>
<td>Less than 10 exits for a selected capability in the deterministic analysis.</td>
<td>Less than 10 entries for a non-selected capability in the deterministic analysis.</td>
</tr>
<tr>
<td>Greater than 85% selection record for a selected capability in the Monte Carlo.</td>
<td>Less than 15% selection record for a non-selected capability in the Monte Carlo.</td>
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<td>2.1.1.A Protect/Prevent Abnormal Operations &amp; System Failures</td>
<td>2.2.1.B Low emission supersonic vehicles</td>
</tr>
<tr>
<td>2.1.1.B Detect &amp; Mitigate Natural Hazards</td>
<td>2.2.1.F Low emission UAVs</td>
</tr>
<tr>
<td>2.1.1.C Prevent Breakdown of Human/Machine Interface</td>
<td>2.2.2.B Low noise supersonic vehicles</td>
</tr>
<tr>
<td>2.1.1.D Integrity &amp; Efficiency of Accepting Advanced Software Systems</td>
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<td>2.1.2.B Mitigate Consequences from Intentional Attack</td>
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<td>2.1.2.C Detect &amp; Contain Diseases &amp; Bio/Chem Agents</td>
<td>2.3.2.A Efficient subsonic vehicles</td>
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<td>2.2.1.A Low emission subsonic vehicles</td>
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<td>2.2.2.A Low noise subsonic vehicles</td>
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<td>2.3.3.A Capacity En-Route Commercial Operations in NAS</td>
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Table 1: Recommended Portfolio Composition for the Next Generation Air Transportation System at a budget level of $15B.
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
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

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REFERENCES


BIography

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