START Analysis for ESAS Capability Needs Prioritization

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Abstract

START is a tool to optimize research and development primarily for NASA missions. It was developed within the Strategic Systems Technology Program Office, a division of the Office of the Chief Technologist at NASA's Jet Propulsion Laboratory.

START is capable of quantifying and comparing the risks, costs, and potential returns of technologies that are candidates for funding. START can be enormously helpful both in selecting technologies for development -- within the constraints of budget, schedule, and other resources -- and in monitoring their progress.

START's methods are applicable to everything from individual tasks to multiple projects comprising entire programs of investigation. They can address virtually any technology assessment and capability prioritization issue. In this report, START is used to analyze the capability needs using data from NASA’s Exploration Systems Architecture Study (ESAS).

1. Introduction

START is used to analyze the capability needs using data from NASA’s Exploration Systems Architecture Study (ESAS).

Exploration Systems Architecture supports NASA’s vision for space exploration:

- Requirements-driven technology program
- Annual “go-as-you-pay” budget planning
- Develop and fly the Crew Exploration Vehicle (CEV) no later than 2014.
- Return to the Moon no later than 2020.
- Implement a sustained and affordable human and robotic program.
- Develop supporting innovative technologies, knowledge, and infrastructures.
- Develop a U.S. system capable of servicing the International Space Station
- Enable a permanent human presence while preparing for Mars

It's important to note, however, that analysis isn't a one-time event, and changes occur. Assessment is a continuous process throughout a project lifecycle and, commensurately, data such as cost estimates should be frequently updated to provide the best information for management decisions.

Key questions

This study was part of an effort to develop a systematic process to help NASA select a group of capabilities for development, based on the probability that they will lead to mission success.

Key questions addressed include how budget allocations are affected by:

- Cost uncertainties
- Reduction in available budget levels
- Shifting funding within constraints imposed by mission timeline

2. Input Database

Our sponsor at NASA Headquarters provided a database of inputs to our analysis. This section describes the organization of the data.

Capability Hierarchy

The capabilities are organized into twelve capability areas shown in Table 1. This hierarchy helps to organize the requirements and capabilities.

1	Structures
2	Protection
3	Propulsion
4	Power
5	Thermal Control
6	Avionics & Software
7	Environmental Control & Life Support
8	Crew Support & Accommodations
9	Mechanisms
10	In-Situ Resource Utilization (ISRU)
11	Analysis & Integration
12	Operations

Table 1: Top-Level Capability Areas

Mission Set

The four missions are:

- CEV to ISS
- Lunar sortie – CEV to moon (short stay)
- Lunar outpost base
- Mars outpost base

Mission importance weights

The four missions have different relative importance, as shown by their given weight in Table 2. This is an illustrative weighting demonstrating the form of the inputs needed.

Mission	Importance weight
CEV to ISS	9
CEV to moon	6
Lunar outpost base	1
Mars outpost base	0.1

Table 2: Mission Importance Weights

Although the Mars mission was included structurally in the analysis, a complete dataset was not available; thus incorporation of R&D for human-robotic Mars missions was deferred to a subsequent study.

Figures of Merit

Six figures of merit (FOM) defined by the sponsor are associated with each capability for each mission (3). The FOMs are defined in Table 3. Each FOM is assigned a High/Medium/Low label corresponding to weights 9, 3 and 1 respectively.

Figure of Merit	Definition
Overall criticality	Impact of the need on the architecture
Safety and mission success	Probability of loss of crew, Probability of loss of mission
Extensibility / flexibility	Lunar, Mars, other destinations, Commercial activities, National security
Programmatic risk reduction	Technology development risk, Cost risk, Schedule risk, Political risk
Affordability	Technology development cost, Facilities cost, Ops cost, Cost of failure
Technical performance	How the technical performance affects the architecture

Table 3: Figures of Merit Defined

Cost profiles

Each capability has a cost profile outlining its cost requirements per year to bring it to TRL 6. The database also contains absolute start and end years for each cost profile. The base case does not allow time shifting of the funding profiles, thus fixing the cost profiles in time. Later a temporal analysis relaxes this such that profiles are only constrained to fit within the missions' capability development timelines.

Probability of Successfully Developing a Capability

Success in fulfilling a capability for a mission is defined for this study as the capability development reaching a technology readiness level (TRL) of 6 within the specified budget and schedule. TRL 6 requires a system/subsystem model or prototype demonstration in a relevant environment.

A measure of the probability of this success can be taken from the parameter for quantifying the difficulty of maturing a particular capability, the "Research and Development Degree of Difficulty" (R&D^3) [Mankins, 1998]. The sponsor provided the R&D^3 levels for each capability for each mission, and each level was then linked to a corresponding probability of success for fulfilling the capability for each mission using table 4.

R&D^3	**Probability of Success**
1	99%
2	90%
3	80%
4	50%
5	20%

Table 4: Probability of success of "Normal" R&D effort for different R&D^3 levels.

Center splits

Multiple centers can contribute to a capability. Individual center contributions associated with each capability have been provided as a percentages of the cost. Validation of the center splits is needed since the capabilities were not broken down into individual tasks, where center splits can be easily identified.

3. Assumptions and Caveats

Capabilities Require Full Funding

We assume a capability needs to be fully funded each year to achieve its mission impact. Therefore, partial funding does not provide any benefit and therefore partial funding of a capability is not allowed.

Capability Dependencies Are Not Included in Input Data

The analysis assumes independent capabilities, i.e., the decision on whether or not to fund a capability is independent of the decision of whether or not any of the other capabilities are selected. The results may be inconsistent where dependencies actually exist. The analysis can be updated when dependency data becomes available.

Data Validation/Verification May Be Warranted in Some Cases

The analysis assumes priority is based only on FOM data. Large cost capabilities without correspondingly large FOMs should be reviewed. An example of such a capability is 8e, Crew Healthcare Systems. Due to this, the results may not reflect actual priorities.

4. Optimization Formulation

The objective was to assemble an optimal portfolio of capabilities for development. To do this, a unitless value of utility is calculated for each capability (see section below) representing its predicted effective benefit to the Exploration Systems Architecture. The optimization algorithm then builds portfolios with the highest possible total benefit, subject to budget and schedule constraints.

Defining the Benefit Function

$N_{missions}$	Number of missions under consideration
W_i	Weight of the i^{th} mission
$M_{capabilities}$	Number of capabilities under consideration
$P_{i,j}$	Probability of fulfilling the j^{th} capability for the i^{th} mission
R	Number of Figures of Merit
$FOM_{i,j,k}$	k^{th} Figure of Merit, of the j^{th} need, with respect to the i^{th} mission
$X_{i,j}$	Binary control variables indicating if capability j for mission i is selected for funding. $X_{i,j} = \{0,1\}$.

Table 5: Benefit Function Parameter Definitions

The benefit function (BF) is a weighted sum of expected Figures of Merit (summed per capability, per weighted missions).

If $X_{i,j}$ equals 1, the capability is selected for funding; if it equals 0 then it is not funded. The portfolio is optimized by finding the set of $X_{i,j}$ that maximizes:

$$\sum_{i=1,N_{missions}} W_i \sum_{j=1,M_{capabilities}} X_{i,j} * P_{i,j} \sum_{k=1,R} FOM_{i,j,k} \tag{1}$$

Subject to annual cost constraints:

$$\sum_{i=1,N_{missions}} \sum_{j=1,M_{capabilities}} X_{i,j} * C^{(t)}{}_{i,j} \leq B^{(t)} \quad for\ all\ years\ \ t \tag{2}$$

Where t = 2006, 2006+T (T number of years in portfolio).

The optimization problem is solved using the Branch and Bound algorithm [Martello & Toth, 1988].

5. Sensitivity Analysis

Sensitivity analysis involves adjusting model input values to determine the impact on portfolio. Our sensitivity analysis estimates robustness of the funding for each capability. Funding recommendations are compared under perturbations of the cost and different budget levels.

A number of cases using various budget scenarios were examined. A representative example is reported here.

1) Case 1: The baseline – the full capability set at the full budget
2) Case 2: $100M/year budget reduction

The Beta Density Function and Cost Uncertainties

Ideally, cost distributions should be based on engineering estimates, with the costs and probabilities for various contingencies provided by engineers and cost analysts. If details of this type are unavailable, the beta distribution is commonly used to model cost uncertainty.

This study fits a beta density function distribution based on three costs: minimum, mean, and maximum values. It is a rounded version of a triangular distribution. The random value from the beta distribution is the percent cost variation from nominal. The beta function parameters are $\alpha = 1.5$, $\beta = 3$, minimum = 98 %, maximum = 300 %.

Monte Carlo Simulation

The Monte Carlo simulation repeatedly generates random values used to model the cost uncertainties. An iteration of the Monte Carlo simulation starts by multiplying a random number drawn from the Beta distribution by each cost for each year for each capability. The optimization algorithm is then run on this modified data. The optimum portfolio is found. Each capability's status as in or out of the portfolio is recorded.

Once 1000 iterations have been completed, the percentage of time each capability was chosen in the optimization is tabulated and is used as the measure of robustness for the given capability. The accuracy of the Monte Carlo estimate is based on the number of iterations; with 1000 iterations the 95% confidence interval for true percentage is +/- 1.5%.

Case 1: The Baseline

The initial optimization with no cost uncertainties resulted in each capability being funded. However, for the first 6 years, the cost of the capabilities met the budget line exactly as shown in figure 1 below. In this case the slightest cost overrun by a capability during any of these years would cause a cost overrun in the portfolio. A sensitivity analysis was run on the baseline to see which capabilities would be recommended for a budget cut if an overrun occurred.

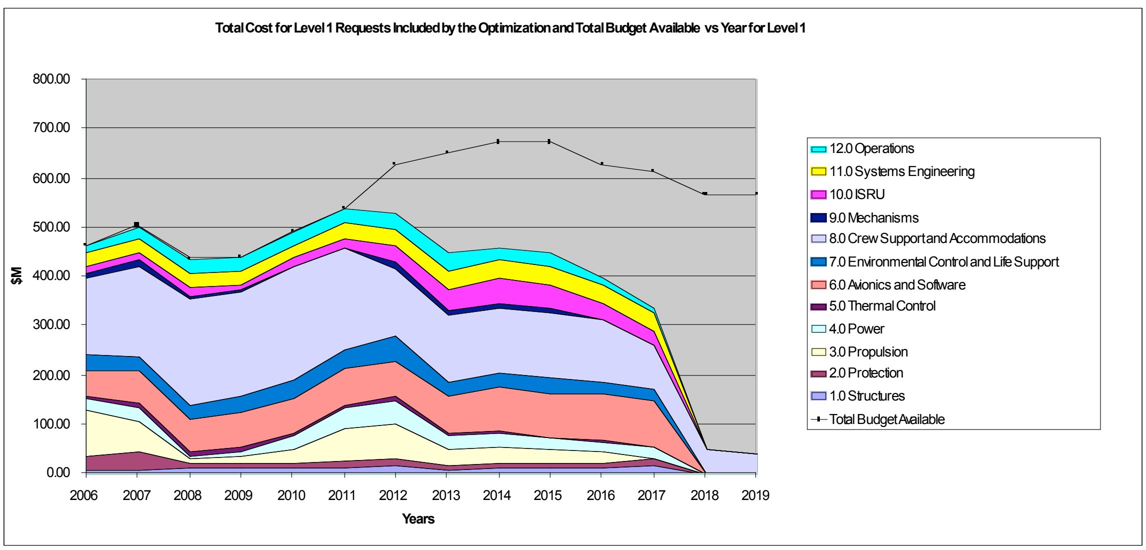

Figure 1. The total capability costs for the first 6 years all meet the budget exactly, threatening budget overruns if a capability cost is underestimated. Optimization of the portfolio is trivial since all requested capabilities' costs fit under the given budget cap for each year, thus allowing for all capabilities to be funded.

The results are shown in table 6. Nine of the 52 capabilities from the baseline set enter the portfolio less than 90% of the time, and four of those twelve enter less than 50% of the time. Capability 8e never enters the portfolio.

8e	Crew healthcare systems (medical tools and techniques, countermeasures, exposure limits	0.0%
8f	Habitability systems (waste management, hygiene)	10.1%
8b	EVA Suit (surface including portable life suppport system)	23.8%
3a	Human-rated, 5-20 K lbf class in space engine and propulsion system	47.2%
5b	Surface heat rejection	52.7%
6l	Low temperature electronics and systems (permanent shadow region ops)	57.4%
3h	Long-term, cryogenic, storage, management and transfer (for lunar surface module)	76.2%
6j	Autonomous precision landing and GN&C (Lunar & Mars)	84.6%
10c	Demonstration of polar volatile collection and seperation	88.4%

Table 6: Capabilities selected for full funding less than 90% in the Baseline Monte Carlo case.

Data such as this indicates a preliminary suggestion to reprioritize capabilities due to insufficient availability of funding, provided that the given figures of merit, costs, and probabilities etc. were accurate, and there were no other extenuating circumstances. Review of this table is an excellent starting point for contingency mitigation; it is not meant as a final recommendation.

Case 2 – Baseline Minus $100M/year

Case 2 is a repeat of case 1, but with the budget cap decreased by $ 100 M/year.

The results are shown in table 7. In Case 2 there are 12 capabilities below the 90th percentile.

Compared to case 1, there are some changes in the rankings of the capabilities. The bottom 5 capabilities keep their rankings, but 10f, which was in the 90th percentile before reducing the budget by $100 M/year, is now the 6th least robust capability. For non-robust capabilities competing to enter a portfolio, the change in rankings at different budget levels is a result of the changing "competition border" [Derleth, 2005]. For a given budget level, the first capabilities entering the portfolio are the highest scoring capabilities that can enter without putting the portfolio over budget. As the budget cap is approached, a weaker scoring capability can become more competitive by simply fitting into the portfolio better when other remaining, better scoring capabilities are too large cost-wise to fit. This dynamic drives the changing of the order of robustness rankings seen here and in the results that follow as well. From this it can be concluded that while a capability might be one of the most robust at one budget level, it can be eliminated from the optimum portfolio by lesser capabilities as a large budget change shifts the location of the competition border.

While the competition border can lead to drastic drops in robustness for some capabilities, it can also boost the robust for other capabilities. The budget reduction of

$100 M/year raised 8b's robustness from 23.8% to 30.5%, and bumped 10c into the 90th percentile. The number of capabilities who see their robustness increase by budget cuts, however, is only a few.

8e	Crew healthcare systems (medical tools and techniques, countermeasures, exposure limits	0.0%
8f	Habitability systems (waste management, hygiene)	9.8%
8b	EVA Suit (surface including portable life suppport system)	30.5%
3a	Human-rated, 5-20 K lbf class in space engine and propulsion system	40.7%
5b	Surface heat rejection	47.5%
10f	Extraction of water/hydrogen from lunar polar craters	64.0%
6l	Low temperature electronics and systems (permanent shadow region ops)	64.8%
3h	Long-term, cryogenic, storage, management and transfer (for lunar surface module)	73.1%
4i	Surface power management and distribution (e.g., efficient, low mass, autonomous)	75.1%
6j	Autonomous precision landing and GN&C (Lunar & Mars)	84.2%
12c	Surface handling, transportation, and operations equipment (Lunar or Mars)	85.1%
4f	Surface solar power (high efficiency arrays, and deployment strategy)	88.7%

Table 7: Capabilities selected for full funding less than 90% for case with reduced budget of $100M/year.

6. Temporal Optimization

As seen earlier, figure 1 shows the baseline case had the feature that funding every capability resulted in total costs meeting the budget cap in the early years, but lying far below the budget cap in later years. Due to this, another optimization was run in parallel to the sensitivity analysis to try to take advantage of this untapped budget in the later years of development. This temporal optimization calculates not only which capabilities to fund, but also when to fund them, by moving the cost distribution profiles for each capability against the development timeline. The capability portfolio is optimized while taking advantage of budget surpluses by allowing capabilities costs are to move to different years.

There are many methods to explore the possible combinations of capability funding schedules. One option is a "just in time" (JIT) approach, in which capability development for each mission is funded as late as possible while enabling the mission to launch at its scheduled time. This approach reduces the risk that funds will be spent prematurely for a capability or a mission that is ultimately canceled, or that capabilities will become obsolete before utilized. It also increases the ability to take advantage of separate technological improvements, such as faster computers, developed outside of the mission itself.

However, this system increases the risk that one or more capabilities will have to remain unfunded in order to avoid exceeding the development budget for a given year. This problem can be avoided by eliminating the "just in time" constraint and permitting the development schedules to slide to earlier years if that would better accommodate the total aggregate of capabilities in the portfolio.

By eliminating the just in time constraint, our temporal optimization searches all possible combinations of capability funding schedules across all capabilities and all missions. In essence, the optimization explores the total development costs of each configuration by "sliding" each capability cost distribution along a timeline.

The temporal model, shown in figure 2, takes into account a capability development time range where all development for a given mission would occur. Before this development time, one year of delay is allocated for the time between the funding decision and the start of development.

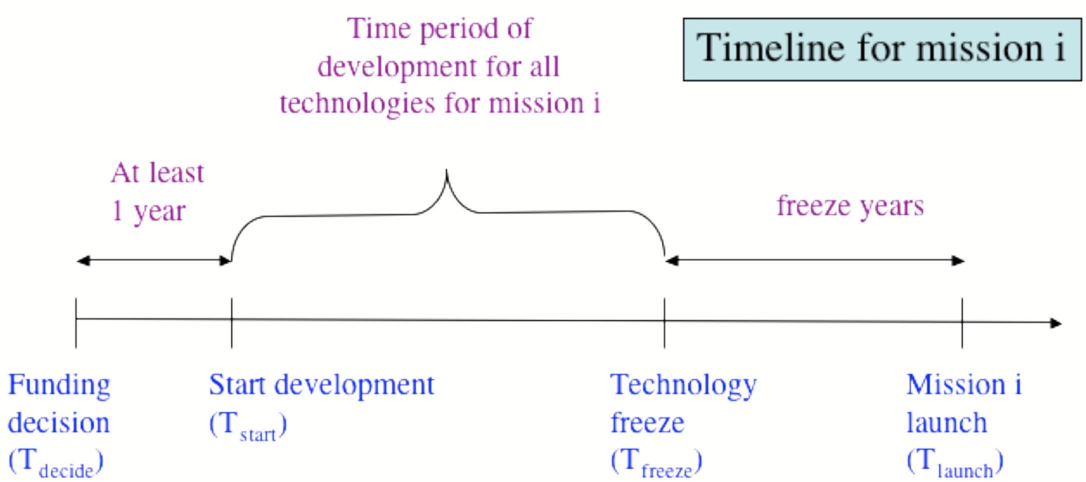

Figure 2: Mission Capability Development Timeline

All capability development of a mission occurs between T_{start}, and T_{freeze}. This is the length of time required by the most demanding capability in the mission; all other capabilities either have an equivalent or lesser time to full development. Figure 3 shows the temporal alignment of the developments.

Assumptions for Time Dependence

For the ISS mission with launch date 2011, all capability development must be complete by 2007. This yields a 4-year freeze time duration for ISS. For Lunar Sortie with a launch date of 2020, a 6-year freeze time was given. However, some capabilities required for Lunar Sortie have 10-year development requirements. If the earliest development can start is next year, then the earliest time the development could possibly finish is in 2015 - yielding a 5-year freeze time, which we have assumed. For Lunar Outpost, we used the typical 3-year freeze time.

The temporal optimization assumes that the portfolio investment is of independent capabilities (no dependencies), that the funding profile for individual capability development is constrained within the mission timeline, and that capabilities must be either fully funded or not funded at all for each mission.

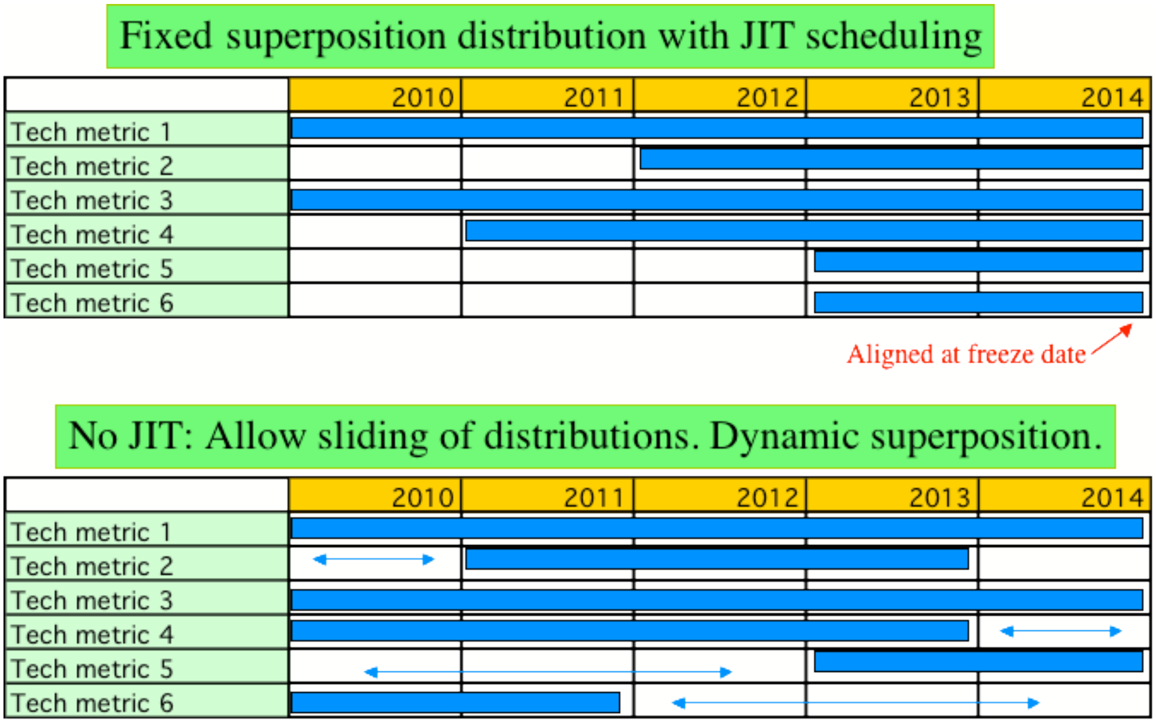

Figure 3: Exploration of cost distribution profiles for each capability. With the just in time method, all capabilities' funding is constrained such that their last year of funding ends at the freeze date. Relaxing this constraint allows the funding profiles of each capability to be moved in time (blue arrows) to find the best total portfolio funding profile.

Temporal optimization formulation

The optimization in equations 1 and 2 is generalized by adding multiple cost profiles for each capability. Additional constraints force the restriction of only funding a capability at most once. If $X_{i,j}$ equals one then capability *j* for mission *i* is selected for funding; if it equals zero then it is not funded. The portfolio is optimized by finding the set of $X_{i,j}$ and $Y_{i,j,q}$ that maximizes equation 3 subject to constraints 4 and 5.

$$\sum_{i=1,N_{missions}} W_i \sum_{j=1,M_{capabilities}} X_{i,j} * P_{i,j} \sum_{k=1,R} FOM_{i,j,k} \tag{3}$$

If $Y_{i,j,q}$ equals one then the q^{th} cost profile is used for funding capability *j* for mission *i*. The annual cost constraints are given by equations 4 and 5:

$$\sum_{i=1,N_{missions}} \sum_{j=1,M_{capabilities}} \sum_{q=1,Q_{cost\ profiles}} Y_{i,j,q} * C^{(t)}{}_{i,j,q} \le B^{(t)} \quad \textit{for all years } t \tag{4}$$

$$\sum_{i=1,N_{missions}} \sum_{j=1,M_{capabilities}} \sum_{q=1,Q_{cost\ profiles}} Y_{i,j,q} = X_{i,j} \quad \textit{for all i and j} \tag{5}$$

Where t = 2006, 2006+T (T number of years in portfolio). Each cost profile $C_{i,j,q}$ is checked that it ends by the freeze date of the capability for the mission. Equation 5 enforces the constraint that only one cost profile is used to fund a capability for a mission. The optimization problem is solved using the Branch and Bound algorithm [Martello & Toth, 1988]. Figure 4 shows an example showing two capabilities and representative cost profiles.

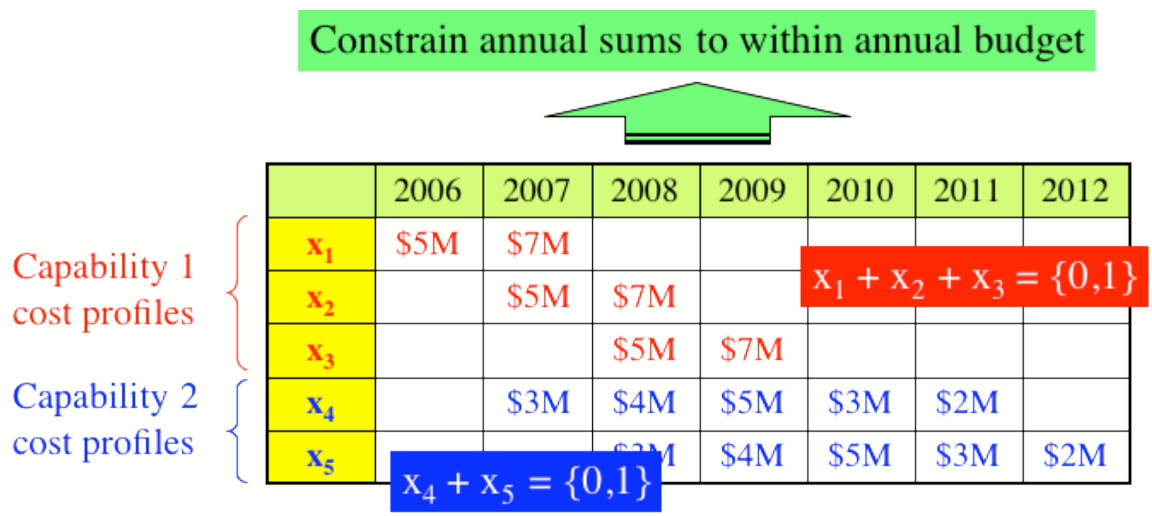

Figure 4: Model constraints where only one cost profile should be chosen such that the annual cost sums are within the annual budget cap.

Temporal Optimization Results

We ran several temporal optimizations based on different scenarios from the ESAS dataset. Again, since the given capabilities all fit under the given budget constraint, we wanted to stress the data to identify the least robust capabilities when taking into account all time shifted schedules.

To do this, the given annual budget curve was adjusted by adding and subtracting funds uniformly across all years. After running temporal optimization runs of different annual budget below and above the given budget, from -$250M to $200M, we computed the percentage of times each capability was selected by the optimization. The following shows which capabilities were selected the least amount of times.

Percentage Selected	Mission	Capability	Capability Name
25%	Lunar Outpost	8e	Crew healthcare systems (medical tools and techniques, countermeasures, exposure limits)
58%	Lunar Sortie	8f	Habitability systems (waste management, hygiene)
58%	Lunar Outpost	2a	Detachable, human-rated, ablative environmentally compliant TPS
58%	Lunar Outpost	5b	Surface heat rejection
58%	Lunar Outpost	6d	Integrated System Health Management - ISHM
58%	Lunar Outpost	7c	Advanced air and water recovery systems
58%	Lunar Outpost	8f	Habitability systems (waste management, hygiene)
67%	Lunar Sortie	8b	EVA Suit (surface including portable life suppport system)
67%	Lunar Sortie	8e	Crew healthcare systems (medical tools and techniques, countermeasures, exposure limits)
67%	Lunar Outpost	1a	Lightweight structures -- pressure vessel, insulation (vehicle)

Figure 5: Temporal optimization results showing least robust capability needs.

A summary of the results is shown in figure 5. The results show that capability 8e, "Crew healthcare systems (medical tools and techniques, countermeasures, exposure limits)" is least robust and highly likely to be flagged for funding cuts, even with increased funding to the annual budget.

The classification of capability 8e as one large conglomerate makes it highly volatile in the temporal optimization. There is also no room for temporal displacement as the cost distribution covers the full 14-year timeline. By breaking up capability 8e up into smaller parts on the order of magnitude of those capabilities it is competing with, a more optimal scenario may be achieved.

Finding a Better Annual Budget Curve

The given annual budget had a maximum annual cost of $527.9M at year 2012. We asked the question of whether or not there is a better annual budget distribution profile that would fund all capabilities while requiring a smaller maximum annual budget. We were able to compute a better annual budget curve by using a flat annual budget curve of varying levels of funding.

The results shown in figure 6 indicate that the smallest annual budget that can be used and still fund all capabilities is $459.5M per year. This does not necessarily mean that all funds are used. Rather, this explores all time displacements at multiple annual budget caps to find the best annual budget curve.

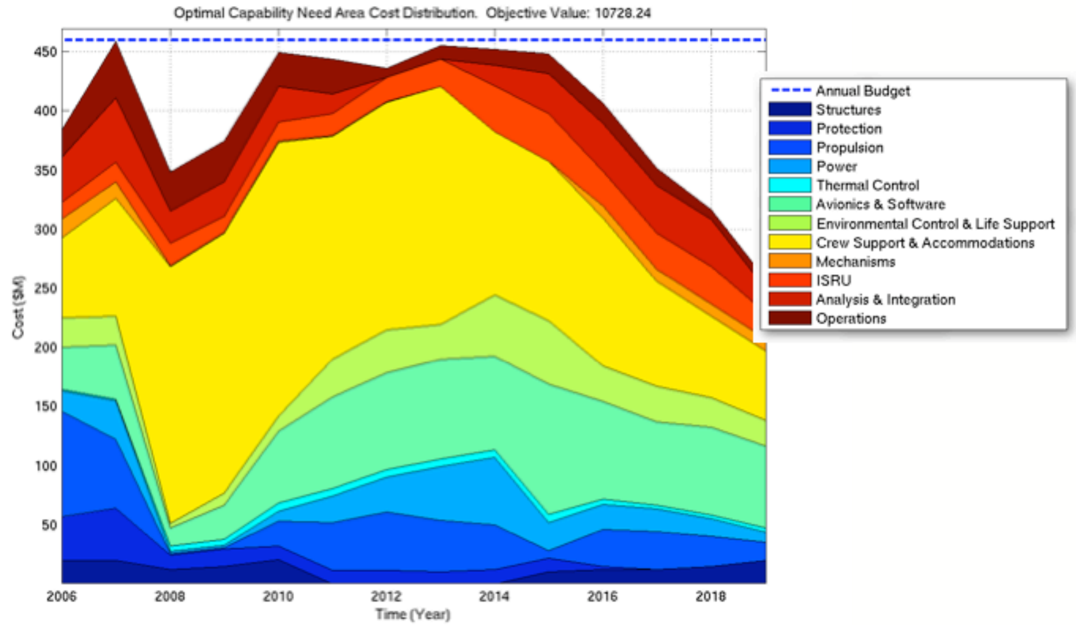

Figure 6: Optimal Annual Curve by Areas for Flat Budget of $459.6M. Given annual budget curve has peak of $528M.

This computed annual budget decreases the given just-in-time annual budget curve by funding all capabilities at a maximum annual budget of $459.6M, as opposed to $528M. This computed sliding-schedule curve also provides a relatively flatter cost utilization.

7. Conclusions

Results of the START system are reported based on data from ESAS capability needs prioritization. The key questions addressed are sensitivity of budget allocations to cost uncertainties, reduction in available budget levels, and shifting funding within constraints imposed by mission timeline.

The capability now exists to optimize portfolio investment including annual as well as total cost constraints. The process is transparent and auditable, and would benefit by continuous update and data validation. A methodology is demonstrated for systematically dealing with uncertainties in costs and in available budgets. The methodology allows one to include non-technical constraints if such is desired. Temporal optimization gives the decision maker the ability to analyze scheduling capability developments in time.

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