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Comparative cost and utility analysis of monolith and fractionated spacecraft using failure and replacement Markov models ☆

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ABSTRACT

Failure of a single component on-board a spacecraft can compromise the integrity of the whole system and put its entire capability and value at risk. Part of this fragility is intrinsic to the current dominant design of space systems, which is mainly a single, large, monolithic system. The space industry has therefore recently proposed a new architectural concept termed fractionation, or co-located space-based network (SBN). By physically distributing functions in multiple orbiting modules wirelessly connected, this architecture allows the sharing of resources on-orbit (e.g., data processing, downlinks). It has been argued that SBNs could offer significant advantages over the traditional monolithic architecture as a result of the network structure and the separation of sources of risk in the spacecraft. Careful quantitative analyses are still required to identify the conditions under which SBNs can "outperform" monolithic spacecraft. In this work, we develop Markov models of module failures and replacement to quantitatively compare the lifecycle cost and utility of both architectures. We run Monte-Carlo simulations of the models, and discuss important trends and invariants. We then investigate the impact of our model parameters on the existence of regions in the design space in which SBNs "outperform" the monolith spacecraft on a cost, utility, and utility per unit cost basis. Beyond the life of one single spacecraft, this paper compares the cost and utility implications of maintaining each architecture type through successive replacements.

1. Introduction

Failure of a single component on-board a spacecraft can compromise the integrity of the whole system and put its entire capability and value at risk. This fragility of space systems is mitigated to some extent during the design phase by careful parts selection, extensive ground testing, and redundancy allocation. However, a residual fragility remains and is in effect intrinsic to the current dominant design of space systems, which is mainly a single, large, tightly coupled monolithic system. Partly in response to these limitations, the space industry has recently embarked on the exploration of a new architectural concept for space systems termed fractionation, or co-located space-based network (SBN) [1–4]. By physically distributing functions in multiple orbiting modules wirelessly connected to each other, this new architecture allows the sharing of resources on-orbit (e.g., data processing, data storage, downlinks, and bandwidth).

While both types of architecture are subject to malfunctions, their inherent failure mitigation strategies differ. SBNs not only enable the transfer of capability to functioning modules, but also offer ways of reducing the cost penalty associated with an on-orbit failure, by targeting replacements to the failed subsystem(s) only instead of the entire system. Sources and localizations of

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Nomenclature

SBN	space-based network
C&DH	command and data handling
TT&C	telemetry, tracking and command
LCC	lifecycle cost
P_{ij}	probability to transition from state i to state j
τ_{ops}	time horizon of the simulations
n	number of modules in a space-based network
P_{MONO}	transition matrix for a monolithic spacecraft
P_{SBN}	transition matrix for a space-based network
α	probability of spacecraft failure
T_F	random variable time of spacecraft failure
λ_F	spacecraft failure rate
ΔT	time unit of the simulations
γ	responsiveness parameter
λ_r	rate of replacement of a spacecraft
$MTTR$	mean-time-to-replacement
C_{MONO}	cost matrix for a monolithic spacecraft
$c_{MONO\ op}$	cost of operating a monolithic spacecraft
C_{SBN}	cost matrix for a space-based network
$c_{SBN\ op}$	cost of operating a space-based network
$cost_{MONO}$	cost of developing and launching a new monolithic spacecraft
$cost_{SBN}$	cost of developing and launching a new SBN module
β	cost penalty of developing an SBN module compared to a monolith ("cost intensity")
c_{TFU}	cost of the first spacecraft developed (theoretical first unit)
c_N	cost of the Nth module developed
R	cost learning rate
u_{MONO}	utility per unit time provided by a monolithic spacecraft
u_{SBN}	utility per unit time provided by a space-based network
T^*	instant of the intersect point between the lifecycle cost curves of monolith spacecraft and SBNs
u_{part}	partial utility per unit time provided by a space-based network in a failed state

failures constitute a diverse set in which the spacecraft subsystems that are potential candidates to fractionation represent a significant fraction. For example, a recent study of 156 on-orbit failures which occurred on 129 different spacecraft from 1980 to 2005 showed that 15% of the failures were due to the command and data handling system (C&DH) subsystem, and that 12% of the failures were due to the telemetry, tracking and command (TT&C) subsystem [5]. A more comprehensive statistical analysis of spacecraft reliability and subsystems failures can be found in Castet and Saleh [6]. In a monolithic spacecraft, the failure of a subsystem, especially a critical one such as the C&DH or TT&C subsystem, often results in the loss of the spacecraft. As a result, the cost of a subsystem failure in the monolith spacecraft is significantly high, and the service provided by the spacecraft cannot be restored unless a new (complete) spacecraft is launched.

The situation can be quite different with a fractionated spacecraft or SBN. For example, the C&DH and TT&C subsystems can be implemented in separated modules wirelessly interconnected within an SBN. For example, if a failure of the C&DH occurs, it need not render the whole system/network useless (failed) as in the case of the monolith spacecraft. Instead, the hosting module of the C&DH function can be replaced at a reduced cost compared with the replacement of the whole spacecraft in the monolithic case. In short, the consequences of subsystem failure in an SBN may not be as dramatic as in a monolith spacecraft, and the cost of restoring the system's services in case of subsystem failure may be smaller with the former architecture than with the latter.

This failure mitigation strategy of fractionation and the resulting reduced replacement costs come however at the price of SBN-enabling technologies that could prove expensive to implement in the different modules of the network. Careful quantitative analyses are therefore required to identify the conditions under which SBNs can "outperform" the current monolithic spacecraft architecture on a cost, utility, and utility per unit cost basis. Spacecraft failures being non-deterministic by nature, a probabilistic modeling framework is required to estimate these lifecycle costs and utility (or normalized utility as will be discussed in Section 5.4), and to capture the cost risk associated with these failures. In their review of lifecycle cost (LCC) analysis, Asiedu and Gu [7] state that "operating and support costs are the most significant portion of the LCC and yet the most difficult to predict". The authors also emphasize that "a product which is reliable and easily serviceable leads to maximum availability and maximum customer satisfaction" and that the time needed to perform maintenance action (the "responsiveness" of the spacecraft development in our case) must be minimized, since "each minute out of service is […] going to result in considerable financial loss to the system user". In other words, an estimation of lifecycle costs will be more relevant if completed with an assessment of the utility provided to the customer, which is related to the frequency of failures and the rapidity of the response to failures. These considerations set the ground for the probabilistic model presented in this paper, and which is used to quantitatively compare the performances of the SBNs and monolithic architectures.

To do so, we first provide in Section 2 a brief overview of Markov chains and Monte-Carlo simulations. Section 3 presents the structure of our Markov model of failures and replacement as well as its underlying assumptions. In Section 4, we run Monte-Carlo simulations of the model and generate probability distributions for the lifecycle cost and utility of the two considered architectures that serve as a basis for our comparative analysis. Important trends and invariants are identified and discussed. For example, changes in average lifecycle cost and utility

$$\begin{array}{cc} & \text{To} \\ & \begin{array}{cccc} S1 & S2 & S3 & S4 \end{array} \\ \text{From} \begin{array}{c} S1 \\ S2 \\ S3 \\ S4 \end{array} & \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix} = P \end{array}$$

Fig. 1. Transition matrix for a system with four states.

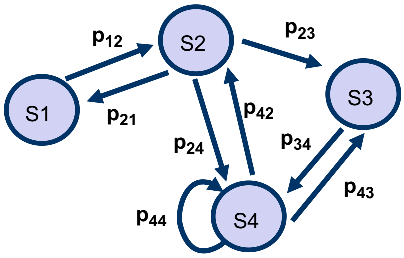

Fig. 2. Typical transition graph for a Markov chain.

resulting from fractionation are observed, as well as reductions in cost risk. Finally, we investigate in Section 5 the impact of the model parameters (such as the probability of module failure, the cost of an SBN module relative to that of a monolith, and the time needed to replace failed modules) on the existence of regions in the design space in which SBNs are less costly or provide more utility (or normalized utility) than monolith spacecraft. We conclude this work in Section 6.

2. Markov chains and Monte-Carlo simulations

2.1. Markov chains

Reliability analysis aims at capturing the probabilistic nature of the failures to which a system is subjected. One powerful theoretical framework frequently used in reliability analysis is the Markov chain. Markov chains are based on a state representation of a system in which the next future state only depends on the current state and not on the previous history of the system (this assumption is referred as the Markov property). Mathematically, a discrete-time Markov chain $\{X_n | n=0, 1, \ldots\}$ is defined as a discrete-time, discrete-value random sequence such that given $X_0, \ldots, X_n$, the next random variable X_{n+1} depends only on X_n through the transition probability expressed as follows:

$$\begin{aligned} P[X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \ldots, X_0 = i_0] \\ = P[X_{n+1} = j | X_n = i] = P_{ij} \end{aligned} \quad (1)$$

where X_k represents the state of the system at the discrete time k and P_{ij} is the probability to transition from state i to state j. Eq. (1) states that the probability of transition from state i to state j applies anytime the system is in state i regardless of how it got there. For a Markov chain with a finite number of states, the transition probabilities from one state to the next can be expressed in the one-step transition matrix whose elements are the P_{ij} coefficients. Fig. 1 shows an example of a transition matrix for a system with four states.

A common representation of a Markov chain is a directed graph with nodes representing the states of the system, connected by arcs representing the possible transitions between those states, along with their probabilities. An example transition diagram of a system with four states is provided in Fig. 2.

Markov chains have been used in a wide variety of contexts and for different applications in health care [8], economic valuation [9], and system reliability to name a few. More information about Markov chains can be found in several textbooks including [10–12].

2.2. Monte-Carlo simulations

Performing estimation and risk analysis in the presence of uncertainty requires a method that reproduces the random nature of certain events (such as failures in the context of reliability theory). A Monte-Carlo simulation addresses this issue by running a model many times and picking values from a predefined probability distribution at each run [13]. This process allows the generation of output distributions for the variables of interest, from which several statistical measures (such as mean, variance, skewness) can be computed and analyzed.

In this work, we conduct a Monte-Carlo simulation on the Markov chains representing the two types of space system architectures considered (monolith and space-based network). These Markov chains are discussed in Section 3.1. The probabilistic nature of these models is directly used to feed the Monte-Carlo simulations, and generate the distributions of cost and utility that serve our comparative analysis. In our case, the randomness of the process results from the multiple applications of the transition matrix of the Markov models over time. Depending on the current state of the Markov chain, the models "select" the next state according to a probability mass function that corresponds to a row of the transition matrix. Since we are interested in the lifecycle cost and utility of each architecture, we define a time horizon for our analysis τ_{ops}. When $t=\tau_{ops}$, the models stop running, and the lifecycle costs and cumulative utilities are compared. Different results will be obtained for every

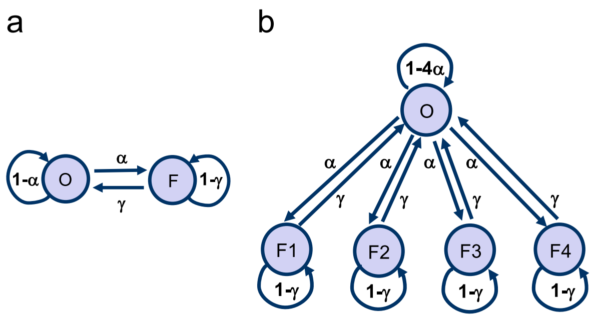

Fig. 3. (a) State representation of the failure-based model of a monolithic spacecraft and (b) State representation of the failure-based model of a space-based network.

run once the time horizon is reached. It is the repetition of these runs that constitutes a Monte-Carlo simulation from which useful statistics are computed.

3. Failure and replacement model

3.1. Model structure

In the following, we present and compare the model structure of a monolithic architecture (only one spacecraft) and an SBN containing n separated modules. We will use the term "spacecraft" to refer to a monolithic spacecraft or one module of an SBN. The system (or architecture) is said to be operational when it is functioning and providing the intended services to the user. In a failed state, the system is experiencing some malfunction that prohibits it from delivering part or the totality of the capability. As shown in Fig. 3a, the Markov model representing a monolithic architecture contains only two states: operational (O) and failed (F). For the SBN case, $(n+1)$ states are used to describe the system: the operational state (similar to the monolithic case), and n different failed states, named "Fi", each one of them representing a failure occurring to one of the n modules constituting the SBN.

Two major structural assumptions are made in the formulation of these models:

A1. Only one failure can occur at one time, as the states are mutually exclusive in a Markov chain. While this assumption is trivially verified in the case of the monolithic architecture, it can represent a restriction of the model of the SBN. This restriction can be lifted by defining additional failed states for the combination of failures considered (e.g., F13 would be the state corresponding to the simultaneous failure of module 1 and module 3).

A2. The probabilities of failures are considered constant over the lifetime of the modules (the Markov chain is time-homogeneous). In this case, the transition matrix describing the transition probabilities from state to state remains constant during the simulation (i.e., no aging or infant mortality of the modules is considered).

3.2. Model parameters

3.2.1. Transition matrix

Following the model structure described in Section 3.1, we characterize the transition matrices for both architectures, P_{MONO} and P_{SBN}, with two parameters, a failure parameter α and a responsiveness parameter γ. These two parameters are included in the transition matrices as shown in Eq. (2) and further explained herein. In the following, we set the number of modules of the SBN to four (n=4):

$$P_{MONO} = \begin{bmatrix} 1-\alpha & \alpha \\ \gamma & 1-\gamma \end{bmatrix}; \quad P_{SBN} = \begin{bmatrix} 1-4\alpha & \alpha & \alpha & \alpha & \alpha \\ \gamma & 1-\gamma & 0 & 0 & 0 \\ \gamma & 0 & 1-\gamma & 0 & 0 \\ \gamma & 0 & 0 & 1-\gamma & 0 \\ \gamma & 0 & 0 & 0 & 1-\gamma \end{bmatrix} \tag{2}$$

These matrices can be read according to the convention shown in Fig. 1, where the first row represents the probabilities of reaching a state from the operational state, and the first column represents the probabilities of reaching the operational state. Specifically, α is the probability that a spacecraft will fail within the next time unit and is defined as a conditional probability:

$$\alpha = Pr[T_F \le t_{k+1} | T_F > t_k] \tag{3}$$

where T_F is the random variable time of failure of the spacecraft. Under assumption (A2), the probability of failure follows an exponential law. Hence, Eq. (3) becomes

$$\alpha = \frac{e^{-\lambda_F t} - e^{-\lambda_F (t+\Delta T)}}{e^{-\lambda_F t}} = 1 - e^{-\lambda_F \Delta T} \tag{4}$$

where λ_F is the failure rate (constant for an exponential distribution) and ΔT is the time unit (equal to 1 year in the rest of this paper). Typical values of α used in this paper are 0.1, 0.05, and 0.02. Recent work on spacecraft reliability [14] suggests that the lower end of this range of α is a reasonable approximation of satellite failures.

The second parameter of the transition matrices γ characterizes the transition from a failed state to an operational state. When a spacecraft fails, it may need to be replaced by a new one for the services to be restored. However, developing and launching a new spacecraft is a process subject to schedule uncertainty, which justifies the use of a probabilistic model to describe this transition. The parameter γ is therefore the probability of launching a new module within the next time unit. High values of γ represent systems that are quickly transitioning to the operational state (within a few time steps). For this reason, γ will be referred to in the rest of the paper as *responsiveness parameter*. As a conditional probability, γ is related to the rate of replacement of module λ_r via the relation

$$\gamma = 1 - e^{-\lambda_r \Delta T} \tag{5}$$

Using terminology from reliability engineering, the responsiveness parameter γ can be used to define the mean-time-to-replacement (MTTR) of a spacecraft through the equation

$$MTTR = \frac{1}{\lambda_r} = -\frac{\Delta T}{\ln(1-\gamma)} \tag{6}$$

The *MTTR* provides a direct and intuitive measure of the responsiveness (or lack thereof) of the replacement operation performed to keep the architecture in the operational state.[1] High values of the parameter γ correspond to highly responsive development and launch and therefore short *MTTR*. Some typical values used in the simulations are γ=0.25 and γ=0.50, which correspond to *MTTR*=3.5 years and *MTTR*=1.4 years, respectively (with ΔT=1 year). The reader interested in the concept of space responsiveness is referred to Saleh and Dubos [15] for additional details on this important subject for the space industry. The values of γ used in this work and the

[1] Degraded or partially operational states can be easily defined and added in a Markov modeling framework.

corresponding *MTTR* are reasonable reflections of the replacement time scale in the space industry.

3.2.2. Cost matrix

A quantitative comparison of both types of architectures in terms of lifecycle cost calls for the attribution of cost to states as well as transitions in the models. For each architecture, we define a cost matrix whose structure is identical to that of the transition matrix (one line and column for each state), as reflected in Eq. (7) (with $n=4$ for the SBN). Coefficients are no longer probabilities, but costs associated with remaining in a given state for one time step or transitioning from one state to another:

$$C_{MONO} = c_{MONO\ op}\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ c_{MONO2,1} & 0 \end{bmatrix}$$

$$C_{SBN} = c_{SBN\ op}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ c_{SBN2,1} & 0 & 0 & 0 & 0 \\ c_{SBN3,1} & 0 & 0 & 0 & 0 \\ c_{SBN4,1} & 0 & 0 & 0 & 0 \\ c_{SBN5,1} & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

The first term in the decomposition of each matrix ($c_{MONO\ op}$ and $c_{SBN\ op}$) is applicable to each state and represents the cost of operating the entire architecture. This mostly accounts for overhead costs. In the rest of the study, $c_{MONO\ op}=c_{SBN\ op}=1$. Coefficients of the second matricial term of the decomposition represent the cost of replacing a failed spacecraft with an operational one. This cost can result from the development and launch of a brand new spacecraft or also the reconfiguration of an in-orbit spare spacecraft. We parameterize the cost of an SBN module relatively to the cost of a monolith in the following equation:

$$cost_{SBN} = \beta\frac{cost_{MONO}}{n} \tag{8}$$

In this equation, $cost_{MONO}$ represents the cost of developing and launching a new monolith ($c_{MONO2,1}=cost_{MONO}$), $cost_{SBN}$ represents the cost of developing and launching a new module in the SBN ($c_{SBN2,1}=c_{SBN3,1}=c_{SBN4,1}=c_{SBN5,1}=cost_{SBN}$), and n is the number of modules in the SBN. The scaling parameter β, or "cost intensity", reflects the amplitude of the cost penalty of developing a module for an SBN compared to a monolithic spacecraft. (When $\beta=1$, the total cost of the n modules of an SBN and the cost of a monolithic spacecraft are identical.)

By cumulating the costs associated with the transitions and states visited by the system, the Markov models simulate the lifecycle costs of maintaining and operating each architecture, starting from an initial cost that corresponds to their initial development cost. In the simulations, this initial cost has been set to $cost_{MONO}$ for the monolith, and the sum of the module costs $\Sigma(c_{SBN\ i,1})$ for the SBN. Learning effects in the development of modules already designed and built in the past have also been considered. To do so, we implemented a typical learning effect to the cost of developing identical spacecraft (or modules) as shown in the following equation:

$$c_N = c_{TFU}N^b \tag{9}$$

with

$$b = \frac{\ln(R)}{\ln(2)} \tag{10}$$

where c_N is the discounted cost for the Nth module developed, c_{TFU} is the cost of the first spacecraft or module developed, and R is the cost learning rate. "The learning rate (R) for the space and aerospace industry is such that, on average, the Nth unit will cost between 87% and 96% of the previous unit" [16]. Typical values for R in the space industry are therefore between 0.78 and 0.93.

3.2.3. Utility

Along with the quantitative assessment of the lifecycle costs, we propose to compare the cumulative utility provided by both architectures over time. Utility is here defined as a scalar that represents the satisfaction derived from the services provided by the system to the customer. Since the notion of utility is only meaningful when associated to states and not transitions, we define a vector whose components represent the utility provided by the system per unit time in each corresponding state. We make a conservative assumption by considering that the utility of failed states in an SBN is zero, as shown in Eq. (11). In practice, these zero coefficients could be tuned to reflect the fact that certain failures may not totally impair an SBN (as will be done in Section 5.4), because of the possible reallocation of tasks from the failed module to the non-failed ones, resulting in a "partial utility" provided to the customer. The motivation for this and other "conservative assumptions" is discussed in the following paragraph:

$$u_{MONO} = u_0\begin{bmatrix} 1 \\ 0 \end{bmatrix}; \quad u_{SBN} = u_0\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{11}$$

In the rest of the paper, u_0 is set to 1.

3.2.4. Other assumptions

Several "conservative assumptions" have been applied to the models previously described, as shown in the transition and cost matrices, and the utility vectors. These assumptions in effect set up the SBN with a definite handicap compared with the monolith spacecraft. Our purpose for doing so is to set up "tough conditions" under which an SBN would compete against the monolith architecture. If advantages result despite these conservative assumptions, the findings in favor of SBN should be more credible. In short, our conservative assumptions allow the assessment of the possible cost and utility benefits that are inherent to the fractionated nature of SBNs. The conservative assumptions are the following:

A3. The failure probability of each module of an SBN is equal to α, which is identical to the probability of failure of a monolithic spacecraft. The reality is that given that SBN modules are expected to be less

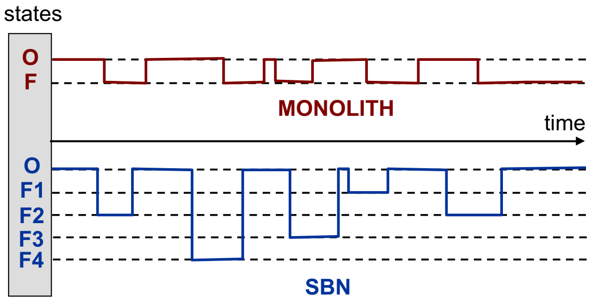

Fig. 4. Example of a single run in a Monte-Carlo simulation of the models.

complex than the monolith spacecraft, their probability of failure is likely to be smaller.[2]

A4. The responsiveness parameter γ of an SBN is equal to that one of a monolithic spacecraft. It is likely however that a smaller spacecraft can be developed and launched faster than a larger one. The reader is referred to [17] for a study of the impact of spacecraft size on the responsiveness of the development.

A5. The utility provided by a failed spacecraft is zero. Failed monolithic spacecraft (and not degraded) satisfy this condition. For SBNs though, partial utility can be obtained when tasks and resources are transferred from a failed module to the remaining operational modules. This situation will be studied further in Section 5.4 with non-zero coefficients in the utility vector.

In addition, the following assumption is made during the calculation of the cost and utility:

A6. No discounting of the cost and utility over time was considered in this model. While the implementation of a discount rate for those metrics constitute an interesting direction for future research, it involves the use of additional parameters (with the crucial choice of their values), extending the dimensionality of the problem beyond the scope of this paper.

3.3. Running the models

We characterize a Monte-Carlo simulation of the models by the triplet (α, β, γ) representing, respectively, the failure probability, the cost intensity, and the responsiveness parameter. One simulation is obtained by running the stochastic model a large number of times, yielding different state trajectories at each run. An example of a run for both architectures is represented in Fig. 4.

The clock starts when architectures are deployed and operational (t=0). For all simulations presented here, the time step (or time unit) is ΔT=1 year. For each run, the lifecycle cost and utility are recorded to generate, once the given time-horizon τ_{ops} is reached, probability distributions characterized by a mean and a variance as discussed and illustrated in the following section.

4. Illustrative example of models outputs and preliminary findings

Comparing the performance of SBN versus the monolith spacecraft requires collecting simulation data about the central tendency of the lifecycle cost and cumulative utility of both architectures, as well as the variability of those performance metrics around their mean. In the following, we provide an illustrative numerical example of the type of results that can be obtained by running the models. In addition to its illustrative purpose, the example provides an indication of the type of parametric analyses that should be conducted to capture the fundamental differences between the SBN and the monolith spacecraft, and to identify the conditions, if any, under which the former "outperform" the latter.

4.1. Cost-utility clouds

Fig. 5 shows typical lifecycle cost and cumulative utility for a Monte-Carlo simulation of the Markov models for both architectures. The time horizon τ_{ops} for this simulation was set to 35 years. Each point in Fig. 5 represents the final values of the lifecycle cost and utility after 35 years for one single run (i.e., one single "state trajectory" of the Markov model). The set of points results from thousands of runs of the Markov models, and thus constitutes a "cost-utility cloud" for each architecture for the time-horizon considered. These "clouds" facilitate the visualization of extreme values and dispersion of cost and utility along both dimensions simultaneously. It is the dynamics of these clouds, their comparative expected values and dispersions, and their dependence on the three critical model parameters, α, β, and γ (the failure probability, the cost intensity, and the responsiveness parameter, respectively) that contain the information about the fundamental differences between the SBN and the monolith spacecraft architecture. In the following, we search for this information through various analyses. Let us first interpret Fig. 5a and b.

The vertical line of points on the far left of Fig. 5a and b corresponds to spacecraft that have not been replaced. These spacecraft might have failed at different points in time, hence they have different cumulative utility, but they have an identical lifecycle cost since they have not been replaced. The cost of developing a spacecraft to replace a failed one (i.e., $cost_{MONO}$ or $cost_{SBN}$) is reflected by the spacing between the vertical lines.

[2] In past studies, spacecraft reliability has been related to system complexity, at least qualitatively [18,19]. The distribution of functions across modules of an SBN will reduce the number of subsystems and interfaces per spacecraft. In this case, this could result in a reduction of complexity and therefore an increase in spacecraft reliability. In the light of these considerations, assumption (A3) appears conservative.

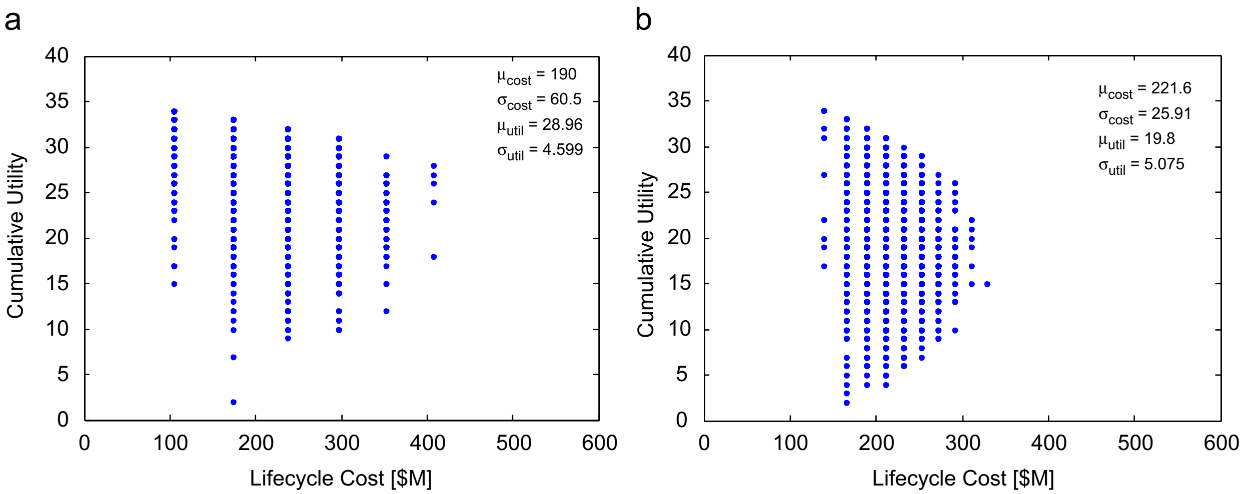

Fig. 5. (a) Lifecycle cost and utility for a monolithic spacecraft for τ_{ops}=35 years, for α=0.05 and γ=0.25 and (b) Lifecycle cost and utility for a space-based network for τ_{ops}=35 years, for α=0.05, γ=0.25, and β=1.5.

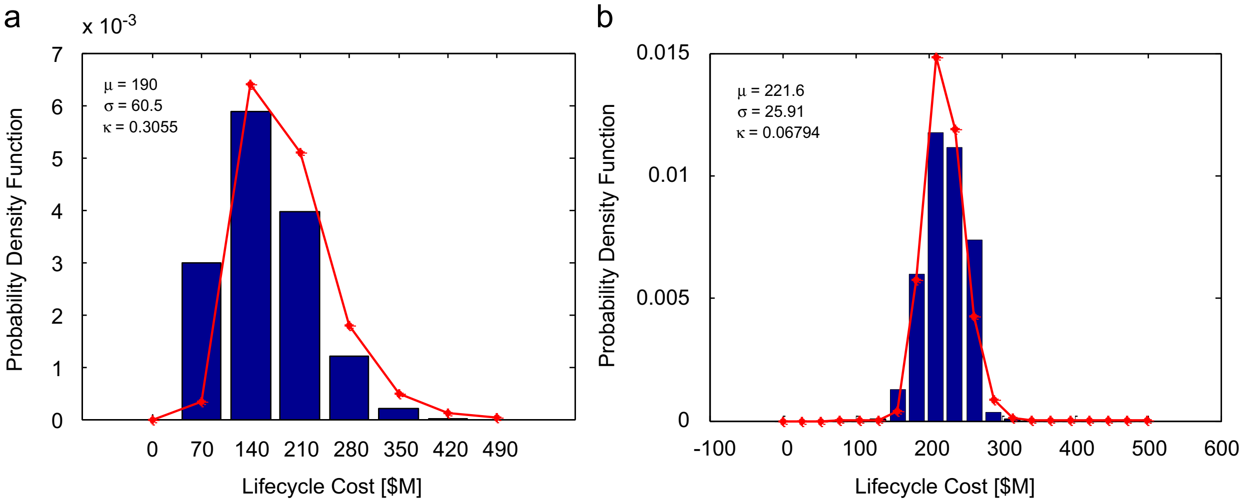

Fig. 6. (a) Lifecycle cost distribution for a monolithic spacecraft for τ_{ops}=35 years, for α=0.05, γ=0.25 and (b) Lifecycle cost distribution for a space-based network for τ_{ops}=35 years, for α=0.05, γ=0.25, and β=1.5.

For this particular example of Monte-Carlo simulation (with α=0.05, γ=0.25, and β=1.5), several observations can be made as follows:

- First, the expected lifecycle costs for both architectures are comparable, although a cost advantage of the monolith spacecraft over the SBN is observed. This should not be surprising, since with β=1.5, the SBN starts with a 50% cost penalty over the monolith spacecraft. In addition, a larger number of spacecraft failures and replacements occur in the SBN (assumption (A3)), than with the monolith. While the interplay of the three parameters, α, γ, and β, determine the resulting lifecycle costs, the cost intensity parameter β is the major determinant of the relative lifecycle cost of the SBN versus the monolith spacecraft. We therefore conduct in Section 5 a parametric analysis of the lifecycle costs of both architectures as a function of β to identify the conditions, if any, under which SBNs "outperform" monolith spacecraft on a lifecycle cost basis.
- Second, the cumulative utility obtained when the time horizon τ_{ops} is reached is on the average lower in the SBN than in a monolithic architecture for this particular simulation. This also results directly from assumption (A3), combined with (A4), which reduces the availability of the SBN compared to that of the monolith, which in turn reduces its utility.
- Third, and most importantly, the cost dispersion is significantly lower for the SBN than for the monolithic spacecraft. This result is robust to parameters variation and is indicative of a fundamental performance difference between SBNs and monolith spacecraft (further discussed in Section 5.1 and illustrated in Fig. 8b). By distributing the sources of failure across modules that are more easily replaceable, the SBN takes less severe cost hits than the

Table 1
Lifecycle cost estimates after τ_{ops}=35 years, for α=0.05, γ=0.25, and β=1.5.

	Cost average ($ Millions)	Cost standard deviation ($ Millions)	Skewness of cost distribution
Monolith	190.0	60.5	0.3
SBN	221.6	25.9	0.07

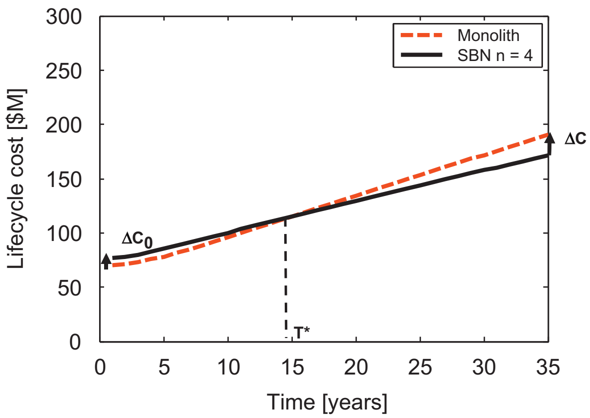

Fig. 7. Lifecycle cost for monolith and space-based network for α=0.05, γ=0.25, and β=1.1.

monolith (should failure occur and replacement be launched), which explains the reduced cost dispersion. We interpret this feature of SBNs as a reduction in the cost risk compared with the monolith.

4.2. Lifecycle cost distributions for a fixed time horizon

While cost-utility clouds are useful to simultaneously visualize the average and the dispersion of lifecycle cost and utility for one Monte-Carlo simulation, final cost distributions show what ranges of cost are more likely to occur. As represented in Fig. 6a, the right-skewed distribution (skewness κ=0.3055) obtained with a monolithic architecture after τ_{ops}=35 years, for α=0.05, γ=0.25, reflects the large diversity of cost overruns resulting from the traditional, monolithic design paradigm. On the contrary, Fig. 6b shows that the distribution obtained in the SBN case exhibits a much smaller skewness (κ=0.06794). This observation indicates that the lifecycle costs computed by the models are more symmetrically distributed around their mean in the case of SBNs (and with a smaller dispersion) than in the case of monolith spacecraft; in other words, there is a smaller likelihood of high cost hits or worst case cost scenarios with the SBN than with the monolith.

Table 1 summarizes the results obtained for the simulation presented for each architecture.

4.3. Mean lifecycle costs evolution with varying time horizon

In what preceded, the time-horizon τ_{ops} was set to the fixed value of 35 years. Previous results can therefore be considered as instant "snapshots" of lifecycle cost and cumulative utility after 35 years of operation of the space system. Further insight regarding the performance of a space-based network can now be gained by studying the evolution of the lifecycle cost *over time*. Fig. 7 shows the results obtained for a given set of parameters for which the mean lifecycle cost curves of a monolith and an SBN intersect. This suggests that, under certain conditions on the parameters (α, β, γ), there exists an instant when the expected lifecycle cost of an SBN falls below the lifecycle cost of a monolith. The existence and location of the intersect point T^* is of significant importance to investigate the potential advantages of SBNs. In the simulations, the triplet (α, β, γ) was found to be the major determinant of T^* (the learning effects have a limited impact on the lifecycle costs over the range of time horizons considered in this study). The intersect point T^* is further analyzed in Section 5.3.

In the next section, we focus on three key parameters of our Markov models, the failure probability α, the cost intensity β, and the responsiveness parameter γ, and explore regions or ranges of values for the triplet (α, β, γ) that result in a reduction of lifecycle cost and cost risk for an SBN compared to a monolith.

5. Design space exploration

5.1. Impact of α and β on average and standard deviation of lifecycle cost for a fixed time horizon

We previously presented the results obtained by the models for a fixed set of values of the parameters (α, β, γ). We now perform a full sweep of the values of the cost intensity β, for various values of the probability of failure α, and a responsiveness parameter set to γ=0.25. Fig. 8a shows the ratio ρ of the mean lifecycle cost of an SBN relative to that of a monolith, after 35 years of operation. The horizontal line ρ=1 splits the (ρ, β) space in two: the upper region where monolithic designs are on average less costly ($\rho > 1$), and the lower region were SBNs are on average less costly ($\rho < 1$). Curves for three different values of the probability of failure α are represented, and exhibit a linear relationship between the ratio ρ of the mean lifecycle costs and the cost intensity β. This dependency is not surprising since the cost of an SBN module scales linearly with the cost of a monolith via Eq. 8 that involves β. There exists a small range of values of $\beta > 1$ that yield a mean lifecycle cost lower for the SBN than for the monolith over a 35-year period. The size of this range increases as the probability of failure α increases. For example, for α=0.05, SBNs have a lower expected value of the lifecycle cost than monoliths for values of β up to 1.2. This result should however not be over-interpreted. Under assumptions (A3) and (A4), an SBN tends to spend more time in failed states, which is also reflected by a lower cumulative utility. If launches of new SBN modules have not yet occurred before the time-horizon τ_{ops} is reached, the final lifecycle cost for an SBN will then be lower than for a monolith.

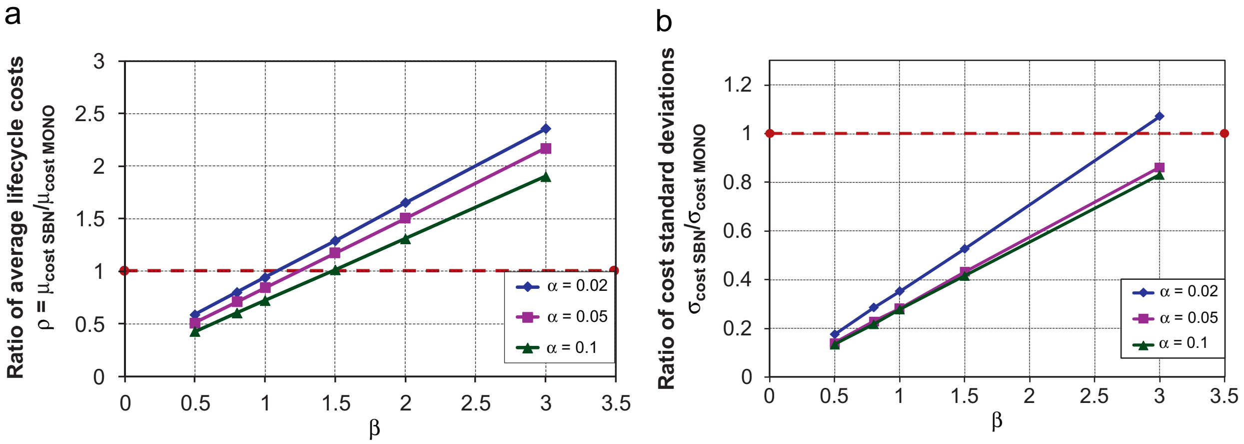

Fig. 8. (a) Ratio of the mean lifecycle costs ($\rho = \mu_{cost\ SBN}/\mu_{cost\ MONO}$) as a function of the cost intensity β, for τ_{ops}=35 years and γ=0.25 and (b) Ratio of the standard deviations of the lifecycle cost ($\sigma_{cost\ SBN}/\sigma_{cost\ MONO}$) as a function of the cost intensity β, for τ_{ops}=35 years and γ=0.25.

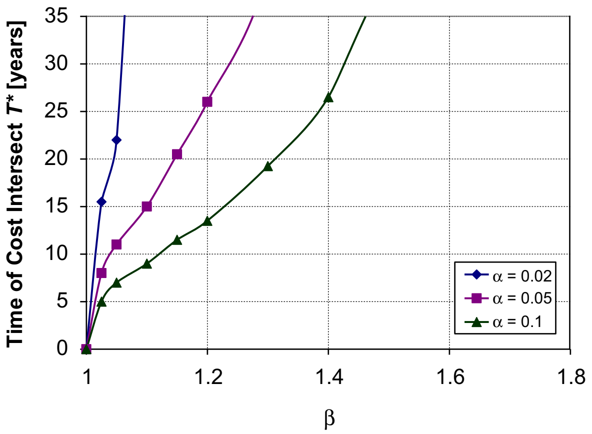

Fig. 9. Location of the cost intersect T^* as a function of the cost intensity β and for different probabilities of failure α.

Fig. 8b shows the ratio of the standard deviations of the cost of monolithic and SBN architectures, i.e., $\sigma_{cost\ SBN}/\sigma_{cost\ MONO}$, for various values of the cost intensity β. This illustrates an important and robust trend: the standard deviation of the lifecycle cost of an SBN remains lower than that of a monolith for a very wide range of values of the cost intensity β. In the previous section, Fig. 5b exhibited intrinsic differences in cost dispersion between a monolith and an SBN, for a single value of β. Fig. 8b demonstrates here how this result still holds for higher values of β (up to 2.8 in this example). In other words, cost risk (as represented by the standard deviation of cost) can be significantly reduced by the distribution of sources of failures across modules of an SBN, despite a strong initial cost penalty.

5.2. Dynamics of cost intersect point T^* with varying time horizon

The lifecycle cost of the SBN relative to that of the monolith spacecraft represented in Fig. 8a corresponds to a fixed time horizon for the analysis, i.e., τ_{ops} is set to 35 years. For values of β that place the SBN design in the region $\rho < 1$, the average lifecycle cost curve of the SBN goes below the lifecycle cost of the monolith at a time T^*, as shown in Fig. 7. The existence and location of the intersect point T^* is of significant importance to help choosing between an SBN and a monolith for a space program, and is highly dependent on the values of the parameters (α, β). To investigate the dynamics of T^*, we varied the cost intensity β and the time horizon until an intersect point emerged ($T^* < \tau_{ops}$). We conducted the analysis for three values of the probability of failure α. The result is the family of curves of T^* as a function of β shown in Fig. 9.

Fig. 9 is particularly rich in implications for the fractionated architecture or space-based network compared with the traditional monolith spacecraft:

- First, we note that if we increase the time horizon of the analysis, that is if we benchmark SBNs against monoliths over a longer period of time, the cost advantage of the SBN over the monolith is ensured for higher values of the cost intensity β. For example, consider the case of α=0.1: if the time horizon is set to 8 years, T^* exists only for $\beta < 1.075$. In other words, SBNs cannot break even within 8 years unless their cost intensity is less than 7.5% above the cost of a monolith. On the contrary, if the time horizon is 15 years, SBNs would break even for β up to 1.225. Stated differently, if the time horizon is given (defined by the decision-maker), the curves of Fig. 9 provide the maximum value of the cost of an SBN module that results in a lifecycle cost lower than that of a monolith (i.e., where T^* exists).
- Second, we note that SBNs are particularly appealing in a low reliability environment. In other words, as the probability of failure α increases, SBNs break even sooner and become more advantageous on a cost basis than their monolith counterpart. For example, consider the case of β=1.1: $T^* > 35$ years for α= 0.02, whereas T^* drops to 9 years for α=0.1.
- Finally, Fig. 9 indicates that the adoption of fractionation will be contingent on the decision-makers'

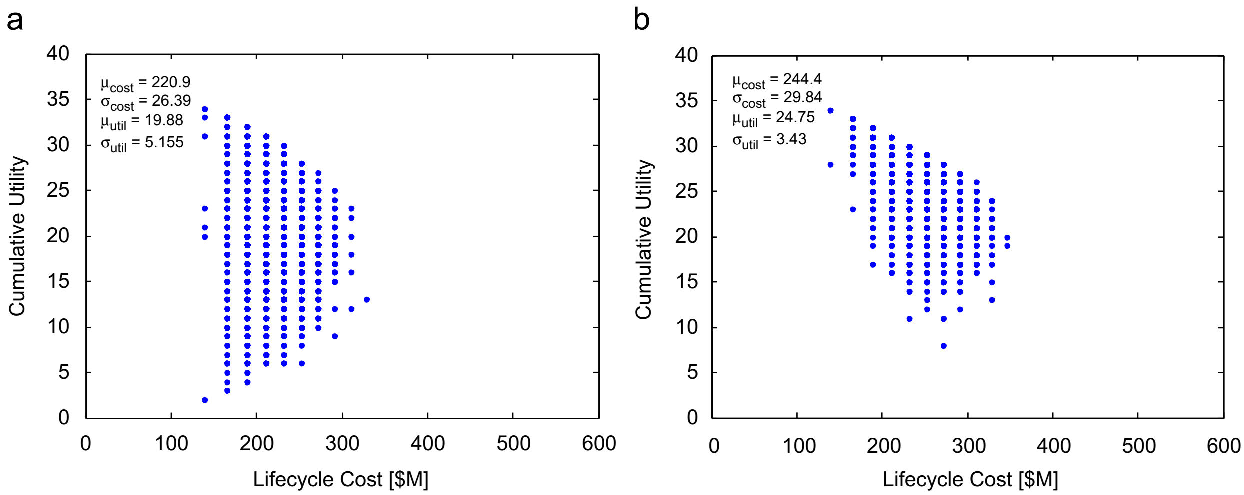

Fig. 10. (a) Lifecycle cost and utility for a space-based network for τ_{ops}=35 years, and γ=0.25 (α=0.05 and β=1.5) and (b) Lifecycle cost and utility for a space-based network for τ_{ops}=35 years and γ=0.50 (α=0.05 and β=1.5).

incentives and planning horizon. Short-term planning horizons are not favorable to fractionation from a cost standpoint, whereas longer-term horizons enable fractionation to better reveal its advantages.

5.3. Influence of responsiveness

To understand the impact of responsive development and launch of spacecraft on the lifecycle cost and cumulative utility, we first generated cost-utility clouds for two values of the responsiveness parameter γ. Fig. 10a and b shows how the cost-utility cloud of the SBN is affected when γ increases from the initial value of 0.25 to 0.5, that is, when the *MTTR* is reduced from 3.5 years to 1.4 years.

Increasing γ corresponds to developing and launching modules faster to replace failed ones (i.e., higher responsiveness). This has several consequences on the cost and utility performance of the space system:

- The time spent by the system in the operational state (or its availability) increases, which in turn increases the cumulative utility provided. In our example, raising γ from 0.25 to 0.5 (i.e., improving the space responsiveness from 3.5 years to 1.4 years) increases the average cumulative utility by 25%. This utility increase can be mapped into the value of responsiveness (or one aspect of the value of space responsiveness).
- In addition to the utility increase, increasing γ results in a reduction of the dispersion of the utility. Indeed, systems with high values of γ are spending more time in the operational state, which reduces the variability of the provided utility.

The combination of these two trends is seen by comparing Fig. 10a and b where the cost-utility cloud is compressed upwards as γ increases. This implies that a minimum utility can be guaranteed and increased as γ, the responsiveness parameter, increases. This result can be of significant importance for customers and users of the space architecture, as it relates a given requirement on utility to the responsiveness of the development.

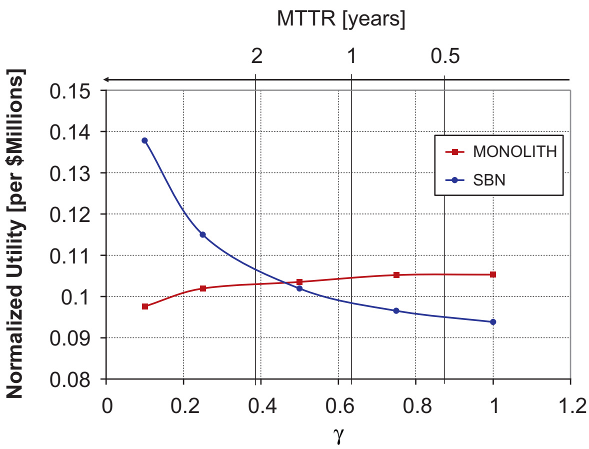

Fig. 11. Normalized utility of a monolith and an SBN as a function of the responsiveness parameter γ and the *MTTR* (α=0.1; β=1.5; τ_{ops}=35 years).

- Finally, raising γ while holding the failure probability α constant increases the number of modules developed and launched during the time horizon of the analysis. As a result, the average lifecycle cost increases as well.

5.4. Normalized utility provided by an architecture as a function of responsiveness

In this section, we propose to go further in the analysis of the relationship between responsiveness and the joint cost-utility performance by analyzing the "normalized utility" of the two space architectures. We define the normalized utility after τ_{ops} as the ratio of the cumulative utility provided by the system and its lifecycle cost. In other words, the normalized utility measures the amount of utility provided by unit cost (i.e., for every dollar spent). As such, the normalized utility is a proxy for the proverbial "bang for the buck" of the system. We modify assumption (A5) to reflect one of the major advantages of SBNs over monolithic spacecraft: the failure of one single module does not fail the whole system but only partially degrades its capability. For illustrative purposes, we make the following assumption regarding the partial utility delivered by an SBN constituted of n modules, in case of a single module failure as shown in the following equation:

$$u_{part} = \frac{n-1}{n} u_0 \tag{12}$$

In our example of an SBN with four modules, the new utility vector becomes

$$u_{SBN} = u_0 \begin{bmatrix} 1 \\ 0.75 \\ 0.75 \\ 0.75 \\ 0.75 \end{bmatrix} \tag{13}$$

Fig. 11 shows the results of the normalized utility delivered by each architecture for various values of the responsiveness parameter γ after 35 years.

Monolithic spacecraft prove more profitable than SBNs when responsiveness is high. This trend becomes significant when $\gamma > 0.65$. This result applies to our example when the mean-time-to-replacement remains below 1 year. In this situation, monolithic spacecraft are rapidly replaced in case of failure. As a result, the advantages related to the partial utility provided by SBNs remain inconsequential compared to the cost benefits of a monolith (in the case where β=1.5). However, spacecraft are at present rarely developed and launched in less than a year. 2 or 3 years are more likely yet still optimistic estimates of the space industry's *MTTR*. When responsiveness is lower ($\gamma < 0.4 \Leftrightarrow MTTR > 2$ years) the result highlighted in Fig. 11 is particularly interesting and reveals the opportunities offered by SBNs: when the *MTTR* is greater than 2 years, SBNs offer a significant advantage over monolithic spacecraft in terms of normalized utility, due to their higher survivability.

This important result indicates that a "low-responsiveness" environment enables fractionation to better reveal its advantages (on a normalized utility basis) over the monolith spacecraft.

5.5. *Impact of the degree of fractionation of the SBN*

All the previous findings were based on a space-based network with a fixed number of modules n=4. In this section, we extend these results by investigating the influence of the number of modules n of the SBN (i.e., its degree of fractionation) on the mean lifecycle cost, cost risk, and normalized utility. The case n=1 corresponds to a monolithic spacecraft. A partial utility for the SBN similar to the one described in the previous section is used and values of τ_{ops}=35 years, α=0.05, β=1.2, and γ=0.25 (or *MTTR*=3.5 years) are selected for this illustrative example. Fig. 12a and b show how mean lifecycle cost and mean normalized utility vary as the degree of fractionation increases. Several important observations can be made:

- The average lifecycle cost of an SBN, shown in Fig. 12a, decreases when the degree of fractionation n increases above two modules, for a given β. Furthermore, on a cost basis, it is rarely justifiable to fractionate with two modules only (n=2) for a broad set of conditions on the parameters (α, β, γ).
- A minimum degree of fractionation exists that ensures that the lifecycle cost of the corresponding SBN will be lower than that of its monolithic equivalent for a given β. In the example of Fig. 12a, an SBN will offer cost benefits over the monolith only for a number of modules equal or greater than 4.
- The average normalized utility increases with the degree of fractionation for a given β, although a marked increase occurs for $n \geq 3$, as shown in Fig. 12b. In other words, for an equivalent amount of money, a more fractionated

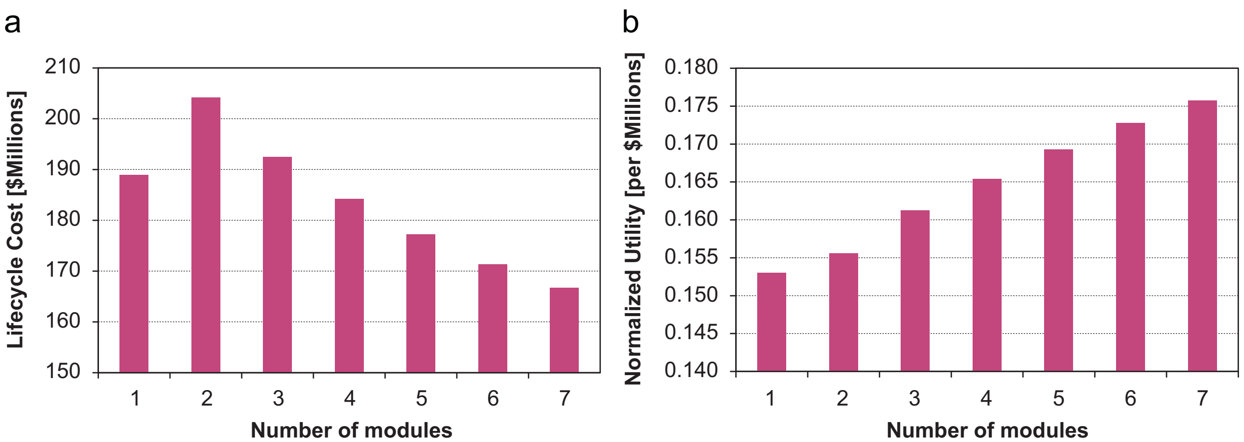

Fig. 12. (a) Impact of fractionation on the lifecycle cost for a space-based network for τ_{ops}=35 years (α=0.05, β=1.2 and γ=0.25) and (b) Impact of fractionation on the normalized utility for a space-based network for τ_{ops}=35 years (α=0.05, β=1.2 and γ=0.25).

space architecture will prove more useful or "valuable" to the customer. Furthermore, the degree of fractionation $n=3$ (i.e., three modules for the SBN) appears as a robust threshold above which this normalized utility advantage is maintained for a broad set of conditions on the parameters (α, β, γ).

We identified additional trends by varying the probability of failure α along with the degree of fractionation n. We found that

- For systems with higher probability of failure α, increased fractionation reduces the average lifecycle cost more significantly than for systems with low probability of failure. Said differently, on a cost basis, fractionation is more advantageous for less reliable systems.
- For systems with higher probability of failure α, increased fractionation increases the mean normalized utility more significantly than for systems with low probability of failure. This finding is similar to the previous one, and shows that fractionation is more advantageous on a normalized utility basis for less reliable systems.

Similarly, variations of the responsiveness parameter γ yield the following result:

- On a normalized utility basis, increased fractionation is more advantageous at low levels of responsiveness than at high levels. For example, when $MTTR=3.5$ years ($\gamma=0.25$), two modules are sufficient for an SBN to present benefits in terms of normalized utility. When $MTTR=1.4$ years ($\gamma=0.5$), four modules are required to present a similar advantage over a monolith.

The combination of the previous findings could be summarized by the following:

If the environment is not responsive and the system is not reliable, fractionation can be beneficial.

Finally, Fig. 13 shows the influence of the degree of fractionation of an SBN on the standard deviation of the lifecycle cost, indicative of the cost risk:

- Cost risk is reduced when the degree of fractionation increases.

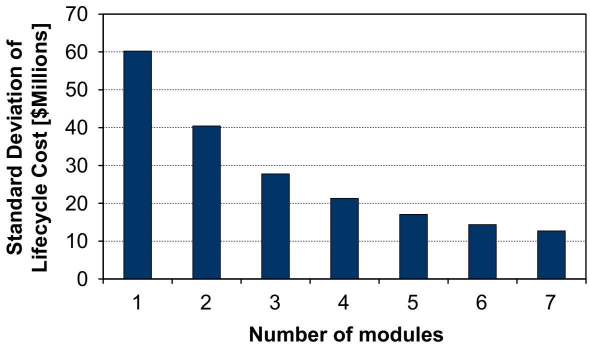

Fig. 13. Impact of fractionation on cost risk.

- The asymptotic trend visible in Fig. 13 shows that significant improvements in terms of cost risk are achieved when fractionating a monolith spacecraft into up to 4 modules. Increasing fractionation further ($n \geq 4$) does not provide additional major improvements.

6. Conclusion

Spacecraft are complex systems that are not easily accessible on-orbit for maintenance operations when failures occur. In the current dominant design of spacecraft as monolith systems, a single subsystem failure often results in the failure of the whole and requires the replacement of the entire spacecraft to restore the initial services provided, a solution that is highly cost inefficient. Partly in response to this problem, a new design paradigm has recently been proposed: the fractionation of a spacecraft into a space-based network of modules wirelessly connected. An immediate consequence of this physical decoupling of functions is the new ability to only replace the faulty module(s) in case of malfunction, at a cost significantly lower than that of replacing the entire monolithic equivalent. The total cost of initially developing a space-based network may however exceed that of a monolith, as SBN-enabling technologies must be implemented in every module of the network. Furthermore, in addition to the lifecycle cost of a space architecture, it is essential to assess how well the system serves its intended function, i.e., how much utility it provides to its users. Careful quantitative analyses are therefore required to identify the conditions under which SBNs can "outperform" the current monolithic spacecraft architecture.

In this work, we developed failure and replacement Markov models of both monolithic and SBN architectures to quantitatively compare the lifecycle cost and utility of both architectures, and identify conditions under which one architecture is more advantageous than the other. Three main parameters constitute the core of our models, namely the probability of spacecraft failure α, the responsiveness parameter γ, and the cost intensity β. Results obtained by Monte-Carlo simulations offered a number of insights into the performance of an SBN compared with a monolith. For example, while the initial cost of an SBN is likely to be higher than that of a monolith, its total lifecycle cost is much less subject to the variability that would be caused by unpredictable failures.

The models also exhibited cases for which the total lifecycle cost of an SBN could fall below that of a monolith after a certain time. Conditions governing the existence and instant of this intersect point include specific ranges of values of the model parameters. The design space exploration we conducted showed that the average lifecycle cost of the SBN could be equivalent or lower than that of a monolith for a small range of values of the cost intensity β around 1. On the other hand, the advantage exhibited by space-based networks regarding the dispersion of the lifecycle cost (cost risk) proved very robust, effective for high values of β. We found that the cost benefits of the SBN over the monolith (average lifecycle cost and cost dispersion) were magnified when the reliability of the spacecraft decreased (via the parameter α). Similarly, the average lifecycle cost of an SBN falls under the cost of a monolith sooner for higher values of the probability of spacecraft failure α. Furthermore, we confirmed the intuitive relationship between responsiveness of the spacecraft development (represented by the parameter γ) and utility provided to the user. The higher the value of the responsiveness parameter γ, the higher the value of the minimum utility guaranteed to the customer. Finally, we considered the partial utility that an SBN could provide in case of failure. We showed that for systems characterized with a relatively high probability of failure and with lowly responsive development and launch, fractionation could present significant advantages in terms of mean lifecycle cost, cost risk, and normalized utility delivered to the user over time.

The framework and models developed in this work offer rich possibilities for future research and many opportunities for improvement. For example, additional states can be added to the Markov chain, and the aging of modules can be modeled with time-dependent failure rates. In addition to the failure-based replacement strategy considered here, a retirement model driven by the design lifetime of the spacecraft can be implemented (and different modules in an SBN can have different design lifetimes). Finally, technology obsolescence can be accounted for in the models and its impact analyzed for both architectures. These future research directions constitute important steps towards a realistic assessment of the potential benefits of SBNs compared to the traditional monolithic spacecraft.

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