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Comparison of Spares Logistics Analysis Techniques for Long Duration Human Spaceflight

Andrew Owens[1] and Olivier de Weck[2]
Massachusetts Institute of Technology, Cambridge, MA, 02139

Bryan Mattfeld[3] and Chel Stromgren[4]
Binera, Inc., Silver Spring, MD, 20910

and

William Cirillo[5]
NASA Langley Research Center, Hampton, VA, 23681

As the durations and distances involved in human exploration missions increase, the logistics associated with the repair and maintenance becomes more challenging. Whereas the operation of the International Space Station (ISS) depends upon regular resupply from the Earth, this paradigm may not be feasible for future missions. Longer mission durations result in higher probabilities of component failures as well as higher uncertainty regarding which components may fail, and longer distances from Earth increase the cost of resupply as well as the speed at which the crew can abort to Earth in the event of an emergency. As such, mission development efforts must take into account the logistics requirements associated with maintenance and spares. Accurate prediction of the spare parts demand for a given mission plan and how that demand changes as a result of changes to the system architecture enables full consideration of the lifecycle cost associated with different options. In this paper, we utilize a range of analysis techniques – Monte Carlo, semi-Markov, binomial, and heuristic – to examine the relationship between the mass of spares and probability of loss of function related to the Carbon Dioxide Removal System (CRS) for a notional, simplified mission profile. The Exploration Maintainability Analysis Tool (EMAT), developed at NASA Langley Research Center, is utilized for the Monte Carlo analysis. We discuss the implications of these results and the features and drawbacks of each method. In particular, we identify the limitations of heuristic methods for logistics analysis, and the additional insights provided by more in-depth techniques. We discuss the potential impact of system complexity on each technique, as well as their respective abilities to examine dynamic events. This work is the first step in an effort that will quantitatively examine how well these techniques handle increasingly more complex systems by gradually expanding the system boundary.

Nomenclature

1	=	Matrix in which every entry is equal to 1
$\phi_{i,j}(t)$	=	Time-dependent state probability
EF_i	=	Number of failures of an element in Monte Carlo run i
$E_{i,j}(t)$	=	Expected time in state

[1] Graduate Research Fellow, Department of Aeronautics and Astronautics, Building 33-409, 77 Massachusetts Ave.
[2] Professor of Aeronautics and Astronautics and Engineering Systems, Department of Aeronautics and Astronautics, Building 33-410, 77 Massachusetts Ave.
[3] Junior Analyst, 912 Thayer Ave. Suite 209.
[4] Vice President / Chief Scientist, 912 Thayer Ave. Suite 209.
[5] Senior Researcher, Space Missions Analysis Branch, MS 462.

$\boldsymbol{f(t)}$	=	Semi-Markov probability density function matrix
$f_{failure}$	=	Failure frequency
$G_{i,j}(t)$	=	Cumulative distribution function of first passage time
$g_{i,j}(t)$	=	Probability density function of first passage time
$\boldsymbol{H(t)}$	=	Semi-Markov process unconditional waiting time density matrix
$\boldsymbol{I}$	=	Identity matrix
m	=	Mass
n	=	Number of Monte Carlo runs in a simulation
$\boldsymbol{Q(t)}$	=	Semi-Markov process kernel matrix
RF	=	Replacement factor
$V_{i,j}(t)$	=	Markov renewal process probability

CCAA	Common Cabin Air Assembly
CDF	Cumulative Distribution Function
CDRA	Carbon Dioxide Removal Assembly
CO_2	Carbon Dioxide
CRS	Carbon Dioxide Removal System
DSH	Deep Space Habitat
DSV	Deep Space Vehicle
ECLSS	Environmental Control and Life Support System
EMAT	Exploration Maintainability Analysis Tool
ISS	International Space Station
LEO	Low Earth Orbit
LiOH	Lithium Hydroxide
MADS	Modeling and Analysis Data Set
MTBF	Mean Time Between Failures
PDF	Probability Density Function
PLOC	Probability of Loss of Crew
PLOM	Probability of Loss of Mission
SMP	Semi-Markov Process

I. Introduction

ALL human spaceflight to date has occurred within the Earth-Moon system, with the vast majority of it occurring in Low Earth Orbit (LEO). This close proximity to home has enabled logistics paradigms that rely on regular resupply of spare parts and consumables from the Earth, exemplified by the resupply logistics of the International Space Station (ISS). However, these logistics paradigms will not be as feasible in future missions, when humans travel further away from Earth and remain in space for longer durations than ever before. Longer mission durations increase the probability of component failures, and longer distances increase the complexity of resupply as well as the speed with which a crew can abort to Earth in the event of an emergency.[1–4] These challenges imply that in order to execute long-duration, deep space missions in a cost-effective manner, mission planners must take into account the logistics requirements and risks of proposed system architectures, particularly with regard to spare parts and consumables demand.[5] Specifically, there is a need to rigorously examine the relationship between maintenance supplies such as spare parts that are provided and the risk taken on by a mission. In addition, a clear understanding of the potential impact that different system architectures or the introduction of new technology can have on logistics requirements can help guide technology development efforts.

In this paper, we present a comparison of four different techniques for the prediction of spare parts requirements: Monte Carlo,[5–7] semi-Markov processes (SMPs),[8,9] binomial,[10] and heuristic methods.[11–13] As a case study, we apply each of these techniques to the spares logistics requirements of the Carbon Dioxide (CO_2) Removal System (CRS) on the ISS. We develop a curve representing the relationship between the mass of spares required and the resulting probability of loss of the CO_2 removal function using each technique and compare the results. This comparison enables the validation of the different techniques against each other for this simple case, and provides a baseline for future comparison as the complexity of the modeled system increases. Using these results, we discuss the pros and cons of each approach and their potential applicability as system complexity increases. In particular, the limitations of heuristic methods are described.

Section II describes each of the techniques listed above, including background information on their development as well as the technical approach behind that method. Section III describes the case study using a simplified version of the ISS CRS in a notional mission profile, and Section IV presents the results of this analysis. In Section V we discuss these results, examining the pros and cons of each technique as well as the potential impact of increased system complexity. Conclusions are presented in Section VI, and the plan for future work is discussed in Section VII.

II. Methodology

A. Exploration Maintainability Analysis Tool

The Exploration Maintainability Analysis Tool (EMAT) has been developed to aid in the understanding of maintainability requirements and alternate maintainability strategies for Deep Space Vehicles (DSVs) for human exploration beyond LEO. EMAT is a probabilistic simulator of spacecraft system failures and repair activities. A Monte Carlo environment is used to simulate stochastic component failures and repair activities in representative beyond LEO missions (e.g. Near-Earth Asteroid and Mars missions). System logic diagrams and spares availability are utilized to evaluate system and mission impacts of failures.

The objective for the development of EMAT is to provide a capability to evaluate the feasibility of different sparing approaches and associated spares mass, and to estimate the contribution to mission safety and mission reliability that will come from modeled systems. EMAT results can be utilized to determine the minimum achievable probability of loss of crew (PLOC) and probability of loss of mission (PLOM) for the DSV based on the number of spares brought on the mission.

EMAT is structured in several nested layers, each of which executes a different level of analysis. Inputs to the model define system components and operations, element reliability, and available spares. System operations are defined through description of the logical relationships between the components in a specific system. A mission is evaluated on a day-by-day basis for a specified mission length, with system failures and repair activities simulated for each day. EMAT monitors two states for each system and its component - whether it is currently functional and/or currently operational. A system or component may be functional (i.e., not in need of repair) but not operational due to component failures elsewhere in the system. Monitoring these two states is necessary since components are less likely to fail while not operating.

The Monte Carlo engine executes a large number of mission simulations (cases), each with independent stochastic failures. The tool monitors statistical convergence of simulation results in order to determine the required number of cases. Finally, a post-processor statistically evaluates the results from Monte Carlo cases to produce probabilistic results.

The model requires several types of input: system descriptions and logic relations, reliability data, spares inventory, spares mass, repair time, and mission description data. The system descriptions and logic relations define the interdependencies of the system components, which components are removable and replaceable, and which components are consumables with a limited lifetime. The reliability data is used to simulate failures of the base components. The spares inventory is a running total of the spares available for the removable and replaceable components. The spares mass is the mass associated with both the removable and replaceable components and the consumable items. The repair time is used to simulate the repairs of the components that have already failed in the mission simulation. The mission description data includes the mission duration, crew size, and initial states of the components.

The iterative simulation structure of EMAT examines element functionality on a per day basis. When an element failure occurs, the repair procedure is applied immediately to that element. It is assumed that, given the availability of a spare onboard the vehicle, repairs are always successful. In the future, including the probability of a successful repair within the model can extend EMAT analysis capability further by modeling the relative difficulty of repair for various system elements.

EMAT includes a built-in capability to conduct sensitivity analyses of the spares inventory to quantify the impact of the spares mix on mission safety and reliability. This capability structures a set of Monte Carlo runs, beginning with no spares manifested and progressively adding spares to the manifest. Using a mass weighted replacement factor, Eq. (1), the tool will increment system spares inventories to reduce subsequent system failures in subsequent simulation runs. Here RF is the replacement factor, n is the number of Monte Carlo runs per simulation, EF_i is the number of failures of this element in run i, and m is the mass of this element. At the conclusion of each Monte Carlo run (including a specific set of spares) possible added spares are ranked and selected for the next Monte Carlo run.

$$RF = \frac{\sum_1^n EF_i}{m} \quad (1)$$

By assigning replacement factors, inventory allocations are chosen to offer the most efficient failure mitigation per spares mass. When using automated spare allocation, the tool does not require user input for spares inventory.

Figure 1 provides the procedural flow used by EMAT to select new spare additions. After a discrete set of mission simulations, elements are sorted by number of failures. These elements are then ranked by the replacement factor given in Eq. (1), at which point EMAT allocates additional spares to the highest ranked components. A new set of mission simulations is then conducted using the newly allocated spares distribution. This process is repeated until a stopping criterion is achieved. Stopping criteria is given as a target PLOC/PLOM value, an error tolerance, or a maximum run count.

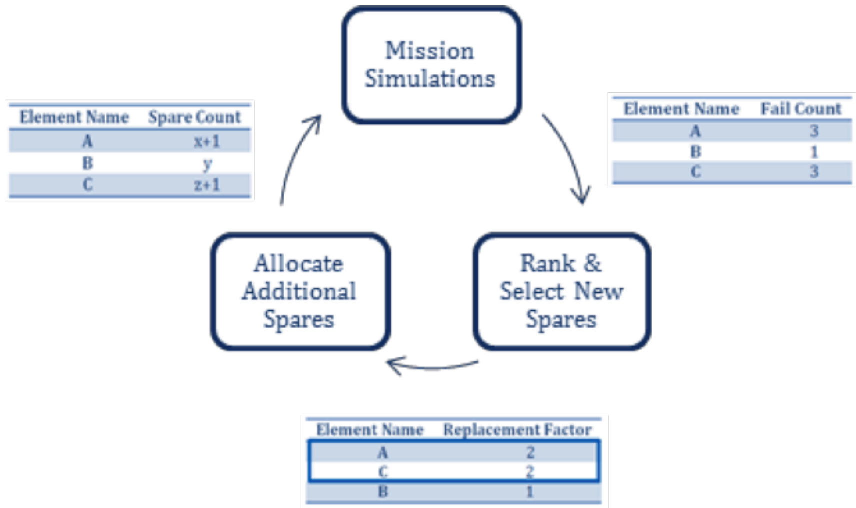

Figure 1. Procedural flow for adding spares in EMAT.

B. Semi-Markov Processes

Semi-Markov Processes (SMPs) are probabilistic, state-based models of system behavior. Similar to Markov chains, SMPs represent systems as networks of states and various transitions between them. These transitions are described by probability density functions (PDFs) representing the time until that transition occurs once the system enters that state.[14–16] However, whereas in Markov chains these transitions must be described exclusively by exponential distributions, SMPs are an extension of Markov chains that enable the use of any PDF to describe the time to transition.[14,15] This added flexibility makes SMP analysis a powerful and flexible tool for system analysis.[16] SMPs were independently introduced by several mathematicians in the mid 1950s,[17–20] and general solutions for several values on interest were presented in the early 1960s[21,22] (as described by several authors[14–16]). However, these solutions utilized the Laplace domain, and at the time numerical algorithms for Laplace transform inversion - as well as the computational power to execute them - did not exist. As a result, SMPs were not adopted as a common analysis technique. However, later advances in computing technology and development of numerical Laplace transform inversion techniques - such as EULER,[23] which is used here - have facilitated their application to a wide variety of problems.[14]

SMPs enable the calculation of several metrics, as shown in Table 1, based upon the kernel matrix ***Q(t)*** and unconditional waiting time density matrix ***H(t)***. ***Q(t)*** contains entries $Q_{i,j}(t)$

Table 1. Symbols, names, and descriptions of metrics that can be calculated using SMPs, as well as the equations that describe them. All metrics assume that the system starts in state *i* at time 0.[9,14]

Symbol	Name	Description	Eqn.
$\phi_{i,j}(t)$	Time-dependent state probability	Probability that the system will be in state *j* at time *t*	(4)
$E_{i,j}(t)$	Expected time spent in state	Expected amount of time the system will have spent in state *j* up to time *t*	(5)
$g_{i,j}(t)$	PDF of first passage time	PDF describing the time taken to reach state *j*	(6)
$G_{i,j}(t)$	CDF of first passage time	CDF giving the probability that the system has reached state *j* by time *t*	(7)
$V_{i,j}(k,t)$	Markov renewal process probability	CDF giving the probability that the system has reached state *j* a total of *k* or fewer times by time *t*	(8)

that give the PDF describing the time until transition from state i to state j, given that the last transition was into state i at time 0 and the system does not transition to some other state in the interim. ***H(t)*** is a diagonal matrix with entries that give the PDF describing the amount of time spent in state i, given that the last transition was into state i at time 0. These matrices are defined using the PDF matrix ***f(t)*** according to eqns. (2) and (3), where each entry $f_{i,j}(t)$ encodes the PDF describing the time spent in state i before a transition to state j occurs, given that the system transitions to state j.[14,15] As mentioned earlier, these metrics are solved for using the Laplace domain, as shown in eqns. (4)-(8).[14] To save space, the Laplace transform operation is shown using a tilde (~). Here I is the identity matrix, **1** is a matrix of ones, and ∘ is the Hadamard product of two matrices (elementwise multiplication). Once the Laplace transform of the solution is determined, the EULER numerical inverse Laplace transform algorithm is used to find the metric in the time domain.[14,23]

$$Q_{i,j}(t) = f_{i,j}(t)\prod_{k\neq j}\left(1-\int_0^t f_{i,j}(t)\,dt\right) \tag{2}$$

$$H_{i,i}(t) = \sum_j Q_{i,j}(t) \tag{3}$$

$$\tilde{\phi}(s) = \frac{1}{s}\left(I-\tilde{Q}(s)\right)^{-1}\left(I-\tilde{H}(s)\right) \tag{4}$$

$$\tilde{E}(s) = \frac{1}{s}\tilde{\phi}(s) \tag{5}$$

$$\tilde{g}(s) = \tilde{Q}(s)\left(I-\tilde{Q}(s)\right)^{-1}\left[I\circ\left(I-\tilde{Q}(s)\right)^{-1}\right]^{-1} \tag{6}$$

$$\tilde{G}(s) = \frac{1}{s}\tilde{g}(s) \tag{7}$$

$$\tilde{V}(k,s) = \frac{1}{s}\left(\mathbf{1}-\tilde{g}(s)\circ\left[\mathbf{1}\left(I\circ\tilde{g}(s)\right)^{k}\right]\right) \tag{8*}$$

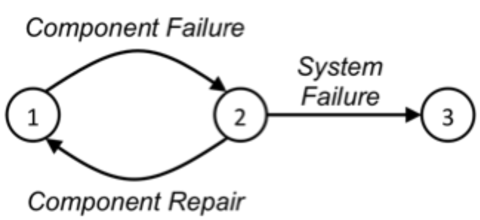

Figure 2. SMP diagram for a notional single-string system with limited survival time after component failure, showing transitions between the nominal state (1), an offline but recoverable state (2), and a state in which the system has reached an unrecoverable failed state (3).[8]

When SMPs are used to examine spare parts requirements and probability of failure for Environmental Control and Life Support Systems (ECLSS), the primary metrics of interest are the time-dependent state probabilities $\boldsymbol{\phi}$ and the Markov renewal probabilities $\boldsymbol{V}$. For this type of analysis, the states in the SMP are defined by the status of the components within the system (nominal, failed, or offline due to external conditions), and the transitions represent component failure or repair. Exponential distributions are used to describe component failures, as they provide a good first-order model of random component failure and their memorylessness enables the use of Markov renewal probabilities to examine spares requirements.[24] Lognormal distributions are used to describe repair transitions, as they provide a good estimate of corrective repair time.[25,26] In general, a component failure causes a system to transition to a state from which

[*] This equation contained a typographical error when originally presented at the 44th ICES (in ICES-2014-116[8]) as a result of a similar typographical error in a referenced manuscript.[13] Through consultation with the authors of the referenced manuscript, this error has since been corrected and the equation shown here is accurate.

either additional failures could occur or the failed component may be repaired. For example, in a single-string system that can survive for a limited time without functionality, the SMP would take the form shown in Figure 2. The Markov renewal probabilities for state 2 in this case give a cumulative distribution function (CDF) describing the number of component failures that would occur, and therefore the number of spares that are required. In addition, the time-dependent state probability for state 3 gives the probability that the system will fail completely due to a repair not being executed in time.[8] In more complex systems that may involve multiple concurrent failures and therefore multiple simultaneous repair processes, additional states may be created to show all possible pathways back to a nominal state, with transition PDFs updated as needed using a difference distribution.[9] Thus, by creating an SMP state network using possible failure and repair processes of a system and using it to solve for the metrics shown in Table 1, the relationship between the probability of failure for a system and the number of spares manifested can be determined.

C. Binomial Methods

Binomial modeling methods utilize component failure rates to estimate the binomial probability of a given number of failures for each element within a system. Element mean time between failures (MTBF) and k-factors are used to generate the failure frequencies for each system element, which are then in turn used to generate the probability distribution of failures given a set of mission assumptions. Spares are assigned to the system by choosing those spare components which will provide the most efficient increase in system survival probability per unit mass. For single string systems, the total probability of failure for the system as a whole is a direct combination of the independent failure probabilities computed for each element, allowing for individual element probability contributions to be directly compared.

The model employed in this study generates the expected failure frequency of each system component based on individual MTBFs and k-factors, given in eqn. (9).

$$f_{failure} = \frac{k_{factor}}{MTBF} \tag{9}$$

The binomial probability distribution is then individually generated for each system component, where the count of binomial trials n is set to the mission duration in days. These distributions can then be used to determine the discrete probability for any number of element failures k, where k may be any number 1 to n. The spares selection process is initialized by computing the failure probability such that $k = 1$ for all elements in the system – e.g. there are no spares available and a single failure occurs during the mission. Spares are chosen by progressively selecting the system element that is contributing the greatest failure probability per unit mass of its spare component. This spare component is then allocated to the system, and the failure probability for the newly spared-for element is recalculated for $k+1$ failures before a new spare is then selected again. This process may be repeated until the desired end condition is met, typically defined as a maximum spares mass or overall probability of system failure threshold.

For multi-string systems with multiple redundancies, the binomial modeling approach used in this study must be modified. Initialization of the binomial model requires an exhaustive mapping of all possible system component relationship permutations as the total system probability is no longer a direct multiplicative result of individual component failure frequencies. For highly complex systems, this will likely require exponentially large definition sets to adequately characterize all branch probabilities for the system, requiring approximations or simplifications to system structure to maintain feasibility.

D. Heuristic Methods

Heuristic mass allocation techniques provide rough, "rule of thumb" estimates for required spares mass. Estimates are generally based on historical examples and results of detailed studies. Typically, heuristic estimates calculate required spares as a percentage of the overall system mass. A commonly used heuristic estimate for spares mass is provided by Larson et al. in *Human Spaceflight Mission Analysis and Design*, in which the authors suggest that a good estimate for the mass of spares required per year is 5% of the total dry mass of the system (the habitat dry mass in this case).[11–13] This estimate is based on analysis of historical sparing data for Salyut, Mir, and ISS.[13]

A total mass estimate for the Mars transit habitat can be developed by applying the 5% figure. Typical habitat analysis for a 4-crew, 1000 day habitat produces a total habitat dry mass of approximately 20,000 kg. This would yield a total spares mass estimate (without overhead and packaging) of 1000 kg/year, or 2,740 kg for the full 1000 day duration. If that total spares mass were allocated to individual, repairable systems proportionally to the mass of each system, the estimate of the mass of spare parts for the CRS would be approximately 220 kg. With the inclusion of a 30-day lithium hydroxide (LiOH) supply (210kg), the total mass estimate for the heuristic method is 430kg.

This percentage-based spares mass calculation is the simplest method to estimate spare parts mass, and can provide a useful back-of-the-envelope estimate for early phase mission planning. However, because heuristic methods are generally based on historical spaceflight data, they may not reflect the challenges involved in an endeavor as complex as a human mission to Mars. In the provided example, the 5% method provided by Larson was derived from historic sparing estimate for space stations in LEO. But each of these systems allowed for some amount of just in time sparing resupply from Earth. On a Mars mission, where there would be no resupply, the total required spares mass is potentially greater.

In addition, the simplicity of heuristic methods dictate that they will inherently not provide as rich a data set as other, more analytical techniques. Whereas Monte Carlo, semi-Markov, and binomial techniques yield a curve relating the mass of spare parts to probability of failure (thus enabling system trades along those two metrics), percentage-based heuristics only provide a single value for spares mass.

III. Case Study Description

In order to compare the four analysis techniques described above, we implement each of them on a case study and compare the results. The case study examines a notional CRS based upon the ISS Carbon Dioxide Removal Assembly (CDRA) and backup LiOH CO_2 scrubber system. The operational structure for the CRS presented in this study is given in the appendix. The notional model includes a dual swing bed CDRA, primary pumping and cooling architecture, and supporting controlling/sensing componentry. To maintain simplicity for this preliminary study, interfacing fluid supply and distribution subsystems – such as the Common Cabin Air Assemblies (CCAAs) and gas distribution lines – were omitted from the model. As such, the notional model presented here represents only those operational components whose primary functional responsibility is to directly support CO_2 removal. Similar to the operational structure observed on ISS, the LiOH scrubber system is arranged as a limited lifetime redundancy capability that is used only in the event of primary CDRA failure.

The notional 1000-day mission assumes the CRS system will act as the only source of CO_2 removal for the 4 crewmembers, with the limited lifetime LiOH scrubber system providing contingency CO_2 removal capability for up to 30 days. Maintenance is assumed to follow the ISS remove-and-replace paradigm.[27] That is, when a failure occurs within the CDRA, it is taken offline and the backup system (the scrubber) is brought online while the failed part is replaced within CDRA. Once the part is replaced, CDRA is brought back online and the scrubber is taken offline. Both CDRA and the scrubbers contain components that can fail, but it is assumed that components can only fail when they are online. For example, the scrubber fans can only fail while they are online due to some CDRA component failure. Failure, repair time, and mass characteristics of each component are based upon data from the ISS Modeling and Analysis Data Set (MADS). Failure distributions for each part are characterized using an MTBF value derived from Bayesian updating of estimates using ISS operational data, as well as k-factors. Repair times are assumed to be deterministic for the purposes of this analysis, and are similarly based on ISS operations. In order to model deterministic repair times in the SMP framework described above, a lognormal distribution is used with a mean equal to the repair time and a standard deviation of 0.01d. When repair time data for a specific component were not available, a value was estimated based upon analogy to another component.

This case study focuses exclusively on the CO_2 removal system. Therefore, for the purposes of this paper, the probability of interest is the probability of failure of the CRS. This probability is calculated differently by each applied technique, as described in the methodology section. In the context of this case study, EMAT calculates this probability via a Monte Carlo simulation to determine the probability that the CO_2 removal system will fail, given a certain number of spares. SMP calculates it by combining the probability distributions of the number of spares required for each component, the probability distribution of the amount of time that the scrubber system will need to be active, and the probability that both the CDRA and LiOH scrubber system are ever failed at the same time. Binomial modeling combines the independent probabilities that the given number of spares for each component in the system will be sufficient. The curve relating the probability of CRS failure to the mass of spares required for the given system was calculated using EMAT, SMP, and binomial methods, and a spares mass value was determined using the heuristic method. These results are shown in Figure 4.

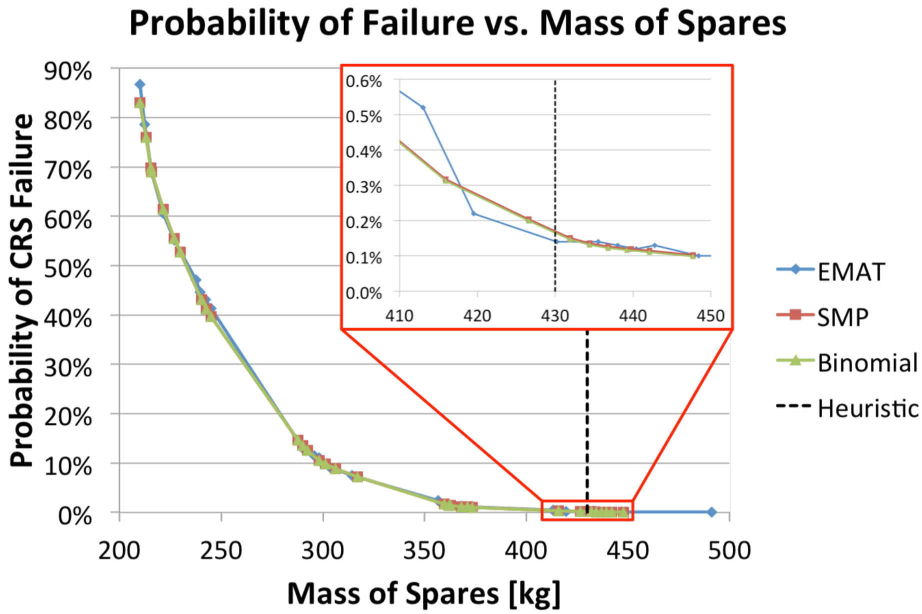

Figure 4. Probability of CRS failure as a function of spares mass, as calculated using EMAT, SMP, and the binomial method. The mass value estimated by the heuristic method is also shown. The red inset figure shows a detailed view of the region immediately around the heuristic mass estimate. The mass of spares includes spare components for CDRA and the LiOH scrubber as well as the mass of a 30-day contingency LiOH supply.

IV. Results

The results of the application of each of the methods described in Section II to the case study described in Section III are presented in Figure 4. The blue, red, and green lines show the Pareto front that minimizes both the mass of spares and the probability of CRS failure for the EMAT, SMP, and binomial analyses, respectively. Individual points along each of these curves represent individual solutions, characterized by a particular number of spares for each component. Since the heuristic technique produces only a mass estimate and not any indication of probability of CRS failure, its mass estimate is represented by the vertical dotted black line. For each case, the mass of spares includes the 210kg mass of the 30-day contingency supply of LiOH.

V. Discussion

Each of the four evaluated spares analysis methodologies were utilized to evaluate sparing requirements and trades for a representative, but simplified, CRS. The results of the four assessments were compared to assess the utility of each method and the potential to use that method for full-scale analysis.

A. Heuristic and Analytical Techniques

The most basic form of the analysis – the heuristic formula – produced a spares mass estimate that was roughly consistent with the estimates for the amount of mass required to achieve a low probability of CRS failure produced by using the other, more analytical methods. This single point estimate, however, provides no information on the level of reliability that is achieved, nor does it provide any information about how many spares should be provided for each component. Since the output of the heuristic estimate is a single mass value without any associated reliability, it does not allow for trades between spares mass and reliability or consideration of the impact of a change in the number of spares. The heuristic estimate does not take into account the specific characteristics of the system itself or any assessment of individual component reliability. Therefore, the method is usable only as a first rough estimate of spares mass and cannot be used to evaluate detailed sparing requirements or to perform trades in system design.

The three analytical methods – Monte Carlo, semi-Markov, and binomial – each produced a set of points along the Pareto front minimizing both the mass of spares and the probability of loss of CRS function. For the given case study, all three methodologies produced nearly identical results. This makes sense, given that the case study examined here is relatively simple. Each of these three methods evaluates system performance at the component level, including the reliability of individual components. In addition, each point is characterized not only by the objective metrics presented in Figure 4, but also by the number of spare parts required for each specific component. Since the results yield both mass and probability metrics for a set of different options, these three methods allow the assessment of trade-offs between the number and type of spares and the overall system reliability.

B. Complexity of the Evaluated System

The case study presented here was a relatively simple example focusing on a single ECLSS subsystem. A primary area of concern that will require additional assessment is the practicality and accuracy of each of these methods as the size and complexity of the evaluated system increases. This is of particular interest for the three analytical methods. While all three analytical methods produced nearly identical results for this simplified case study, it is anticipated that this may change for systems with greater complexity. As system complexity grows, these analytical modeling techniques may require that some level of simplifying assumptions be made in order to facilitate their use in spares logistics analysis. These simplifying assumptions will likely be different depending on the analysis method, and may have an effect on the overall accuracy of the analysis. The relationship between the assumptions made, the accuracy of the results, and the practicality of implementation for each method is the topic of ongoing research, as discussed in Section VII.

The binomial approach provides an effective method for the modeling of low complexity systems that requires minimal investment in both analysis initialization and run times. However, given the complexity of proposed habitation systems, a significant level of simplifying assumptions may be required to model these systems in their entirety. Exploration habitat systems include complex behavioral relationships between individual components that can easily number in the hundreds, if not thousands. As system complexity increases, the initialization requirements for a binomial analysis rapidly increase. Every possible component state combination must be explicitly modeled to produce valid probability distributions, and as a result the model grows exponentially as additional branches of a system are added. It would be exceedingly difficult to capture all of the possible operational permutations and states in a binomial model without significantly simplifying the operational behavior and level of modeling. Thus the uncertainties associated with the approximations necessary to enable realistic application of a binomial approach become a direct function of system complexity, which may in turn reduce the usefulness of binomial models in examining highly intricate space exploration systems. Additional investigation is required to assess the level of simplifying assumptions required to develop a practical binomial model of an exploration habitat as well as the impacts of those assumptions on the overall accuracy of the result.

Semi-Markov modeling offers a more flexible modeling approach than binomial methods, since it includes the capacity to examine repair time and incorporate the effect of system downtime on the number of failures that will be experienced by each component, as well as the probability of system failure due to failed repair. In this case study, for example, the SMP model captures the probability that the amount of time spent with the CDRA offline will be greater than the amount of time that the contingency LiOH can support the crew (which is negligible for the system studied here), information that would be useful for a more complex case study where LiOH mass is also allocated rather than being prescribed up front. However, the SMP approach potentially faces similar challenges to binomial modeling since it relies on the identification of each possible system state. As the system becomes more complex, the number of states in the SMP model will grow rapidly, resulting in increased required effort to generate the SMP model based on the system parameters. Currently, SMP networks are generated manually, but ongoing research (discussed further in Section VII) is developing methods to automate this generation process. These tools will require further development and validation before an automated approach is practical. As with binomial analysis, some degree of simplifying assumptions will be required to facilitate the application of SMPs to complex systems analysis. However, the degree of simplification required will likely not be as severe as that required for binomial methods. As with the binomial methods, the impact of these simplifying assumptions on the practicality and accuracy of SMP models will need to be investigated.

Monte Carlo approaches such as EMAT are more immune to the impact of system complexity during model setup, since they are simulation-based. Since these simulations are event-driven at the element level, the definition of primary component interactions allows for any possible system state to occur naturally as the model is run. Thus there is no need to pre-define all possible system states. Generation of the set of component relationship rules is rapid, as only the basic logical structure of the system of interest needs to be defined. As a result, the Monte Carlo method implemented in EMAT remains stable even when applied to large or highly intricate systems. Since closed-form definitions are not necessary, highly coupled systems with many branch interactions can be handled with the same capabilities used to model low complexity systems. Modifications to system descriptions without significantly disrupting previously generated portions of the model – such as the incorporation of a new component, which requires only the definition of its relationship to existing system elements – can be implemented relatively easily. As a result, sensitivity analyses examining the impact of changes to system arrangement, component content, or level of redundancy can be implemented while avoiding complete model rebuilds. However, Monte Carlo approaches rely on iterative simulation of the system, and greater system complexity increases the processing time to simulate a given case as well as the number of iterations required to achieve statistically significant results. As a result, increasing system complexity rapidly increases the run time required to perform an assessment. It is possible that simplifying assumptions can be implemented in the case of Monte Carlo analyses, but as with other methods there is a need to examine the impact of these assumptions on the accuracy of the results.

C. Dynamic Effects

Another important consideration when modeling habitat systems, particularly over long mission durations, is sufficiently capturing dynamic system events. These events may include variable repair probabilities, degradation of crew performance, and variable system performance, as well as crew-induced, cascading, and/or common cause failures. Whereas simulation-based Monte Carlo methods can include parameters capturing these system characteristics and allow for their occurrence during the analysis, the closed-form nature of binomial and semi-Markov models restrict opportunities to capture these dynamic effects. In addition, many critical system failures are the result of concurrent failures of components that are non-critical. Non time-based analyses such as the binomial method are unable to capture this type of examination, whereas more dynamic semi-Markov and Monte Carlo methods can model concurrent failures.

D. Value of ISS Experience

The feasibility and accuracy of any sparing analysis methodology depends upon the availability of historical data. The long-duration experience gained on the ISS is invaluable in enabling a robust analysis of spares for exploration missions. The heuristic formulas for sparing that are generally used are based upon analysis of long-duration spaceflight experience from several sources, including the ISS. The three analytical methods depend on the use of detailed system descriptions and component-level reliability and maintenance data. Long-term experience on the ISS and the subsequent collection and analysis of reliability and sparing analysis provide a rich data source to drive sparing models. Future exploration systems will likely differ somewhat in form and arrangement from the current ISS system. However, since the analytical sparing methodologies presented here model at the component level, data from the ISS can effectively be used to produce accurate analyses of proposed exploration systems.

E. Level of Design Activities

Ultimately, the applicability of each of the methods described above depends upon the level of design activity being conducted, the complexity of the system at hand, and the level of accuracy in the results that is required. Heuristic methods may be appropriate for early concept design, when only basic estimates of mass allocations are required, a specific system design is not typically available, and rapid analysis is required. For more detailed design activities, other approaches may be more applicable – ones that provide an appropriate level of accuracy (even when considering simplifying assumptions) to allow for trades between spares and reliability, examination of the impact of changes to system architecture, and provide other desired results within a reasonable timeframe. Further assessment and comparison of the applicability of each of these methods to more complex systems will help illuminate the relative merits of each approach during different phases of the design process, as discussed in Section VII.

VI. Conclusions

This paper presents a comparison of four techniques for the analysis of spare parts requirements for long-duration human spaceflight, based upon an examination of a simplified model of a notional CRS for a 1000-day mission. The analytical techniques – Monte Carlo, semi-Markov, and binomial – were used to generate Pareto fronts that minimize both the mass of spares and probability of CRS failure, while the heuristic method was used to produce a mass estimate. Since the analytical techniques yield both a probability and a mass, they facilitate trades with respect to sparing and reliability whereas the heuristic method provides only a single point mass estimate. For this simple case study, the three analytical techniques produced nearly identical results. However, it is expected that as the complexity of the system grows, the practicality of these methods will change. Different methods may require different simplifying assumptions that will impact the accuracy of the outputs. The examination of the impact of increasing system complexity on the implementation cost and output accuracy of each method will help inform which methods are most suitable for different phases in the design process. This paper is the first step in a research effort to quantitatively examine these impacts, providing a baseline case from which to gradually increase the complexity of the system and examine the effect on different spares analysis techniques.

VII. Future Work

A. Increasing Complexity

The case study examined in this paper was a single ECLSS subsystem, and its relative simplicity means that the results for the three analytical methods were nearly identical. The next steps for this research direction is to gradually increase the complexity of the system to be modeled in order to view how each analytical technique handles the change. This will be accomplished by gradually expanding the system boundary to include more subsystems, as well as by incorporating more complex system behavior such as multiphase missions or other dynamic effects discussed in Section V. As the semi-Markov and binominal methods are more sensitive to increased model complexity than Monte Carlo methods, their capacity to examine increased complexity is of particular interest. EMAT, the Monte Carlo based tool used here, is already mature and has a full implementation of a proposed Deep Space Habitat (DSH) ECLSS based upon ISS technology already prepared. As such, EMAT will be used as a baseline to examine the accuracy of semi-Markov and binomial methods as simplifying assumptions are implemented to facilitate analysis of more and more complex systems. As part of this effort, automated SMP generation techniques will be developed to enable the rapid generation of SMP models of systems based on design information. These automation techniques will incorporate tunable parameters that control how simplifying assumptions and approximations are made to represent complex systems in a semi-Markov framework, thus facilitating a direct examination of the impact of a range of simplifying assumptions on the output.

B. Metrics

In future studies, a set of metrics will be developed to examine the relative performance of various modeling approaches. The creation of a set of quantitative measures will not only provide a basis for comparison in terms of computational performance and accuracy, but also identify any limitations these methodologies may encounter when applied to increasingly complex systems. Assessing the time required to generate state/response networks, the raw model size, and the maximum input capacity for each technique will allow for a more complete understanding of their respective setup requirements. By tracking growth in initialization requirements as system complexity progressively increases, realistic limits can be placed on the level of detail that a given model can accommodate. Runtime analyses will also be conducted to define the time complexity for each methodology. The evaluation of both the initialization and execution loads for each method will enable a more complete understanding of the performance limitations of each method. Additionally, as discussed in Section V these methods may require the use of simplifying assumptions and other approximation techniques as they are applied to more intricate exploration systems. The development of a comprehensive set of performance metrics will assist the identification of the limitations of each model and the impact of these approximations, as well as highlight critical points in the analysis process where approximation may provide the greatest performance gain.

C. Additional Methods

The four methods discussed in this paper are by no means the only methods that can be used to examine spares logistics and system reliability. Future research will also examine other methods such as Bayesian networks, Petri nets, and Markov chains. In addition, hybrid and/or hierarchical methods that combine different techniques may also be developed and examined.

Appendix: CRS Operational Structure

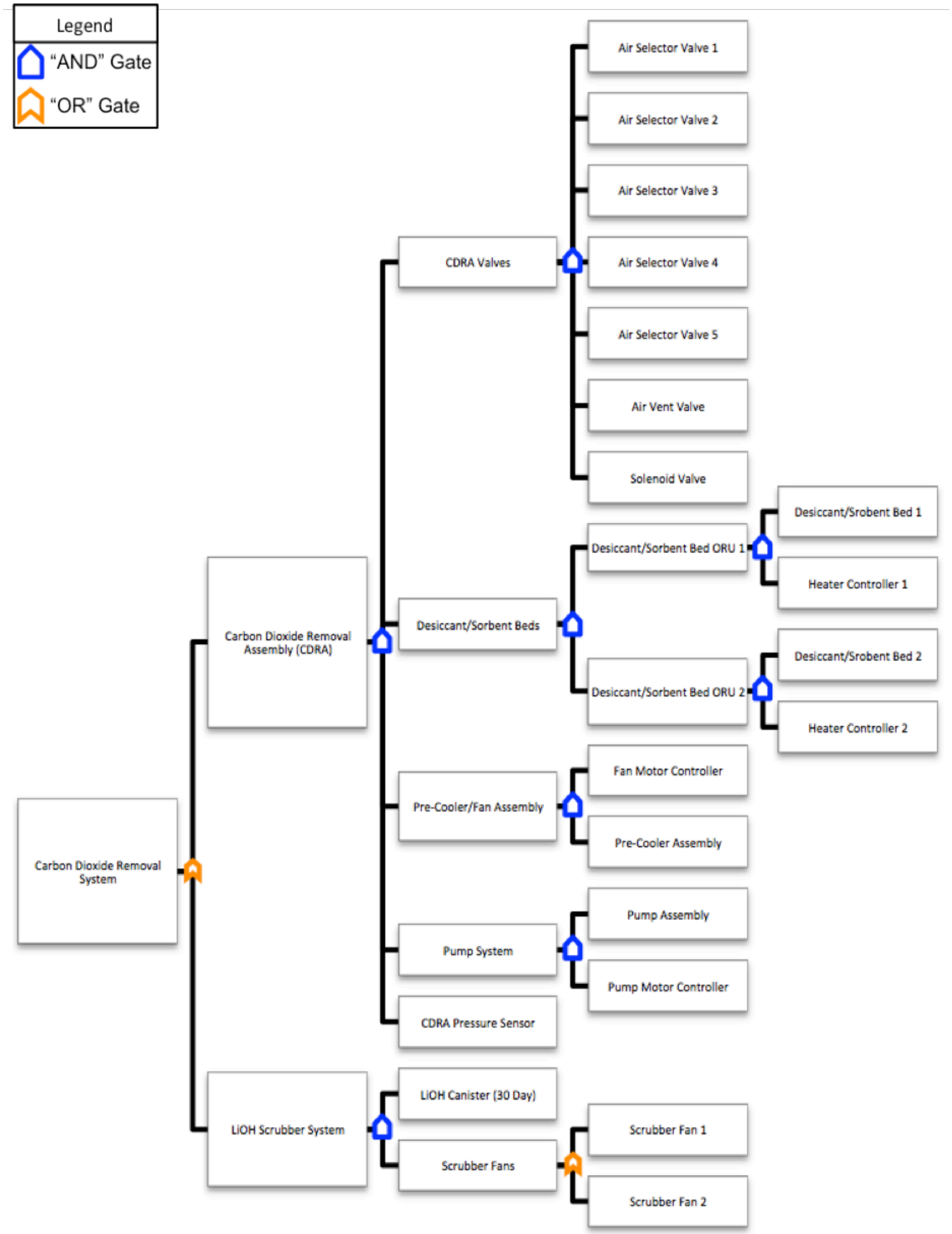

Figure 5. CRS operational structure used in the case study presented here.

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