



# A Decision Support System for Technology R&D Planning: Connecting the Dots from Information to Innovation

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## ABSTRACT

*Investment in technology research and development (R&D) is a critical component of the strategic planning process for private and public sector organizations. The R&D planning process is fraught with uncertainties, risks, dependencies, and a host of interrelated complexities. Each of these elements often bring stores of information, both conflicting and synergistic, that serve to confound the R&D planning process. This paper describes an information technology innovation developed to assist decision makers faced with complex R&D planning tasks. The decision support system (DSS) was developed and applied to the analysis of a 10-year, 700 million dollar technology program for the exploration of Mars. The technologies were to enable a 4.8 billion dollar portfolio of exploration flight missions to Mars. NASA's Mars Exploration Program is charged with developing a series of missions to the planet Mars that will return a variety of scientific products [1, 2, 3]. Each of the mission concepts requires a host of innovative technologies to enable various levels of scientific return. While a recent critique of the program by the Office of Management and Budget found the program to be the highest rated government program (out of 234 programs), their report encouraged the program to "Develop long-term, quantitative, outcome oriented performance measures [4]." A decision support system was developed herein that implemented a solution approach to the R&D portfolio selection problem. The DSS was used to address the question, "Given a Mars program composed of mission concepts dependent on a variety of alternative technology development programs, which combination of technologies would enable missions to maximize science return under a constrained budget?" The decision support system provided a mechanism to focus and manage the vast assortment of science, mission, and technology information surrounding the problem.*

## INTRODUCTION

A diverse mixture of programmatic issues faced the Mars Exploration Program. The complex interactions between scientific interests, mission planners, and technology developers amplified the need for an organizing structure to provide insights about high-value technologies and mission sensitivities to technology development uncertainties and budget constraints. The setting of the problem was distributed among three communities: the science community that defined the scientific requirements of the overall exploration program; the mission planning community that designed mission concepts to achieve the scientific

goals; and the technology development community charged with developing the component technologies to enable one or more of the mission concepts. Much of the information emerging from these disparate communities did not have shared definitions, mutually understood assumptions, or common formats. An aim of the DSS was to establish a framework for communicating a clear understanding of the wide variety of changing definitions and assumptions.

The challenge facing decision makers was to capture the innumerable connections and dependencies between the proposed missions, the required technologies, and the large number of possible investment combinations. The decision making problem was formidable—there was extensive information knowledge about each mission and its required technologies and there were numerous procedures to be followed in linking the developments from one mission to another. Holsapple and Winston have characterized these features as "know-what" and "know-how" [5]. Coupled with a need to develop the reasoning of how to map the relevant information to the procedures while accounting for the numerous dependencies pointed to a model-driven desk-top DSS [6].

The DSS involved a combined approach developed for analyzing portfolios of technology investments. Multi-criteria decision analysis, Monte Carlo simulation, and mathematical programming techniques were used to enumerate every possible technology portfolio combination to identify high science-value missions and technologies that could be funded within a specified budget [7, 8, 9]. This was done in a stepwise fashion by simulating the uncertainties in every technology required by every mission.

## THE APPROACH

The methodology implemented within the DSS was composed of steps to define and specify the inputs for the calculation portion of the DSS software. The five steps are listed below:

- Step 1. Define projects to deliver science benefits
- Step 2. Define technology developments needed to enable projects.
- Step 3. Build road map to link required technology to projects and identify dependencies between technologies.
- Step 4. Gather data for each technology.
- Step 5. Exercise the computational portion of the DSS to identify the highest value technology portfolio.

Table 1 . Projects Defined for Case Study

Mission Name	Description
Mars Science Laboratory	Mission to measure science in-situ with a rover
Volcanology Rover	Rover mission to characterize volcanic region with in-situ sampling
Polar Layer Deposit Rover	Rover mission to characterize polar regions with in-situ sampling
Synthetic Aperture Radar Orbiter	Orbiter sounding for surface science experiments and mapping
Imaging/Atmospheric Sounding Orbiter	Next generation remote sensing orbiter (Imaging and atmospheric sounding)
G. Marconi Orbiter	Telecommunications orbiter relay for high data rate communications
Telesat Orbiter	Small Mars telecommunications orbiter for high data rate communications
MSR Sample Ground Breaker	Sample return with a Mars ascent vehicle
Wildcat Lander	Lander with 30 m depth drilling system

Table 2 . Technology Categories and Attributes

Technology	Attribute Definition
Precision Landing	Semi-major axis ellipse distance, kilometers. Width of landing ellipse with 99% landing probability
Impact Attenuation	Landing survivability, meters. Free-fall distance at terminal landing phase for pallet-based landers
Hazard Avoidance	Average size of identifiable rock on 30-degree slope to be avoided during landing.
On-orbit Science resolution	Resolution of primary instrument, meters/pixel.
On-orbit Science wavelength	Specific wavelength of primary instrument, meters.
Forward Planetary Protection	Number of organisms present on the spacecraft (thousands)
Forward Planetary Protection	Measurement time after cleaning to process spacecraft (hours)
Surface Sample Characterization	Technology Readiness Level of instrument package designed for Mars surface sampling. Measured on 1-9 scale using a narrative definition [10].
Subsurface access (drilling) technologies	Achievable depth of drilling subsystem, meters. Two cases: shallow (30 m) and deep (1000 m) technologies
Surface Mobility	Distance capable of roving, meters per sol (Martian day)
Surface Sample Handling	Sample cross-contamination limit, parts per million.
Back Planetary Protection	Minimum containment size of particle within sample return system, microns.
Mars Proximity Data Rate	Data rate among communications systems (and missions) at Mars, megabits/second.
Mars-to-Earth Data Rate	Data rate for transmission to Earth, megabits/second.
Mars Orbit Rendezvous	Sample capture system time to acquire sample, sols
Multi-mission Survivability	Infrastructure technologies to extend component lifetimes, sols. Two cases: on-orbit and surface technologies.
Surface instrument approach and placement	Time for rover to plan, traverse to target, and place instrument on sample, sols.
Mars Ascent Vehicle	Qualification temperature of ascent engines, °C.

The first step (Step 1) defined a series of projects (missions) that would provide a measure of science return value. Table 1 lists the set of missions analyzed that consisted of landers, orbiters, and rover missions. Each of these missions sought to return scientific measurement values derived from a comprehensive list of scientific measurements defined by a science working group [3].

Table 3 . Technology Data Requirements and Definitions

Data Item	Description
Technology Capability Estimate	Estimate of technology attribute requirement outcome given technology development budget and development task is 100% successful. Value can be a point estimate, range, or probability distribution.
Probability of Success	Estimate of probability of technology development task success (based on likelihood of budget changes, dependencies on external developments, or task complexity).
Default outcome	Likely value of technology attribute outcome if technology development fails completely or partially. Use state-of-the-art or descope option.
Technology Cost Profile	Resources planned for development task in 3-year increments over a 12-year planning horizon, real-year dollars.
Dependencies	Identifier of parent technology and type of dependency (technical, mission, cost).

The second step identified the technologies required to enable the missions in Table 1. The technologies were identified at the development task level and characterized by a measurable technology attribute to represent the performance of each technology. Table 2 presents the list of technologies required and their attributes.

Step 3 required development of a simple roadmap that would link each technology development with a corresponding mission. At the same time, dependencies between technologies were noted by referencing the parent (predecessor) technology. For the case study described in this paper, the main dependency was on the Mars Science Laboratory (MSL) mission that was funding a number of technology developments for later missions. Figure 1 displays the technology roadmap identifying the technologies in Table 2 in the column headings and the missions from Table 1 in the row headings.

Step four gathered information about each task to characterize its uncertainty, risk, costs, and dependency on other tasks. For this step, a template was defined to collect the information using a simple one-page datasheet per technology. The data items collected are listed in Table 3 with brief definitions.

The fifth input noted the dependency of the technology on other predecessor technologies. In the selected example, the precision landing technology was being developed for the Mars Science Lab (MSL) project and was the predecessor for other projects. This can be seen in the Figure 1 roadmap where the Polar Layer Deposit Rover (POL), Mars Sample Return—Ground Breaker (MSR-GB), and Wildcat landed drilling system projects were relying on the development of precision landing by the MSL mission. The implication of the 3 dependencies reveals that a failure in the development of precision landing technology for MSL would also impact the 3 dependent missions (POL, MSR-GB, and Wildcat).

Step 5 involved running the DSS after entering the data from steps 1-4. The DSS was an object-oriented C++ software program that treated the technologies as individual objects with attributes of performance, uncertainty, risk, cost, and dependency. The technology objects were associated by the computer program with each project according to the technology roadmap (Figure 1) and every portfolio of projects was enumerated (511 portfolios for the projects in Table 1). Within each portfolio, a Monte Carlo simulation of the uncertainties was performed to compute the effects of uncertainty and risk on the science value of the portfolio.

This is was represented mathematically as follows:

let  
 $E[V_n]$  = expected science value of mission portfolio, n.  
 $s_i$  = science value of mission i (i=1,2,...,N)  
 $p(s_i)$  = probability science value of mission i realized.  
 $t_{ij}$  = performance of technology task j within mission i.  
 $p_s(t_{ij})$  = probability of success of technology task j within mission i.

$f_r(*)$  = dependency transformation maps technology uncertainties to mission realization probability (Monte Carlo simulation of dependencies).

Given the dependencies between technologies, the probability the science value of a mission is realized depends on each set of uncertain technologies.

$$p(s_i) = f_r(p_s(t_{i1}), p_s(t_{i2}), \dots, p_s(t_{ij}))$$

The problem stated as a mathematical program becomes:

$$\max \left\{ E[V_n] = \sum_{i=1}^n s_i p(s_i) \right\} n = 1, 2, \dots, (2^N - 1)$$

subject to:

$$\sum_t TechnologyCost(t) \leq TechnologyBudget(t)$$
  
and  
$$\sum_t MissionCost(t) \leq MissionBudget(t)$$

The DSS was designed to find the set of missions and technologies that maximized the expected science return value,  $E[V_n]$ , within the budget constraints. This was a portfolio-within-a-portfolio problem where the outer portfolio contained the missions which in turn contained the inner portfolios of technologies. During this process, technology tasks failed in accordance with their estimated task probabilities of success, and in those cases, the predefined default value was used in place of the sampled value. If a technology development failed during the simulation, its parent mission was removed from the portfolio and any dependent technologies and missions were also removed. After the simulation was completed, the total technology costs in the portfolio for each year in the planning horizon were subtracted from an externally specified budget constraint value to determine whether the portfolio was economically feasible. Three budget profiles were examined: 25, 50, and 75 million dollars per year (real-year dollars). A first-order feasibility criterion was used to determine cost feasibility—if the total technology costs exceeded the budget for any year, the portfolio was declared infeasible and discarded. A search was conducted by sorting the results to find the portfolio with highest expected science value based on the enabling technologies that could be developed within a given budget. The resulting outcomes were sorted by expected science value, variance, and cost feasibility.

RESULTS

After a sensitivity analysis on technology budget it was determined that most of the trade-offs occurred at the \$50M/yr level—an additional \$25M/yr allowed only one added technology beyond the \$50M/yr case was an indication that many of the technology trade-offs were likely to be in the neighborhood of \$50M/yr (from \$40M—60M/yr). Figure 2 displays all 511 portfolios in three dimensions for the \$50M/yr. case. Rectangular polygons display the expected science value plus or minus one standard deviation for each portfolio. (The expected science value is in the vertical center of each polygon.) The portfolio science polygons are centered on the location corresponding to the total portfolio mission cost and total portfolio technology costs. Also shown are the total budget constraints (planes) for mission and technology costs. Embedded within the display is the optimum solution. A number of observations were noteworthy.

First, a number of portfolios were too expensive—these were eliminated from further consideration. Second, most of the technology budget violations occur in the first 5 years with excess funds in years 6-12. This highlighted the need to reallocate resources from the long-term forward to the early years. In fact, the total budget could be significantly

Figure 1. Project technology roadmap showing project-specific technologies and dependencies

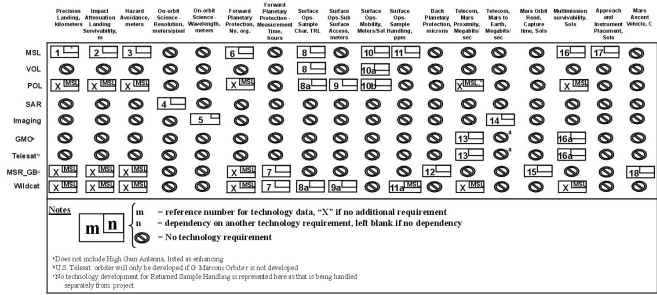
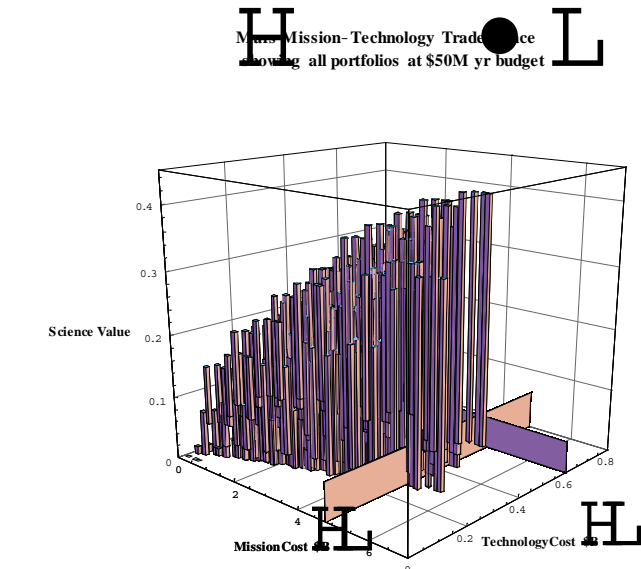


Figure 2. Sample results for Mars technology portfolios



less if an actual rather than parametric budget profile were used. Third, it was observed that expected science value, portfolio uncertainty, mission portfolio cost, and technology portfolio costs generally increased together (although technology costs increased at a diminishing rate). This was due to the increasing number of missions in the portfolio, that added science value, and carried additional technologies which brought added risk.

DISCUSSION AND CONCLUSIONS

The results were presented to the Mars Program Systems Engineering Team and endorsed by that group as providing valuable insights and benefits for Mars Program planning. During the course of their review, a number of key areas were also identified for further improvements.

Benefits Provided by the Decision Support System

The DSS enabled a systematic approach to four critical issues facing the Mars Exploration Program:

- 1. Identifying key technologies and their risks to candidate mission concepts;
- 2. Linking science objectives to technology selection;
- 3. Including technological uncertainties;
- 4. Cost and budget limitations on the selection of feasible technologies.

In particular, the ability to provide an audit trail through the process from science objectives, to technology capabilities, to enabled missions, and ultimately to the feasible technology portfolios was viewed as a major contribution.



A second benefit was in capturing key aspects of the problem facing Mars Program planners. The relationships between technologies, risks, costs, missions, dependencies, and budget constraints embodied a complex nest of interactions making it difficult to unravel the effects of adding or deleting technologies, modifying science objectives, or changing budgets and costs. The DSS was seen as useful for managing these effects by modeling important relationships in a consistent manner that allowed a variety of planning assumptions to be tested.

A third benefit was the ability of the DSS software tool to rapidly enumerate and evaluate every mission technology portfolio combination. This provided an additional level of confidence in the approach that a comprehensive view had been considered rather than some limited set produced by a time-constrained committee or because of modeling limitations.

A fourth benefit was the enhancement of communication between Mars Program mission planners and technologists. It was observed that mission planners sometimes levied requirements they viewed as goals whereas the technologists viewed the requirements as fixed and had assumptions and constraints about the requirements not communicated clearly to the mission planners. In some cases, missions were surprised to discover they were assumed to be developing predecessor technologies for subsequent missions. Technologists were similarly amazed to find that expectations about their development tasks exceeded their own objectives. The interactive process of gathering the data for Table 3 raised awareness and clarified understanding about assumptions, budgets, and work efforts not clearly understood or defined prior to the exercise.

Notwithstanding these benefits, the approach did have a number of limitations. The first issue surfaced by the Mars Program Systems Engineering Team involved questions about the uncertainties in technology definitions and data quality. While it was acknowledged that estimation of costs and technology development over a 12-year horizon was difficult, it was argued that having the ability to examine the effects of data variability was at least a first step toward understanding how such estimates might be improved.

A second issue was the effect of temporal dependencies between missions in a portfolio. The sequencing of missions is a process designed to provide "feed-forward" information from one mission to the next. For example, mapping by an orbiter could be used to improve knowledge about future landing sites for landed missions. The current methodology did not attempt to explicitly model this "learning" aspect of mission success. A third limitation was the focus on technology investment cost feasibility as simply the difference between total technology cost and budget within each time period. The addition of techniques to optimize the budget resource profile should be incorporated to allow the movement of excess budget funds (subject to constraints) from adjacent years into years where insufficient funds have identified a potentially viable portfolio infeasible.

During the course of applying R&D DSS to the Mars Exploration Technology Program, a number of conclusions were drawn.

1. The DSS revealed a wide variety of tradeoffs and patterns not previously studied. The tool was used to organize and manage the project, technology, and cost data in a manner that enabled a comprehensive analysis of numerous programmatic dimensions.
2. The DSS provided a systematic tool for linking science objectives to enabling technologies to missions and identified high-science value technology portfolios that minimized technology costs and risks.
3. The R&D portfolio approach helped clarify understanding between mission planners and technology developers
4. The inclusion of technology cost profiles and budget constraints immediately focused attention on feasible options by eliminating infeasible portfolios.

The application of the systematic tools and techniques described in this paper to Mars technology and mission planning provided a quantifiable and traceable approach to Mars Program personnel about science, technology, and mission interdependencies. The identification

of high-value portfolios was seen as a useful step toward making appropriate technology investments for the Mars Exploration Program.

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