Probabilistic Simulation of Multi-Stage Decisions for Operation of a Fractionated Satellite Mission

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Abstract—We present two complementary analysis models to study the effect of programmatic management decisions on the distribution of net present value for a fractionated satellite constellation. The goal is to begin development of an approach to quantify when system attributes associated with design flexibility have realizable benefits for space systems. The first approach is a heuristics-based decision model, which utilizes a Monte Carlo simulation to produce value distributions for satellite operator decision sets; the second approach is a multi-stage decision process model, which utilizes a dynamic programming algorithm to find value-optimal decisions. We use a generic Department of Defense (DoD) terrestrial weather satellite program as a case study for analysis. We find evidence that technological evolution of a fractionated satellite system within the scope of a single program may not be desirable due to cost and schedule risks.

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1. INTRODUCTION

Research & Development Investment

This paper seeks to provide insights to a hypothetical decision maker in the Defense Advanced Research Projects Agency (DARPA) or an equivalent funding organization for research and development. DARPA is a technology development agency for the U.S. Department of Defense, and focuses on funding programs to bridge fundamental discoveries and new capabilities. Program managers from the Agency fund researchers at private companies and universities to bring new technical concepts into a useful state for the American technology base and national security programs.

Fractionated Satellites

While ideas regarding networked satellites have existed for some time, DARPA defines the concept of spacecraft fractionation as "a cluster of satellites that are linked together via a wireless network, creating a virtual spacecraft with the same or better capability than a traditional monolithic, multi-payload spacecraft"[1].

This paper considers the operation and management of such a space mission architecture, whereby spacecraft function-

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ality for a generic meteorological satellite system with two payloads is distributed across three wirelessly-interacting spacecraft modules operating together in orbit. DARPA's Future, Fast, Flexible, Fractionated, Free-Flying Spacecraft United by Information Exchange (F6) Program focuses on developing and maturing the technology necessary for this type of mission approach [2][3][4][5]. In the F6 concept, each module corresponds to a particular subsystem or package of subsystems with the capability to contribute a specific functionality to the overall system such as communications, computing, or a payload.

Two types of fractionation may be defined when comparing monolithic and fractionated satellite systems: heterogeneous fractionation and homogeneous fractionation. Heterogeneous fractionation can be qualitatively expressed as the degree to which the original spacecraft is disaggregated into independent modules with different functions (such as individual payload, communications, and data handling modules). Homogeneous fractionation can be understood as the degree to which the original system is decomposed into functionally similar modules (such as multiple identical payload modules) [6].

Value Centric Design

Value models are increasingly part of the design and analysis process for aerospace systems [7]. The practice of value-centric design is commonly defined as the incorporation of value metrics, in particular net value and variance in net value, into the systems engineering and engineering design process [8]. This approach can be contrasted to traditional spacecraft engineering practice, which focuses on cost minimization subject to fulfillment of engineering requirements.

Value-centric design seeks to incorporate programmatic and operational uncertainty into the assessment of a program through probabilistic analysis of cost, schedule, and system operation. Value-centric methodologies also offer a basis to pursue quantification of system attributes associated with design flexibility, such as a system's capacity for adapting to different missions or receiving technological upgrades – factors that the common requirements-driven, cost-minimization approach does not handle well [8].

2. Analysis Goals & Scope

Risk of Concern

The risk of concern considered in this analysis is the relative net present value distribution given different user decisions regarding a meteorological satellite system using DARPA's fractionated mission architecture.

This metric is important to provide the technology-investment decision maker with knowledge of risk associated with user management of a completed system. We utilize simulation to characterize the management decisions for a fractionated satellite system; this contrasts with approaches that simulate only the performance of spacecraft modules (neglecting or simplifying decisions about when and how modules are deployed). Our approach begins to enable quantification of benefits associated with design flexibility – such as claims about 'upgradability' and 'adaptability' of a particular system architecture, and boundary conditions for when the benefits of these system attributes are realizable.

Space systems that provide national security information should maximize value while managing for acceptable risk; theoretically, a system also should not cost more than the value of the information it provides. The Defense Department's investment distribution across technology programs impacts the quality of the future systems available and their usefulness to the operational user. The risk of concern therefore addresses not just the financial risk associated with technology development, but the future availability of relevant information resources for operational and strategic needs of the military.

The simulation of value distributions given user decisions, and sensitivity to external factors, can inform DARPA's evolution of satellite technology – by focusing on mission regimes where benefits of fractionation are most likely to be realizable.

Scope: Analysis of Programmatic Management

This analysis aims to inform the evolution of requisite satellite technology and choices for investment at specific program margins at DARPA. Some papers discussing the "fractionated satellite" approach and value centric design consider these subjects in the context of both technological implementation and DoD acquisitions practice; [9] we focus on analysis of multi-stage decisions by the DoD user over the life-cycle of a notional fractionated satellite system, and do not address explicitly details of DoD acquisitions practice at this time.

Satellite systems are often procured for a certain number of satellites to be designed, built, and launched on specified dates all to fulfill an uncertain future demand. This can lead to increased cost and lower than expected performance when the satellite must be launched on a deadline for one payload while the other payload is immature. This issue has been recognized by the by the Government Accountability Office (GAO) as a consistent problem for DoD space acquisitions[10].

A fractionated satellite architecture provides flexibility for a decision maker to evolve a system in response to demand increases and technology advancements, theoretically making the system more valuable (generally at the cost of some spacecraft element redundancy). If new technology becomes available during the course of a program, this improved capability can be designed into new spacecraft modules. But what is the best strategy for when to design, build, and launch a module of a fractioned satellite? Do the benefits of technology updates within a program outweigh the costs if you could make these decisions optimally? We approach these key issues as a multi-stage decision process.

The future availability of space-based assets to support the operational and strategic needs of military and intelligence programs is impacted by early-stage technology investment decisions by agencies like DARPA. The goal is to provide knowledge of system value and risk associated with user operation of a fractionated satellite mission, to inform better the development process.

Direct analysis of DoD acquisitions or a detailed comparison of a fractionated mission with a traditional "monolithic" approach would require detailed DoD data and are outside the scope of this initial analysis. The modeling and simulation approaches developed here are meant to be a starting point for analysis, and present the beginning of a process to identify regimes when fractionated systems become viable.

Case Study: Defense Meteorological Satellite System

This analysis uses a generic Department of Defense (DoD) terrestrial weather satellite program as the case study. This type of program is applicable for a value-based analysis because recent government meteorological satellite programs highlight the particular cost and schedule growth issues associated with DoD space systems acquisition generally. (For example, the GAO notes that the National Polar-Orbiting Operational Environmental Satellite System (NPOESS) was originally estimated to cost $6.5 billion, and at latest estimate is now expected to be $13.2 billion; launch of the first NPOESS satellite has likewise slipped 5 years[10]). Programs like NPOESS and the Defense Meteorological Satellite Program (DMSP) are also highly valued DoD programs with fairly public information about their missions, payloads, and costs which makes generating realistic models feasible.

We model a generic version of the Defense Meteorological Satellite Program (with simplified environmental data products), implemented as a fractionated cluster with 3 modules; the satellite modules correspond to imagery data, atmospheric profile data, and infrastructure support. This is consistent with key meteorological requirements from both NPOESS and DMSP[11][12]. The first module hosts a Visible/Infrared Imager (for example, the Advanced Very High Resolution Radiometer (AVHRR)), the second module hosts a microwave sounding unit (for example, the Advanced Microwave Sounding Unit-B (AMSU-B)), and the third module holds the primary communication direct downlink to the ground[13][14][15].

Each module utilizes a common bus structure with power, attitude control, thermal and propulsion. The payload modules require more power for larger payload power consumption and better attitude control for tighter pointing requirements, while the support module requires a larger on-board computer to act as the primary storage, processing and command center for the system. These characteristics are addressed as the model inputs (see Modeling Approach). The payload modules have a backup S-band command/telemetry system and backup computers for data storage and routing if the support module fails. The modules fly in a polar, sun-synchronous orbit.

Modules composing a fractionated satellite system are assumed to orbit in sufficient relative proximity to communicate with each other directly (for example via a mesh network – though this approach would not be necessary, and other approaches including a routing network could work for larger-diameter constellations) and experience approximately the same orbit perturbations. A simple approach is to place all three modules in the same circular orbit with a constant phase offset between the central module and leading and trailing modules. In this configuration, the each module would maintain the same relative position to the other two throughout the entire orbit[16]. (NASA currently utilizes a similar orbital configuration for its A-Train formation of major Earth-observing satellites, though with a larger orbital phase offset than would be utilized here)[17].

Other discussions[2] of fractionated systems have suggested utilizing co-altitude circular orbits with small relative inclination and eccentricity differences, which would enable payload modules to exhibit cross-track and in-plane motion relative to the support module[16].

Because our case study utilizes a sun-synchronous orbit for meteorological data collection, and does not require co-orbiting spacecraft modules, we can focus for simplicity on the former case: each of the three modules in the same orbit-track, with the communications module in the central position and the imager and atmospheric profiling payload modules leading and trailing, respectively. Each payload satellite module flies with a constant orbital phase offset from the communications module.

3. Modeling Approach

Overview: Our Approach

We present two complementary approaches to model program management as a multi-stage decision process. The first approach, Heuristics Based Decision Making (HBDM), models management of the system as a Markov process and applies heuristics to model operator decisions, and corresponding state transition functions, in each state. The overall state transition process retains the Markov property because the state transition function references only the current state and the action selected. This does not model a "decision process" directly, however, because no optimization process occurs to select the highest-value action at each time period; predefined heuristics specific to the simulation are referenced in each state to automatically generate the action.

The second approach, a Markov Decision Process (MDP) model, approximates management of the system as a discrete time stochastic control process and utilizes a dynamic programming algorithm to approximate a decision maker's selection of optimal actions at each time step. Like the HBDM approach, it models the transitions between states as a Markov process because the state transition function references only the current state and the action selected. This method, while computationally limited by the number of elements in its state space, allows for optimal decisions and outcomes to be determined that otherwise may have been ruled out or left unaccounted for in development of traditional decision heuristics.

Both models utilize the same case study, a standard set of input modeled uncertainties, and value function. The HBDM tool provides statistics from which one can derive the best

heuristics to guide management decisions, while the MDP model automatically selects the best actions and provides NPV calculations for various starting states and future actions.
In future studies, the results from the MDP tool can be input into the HBDM tool to compare results and iterate the HBDM process. The results from each model complement each other and in most cases provide similar results.

Model Inputs

Each model utilizes a set of commonly modeled uncertainties and a value function. The uncertainties include reliability, cost, launch failures, user demand and technology evolution. The HBDM models uncertainty in the timeliness for procurement (development and build times), which is currently assumed constant in the MDP model due to state space limitations. Each model also uses the same value function which equates amount of GBytes of data transmitted to the ground for the entire system into a dollar amount discounted to the start of the program. It is this value minus the costs that we want to optimize while limiting the variance.
1. Reliability: The reliability of each module is the probability that the module has not failed up to a specified time in its life. The probability of satellite module failure is modeled as a Weibull distribution with alpha (α) and Beta (β) parameters. α is a scale parameter with units of years and is proportional to the mean mission duration. α is specific to each subsystem and module. β is a unitless parameter related to the design robustness. A value of β equal to 1.0 is characteristic of a single string design, while typical values are between 1.4 and 1.7 for government satellites [18]. We use a β value of 1.4 due to minimal redundancy per subsystem and module. The probability of failure at any point in time is the probability distribution function (pdf), while the probability that the module will fail before a specific age or time in its life is the cumulative distribution (cdf). Reliability can then be calculated according to: Reliability = 1 - F(α, β, time). Figure 3 shows the Weibull pdf, cdf, and resulting reliability for example parameters α = 8.6 and β = 1.4.

For modeling purposes the team assumed each module contains two major subsystem elements: a common bus and unique subsystem. Each module has a common bus with 94% reliability over 5 years. Module 1 has a payload subsystem with 91% reliability over 5 years, Module 2 had a payload subsystem with 90% reliability over 5 years, and Module 3 had a communication (comm.) subsystem with reliability of 92% over 5 years. These are fairly high reliability values but not uncommon for government satellites. The subsystem reliabilities are assumed to be independent so the module reliability can be calculated by multiplying each subsystem's reliability together. These are calculated for the 3 modules according to:

$$R_{Module1} = R_{CommonBus} * R_{Payload1}$$

$$R_{Module2} = R_{CommonBus} * R_{Payload2}$$

$$R_{Module3} = R_{CommonBus} * R_{Comm}$$

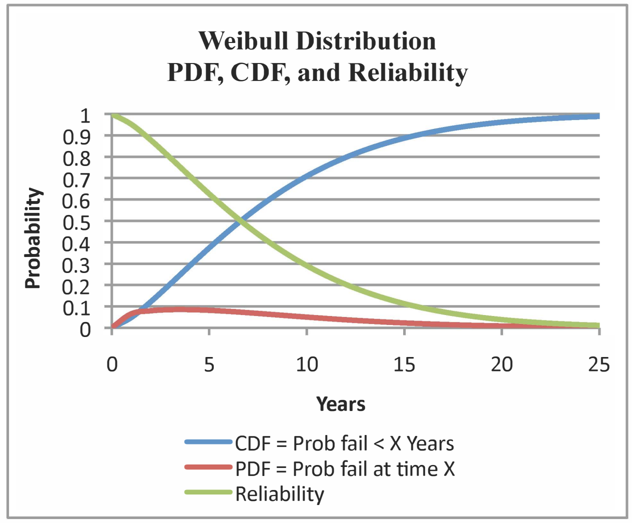

Figure 1. Weibull pdf, cdf, and resulting reliability: The Weibull probability distribution function (pdf) represents the probability of failure at each point in time (X axis). Alpha and Beta are used to shape this distribution. The cumulative distribution function (cdf) represents the probability of failure within X number of years. Reliability equals one minus the cdf.

Component	**5-Yr Reliab.**	**Alpha (Yrs)**	**Beta**
Module 1	0.86	18.8	1.4
a. Common Bus	0.94	36.5	1.4
b. Payload 1	0.91	27.0	1.4
Module 2	0.86	18.8	1.4
a. Common Bus	0.94	36.5	1.4
b. Payload 2	0.91	27.0	1.4
Module 3	0.86	18.8	1.4
a. Common Bus	0.94	36.5	1.4
b. Comm Payload	0.91	27.0	1.4
System	0.63	8.6	1.4

Table 1. Reliability Parameters for Each Subsystem, Module, and System: Each Module is comprised of independent subsystems whose reliabilities multiply together. Similarly, the system reliability is the product of each module reliability.

Each module failure rate can be modeled as a Weibull distribution with alpha and Beta parameters, as summarized in Table 1.

Finally, we calculate the probability of failure in each time period, given the module has not already failed. This calculation is performed using Equation (1):

$$f(t)|\bar{f}(t-1) = \frac{F(\alpha, \beta, t) - F(\alpha, \beta, t-1)}{1 - F(\alpha, \beta, t-1)} \quad (1)$$

Where t is the current time in years, $t-1$ is the current time minus one timestep, f is the probability of failure, $\bar{f}$ is the probability of no failure, F is the cumulative distribution

Cost Type	Module 1	Module 2	Module 3
Develop. (NRE)	$46.12M	$46.12M	$38.77M
Build Cost (RE)	$37.19M	$37.19M	$28.75M
Maint./Storage	$0.95M/yr	$0.95M/yr	$0.76M/yr
Launch	$7.83M	$7.83M	$7.83M
Operations	$2.51M/yr	$2.51M/yr	$3.3M/yr

Table 2. Costs for Each Module: Costs are broken out into NRE, RE, Maintenance/Storage, Launch, and Operations for each of the 3 modules.

function, α is the Weibulll distribution scale parameter with units of years, and β is the Weibull distribution unitless parameter related to design robustness.

At this point in development of the MDP code, the average probability of failure given that the module did not fail in the previous timestep over 15 years was used for each timestep.

2. Demand: One of the primary reasons for analyzing programmatic decisions with a value centric methodology is to understand the effects of a change in user demand. We model demand in three ways for the HBDM model analysis: 1) increasing 10% every year, 2) increasing by 3% every year and 3) maintaining a constant demand rate. For the MDP model, at this stage in development, we model a 10% demand increase every two years.

3. Cost: Costs are categorized as 5 items: development costs (non-recurring engineering (NRE)), build cost (recurring engineering (RE)), maintenance/storage costs to maintain an on-ground spare, launch costs, and operation costs to "fly" the module in orbit. To develop an initial set of cost model inputs, we create a mass and parametric cost estimate for a monolith satellite based on Tables 20-4, 20-5, 20-9 in Space Mission Analysis and Design (SMAD) scaled for FY2010 dollars [19][20]. This includes NRE and RE cost breakdowns by subsystem. We then allocate the mass to each module according to its functions. We leveraged a Geostationary Operational Environmental Satellite (GOES) distribution provided by DoD staff to assist in this process. GOES is a geosynchronous satellite and has much larger mass estimates, but it provides a basis for allocating a mass percentage to each module based on functionality. We calculate the costs for each module by multiplying the monolith costs by the ratio of module mass to monolith mass. It is assumed that each payload on modules 1 and 2 have approximately the same mass and bus requirements resulting in the same total module mass and costs. Storage costs are assumed to be 5% of the RE bus costs per year based on engineering judgment. Launch costs are based on Delta 2 launch costs per kilogram as described in Table 20-14 of SMAD and scaled for consumer inflation from FY 2000 to FY 2010 [19][20]. The operations costs are derived from all other costs and Table 20.9 of SMAD [19]. The costs are summarized in Table 3.

We also assume a 95% learning curve for the recurring costs in the HBDM model, approximating easier, and therefore less expensive, production of new identical modules [21]. We model new technology levels as an increase of 50% in

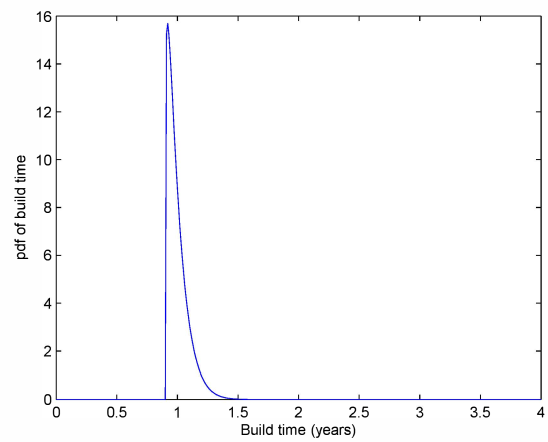

Figure 2. Beta Distribution Applied to NRE and RE Costs for Heuristics Code: The Costs to actually develop and build a module are uncertain and can be modeled with a Beta distribution.

capability. When upgrading to new technologies we assume one increment of development (NRE) cost is incurred; we assume that the NRE costs are equal for an increase in any one level of technology, because the operator is building a new module with extensive heritage (only the payload is being upgraded). However, for each level in technology advancement that is "jumped" an additional factor of 1.5 is applied to the NRE costs to simulate greater differences in module architecture. For example, if the current module is at technology level 2 and it is decided to upgrade to technology level 5, the total NRE cost will be $NRE_{base} * 1.5^2$.

All of the costs are summed at each time period and discounted to time 0, the start of the simulation. We assume a discount rate of 10% compounded yearly.

For the HBDM model, the team simulates cost uncertainty by modeling the NRE and RE costs with a Beta distribution. The team allows the minimum cost to be 80% of the NRE or RE cost and the maximum cost to be up to 300% of the NRE or RE cost. Based on iterative interviews with aerospace engineers, we select a Beta distribution with alpha parameter of 1.1 and an expected value of 1.0, meaning the expected cost is the base NRE or RE cost. Figure 2 shows this cost Beta distribution.

4. Launch success: We use a 92% probability for launch success. This includes a 1% infant mortality rate for satellite modules and a 93% launch success rate based on based on an average of established launch vehicle success rates [22]. Both HBDM and MDP modules currently model spacecraft module launches as separate events.

5. Technology Development: An advertised benefit of a fractionated system is that each spacecraft module is cheaper than an entire system and can be developed and built with the latest technology in order to upgrade the entire system.

We model technology upgrades by considering the effects of new technology on data output. Specifically, we model an increase in technological sophistication as an increase in data output from an instrument per unit time – and thereby an increase data collection rate for the overall instrument module. Similarly, a technology upgrade in a support module corresponds to an increased capability to handle and downlink data from the system's instruments. This assumption allows us to represent changes in user needs regarding both quantity of data and technological sophistication of instruments in the same units (bytes per day). This also maps units of user demand to our measurement of system capability. If user demand increases, the simulations can develop and build a new modules to provide more data collection and throughput to the ground.

Each technology level represents a 50% improvement over the old technology [23].

In the MDP code we model each module as able to be upgraded to a higher technology level at any point over the mission, but only once (currently due to state space limitations in the MDP model). In the HBDM code, satellite modules can be upgraded at any point, and as many times as needed to sequentially-higher technology levels.

6. Value Function: Conducting a value-centric design analysis on a generic mission, in the absence of fully-defined mission parameters, is a significant challenge given uncertainties in both cost and value of the system. We hope to provide a framework for future development with improved model inputs. While parametric methods to estimate spacecraft costs and reliabilities exist and are used, these estimates of these variables are more precise when tied to the specifics of any mission. In the absence of specific engineering designs for each spacecraft module, it is necessary to generate a rough approximation of the satellite cost; similarly, absent specific mission requirements, a rough approximation of data value to the decision maker must be generated. We utilize a common basis to compare differing mission management decisions for a generic mission architecture and value function. For a decision maker seeking to apply these methods to his own project, either more accurate approximations for cost and value could be plugged in to our analysis tools or the decision maker could see if our assumptions match his own system, and use our results accordingly.

Our unit of comparison between cost and the user's valuation of mission data is a monetary value, which requires a translation of the value of the data into a dollar amount. This analysis could be performed equivalently using a non-monetary valuation scheme, though a monetary valuation is a logical approach because we possess cost models for the program that work in units of dollars. A similar approach, utilizing different units, might map system costs and benefits into "military utility" instead of dollars.

The value gained from the meteorological satellite system is modeled as an amount of data transmitted back to earth (approximating the data required to produce environmental data records for end-users). We model a user "demand" for data in bytes per day from the system, and similarly model a capability of the system to provide data in bytes per day to meet the user demand. To match this approach we model technology upgrades by considering the effects of new technology on data output. Specifically, we model an increase in technological sophistication of an instrument module as an increase in data collection rate for that spacecraft. Likewise, a technology upgrade for a support module corresponds to an increased capability to process data from the system's instruments and transmit those data back to earth. This assumption allows us to represent changes in user needs regarding both quantity of data and sophistication of instruments in the same units (bytes per day). This also maps units of user demand to our measurement of system capability.

To estimate the worth of the returned data, and again as a preliminary input, we model the value provided by one year of fully meeting user data-needs as approximately 1.5 times the cost of the system for one year. We observe a willingness to pay up to 50% cost overruns in DoD space acquisitions, and use this fact to infer a value for successful DoD space programs as approximately 150% of the original cost bid. (Note that for the most recent DoD involvement in a meteorological system, NPOESS, there was approximately 100% cost-overrun. This seemed impractical to infer as a rule. See [10]). This approach can be scaled according to user needs or future methods to elicit more precise valuations, as necessary, for DoD space systems.

We model a baseline yearly cost, given a 5-year nominal lifetime for each of the modules, as the following (where AAC: Amortized Annual Cost):

$$\text{AAC} = \frac{1}{5} * \Big[\sum_{i=1}^{3}(\text{Module } i \text{ NRE}) + \sum_{i=1}^{3}(\text{Module } i \text{ RE}) + \sum_{i=1}^{3}(\text{Module } i \text{ Launch Cost})\Big] + 3 \text{ Module Ops} \tag{2}$$

We model the nominal daily total data returned from the system as 100 GB/day (see model inputs). We therefore calculate the fully operational cost per GByte per day (FOC) as a function of the Amortized Annual Cost:

$$\text{FOC} = \frac{\text{Amortized Annual Cost}}{365/100} \tag{3}$$

The user valuation of the returned data is then 1.5 times this value.

Finally, instead of assuming that all data have the same value, we assume four different classes of data, each valued differently as a function of the percent capacity at which the space system is operating. This models initial data, and the ability to produce some Environmental Data Records (EDRs) rather than none, as having greater marginal value to the DoD user than each additional EDR when the system operates at full capability. (A more detailed implementation of this model, tied more closely to an operational mission, could bin, and value, data by discrete requirements for specific EDRs. This paper is more general in focus and approximates this approach with a continuous value function).

Data downlinks of less than 10% of the nominal system capability return zero value, approximating the fact that such minimal data would constitute incomplete global coverage by

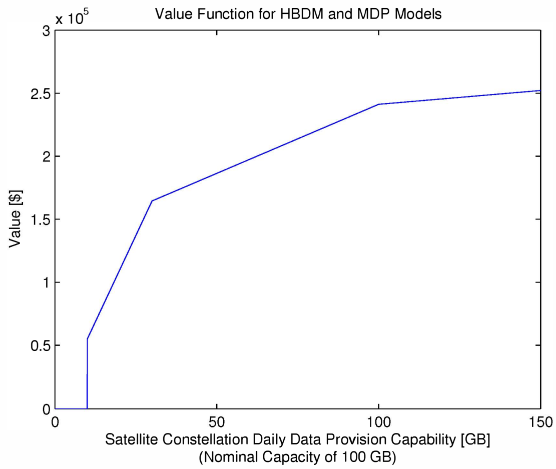

Figure 3. Value Function: Value is modeled as $ for the amount of data transmitted back to the Earth. The value provided by one year of fully meeting user data-needs (100% Capability) as approximately 1.5 times the cost of the system for one year. There are 4 Value data slopes representing importance of varying levels of capability.

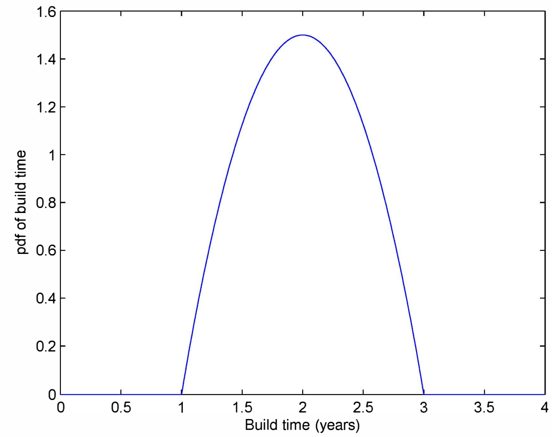

Figure 4. Beta Distribution for Development Times: The time to develop a module is an uncertainty and is modeled with a Beta distribution.

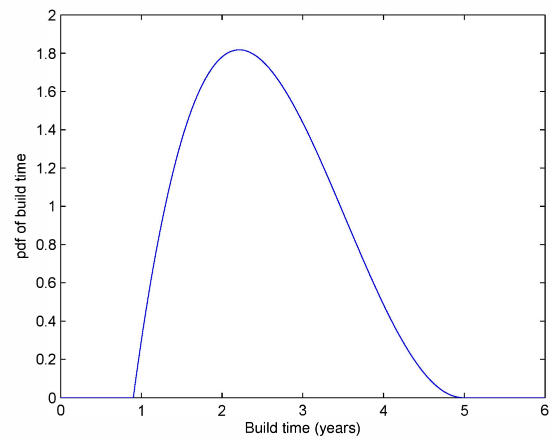

Figure 5. Beta Distribution for Build Times: The time to develop a module is an uncertainty and is modeled with a Beta distribution.

the instruments and would be insufficient to form Environmental Data Records for end users. We assume that an ability to collect between 10% and 30% of the systems capability has a high marginal data value. Data rates fulfilling 30% to 100% demand are considered medium value data, important but with marginal value less than that of the first 10-30% capability. The high-value data are marginally worth 5 times as much as the medium-valued data. Data returns greater than the nominal user demand also provide value, but these low-valued data are marginally worth 20% of the medium-valued data. Using our cost estimates to find amortized annual cost, this approach yields four value slopes for each of the data classes, as a percent of nominal system demand met (to two significant figures):

- Less than the minimum: $0/GB, if data return $\leq$ 10% of full system design capability
- High-Valued Data: $5500/GB, for the first 30% of the demanded data (given that more than 10% of data are provided)
- Medium-Valued Data: $1100/GB, for data between 30% and 100% of demand
- Low-Valued Data = $200/GB, for any data provided above the demand of the system

7. Develop and Build Times (heuristics only): For the HBDM code we model both development and build times with Beta distributions in order to represent uncertainty in these times. Figure 3 shows these distributions. The expected develop time is 2 years and the expected build time is 2.5 years; both times, however, have a significant spread to them, providing uncertainty. In addition, when multiple modules are built, the uncertainty reduces in the build time becoming more narrowly distributed around the expected value of 2.5 years. These values are assigned based on small satellite engineering experience. For the MDP model, the development and build timelines are currently modeled as constant and assumed to be one timestep (2 years).

Model #1: Monte Carlo Simulation with Decision-Maker Heuristics

The first of the two analysis methods is Heuristic-Based Decision Making (HBDM) model. For the HBDM model, we develop a set of parameterized rules which define how the decision maker adjudicates decisions in reaction to the state of the system. As an example, one heuristic rule sets a "minimum number of spares" that the decision maker maintains at all times. The HBDM simulates probabilistic changes to the system (such as in-orbit module failures) as well as reactions to those changes by the decision maker based on the set of parameterized heuristics.

Simulations model a fifteen-year program with four time steps per year. In each time step, the HBDM first updates the demand, checks to see if any under-construction modules are complete and if the any new designs have completed development, and then stochastically determines whether any of the modules in orbit have failed. Given the new state of the system, the HBDM determines decisions made using the input heuristics and calculates the incurred costs based on these decisions. Lastly, the code calculates the total value (time discounted) gained from the in-orbit system for providing data to the ground. Decisions fall into three main categories: launching spare modules into orbit, developing new technologies, and building additional spares.

The specific heuristics parameters and their use are as follows:

Launch: Three heuristics are used while making launch decisions: an age threshold, a minimum demand threshold, and a maximum demand threshold. First, the decision maker checks to see if the constellation is meeting the current demand for data in each of three categories: data from module 1, data from module 2, and support capability for the two modules. The age threshold, if set, causes the decision maker to ignore modules older than the age threshold while calculating data output. This allows the replacing of aging modules preemptively rather than waiting until modules fail. If any piece of the system is unable to meet a higher percentage of demand than set by the "minimum demand" threshold, the code then launches available spares of the appropriate type until either all of the spares are used or the constellation exceeds the "maximum demand" threshold. The minimum threshold allows a tolerance in meeting demand (making meeting demand a "soft cap" rather than a hard one), and the maximum threshold simulates planning ahead for future demand increases. Every time a spare is launched, the code stochastically determines the success or failure of the launch and in either case adds the launch costs to the total costs.

Develop: There are two heuristics used to decide when to design new modules at a higher technology, "MinTechDemandMult" and "MaxTechDemandMult." Similar to the launch decisions, these two act as a soft cap for meeting demand. The decision maker calculates how much demand could be met with a fully functioning constellation in orbit with the current technology levels. If the constellation is unable to meet the demand times the "MinTechDemandMult" (even with a fully functioning constellation), the decision maker decides to upgrade technology. The decision maker calculates demand times the "MaxTechDemandMult," and choses the cheapest technology capable of meeting that level of demand. When it is decided to develop a new technology, the development time and cost are determined stochastically as described above.

Build: Three heuristics guide the build decisions. The first heuristic is "wait for new technology." With this parameter turned on, if there is a technology under development for a certain module type, new spares are not built until the technology has finished development. The second heuristic is a requirement on the number of on-ground spares for each individual module type. If this number is greater than zero, then the code merely checks to see if the requirement is being met. If it is not, then new modules of the highest designed technology level are built until the minimum number of spares is met. If there is no requirement on the number of spares, then the code first checks to see if there is already a spare of that type available. If no spare is available, it checks to see if demand for that module type is being met, and decides to build additional spares if demand is not being met. The third heuristic is that older modules in orbit can be ignored while making these build decisions (like in the "launch" decision section). When new modules are built, the build cost and build time are determined stochastically.

Through Monte Carlo simulations, the distribution of value conditioned on each set of heuristic parameters is determined. The optimal set of heuristic parameters can be found by performing Monte Carlo simulations with different sets of parameters. The HBDM's relative advantage is the ability to incorporate detailed models of uncertainty when simulating the satellite system, and that results from the HBDM translate directly into potential subcontractor requirements. The relative disadvantage of the HBDM is that decision rules must be specified outside the simulation. The heuristics that produce the most favorable value distributions are therefore really "best rules of thumb" within the guidelines of the established heuristics, rather than a truly optimal set of management decisions.

Model #2: Markov Decision Process & Dynamic Programming Algorithm

The second approach models management of the satellite system as a Markov Decision Process. We utilize a dynamic programming algorithm to determine an optimal expected value for the system given any initial state, and then run an iterated stochastic (Monte Carlo) simulation across the dynamic programming results to obtain distributions over the program value.

A dynamic programming (DP) algorithm is an optimization method that can be applied to problems that have discontinuous variables, non-convex feasible regions, and are nonlinear [24][25][26]. A DP algorithm solves problems by combining solutions to sub-problems: the algorithm partitions a problem into overlapping sub-problems, finds optimal solutions for the relevant sub-problems, and then combines the solutions to sub-problems to find an overall optimum.

For a multi-stage decision process, the DP algorithm works by considering the value of each possible state in the final time period, and then works backward to assess the value of each state in preceding time periods. In each state in an earlier time period, the algorithm finds the action which leads to the highest future expected value; the algorithm then stores the value of the immediate state summed with an expectation over future states given the optimal action.

1. State Space: The MDP approach models each system state as a vector consisting of twelve binary elements corresponding to the functionality, technology level, existence of a ground-spare, and technology level of the ground-spare for

each of the three module types:

$$\text{State} = \{F1, F2, F3, TM1, TM2, TM3, S1, S2, S3, TS1, TS2, TS3\} \quad (4)$$

The state space models the functionality of each on-orbit satellite module (F1, F2, F3) as either functional or non-functional. The overall constellation capability to provide meteorological data for a specific time is calculated based on the number and type of functioning modules. This models degraded capability (partial failure) modes for the entire satellite constellation, but not individual modules. Technology level in each module (TM_i and TS_i) is modeled as either a "baseline" technology level at which the operator entered the program, or an upgraded technology level, which the operator can access for additional cost. We model the upgraded technology level as a constant increase in capability, which can be accessed with decreasing cost over time. Finally, the existence of an on-the-ground spare for each module type (S1, S2, S3) can occur when the user has previously decided to build, but not yet launch, a particular module type.

A state space is generated to encompass all 4096 mathematically-possible states ($2^{12} = 4096$). With simple constraining heuristics, corresponding to physically-possible states, only 729 states may ever be inhabited by the system.

2. Actions: To move between states, the decision maker selects an action. Actions are modeled using an action vector with six binary elements:

$$\text{Action} = \{B1, B2, B3, T1, T2, T3, L1, L2, L3\} \quad (5)$$

The action vector carries decisions regarding whether to procure a new satellite of any (or multiple) of the module types (B1, B2, B3) and, if procuring a particular module type, whether to do so at an upgraded technology level (T1, T2, T3). A second module cannot be procured if an on-ground spare of that type already exists. The action vector also carries a decision to launch for each module type (L1, L2, L3). The decision to launch a module can only occur if a spare of that type already exists (i.e., the relevant module has already been procured). Launches are currently modeled as independent events; if more than one module is launched in the same time period they are assumed to launch on different rockets.

3. State Transition Function: The MDP model utilizes a probabilistic state transition function. Given a current state and an action, the state transition function produces a probability distribution over possible states in the next time period. This probability distribution over future states is known to the decision maker, and actions are chosen to maximize future expected value. For example, the decision maker who is considering launch of a replacement satellite module would know in advance the probability of launch success.

4. Dynamic Programming Solution Process: Management of the satellite constellation can be represented as a multi-stage decision process, in which the decision maker's actions probabilistically influence changes in system state between time periods (Figure 6). The DP algorithm starts by calculating the present value associated with each possible state in

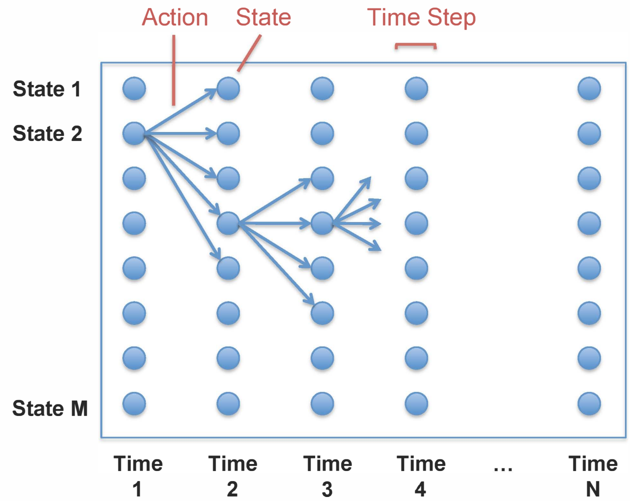

Figure 6. Multi-Stage Decision Process: MDP models decisions at every step to change the resulting state space.

the final time period (Figure 7). For each state, the satellite constellation's available data rate is calculated from the first six elements of the state vector. The system capability is then compared to the current user demand, and a data value is returned using the value function. The cost for operations (modules in orbit) and storage (spare modules on the ground) are subtracted from this value. The remaining quantity is the user value associated with existing in a particular state at the final time step.

The DP algorithm then calculates a value for each system state in the second-to-last time period (Figure 7). For each state, the algorithm queries all possible actions available to the decision maker. Each action has an associated action cost, and produces a known probability distribution over states in the next time period using the state transition function; the value of each possible state in the next time period was also calculated and saved previously. The algorithm then selects the action that maximizes the expected user value.

This optimal action is then saved. The algorithm sums the expectation value of this "optimal" decision, including the action cost, with the value and cost of being in the current state. This provides the expected present value of being in the current state, given optimal actions are chosen at all points forward; this process is repeated for each state in the current time period.

The DP algorithm then continues backward through each time period in a similar manner to the first period. Values calculated and saved in states for the first period correspond to the net expected value of the program given optimal decisions at each time step in the future.

This general approach can be represented mathematically as follows. Start with calculating the value J of each state x in the final time period N:

$$J_N(x_N) = g_N(x_n) \quad (6)$$

Then calculate the value of each state in the immediately preceding $(N-1)$ time period, by selecting the action a that

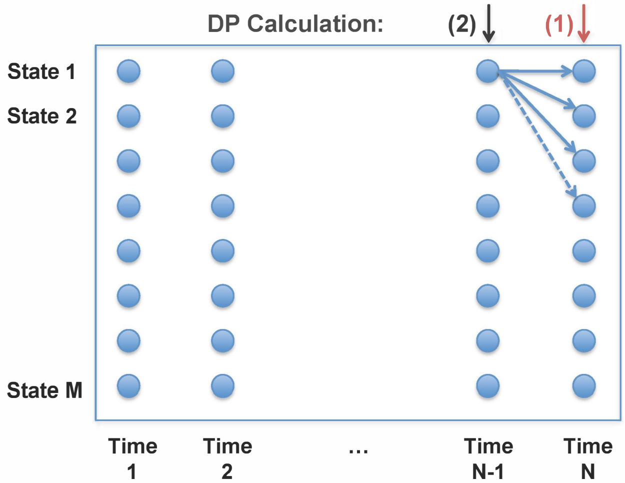

Figure 7. Dynamic Programming Solution Method: DP algorithm solves the problem by starting in the final time step and working 'backward' to the initial time step, finding the optimal actions to maximize NPV.

maximizes expected value:

$$J_{N-1}(x_{N-1}) = \max_{a_{N-1}\in A_{N-1}} \Big[c(x_{N-1}) \\ -c(a) - \sum_{x_N \in X_N} P(x_N|a, x_{N-1}) * J_N(x_N)\Big] \quad (7)$$

Repeat this process for each time period n from n=N-2 to n=1:

$$J_{n-1}(x_{n-1}) = \max_{a_{n-1}\in A_{n-1}} \Big[c(x_{n-1}) \\ -c(a) - \sum_{x_n \in X_n} P(x_n|a, x_{n-1}) * J_N(x_n)\Big] \quad (8)$$

5. Stochastic Simulation: Finally, we run iterated stochastic (Monte Carlo) simulations using the results of the DP solution to obtain a distribution over program value for each relevant set of program parameters.

For this analysis, we initialize the simulation with 3 functional modules on-orbit, all at the baseline (non-upgraded) technology level, and with no spares on the ground. The simulation then queries the optimal action for this state, which was saved in the DP solution process, and obtains a probability distribution over states for the next time period from the state transition function. The simulation then stochastically determines the resulting state, and moves there in the next time period. The optimal action for the new state and time is again queried, and the process repeats through the final time period. At each period the state value is recorded, and after each state transition the action cost is recorded. These quantities are summed at the end to produce the realized program value for the stakeholder. The simulation is repeated one million times to obtain a distribution on net present value.

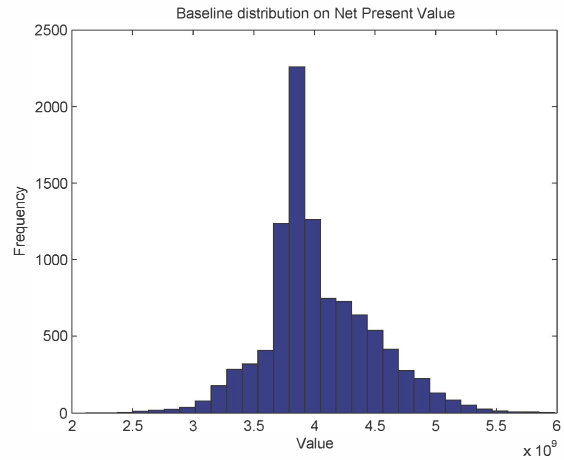

Figure 8. Representative NPV distribution for the baseline set of heuristic parameters: Similar plots are generated for various combinations of heuristic and input parameters.

4. Results & Model Outputs

Primary Results: Heuristics-Based Decision Making Model

Trade studies were performed on a number of the heuristic parameters in order to find the best heuristics. Each instance of input parameters (including both heuristic parameters and general simulation parameters) was run ten thousand times, recording the gross value gained, the expenditures and the final net value. Ten thousand runs are enough for accurate measurement of the distribution on net value except at the tail ends of the distribution. Best and worst case outcomes are not accurately found by running ten thousand simulations due to it being extremely unlikely for everything to go perfectly (or perfectly wrong). It would take many more simulation runs (or more advanced simulation techniques) to accurately model a "plausible worst case scenario." It was determined through comparing different instances of ten thousand runs that the mean and standard deviation are accurate to at least 1%.

A histogram on net value for a baseline set of heuristic parameter inputs and cost breakdown is shown in Figure 8 and 9 below. The baseline case requires one spare of each type to be on the ground, MinTechDemandMult is set to 0.8, MaxTechDemandMult is 1.5, and the demand increases by 10% per year.

1. Number of required spares: The first heuristic studied is the number of required spares to maintain on the ground. Three different scenarios were considered: a nominal demand increase of 10% per year, a smaller demand increase of 3% per year and a constant demand. Recall that a decision maker wants to maximize mean net value while minimizing risk, so the Pareto front is toward the lower right of Figure 11. There are four different spare requirements on the Pareto front. The requirement with the highest expected net value is requiring one payload spare and two support spares at all times, and the parameter with the lowest variance is requiring three support spares and no payload spares. Requiring only three support

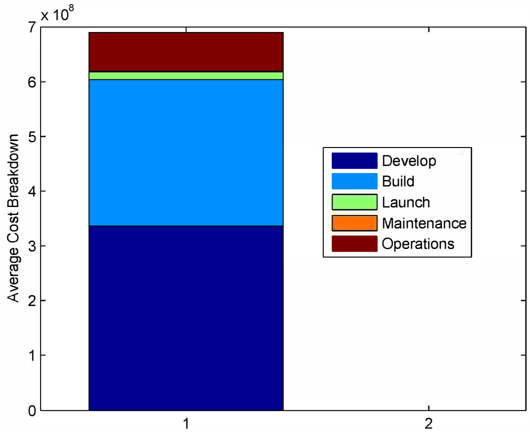

Figure 9. Representative cost breakdown for the baseline set of heuristic parameters: Similar plots are generated for various combinations of heuristic and input parameters.

spares and requiring one payload spare and three support spares are also on the Pareto front. All other settings for required spares are strictly worse in both mean net value and the standard deviation.

When the demand increases more slowly (3% increase per year), the results change. There are now only two choices on the Pareto front, maintaining two spares of all three module types and maintaining one spare each of the two support spares and two support spares. The same trend continues when the demand remains flat (Figure 13), except maintaining one spare of each is now on the Pareto front.

These results highlight two important points. The first is that maintaining spares can be effective in increasing NPV while simultaneously reducing the variance of NPV. Requiring functioning spares to be kept on standby allows for quick replacement when modules fail in orbit. This minimizes losses while the module is inactive which both increases gained value and reduces fluctuations in value. This is especially true for support spares as they are used by both payload systems to function. On the other hand, the usefulness of the spares decreases the faster demand grows. With high demand growth, new technologies are researched to increase system capability. As a result, modules in orbit become obsolete before they fail, and thus having too many spares expends resources needlessly.

2. Technology Improvement Thresholds: Three different cases for MinTechDemandMult and MaxTechDemandMult were examined. The first case, [0.8 1.5], represents the base case where new technology is researched when the system can only meet 80% of the demand and is then upgraded to meet at least 150% of the demand. The second case, [0 0] represents a case where technology is never upgraded. The third case [0.8 4] has the same minimum threshold as the first, but technology, when upgraded, increases in capability to four times larger than the current demand. The results for baseline, and medium demand increases can be seen in Figures 14 and 15 (when there is no demand increase there is no need to upgrade technology and so all three cases yeild the same result).

As in the number of spares, the optimal choice depends on the projected demand increase. With the baseline demand increase, both not upgrading technology and making incremental improvements in technology are Pareto efficient. However, with only 3% per year demand increases, it is not worth it to upgrade technology at all. Due to the costs and variances involved in technology development, it is often better to upgrade technology as little as possible to both increase mean net value and decrease variance.

Ancillary Results: Markov Decision Process Model

While we focus analysis and discussion on results from the HBDM model, which is most similar to prior modeling approaches utilized to consider fractionated satellite technology programs, we present MDP model results here to indicate initial progress and demonstrate the benefits and feasibility of this modeling approach.

After further development of the MPD model, we hypothesize that the DP algorithm should select strategies better than or equal to heuristic-sets tested in the HBDM model. At this stage of development, the MDP and HBDM model inputs diverge sufficiently to make the hypothesis not yet testable.

The primary DP algorithm produces an expected value for starting with 3 modules in orbit, each at baseline technology level, and no spares of \$1.4288*10^9.

Running a stochastic (Monte Carlo) simulation with the output of the DP code, using the same uncertainty functions and one million iterations, provides a distribution over program value (Figure 20):

- Mean: $1.4287 * 10^9$
- Second moment (variance): $3.8150 * 10^16$
- Third moment (skewness): $-1.3298 * 10^25$
- Min: $-1.8537 * 10^8$, Max: $1.5931 * 10^9$

As expected, the mean of the value distribution from the simulation is approximately the expected value from the DP algorithm. The simulation distribution is heavily skewed due to the minimal uncertainty models currently inputted to the MDP model; this statistically favors "nominal" program operation (things going as planned, but not better) with a tail corresponding to launch failure and module failure events. Percentiles demonstrate this behavior clearly:

Percentiles	
5	$1.0388 * 10^9$
25	$1.3447 * 10^9$
50	$1.4869 * 10^9$
75	$1.5931 * 10^9$
95	$1.5931 * 10^9$

We also extract initial action sets from the DP algorithm for comparison against the HBDM model. A few trends

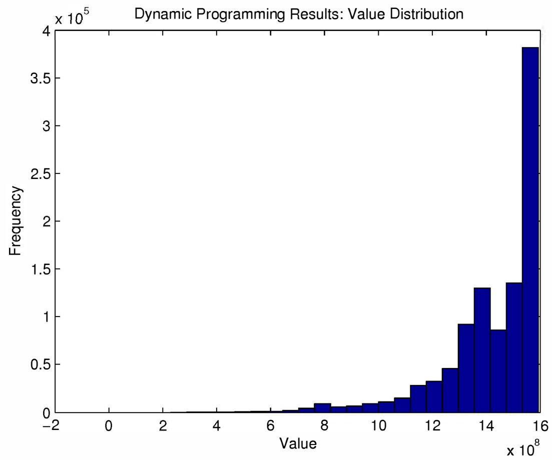

Figure 10. Histogram of NPV from MDP Stochastic Simulation

emerge when converting the optimal decisions into heuristics language. Given the current inputs, an optimal decision maker maintains three functioning modules in orbit, with only one of the payload modules at an upgraded technology level. The choice to upgrade technology is dependent on the demand model utilized (here demand increases at a rate of 10% compounded every two years, set for comparison to the HBDM model). This also reflects the lack of distributions on satellite procurement time and development cost; adding more robust uncertainty models, akin to the HBDM model, may produce a new optimal strategy path for the expected-value decision maker.

A support spare is always maintained to allow rapid redeployment of the support module if it fails, consistent with results from HBDM simulations. Each payload module is rebuilt only after a failure of the corresponding module in orbit. When deciding to launch, an optimal decision maker always launches spares to replace failed modules in orbit, except when the support module has failed and there are no support spares to launch; in this scenario, the decision maker waits until the support spare is rebuilt and then launches all available spares with the support module.

5. Discussion

Method Interface Discussion

The first approach, Heuristics Based Decision Making (HBDM), models the transition of the system across time periods as a Markov process. The state transition function references only the current state and the action selected. In each time step, actions are selected based on the current state and a set of predetermined heuristics. This does not model a standard "decision process" in that no optimization occurs to select the highest-value action at each time period; predefined heuristics specific to the simulation are referenced in each state to automatically generate the action.

The HBDM model provides a means to test sets of management heuristics for the satellite program with detailed uncertainty models. This simulates a decision maker with a constant approach to making decisions in response to external events. A limitation is that the HBDM relies on a single, preset group of decision rules, which neglects being highly nuanced and situation-dependent (except under intensive manual effort by the analyst). A second, and more important, limitation is that results obtained from the HBDM model are not necessarily optimal actions. It is therefore difficult to separate problems with the modeled fractionated satellite architecture from the problems with the management strategies for the architecture. It will be important in future F6 studies to better separate out these two effects as trade-offs between different architecture types are examined.

The second modeling approach, a Markov Decision Process (MDP) model, approximates management of the system as a discrete-time stochastic control process and utilizes a dynamic programming algorithm to approximate a decision maker's selection of optimal actions at each time step.

The MDP model presents the opportunity to explore the viability of a fractionated mission architecture itself, independent of operator decision quality, by simulating a decision process with optimal actions at each step of the program. The MDP model is limited, however, in the detail of uncertainty models it can include while remaining computationally tractable. The DP algorithm searches for an optimal expected outcome to decisions, and therefore models a decision maker with flexible decision making rules dependent not only on the entire state of the system but also predicted future states.

Together, the MDP model and the HBDM model allow the analyst to control for the effects of both decision-making quality and mission architecture on stakeholder value. A combination of these two approaches may help provide a means to separate and analyze the engineering limitations and human operation of a fractionated satellite mission in the future.

Findings & Implications

Our results reveal several trends. First, it may not be worthwhile to upgrade technology due to the high cost and variance of developing new technologies. The DP algorithm produces better results by upgrading one of the payload satellite modules, however, the algorithm does not take into account uncertainties in cost and development length while making that decision. The HBDM tool found different upgrade strategies to be Pareto efficient depending on the demand level. This difference in models suggests a cause for the different results: cost and schedule risk for technology development and module construction can have significant effects on the expected-value for the decision maker.

The ability to upgrade on-orbit technology is often associated with the fractionated satellite approach as one of its main benefits. Our results, however, add caveats to meeting new user demand through technology upgrades. If the demand increase is large, then upgrading technology can provide greater overall value; this higher expected value, however, comes with a greater risk of cost overruns. If the demand increase is small, it is better to not upgrade technology at all, as the costs of upgrading technology, or the probability of cost overruns, may be too high to merit the additional data.

However, both demand cases show that it's better to upgrade incrementally than to make significant changes in module designs. It is important to remember that these results do not address technology upgrades used to re-task a system to fundamentally different needs.

The results further suggest that it is not desirable to keep on-ground spares for every module of the fractionated satellite system in certain situations. For the baseline case of moderate demand increases (10% per year), maintaining no spares at all optimizes expected value. This is consistent with the fact that steady demand increases, and associated technology increases, will cause operators to find less value in building spares at rapidly-obsolete technology levels; seeking the value-increase associated with technology upgrades may limit the benefits of maintaining module spares. In contrast, when there is no demand increase, we find all cases on the pareto-front have full sets of spares. Overall, the results indicate that spares are desirable with stable satellite designs, but are less and less desirable as the configuration changes more rapidly.

These results carry implications for DARPA in the development of technologies for next-generation satellite systems. Realizing the benefits of fractionated satellite constellations, in particular, may depend on early decisions regarding system standards. The potential benefits of upgrading on-orbit technology within a program lifetime may be realizable only if cost and schedule risks associated with technology development are sufficiently controlled. We find that fractionated satellite constellations are still particularly sensitive to human-induced risks associated with procurement and development cycles. This could motivate significant technological standardization across spacecraft modules in a fractionated constellation to manage cost and schedule risk.

Our results also indicate the utility of maintaining a backup ground-spare for the support module, due to its unique role in the system (while maintaining backups for non-unique elements of the system may cost more than the value provided). A common ground spare for the support module, which could appear as an element in multiple fractionated constellations, may be able to provide adequate redundancies for multiple programs at the same time.

More accurate inputs are needed before any firm conclusions can be reached. This paper models a generic fractionated system with assumptions in development costs (and associated uncertainties) and demand increases. New architecture studies should re-examine these results with their own inputs.

Next Steps

Future work ought to focus extensively on improving model inputs, including the derivation of a value function (such as through user or stakeholder interviews), cost models, and technology models.

A significant influence on the results of our analysis is the value function of the decision maker. If there are significant penalties for failing to meet a certain demand threshold, or simply stronger incentives to meet demand, it may be that the cost of procuring more modules becomes dominated by the payout for meeting demand. In this case, it may become worthwhile to store additional modules to avoid paying value penalties when modules fail.

Secondly, an update to the module costs, development times and uncertainties could change our results. We could perform sensitivity analyses to determine if any inflection points exist which would change the decisions.

Each of the models could be improved to increase the fidelity of results. The most important improvement for the MDP model, and DP algorithm specifically, is increasing the number of uncertainties modeled.

Certain near-term improvements are possible:

- Expand the dynamic programming state space to include module age. This will allow the DP algorithm to consider the age of operational satellite modules when quantifying the expected benefit of launching new modules. It would also allow the DP algorithm to address more realistically issues such as preemptive replacement of system elements.
- Utilize a time-dependent weibull failure model to approximate model failure probabilities. (We have already developed this input model, it can be added to the MDP simulation once module age is stored as part of the system state).
- The DP code can be expanded to include more realizations of each variable, such as multiple modules of each type in orbit, and multiple spares of each type on the ground.
- The stochastic simulation of DP results can also be expanded to include uncertainties additional to the state transition function. For example, a stochastic determination of cost could be drawn from the same distributions input to the HBDM model. This will produce more realistic distributions of value from decisions made in the MDP model.

Improvements can also be made to the HBDM simulation, though these would be more fundamental in nature. The next step in the HBDM code is developing more nuanced heuristics. These would account for the year of the program, the predicted future demand, and the predicted future state of technology. All these parameters would require an extensive model not only of a value function for the specific decision maker but of the decision maker's beliefs.

In future studies, the results from the MDP tool can be input into the HBDM tool to compare results and iterate the HBDM process.

Finally, an interesting target for future research might also include accomplishing a sensitivity analysis of program value to the module cost and schedule distributions – seeking to identify cost and schedule accuracy (distribution width) regimes in which benefits of technology upgrades in a fractionated mission architecture may be realizable.

6. CONCLUSIONS

We present two complementary analysis models to analyze the effect of programmatic management decisions on the distribution of net present value of a fractionated satellite constellation. We develop as inputs for both codes uncertainty models concerning launch success, module failures, build times and costs, all of which influence the success of a mission architecture. The first approach, Heuristics Based Decision Making (HBDM), takes into account these uncertainties and through simulation attempts to find the best set of decision rules. The second method, a Markov Decision Process (MDP) model, employs fewer uncertainty models and finds truly optimal decisions to prepare for and react to uncertainties. This analysis focuses on results from the HBDM model, and leaves more complete development of the MDP model for the near future. We hope to provide a framework for future development with improved model inputs, especially in the area of value, cost and technology-improvement models.

The risk of concern and focus of this analysis is the relative net present value distribution given different user decisions for a fractionated satellite mission. We use a Department of Defense terrestrial weather satellite program as a case study for analysis. Given our assumptions, we find situational dependence in the number of spares to maintain on the ground; sometimes maintaining a full subsystem is best but other times the best results are obtained when only certain critical subsystems are maintained on the ground.

Further, we find evidence that technological evolution within the scope of a single fractionated satellite program, while possible, may not be desirable due to cost and schedule risks. It may instead be better to invest in certain systems more heavily at the outset to minimize the number of technological upgrades necessary. Further research can expand these models, and test other possible benefits of the fractionated satellite architecture.

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APPENDIX

Heuristics-Based Decision Model (HBDM) Results

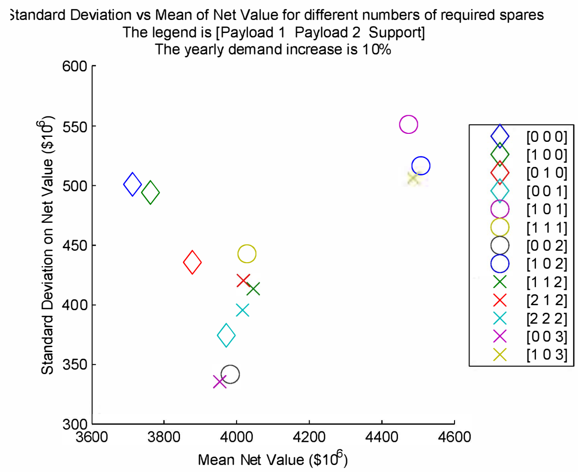

Figure 11. Mean and Standard Deviation of NPV for Number of Spares Required with Baseline Demand.

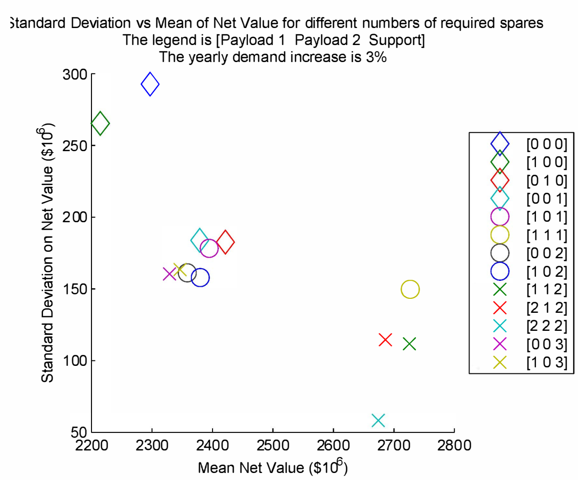

Figure 12. Mean and Standard Deviation of NPV for Number of Spares Required with Medium Demand.

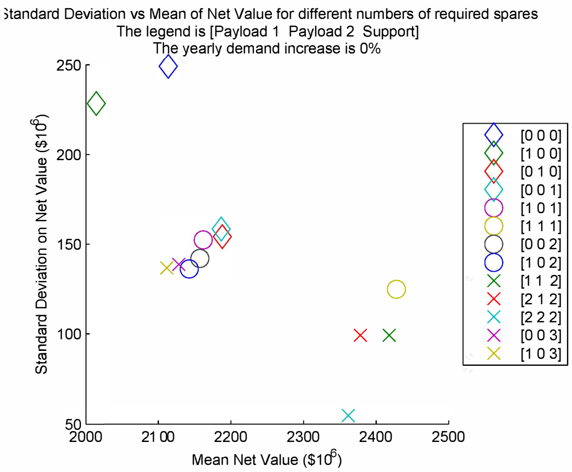

Figure 13. Mean and Standard Deviation of NPV for Number of Spares Required with No Demand Increase.

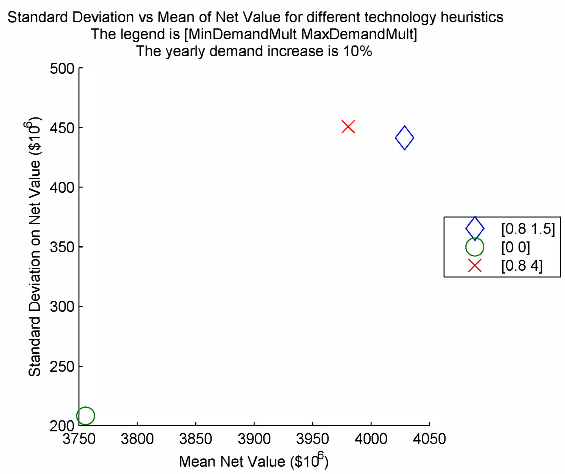

Figure 14. Mean and Standard Deviation of NPV for Technology Parameters with Baseline Demand.

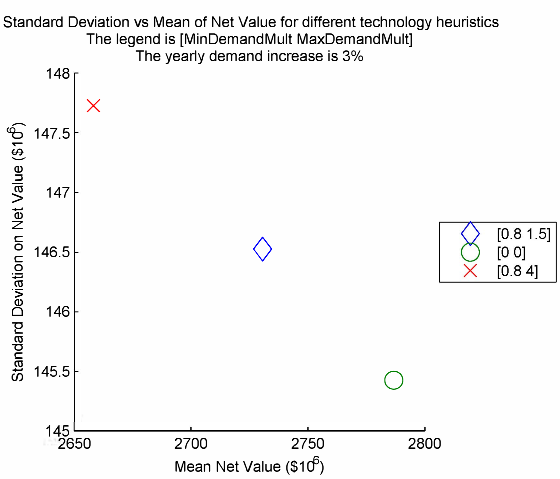

Figure 15. Mean and Standard Deviation of NPV for Technology Parameters with Medium Demand.

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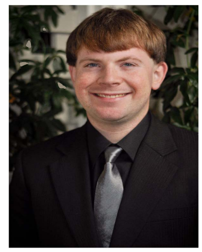

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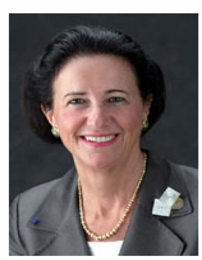

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