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RISK ANALYSIS AND SYSTEM TRADES IN THE MARS SAMPLE RETURN (MSR) MISSION

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Abstract

Risk management advocates have long sought to directly influence the early stages of the systems engineering process through a more effective role in system design trade studies, The principal obstacle to this has been the lack of credible ways to represent and quantify mission risk—that is, *mission return from a probabilistic viewpoint—for* the project manager and the rest of the design team. If it were possible to quantify mission risk, then the effects of proposed mission and system design changes could be calculated, and along with life-cycle costs, could be used to select better designs.

This paper describes the systems analytic framework for calculating risk-based measures of effectiveness (MoEs) for the Mars Sample Return (MSR) mission planned for the early part of the next decade. The framework integrates a number of diverse models and simulations, each of which contributes some vital piece of the puzzle. The integrated models and simulations include: Mars environments models, a rover operations simulation, reliability models and simulations, a precision landing model, and a decision tree model. The paper concludes with results and lessons learned from this approach.

Introduction

Risk management advocates have long sought to directly influence the early stages of the systems engineering process through a more effective role in system design trade studies. The principal obstacle to this has been the lack of credible ways to represent and quantify mission risk—that is, *mission return from a probabilistic viewpoint—for* the project manager and the rest of the design team. In other words, risk managers have often been stymied by their inability to measure what they are trying to manage. If it were possible to quantify mission risk, then the effects of proposed mission and system design changes could be calculated, and along with life-cycle costs, could be used to select better designs.[1]

Calculating mission return in a probabilistic way leads to some very natural measures of effectiveness (MoEs) for the mission. These risk-based MoEs can show the project manager (or other decision maker), *for a given design,* what confidence **is associated with each level of mission** return, or alternatively, what design improvements (or descopes) are needed in order to reach a given level of confidence in a particular level of mission return. Further,

[1] When the concept of probabilistic mission return is introduced, one must be careful in defining what is meant by a "better" design. A strong definition involves stochastic *dominance.* Design Alternative A stochastically dominates Alternative B if As mission return is greater than or equal to B's at each probability level. One might also consider situations in which Alternative A is a little worse than B at near-nominal conditions, but a great deal better when off-nominal conditions are encountered. Alternative A may then be considered a more robust design. Choosing between alternatives in which stochastic dominance does not occur is usually handled by picking the one that maximizes the expected (von Neumann) utility, where the utility function is defined over the domain of mission return.

calculating a probabilistic mission return is an essential step toward building MoEs that can take into account the project manager's risk aversion—that is, how much the project manager is willing to pay to avoid adverse outcomes on the tail of the mission return probability distribution.

Decision analysis and risk models provide the framework for calculating risk-based MoEs. In early work for the *Pluto Fast Flyby* project, since renamed to *Pluto Express,* three related risk-based MoEs were calculated: (1) the probability of returning at least one gigabit (Gbit) of science data, (2) the expected volume (in Gbits) of science data returned, and (3) the *certainty equivalent* science data volume (again, in Gbits).[2] Even though all three measures used probability information generated by a decision analysis model, only the third took into account the project manager's attitude toward risk. These risk-based measures were profitably used in trade studies of alternative mission and system designs—one of the first such uses.

The decision analysis model from which these project-level calculations were made contained detail only down to the system level. For example, overaH spacecraft reliability (as a function of time) was an input, not the reliability of each spacecraft subsystem or component. To gain credibility as a trade study technique, future decision analysis and risk models must take the level of detail to the subsystem level or lower. This paper focuses on the framework for doing so for the Mars Sample Return (MSR) mission planned for the early part of the next decade.

The objective of the Mars Sample Return mission is to return a number of samples of the Martian surface to Earth for detailed scientific studies. The mission is technically difficult because a number of successful transactions must occur among the various systems employed. Those systems must also operate over an extended period of time in the harsh Martian environment, which itself cannot be characterized with a high degree of certainty. In one mission architecture, the MSR involves sending one or more planetary surface rovers to examine, collect, or cache small (c 10 grams) samples of Martian rocks. A separate ascent/return vehicle(s), launched much later than the *caching rover(s),* also carries a rover, but one designed for retrieving the cached samples. This ascent/return vehicle performs a precision landing near a caching rover loaded with samples. The *retrieval rover* sprints to the caching rover and returns to the ascent/return vehicle with the precious samples. These are then transferred to the ascent/return vehicle for the return trip to Earth. Command and communication between Earth and this Martian ensemble are maintain with the help of a separate relay satellite in Mars orbit.

For the purpose of this paper, I have focused on the surface operations portion of the MSR. Some **sophisticated risk-related** questions one might ask about this mission architecture include: (1) what is the probability of a single retrieval rover and ascent/return vehicle combination performing a successful rendezvous and transfer with a single caching rover, (2) what is the cumulative distribution function for the number of samples delivered to ascent/vehicle(s), taking into account multiple such vehicles and rovers, and (3) what is the cumulative distribution function for the utility of samples delivered to ascent/vehicle(s), taking into account multiple such vehicles and rovers. The calculations needed to answer these questions (and to compute risk-related MoEs) are complex because they depend on the details of the design of each of the systems employed and on the Martian environment in which they must operate. The ability, however, to make such calculations would permit trade studies (to be performed) that result in better rover

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[2] *Certainty equivalent* here means the volume of science data (say, x Gbits) that leaves the decision maker (who could be the sponsor, project scientist, or project manager) indifferent between the choice of x with certainty and the uncertain volume they will actually receive from the mission.

design requirements and risk mitigation strategies.

Of course, there are other risks that the project (or risk) manager faces in the design and development phases of the MSR, e.g., the risk of exceeding a fixed development budget, or of falling short on a critical design parameter. Techniques for identifying, analyzing, mitigating, and tracking these risks have been documented elsewhere.[3] In this paper, I will not focus on these risks, but rather on the risks associated with the retrieval rover's ability in returning the cache of samples to the ascent/return vehicle. I plan to calculate a risk-based mission effectiveness metric by characterizing the retrieval rover's reliability in performing that task. The calculation relies heavily on the use of simulations of the rover and its interactions with the Mars environments. The design models and simulations used to make this calculation include a rover operations simulations constructed using a commercial system architecting tool, called FORESIGHT (© NuThena) and a JPL-developed rover reliability simulation written in FORTRAN.

A decision tree model, currently embodied in another commercial tool called DPL[4] (© Applied Decision Analysis, Inc.), is used to represent combinations of Mars environment parameters and their respective probabilities. DPL is also used to complete the analysis as the results provided by the design simulations and models (i.e., the "consequences" of different environmental parameters for the retrieval rover reliability) are returned to the decision tree and used to calculate the risk-based metric for mission/system trade studies. The ensemble of interacting models and simulations is shown as Figure 1.

Technical Approach

The technical approach first involves constructing a decision tree model that represents Mars environmental uncertainties. Three environmental uncertainties are represented in the DPL model: (1) surface roughness, (2) optical depth (also known as atmospheric opacity and denoted by the letter tau), and (3) deviations from the nominal diurnal near-surface temperature cycle. The current tree allows three different values for the surface roughness parameter, six different values for tau, and three deviations for temperature-making 54 combinations in all. All three parameters are treated as site-specific; the latter two are season-specific as well.[5]

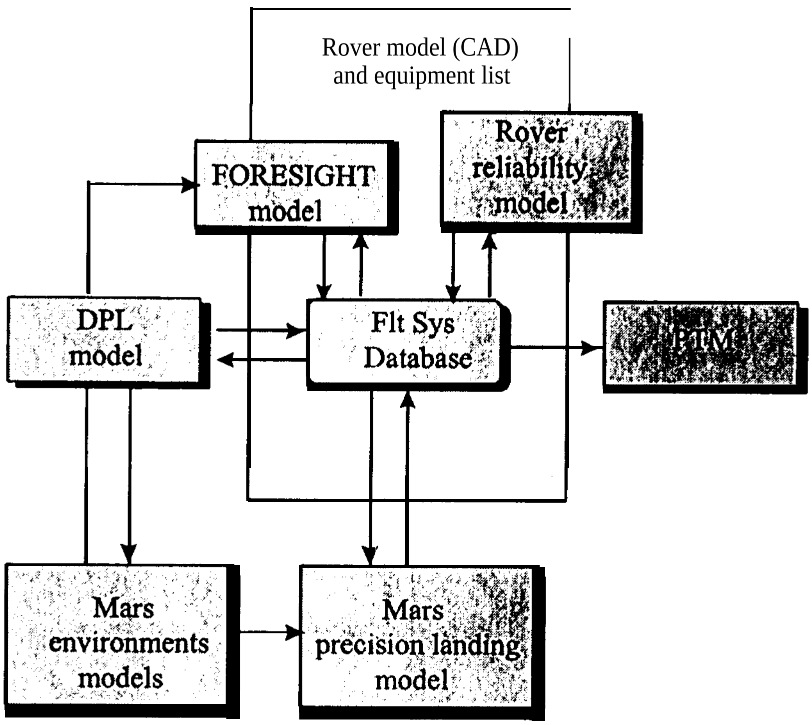
These Mars environmental parameters are the responsibility of the Mars geologists and climatologists. Traditionally, they have provided system engineers with point estimates for these parameters, but the risk analysis approach requires that they provide a range of values and their respective probabilities. While the environmental uncertainties may be interesting it's their effects on the systems that are important for mission effectiveness.

Consider the effect of optical depth. The optical depth affects the rover's solar array power system. In daylight hours, the maximum amount of power that can be **generated is reduced by higher values of** tau. The rover is able to travel fewer hours each sol on average and must spend more time recharging its batteries. The effect of optical depth on the *Sojourner's* solar arrays is shown in Figure 2. (*Sojourner* did not have a rechargeable battery, but the caching and retrieval rovers will.) Next, consider surface roughness. A higher degree of roughness slows the rover's progress toward its target, and increases the total distance traveled (avoiding large obstacles) and energy drawn from the power system.

[3] See, for example, Ref. [1], pp.37-44.

[4] DPL = Decision Programming Language

[5] Time of year on Mars is usually denoted by areocentric longitude, where zero degrees refers to the vernal equinox in the northern hemisphere. The Mars Pathfinder landing occurred, for example, at an areocentric longitude of 143°, which is roughly mid-to-late Summer.



F'igure *l—The ensemble of models and simulations used in the MSR risk analysis. Arrows indicate the flow of information from one model to another. This is usually mediated by the Oracle-based Flight Systems Parameters Database.*

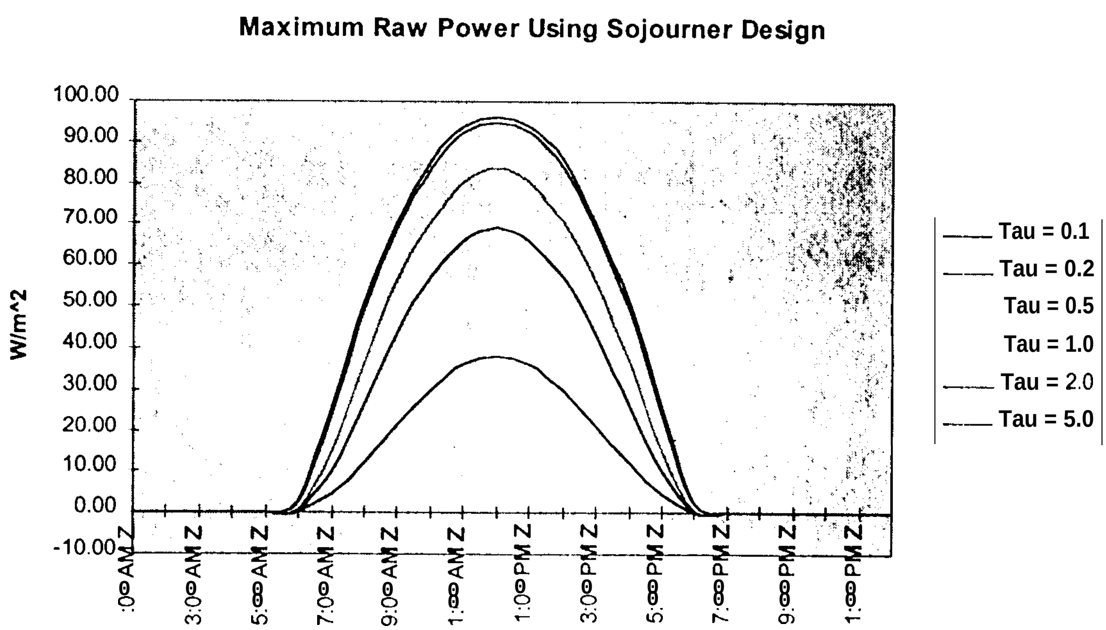


Figure *2—Maximum raw power is reduced by higher values of tau. In dust storms (tau=5.0), power requirements for traversing terrain can exceed power production, even at its peak at noon.*

Figure *3--A synthetic Mars terrain that statistically and geologically mimics the Viking Lander 2 site. This image was generated by the Mars Terrain Simulator.*

One of the important environment models that is needed by the FORESIGHT rover simulation is a high resolution representation of Mars terrain. Fortunately, a capability to generate statistically and geologically correct synthetic Martian surfaces already existed as a result of research conducted in the early 1990s [Ref. 2]. Furthermore, JPL software, called the *Mars Terrain Simulator* (MTS), could be readily adapted to the rover analysis. The simulation produces a topological map of the surface, selected portions of which can be viewed at arbitrarily high resolution (- 1 cm) to accommodate engineering, landing, and exploration studies. The current version of the simulation also adds the illumination effects of an atmosphere. The topographical map can be based on statistically known Martian sites (e.g., from Viking Lander 1 and 2), or on user-provided statistics. A camera model built into the MTS provides a stereo view of the terrain viewed from an arbitrary location, say, a rover. Figure 3 shows a synthetic MTS surface based on the Viking Lander 2 site as *seen* from the *Sojourner's* cameras.

The FORESIGHT rover simulation takes a specific set of environmental conditions and calculates operational outcomes such as the actual distance traveled and actual elapsed time of travel required to cover a specified geodesic distance. This simulation uses rover subsystem design characteristics as key inputs. Changes in the rover design can be quickly accommodated in FORESIGHT, and the model is intended to be reusable over several missions. One role of the rover simulation is to provide quantitative values for the failure drivers (e.g., operating time, distance driven, on-off cycles needed to complete the mission) in the rover hardware reliability model.

The FORESIGHT rover simulation is run many times so as to ensure a sufficient sample of results. These results are then passed to the rover hardware reliability model. This model does three calculations: (1) applies probabilistic physics of failure reliability equations to each component, taking into account temperature variations described in the DPL decision tree model, (2) convolutes these results with FORESIGHT outcomes, and (3) produces failure probabilities for a particular rover design (based on its equipment list). These results are then returned to DPL for final processing into a cumulative distribution function (calf) of the retrieval rover's reliability in the sample return mission.

The geodesic distance the retrieval rover must travel to complete its mission is itself a random variable because the actual landing point of the ascent/return vehicle is seldom the same as the targeted point. The landing footprint can be modeled as a hi-variate normal with independent standard deviations in the longitudinal (σ_x) and transverse (σ_y) directions. A stochastic model is needed to provide the parameters of the landing dispersion. Such a model was developed for the Mars Pathfinder parachute and airbag entry, descent, and landing system [Ref. 3].

For the MSR ascent/return vehicle landing on Mars, a precision propulsive landing has been proposed and a new stochastic landing model is needed. Such a model is being developed by JPL and the NASA Ames Research Center (ARC). Until it is available, we assume σ_x = 3 km and σ_y = 1 km. These parameters are provided directly to the DPL decision tree model.

Clearly, the risk-based MoEs depend on the accuracy of the precision landing system and the inherent reliability of the retrieval rover. The marginal effectiveness of changes in the rover's design or the precision landing system's design can be computed in the analysis. Trades across these two systems can be made at the MSR project level once the marginal costs of the design changes are known.

Because the risk-based MoEs require the interplay of many models (in different languages, file formats, etc.), we use the PDC/DNP[6] Flight System Parameters Database (in Oracle © DBMS) to move data from one model to another. Each model is configured so as to take advantage of this software architecture. The MoEs calculated in DPL are displayed as part of a MSR Project Trades Model (PTM).[7]

Results To Date

For a variety of reasons, the first FORESIGHT rover simulation was built around the *Sojourner* design. We will refer to this as the *Sojourner* simulation. One reason was that the *Sojourner* design was well understood and its technical parameters were known; the MSR retrieval rover, by contrast, is only in conceptual design at present. Experience in building the FORESIGHT rover simulation could better be gained without having to guess at various design parameters at this early stage.

One of the most difficult parts of building the rover simulation model is

[6] PDC/DNP = Project Design Center/ Develop New Products

[7] The Project Trades Model is the principal trade study tool used in the Project Design Center. Each PTM is custom-built for a mission with inputs coming from many Phase A/B tools and simulations.

modeling the behavior of the Control and Navigation Subsystem. The *Sojourner* simulation uses the actual flight software for the controlling the rover's movement over the synthetic Martian terrain. The optical navigation algorithms for the MSR retrieval rover are still under development. So **a** second reason for starting with the *Sojourner* simulation was the ease with which this critical subsystem could be modeled.

A third reason was to use some recently developed *Sojourner* wheel motor failure models, as it was thought that these components had an uncomfortably short life.

As of the time of this writing, we have completed only a single series of test runs of the *Sojourner* simulation. That series of runs involved a single set of environmental parameters and a set of different initial rover positions all of which were 10 meters (geodesic distance) from the target. The Mars environment selected was a very clear day (Tau = 0.1) on a terrain that we describe as a 50% Viking Lander 2 (VL2) site. By that we mean that the statistical size-frequency distribution of rocks and craters was the same as characterized by **Golembek [Ref. 4]** for VL2, except that the **absolute** number of rocks and craters **(centers)** per square meter was only half of the actual VL2 site.[8] This surface roughness parameter was passed to the Mars Terrain Simulator, which created our desired virtual Martian terrain.

The **results** of the *Sojourner* simulation test runs for rover distance actually traveled were converted into a Weibull probability density function using well-known parameter estimation techniques described in Ref. [5]. This curve is shown as Figure 4.[9]

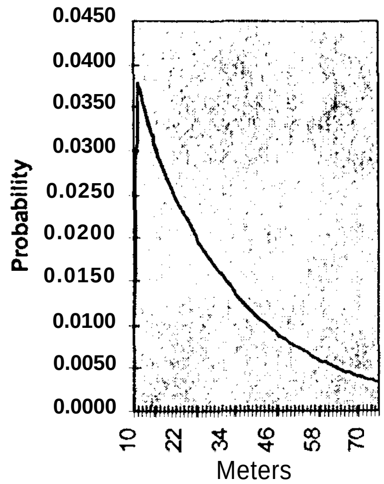


Figure 4—*Weibull Probability Density' for Sojourner Travel Distance To Go 10 Meters Geodesic Distance Based on Simulation Test Runs*

This probability density function is not to be trusted until many more simulation runs have been made with geodesic distance on the order of 100 meters instead of 10. We are currently performing these **runs for all the combinations of Mars** environmental parameters in the MSR decision tree model.

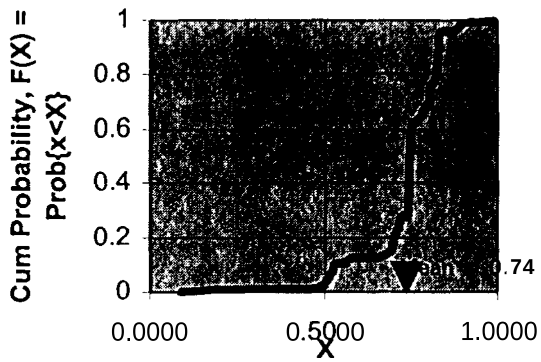
Once these simulations have been run, the results will be passed to the rover hardware reliability model. The resultant reliability outcomes will then be passed to the decision tree model to be merged with the probability estimates for each combination of Mars environmental parameters. Since this has not occurred as of this writing, I can only offer a prospective look at what the decision tree model results might look like.

Figure 5 shows what the results of the decision tree model and analysis might look like. Again the figure does not reflect

[8] Another way to explain this is to say that we effectively removed half the rocks and craters from the Viking Lander 2 site, but retained its relative size-frequency distribution.

[9] **Over these** short distances, the actual travel time exhibited a strong linear correlation with actual travel distance, which implies a probability density function for travel time similar to that in Figure 4.

real data yet, but only what we might see. The vertical axis shows the cumulative probability of the rover's reliability in reaching the cache of samples and returning to the ascent/return vehicle from which it started. The expected value of this distribution is about 0.74, with the median value just slightly higher at 0.75. Another way of interpreting the figure is to say that half of the probability density lies within the reliability range from 0.7 to 0.8.



Note: x = Reliability of Rover in **Retrieving Container**

Figure *5—Potential results from the decision tree model and analysis. The curve results from the uncertainties in the Mars environment at the landing site, the landing dispersion, and the inherent reliability* of *the retrieval rover.*

Several risk-based MoEs could be quantified on the basis of the figure. One could choose the mean, the median, or the confidence that the reliability exceeds some fixed level, say 80 percent. If the project manager believes that the risk-based MoE is unacceptably low, he/she can:

- Change the rover design by adding redundancy, or raise subsystem reliability and/or performance requirements;

- Improve the precision landing capability of the ascent/return vehicle;

- Change the landing site to increase the probability of a "smoother" one, or change the areocentric longitude to reduce the probability of an adverse optical depth; or

- Some combination of the above.

Each of these changes affects the risk-based MoE, but has (mass, power, etc.) implications for the entire project that must be understood. Each alternative proposed change must also be fully costed before one is chosen.

Conclusions

The ultimate results of the decision tree model and analysis are likely to have important implications for the MSR rover design (reliability, autonomy, etc.) and overall risk mitigation strategies (mission redundancy, hedges, precision landing accuracy improvements).

For now, let me share some observations and lessons learned so far. Mission simulation, for risk analysis or other objectives, requires coupling system models/simulations to space environments models. For in-situ missions, such as the Mars Sample Return, the space environments models need to provide a high resolution representation of the terrain likely to be traversed. We needed considerable effort to integrate analytically the terrain model, the Mars Terrain Simulator, with the FORESIGHT rover simulation.

To contribute to risk decision-making and trade studies in a particular project, space environments experts must begin to provide probabilistic assessments for each critical environmental factor. Engineering "design-to" values (or "safe assumptions") for those factors do not capture the full range of values that might be realized on the mission.

Faster simulation execution time is highly desirable in mission risk analysis because of the number of cases (sets of environmental parameters) and trials (to ensure usable statistical characterizations) that typically need to be run. It was even suggested at JPL that we seek the services of the Caltech supercomputer as a way of speeding up the analysis.

Lastly, there appears to be no known obstacle to performing advanced risk analysis using this federation of models and simulations.

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The research described in this paper was carried out by the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration.