A Mission Taxonomy-Based Approach to Planetary Rover Cost-Reliability Tradeoffs

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ABSTRACT
Our earlier work on robot mission reliability provides tradeoff analysis between input parameters such as mission success rate, robot team size, and robot component reliability, but only for specific tasks. Here we take a more comprehensive approach in order to draw more general conclusions about robot mission reliability. The approach is based on a mission taxonomy coupled with detailed reliability analysis of each of the resultant mission classes. This paper describes initial work towards that goal.

In this paper we present the above-mentioned taxonomy, which divides planetary robotic missions into subgroups with common characteristics with respect to the time proportion of tasks involved in the missions. For a given mission class, we show how a mission designer can obtain the optimum robot configuration in terms of robot team size and component reliability that maximize mission success rate under a budget constraint.

Categories and Subject Descriptors
B.8.2 [**Performance and Reliability**]: Performance Analysis and Design Aids;
G.3 [**Probability and Statistics**]: *reliability and life testing, stochastic processes, survival analysis*

General Terms
Performance, Design, Reliability.

Keywords
Mission design, planetary robot, mission taxonomy, reliability, mission cost, failure, robot configuration optimization.

1. INTRODUCTION
Planetary robots built for NASA by the Jet Propulsion Laboratory are notable for their extremely high reliability. To achieve this magnitude of reliability, the robots make use of some of the most reliable components available and provide high redundancy in the design. This design paradigm comes at high financial cost, however, both in the development cost of the robots and in the ongoing operational costs.

One good example of the high cost of NASA robots is the Mars Science Laboratory (MSL). The mission was given the highest scientific priority in NASA's Mars Program of 2002, but then delayed in the 2006 plan as a result of cost constraints [1]. MSL was initially approved at a budget of approximately $1.5 billion [2], but the budget for the mission kept rising until it reached $2.3 billion [3], of which $1.6 billion was development costs for the rover, its instruments and the spacecraft. The fiscal problem has led to the thought of continuing the over-budget MSL mission at the expense of delaying or even cancelling other projects [4].

MSL is one of many in-situ planetary missions NASA plans to launch in the future. If these future robots follow legacy designs, then the increasingly demanding future missions will require robots to be built using components of order-of-magnitude higher quality, rendering the mission eventually infeasible from a cost and availability standpoint.

Reduction of robot development costs can be achieved if overly reliable components are exchanged for ones more in line with the mission requirement. For this, it is necessary to consider the impact of reduced component reliability on the overall mission risk. It is also necessary to regard risk not simply as something to be minimized to the greatest extent possible, but instead as a quantitative design factor to be traded off against other design factors in order to seek an optimal mission configuration. Therefore, tradeoff analysis between mission risk, component reliability and cost is crucial.

A quantitative methodology for doing so has been proposed in our previous work [5] and [6], but has only been used on a limited number of specific examples. As a result, a mission taxonomy is desirable in order to characterize and examine the full range of planetary robotic missions.

A number of taxonomies for robots, robot tasks, and robot teams have been proposed. For instance, [7] provides a taxonomy that classifies multirobot teams in terms of team size and composition, communications, and processing capability. Reference [8] provides a taxonomy which classifies multirobot tasks in terms of criteria such as time, energy and robot capabilities, and [9] & [10] present a taxonomy which categorizes robot tasks in terms of the amount and type of human-robot interaction involved.

In order to have fundamentally different reliability characteristics and therefore tradeoff relationships among mission classes, we

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hypothesize that it may be sufficient for the amount of time spent using various modules to differ significantly.

Our taxonomy differs from the taxonomy mentioned above in that it classifies robot missions with respect to the time proportion of the tasks involved in the missions. The breakdown of the time proportion of the tasks in a mission is important for analyzing the nature/emphasis of a mission.

Drawing from the NASA Roadmap for the exploration of the Solar System over the next 30 years [11] and Mars Exploration Program [1] & [12], we propose three mission classes formed from a set of tasks, which we call "Basic Activities", defined in the next section.

Using the method we introduced in a previous paper [6], we characterize each of the mission classes via state transition graphs and investigate the time proportions of basic activities for the various mission classes. Extending our work in [5], we explore the abovementioned tradeoffs by finding the global optimum robot configuration with respect to the cost and reliability for a specific mission class and setting.

We expect significant differences in time allocation of the basic activities to be reflected in significant differences in the character of the tradeoffs.

2. ROBOT MISSION TAXONOMY

2.1 Taxonomy Criterion

In generating a mission taxonomy, it is crucial to create a standard feature with respect to which different missions are compared and classified. It is also important that the feature be quantifiable so that the classification generated can be studied analytically. Identification of this key feature will allow its systematic variation in the step of determining mission reliability. In this light, we attempted to answer the following three questions:

1. Can different types of missions be identified?
2. If missions can be identified, can their features be isolated?
3. If features of a mission can be isolated, can they also be tailored to form another type of mission?

We comprehensively surveyed future in-situ planetary robotic missions from the NASA Solar System Exploration Roadmap (SSER) and Mars Exploration Program (MEP) and identified several fundamental tasks, independent of each other, that are present in all of the missions but exist in different proportions. The mix of these fundamental tasks, which we term "Basic Activities", is the feature with which we measure and compare different missions. We quantify the proportion of a basic activity in a mission in terms of percentage by comparing the time spent in that particular task to the total mission time.

Analyzing every mission instance we encountered in the roadmap, we concluded that a mission can be characterized using the following nine basic activities:

1. Traverse (e.g., driving, flying)
2. Subsurface Access (e.g., drilling, grinding, digging)
3. Instrument Deployment (e.g., manipulator, camera)
4. Sampling (e.g., image, soil)
5. Assembly
6. Communication
7. Sample Analysis
8. Recharging
9. Idling

We do not expect the percentage proportions of basic activities that constitute a specific mission class to be absolutely fixed. Rather, they will fall into a range such that the character of a mission significantly changes only when the proportions exceed that range.

Initially, we performed qualitative separation between mission classes, thus determining the range mentioned above, based on our analysis of SSER and MEP. Afterwards, we will ground-truth the qualitative boundaries we made for each mission class quantitatively using the methodology outlined in subsection 4.1 and use the resulting boundary for differentiating between missions.

2.2 Mission Classes

For the purpose of generating the taxonomy, we did a comprehensive study of the following NASA-proposed in-situ robotic operations:

- Europa Explorer, Europa Astrobiology Lander,
- Titan Explorer,
- Venus In-Situ Explorer, Venus Mobile Explorer, Venus Sample Return,
- Neptune-Triton Explorer,
- Lunar South Pole-Aitken Basin Sample Return,
- Mars Pathfinder-Sojourner, Mars Scout Phoenix, MER, MSL, Astrobiology Field Laboratory, and
- Comet Cryogenic Nucleus Sample Return

Based on the above study, we propose categorizing missions into three classes followed by their examples:

1. Search and Exploration Mission:
    a. Search for biomarker signatures
    b. Search for water resources
    c. Surface mapping

2. Sample Acquisition and Composition Analysis Mission:
    a. Surface rock sampling
    b. Organic materials sampling
    c. Analysis of chemical and isotopic composition of surface

3. Construction Mission:
    a. Radiation shielded habitat construction (Lunar)
    b. Lunar outpost construction (Lunar)

In order to validate the above classification scheme, we use the methodology introduced in our previous work [6] by stochastically simulating a mission class using a state transition diagram. Each state in the diagram corresponds to a basic activity. The process flow and the resulting time proportion of the basic activities are explained in subsections 3.1 and 4.1, respectively.

3. CONSTRUCTION MISSION SCENARIO

3.1 Mission and Environment

Due to NASA's strong interest in building permanent bases in planetary environments, we use the taxonomy above as a framework to consider a Construction Mission class in a planetary environment to install modules at several sites using a team of robots. The installation task consists of carrying modules from a module depot to the designated sites and then assembling them. We extend our previous work of simply carrying a module to a site and repeating the task [5] into a more mature scenario that better resembles a general planetary in-situ construction mission. This allows us to consider energy limitations on the robots and further elaborate the robot model and the working environment.

Based on [13] and [14], we envision that in a construction mission at least three types of location would exist: a battery recharging station (i.e., solar panel plant, robot base), a module depository and the construction sites. As also stated in the literature, we expect that in a planetary environment there exist areas that receive steadier sunlight; thus, solar power generation on a stationary site would be more efficient than on the peripatetic robots, which would potentially work in a shadowed and dusty environment. However, our methodology also works in the case where a site co-locates with another or in the case where all of them co-locate in one place.

This environment model is shown in Figure 1. The locations are represented as nodes with the distance between locations written as weights (in meters) on the edges. Connected nodes show the possible paths the robots can take. We selected the weights in the figure as our baseline model and varied them in the simulation.

For the purpose of the reliability analysis, the mission is broken down into seven basic activities:

1. Transit to the module depot
2. Fetch modules
3. Transit to the construction site
4. Stack modules
5. Assemble modules
   Repeat 1 – 5 until all sites are completed.
6. Communicate with other robots after every subtask.
7. When needed, return to the recharging site (via depot as checkpoint) and replenish battery.

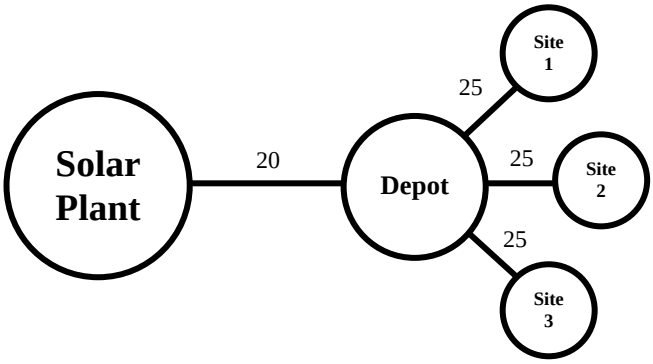

Figure 1. Environment model in graph diagram.

Each robot works independently of the others and coordination to avoid overlapping tasks (e.g., carrying more modules than needed, assigning more robots than needed to install a module, etc.) is done by communication among the robots after the completion of each subtask. In the case of a failure of a robot, a new spare robot will be deployed from the headquarters to continue the mission. The mission is considered a success when all the necessary modules are installed at the sites.

3.2 Robots and Components

For this analysis we assume that the robots are identical. Making appropriate inference from various sources [14], [16], we assume each robot weighs 174 kg and uses two 7.15-kg lithium ion batteries (150 W-h/kg) for energy storage. The power consumption model used in the simulation is listed in Table 1. The robot velocity is assumed to be a constant 0.1 m/s throughout the mission.

The robot subsystem reliabilities are listed in Table 2. The subsystem reliability data were derived from component reliability data provided by the Jet Propulsion Laboratory and are representative of components used in NASA's planetary robots. The usage times of each subsystem for each basic activity are shown in Table 3. These usage times were assigned using reasonable assumptions about the relative durations of different activities and the relative usage of different modules.

We used the above-described model and the methodology in our previous work [6] to calculate the probability of subsystem survival for a given mission activity. In this calculation, we assumed that the battery recharging task is always successful and hence excluded it from the reliability consideration. We also assumed that the recharging station is always capable of generating maximum energy and fully recharging batteries regardless of climate disturbances, e.g., dust storms, dust build-up, or poor sun exposure.

Table 1. Power consumption model

Basic Activity	Power Consumption
Traverse	150 W
Instrument Deployment	52 W
Communication	74 W
Assembly	52 W
Idling	15 W

Table 2. Robot subsystems and reliabilities

Subsystem	MTTF (h)
Power	4202
Computation & Sensing	4769
Mobility	19724
Communications	11876
Manipulator	13793

Table 3. Subsystem usage by task in minutes using baseline constant in Table 1

Subsystem	Transit (Solar Plant -Depot)	Fetch / Stack Modules	Transit (Depot-Site)
Power	33.33	60	4.17
Computation & Sensing	33.33	60	4.17
Mobility	33.33	30	4.17
Communications	0	0	0
Manipulator	0	60	0

Subsystem	Module Assembling	Communication
Power	300	15
Computation & Sensing	300	15
Mobility	120	0
Communications	0	15
Manipulator	300	0

4. APPROACH

We generated a state-transition diagram for the Construction class mission based on the mission flow described in subsection 3.1. The state machines represented by the diagram are then implemented in simulation software. The simulation is repeated many times, with the average score of all trials giving the overall probability of mission completion (PoMC).

For this mission scenario, once the mission flow, the basic activity durations and the baseline module reliabilities are fixed, then the input variables are:

- Number of installation sites
- Number of modules to be installed per site
- Number of robots
- Number of spare robots
- Reliability of the components used
- Maximum number of modules a robot can carry
- Distance between recharging site and module depot
- Distance between module depot and installation sites

Thus, PoMC and the time proportion of the basic activities are functions of these input variables and varying these variables results in a change in the output PoMC and the time proportion.

4.1 Time Proportion of Construction Class

Given the hyper-dimensionality of the model, we simplify the analysis by varying only one variable at a time and fixing the rest, and looking at the relationship between the varied variable and the time proportion of the basic activities in the Construction mission class as well as PoMC.

Graphically, this means that we are reducing the dimensionality of the model by only analyzing a slice of the hyper-plane at a time. Intuitively, the function of PoMC with respect to the variable being varied and the time proportion would only be valid at that particular slice and might not hold at different set of values of the remaining variables. In that light, here we would like to see how much the time proportion of the basic activities will vary for different slices of the hyper-plane.

In every simulation with mission success rate greater than zero, we record the time spent on the basic activities. We set the baseline variables as shown in Table 4 and then increment the variable to be varied along the x-axis from the minimum to the maximum expected value.

Our result shows that the time proportion of the basic activities in the Construction mission class does not vary greatly between different slices of the hyper-plane (see Table 5).

Our sensitivity analysis shows that the number of installation sites and the number of modules to be installed per site have small influence on the time proportions. Intuitively, an increase in the amount of work (i.e., number of sites and/or modules) leads to an increase in the time share of module assembling. However, due to the limitation on the number of modules that a robot can carry, the robots are forced to return to Depot to fetch more modules, hence increasing the time proportion of other activities, as well (see Figure 2).

The variables that have the most influence on the time proportions are the number of robots deployed and the distance (i.e., Solar plant to depot, depot to construction sites) to be travelled by them. For the latter, the reason is straightforward: an increase in either

Table 4. Baseline constants used in the simulation

Variable	Value
#Sites	10
#Modules/site	5
#Robots	2
#Spare robots	0
%MTTF	100%
#Module capacity/robot	3
d(Solar Plant - Depot)	200
d(Depot – Site)	25

Table 5. Time proportion in the Construction class mission

Basic Activities	% of Mission Time (±2%)
Traverse	4
Instrument Deployment	21
Module Assembling	47
Communication	17
Recharging	11
Idling	< 1

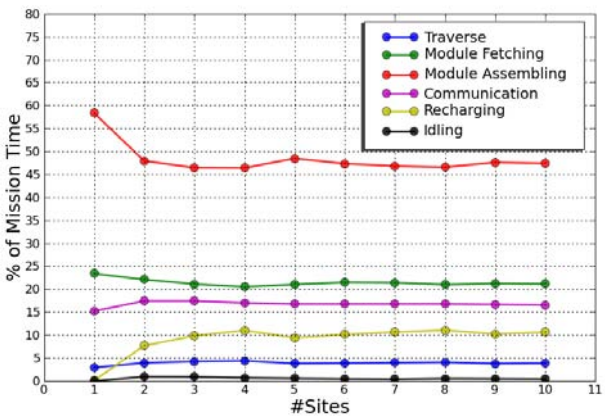

Figure 2. Varying number of installation sites.

of these distances directly increases the time spent in Traverse, thus increasing its relative proportion to the remaining basic activities. For the former, increasing the number of robots proportionally increases the amount of coordination (hence, communication) among the robots. By fixing the amount of work (i.e., number of sites and/or modules), the coordination to avoid overlapping tasks between the robots causes deploying more robots to result in some of the robots' being idle (see Figure 3). However, if the amount of work increases proportionally with the number of robots deployed, then the time proportion of the basic activities will follow the general proportion described in Table 5.

Indeed, the resulting time proportion significantly depends on the robot work rate in performing an activity (see Table 3). However, we also have confirmed that the time proportion for each activity does not fluctuate drastically (still falls within a small range) and observed the same sensitivity pattern in different models.

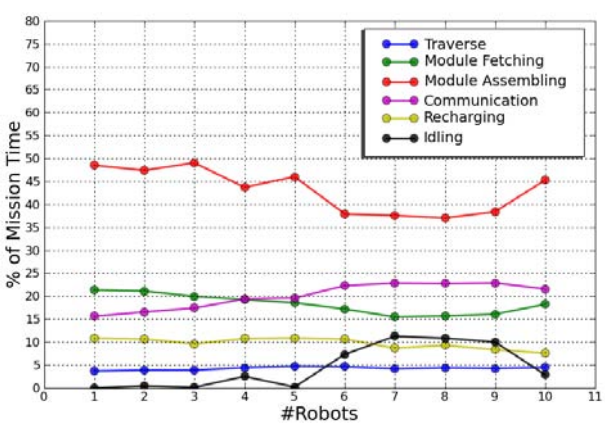

Figure 3. Varying number of robots.

4.2 Designer Questions

In the conceptual mission designing phase, a mission designer might ask questions such as:

Given a fixed budget and a fixed number of sites to build,

1. Which configurations of robots in terms of team size and robot component reliability (%MTTF) give the highest mission success rate?
2. Which is better, a smaller number of robots with highly reliable components or a larger number of robots with less reliable components?

4.3 Cost Function

We adopt the general relationship of reliability and cost, where cost is an exponential function of component reliability. The exponential relation means that, the higher the reliability of a component, the smaller increase in reliability per unit expenditure. We assume that the robot component cost is a linear combination of two types of cost function: component material cost and production cost where each is represented as an increasing exponential function. The total cost function (robot component cost) is then given as follows:

$$C(R) = k_1 e^{k_2 R + k_3} + c_1 e^{c_2 R + c_3}, \qquad (1)$$

where

$R =$ percentage of component reliability compared to the baseline model

$k_1 =$ the weight of component material cost

$c_1 =$ the weight of component production cost

$k_2, k_3, c_2, c_3 =$ parameters to adjust the initial cost (when R=0%) and the cost when R=100%

For analysis purposes, we assume that the component material cost and production cost contribute equally to the total component cost. We also assume that there is still a cost to be incurred even when producing a poor-quality component (i.e., reliability R=0). For this purpose, we set the parameters k_1, k_2, k_3, c_2, c_3 such that the initial component cost (when R=0) is 20% of the total budget. Note that $k_i = c_i$ for $i = 1,2,3$. The details of the parameters are given in Equation 2 and a plot of the cost function for different robot team sizes is shown in Figure 4.

$$C(R) = 2e^{1.61R+2.3}, \qquad (2)$$

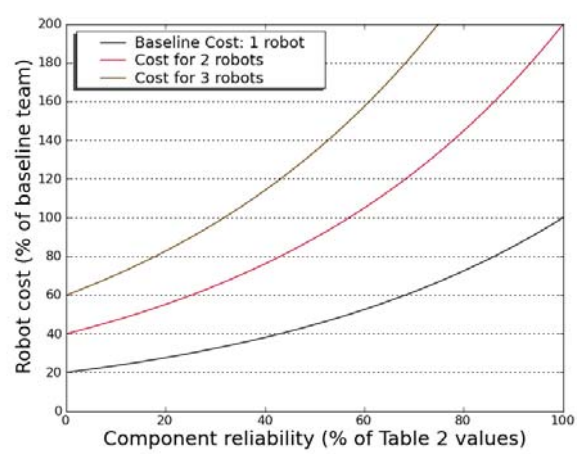

Figure 4. Component cost (=material cost and production cost) as a function of component reliability (%MTTF).

It is noteworthy that our methodology works with any cost function. The cost model described here serves as an alternative example to the cost model used in [5], which was taken from reference [15]. Both cost models are monotonically increasing functions of component reliability. However, the latter has a drastic gradient between low- and high-reliability components such that the cost of a high-reliability component is very high (i.e., an increase in 5% component reliability from 90% reliability to 95% reliability would result in a large price increase from 60% to 100% of the baseline cost) and the cost of a low-reliability component is very low (i.e., an increase in 40% component reliability from 40% reliability to 80% reliability results only in minor price increase from 40% to 47% of the baseline cost). It is possible to attenuate the extreme to some extent by lowering the feasibility parameter provided, but the maximum achievable reliability will also be greatly lowered.

The cost model we propose here provides a more gradual increase in unit expenditure per increase in component reliability. In subsections 4.4 & 4.5, we will observe the outcome of the reliability tradeoff using both cost functions.

4.4 Optimizing Robot Configuration

Using the cost model from the previous subsection, we seek to optimize the robot configuration for the Construction mission class with respect to the criteria posed in subsection 4.2.

A mission designer would presumably like to design as reliable a system as possible under budget constraints while achieving the highest possible mission success rate. This issue relates closely to our tradeoff model between component reliability (%MTTF), robot team size, cost and probability of mission completion (PoMC). The idea is to come up with a robot team size with a certain component reliability that can maximize PoMC under a fixed budget.

In Figure 5, using the data listed in Table 4 as the input variables, we plot several tradeoff relations between component reliability (%MTTF) and mission success rate (PoMC) for different robot team sizes (from 2 to 5 in red, brown, green, yellow lines). We have also fitted a curve to these points, allowing this equalizing %MTTF to be estimated for intermediate points without running additional simulations. The black horizontal line shows the PoMC for the baseline configuration (1 robot with 100% component reliability).

Based on the cost model for one robot (Equation 2), we calculate the respective budget needed for 2 to 5 robots. By doing so, we are able to compute the maximum achievable component reliability (%MTTF) under the budget constraint for each team size. This is shown as dashed vertical lines in Figure 5.

The intersection between the dashed vertical lines and the PoMC curve (a function of %MTTF) then gives the maximum achievable PoMC for each team configuration (using the maximum achievable %MTTF) given the budget constraint.

In this graph, we have 4 intersections (for 2 to 5 robots). Analysis of all the intersections shows that in this mission scenario of the Construction mission class, a configuration of 3 robots with 31.9% MTTF of the baseline reliability (see Table 2) gives the highest probability of mission success under the budget constraint.

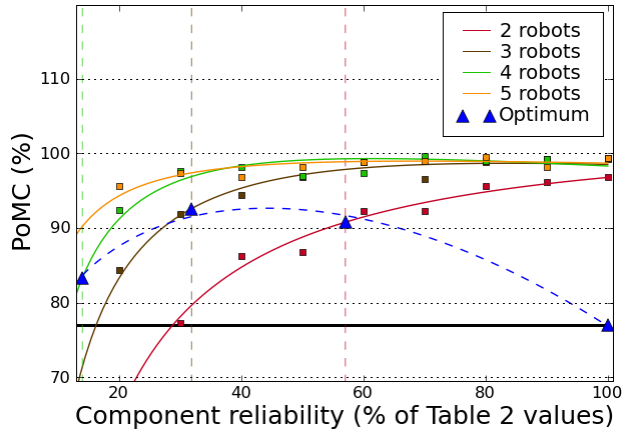

Figure 5. Tradeoff between %MTTF, PoMC and Cost for various team sizes when #Sites = 10.

Mission designers may replace the component reliability – cost model utilized here with their own. Obviously, using a different cost model would potentially result in a different optimum robot configuration. For example, with the same initial component cost (when R=0) of 20% from the total budget, using the cost model we utilized in our previous paper ($R_{min} = 0, R_{max} = 1, f = 0.8$) [5] would result in a robot team size of 4 with 52.7% MTTF of the baseline reliability being the optimum configuration under the budget constraint.

4.5 Robot Team Size-Reliability Tradeoff

Previously in [6], we answered this tradeoff question by providing an example of how a team of 4 robots with less reliable components has a higher mission success rate (PoMC) than a team of 2 robots with more reliable components. Here we would like to corroborate that statement and extend the analysis by observing it through the optimization methodology described above.

Using the same scenario as in the previous subsection and the cost model from Equation 2, we increase the number of construction sites from 10 to 50 and plot the tradeoff graph in Figure 6. Note that increasing the number of construction sites also increases the mission duration. In the figure, we can see that the optimum robot configuration is no longer 3 robots with 31.9% MTTF of the baseline reliability, but 2 robots with 57.1% MTTF of the baseline reliability. In other words, increasing the mission duration causes the preferred configuration to move in the direction of fewer robots with higher reliability.

Our analysis shows that there exists a turning point where a larger robot team with less reliable components will perform exactly the same (in terms of PoMC) as a smaller robot team with more reliable components when we increase the amount of work (i.e., number of sites and/or modules). Going beyond that turning point results in the smaller robot team with more reliable components producing a higher mission success rate.

The turning point can be explained from the reliability engineering point of view. Reliability is a function of time where the reliability of a component with a constant hazard rate is equal

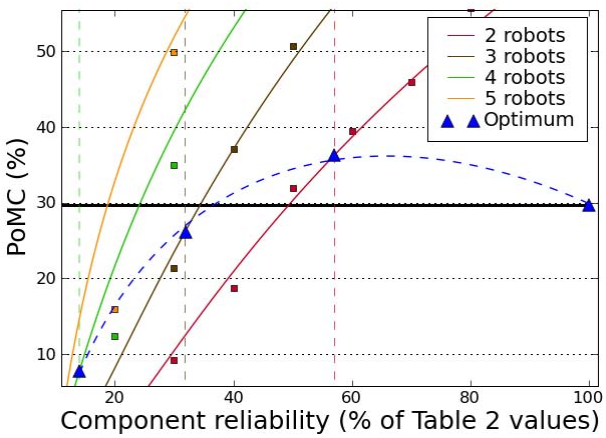

Figure 6. Tradeoff between %MTTF, PoMC and Cost for various team sizes when #Sites = 50.

to one at the beginning of the service life and decays exponentially towards zero. Thus, using components with reduced reliability compared to the baseline component will result in shorter service life and higher failure probability for prolonged usage.

Since we assumed that a failure of any single component leads to a failure of the entire robot, the robot using the components with reduced reliability will likely have a smaller mission success rate for longer mission duration. Likelihood of mission failure can be compensated for by increasing the number of robots. However, this compensation may not be enough to cover the loss in component reliability, especially when the budget is constrained.

Consider a simple example where a robot has a total system reliability expressed in MTTF (hour) of 4202. The budget constraint allows us to double the number of the robots while halving the component reliability of both robots. Now, we compare the mission success rate for both configurations of 1 robot with 4202 MTTF(h) and 2 robots with 2101 MTTF(h). The mission success condition is such that one robot must stay alive in order to complete the mission. For 4000 hours of usage, the mission success rates (PoMC) for both configurations can be calculated as follows:

1 robot, 4202 MTTF(h): $PoMC = e^{-\frac{4000}{4202}} = 0.386$

2 robots, 2101 MTTF(h) each:

For 1 robot, $PoMC = e^{-\frac{4000}{2101}} = 0.149$

For 2 robots,

$$PoMC = 0.149^2 + 2 \times 0.149 \times 0.851 = 0.276$$

Now, we do the same calculation for a mission of 1000 hours:

1 robot, 4202 MTTF(h): $PoMC = e^{-\frac{1000}{4202}} = 0.700$

2 robots, 2101 MTTF(h) each:

For 1 robot, $PoMC = e^{-\frac{1000}{2101}} = 0.621$

For 2 robots,

$$PoMC = 0.621^2 + 2 \times 0.621 \times 0.379 = 0.856$$

Here we can see that for the prolonged 4000 hours mission, for 2 robots 2101 MTTF(h), the loss in PoMC due to the halved component reliability is 0.237 (= 0.386 - 0.149). However, the compensation of doubling the robot number only increases PoMC by 0.127 (= 0.276 - 0.149), which is not enough to cover the loss in PoMC due to reduced component reliability. In the shorter mission of 1000 hours, the loss in PoMC due to halved component reliability is 0.167 (= 0.788 - 0.621) and safely covered by the increase in PoMC of 0.235 (= 0.856 - 0.621) due to the doubling of the number of robots.

In this light, our analysis of various tradeoff cases suggests that, for relatively short missions, the PoMC gain per robot number increase has the likelihood to be larger than the loss of PoMC per component reliability decrease. For relatively long missions, the loss is typically greater than the gain.

Because the maximum achievable number of robots is dependent on the component reliability – cost model, the location of the turning point is also dependent on the cost model. If the cost of mass-producing robots with low-reliability components is cheap enough that PoMC gain per robot number increase is always larger than PoMC loss per component reliability decrease, then the optimization methodology described in the previous subsection would have the general tendency to increase the robot team size and use lower-reliability components.

5. CONCLUSIONS

This paper presents a general framework to explore the tradeoffs among cost, component reliability, and robot team size in planetary robot missions. We comprehensively surveyed every mission instance proposed in NASA's Solar System Exploration Roadmap over the next 30 years [11] and Mars Exploration Program [1] to generate a mission taxonomy. We propose that any mission instances can be characterized by a set of basic mission activities and categorize planetary robot missions based on the time proportion of the activities into three classes: Search and Exploration, Sample Acquisition and Composition Analysis, and Construction. We examined a general mission scenario in the Construction mission class and performed sensitivity analysis of the tradeoff parameters. Our results show the stability of the Construction mission class with respect to the activity time proportions.

In this paper, we also propose a method allowing a mission designer to optimize robot configuration in terms of robot team size and component reliability with respect to probability of mission success (PoMC), given a cost model. The method is not limited to a particular cost model. Mission designers can use an arbitrary cost model and implement the methodology to obtain a specific optimum robot configuration that maximizes mission success rate under a budget constraint.

For the Construction mission class, our analysis shows that for long-term missions, the PoMC loss per component reliability decrease is typically greater than the PoMC gain per robot number increase. Thus, it is more beneficial in terms of the mission success rate to increase the quality of the robot components as opposed to the number of robots, given the budget constraint. For short missions, however, the opposite trend can be

observed, thus, configurations of more robots with less reliable components are preferable.

In future work, we will investigate other mission classes and perform sensitivity analysis of the parameters on the mission classes. We intend to compare the time proportion and reliability tradeoff among the classes to see distinguishable characteristics among them as well as to validate the classification scheme proposed in this paper. In addition, we intend to extend the optimization problem to cost and mission duration. For instance, we seek to answer common mission designer questions like "Under a given mission duration, which configurations of robots result in the highest mission success rate?" or "Given a desirable mission reliability standard, which configurations of robots cost the least?"

6. ACKNOWLEDGMENTS

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