Assessing Uncertain Benefits: a Valuation Approach for Strategic Changeability (VASC)

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Abstract. This paper describes a new technique for investigating the value of changeability in complex engineering systems early in the design process. The work is an extension of Epoch-Era Analysis, a framework that models contextual uncertainties over a system's lifecycle as a sequence of finite-duration periods of time. Strategies, defined as statements of intended change mechanism usage, are used to identify executed change mechanisms across the various contexts. Changeability is then evaluated in both time-independent (multi-epoch) and time-dependent (era) domains, using a proposed set of metrics designed to explore different dimensions of value. A case study demonstrates the application of the technique to a conceptual space system.

Introduction and Background

Changeability is a potentially valuable addition to many engineering systems. Opportunity can be seized and risk avoided by designing a system such that it has the capability to change its form or behavior at some point during its lifetime. The inclusion of changeability typically comes at an increase in cost, both a fixed development and physical inclusion cost and the cost of exercising the option to change. These costs are frequently well known, but the benefits of changeability are significantly harder to capture. This has hindered the inclusion of changeability in the design process of systems: when the costs are known and the benefits hidden, it becomes difficult to justify the inclusion of changeability-enabling features. This research has resulted in a technique, the Valuation Approach for Strategic Changeability (VASC), which attempts to address this problem by clarifying the value of changeability using the Epoch-Era Analysis (EEA) uncertainty framework. The following subsections will provide an introduction to the main concepts of changeability and EEA, in order to give the foundation necessary to understand and implement VASC.

Change Paths. The construct of "change events as paths" is fundamental for a more precise understanding of a system change. A system change event can be characterized with three elements: (1) the agent of change, (2) the mechanism of change, and (3) the effect of change. The agent of change is the instigator, or force, for the change. The role of change agent can be intentional or implied, but always requires the ability to set a change in motion. The mechanism of change describes the path taken in order to reach a future state from the present state, including any costs, both time and money, incurred. Examples of mechanisms include the execution of real options, such as the swapping of modular components, or the procurement of additional system elements. The effect of change is the actual difference between the origin and destination states.

Epoch-Era Analysis. Quantifying the changeability of a system necessitates bringing the dynamic aspects into consideration, as well as a *temporal value-based* perspective. Epoch-Era Analysis (EEA) (Ross, 2006; Ross and Rhodes, 2008) provides an approach for conceptualizing system timelines using natural value centric timescales, wherein the context itself defines the timescales. An *epoch* is a period for which the system context has constant value expectations. Each fixed context is characterized by static constraints, available design concepts, available technology, and articulated attributes. *Eras* are sequences of epochs, which define the evolution of context across the lifetime of the system. As exogenous changes (e.g., new threat, availability of a new technology, new policy, etc.) trigger the start of a new epoch, the system may need to transform in order to sustain value in the new context, or else it may fail to meet expectations as defined for this new context, as illustrated in Figure 1 below. Depending on the scope of a given study, epochs could be defined by both technical and non-technical changes in context or expectations (e.g. political changes, or social changes). Additionally, the needs aspect of an epoch could reflect more than just technical performance, including programmatic and political considerations as well (Nickel 2010).

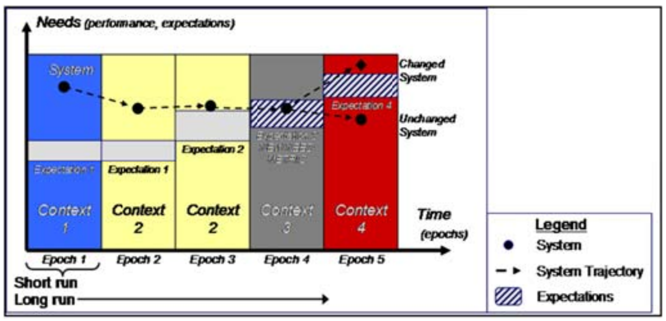

Figure 1. System Needs versus Expectations across Epochs of the System Era

Epoch-Era Analysis provides an approach for visualization and a structured way to think about and model the temporal system value environment, and is used in our research approach as a useful means for specifying strategies over time. The epoch timelines can be assessed at any point during the system lifecycle, not only during early conceptual design. For analysis purposes, epochs can be known in advance, or in the moment, and can be deterministic, or probabilistic. As such, mathematical treatment of the paths, costs, utilities, and times must appropriately match the uncertainty level of the data.

Previous Changeability Quantification/Valuation Research. For all of the potential benefits of changeability, there has been great interest in methods and metrics to identify both the quantity and value of changeability in systems. Perhaps the best-known methods for valuing changeability are the real options methods. Foundational work has been done in regard to valuation of real options and additional research is ongoing. The field of real options was motivated by the desire to apply quantitative financial options valuation methods to capital investment decisions. The term "real options" was first used by (Myers, 1984) in the context of strategic decision-making, where "real" refers to the fact that the underlying asset is real rather than financial. A "real option" gives the decision maker the right, but not the obligation, to exercise an action or decision at a later point in time. The concept of real options analysis is to value investment decisions by taking into account the options that are available to the decision maker in the future. In a general sense, any action or decision that can be taken in the future can be considered to be a real option.

Three major approaches to valuing financial options are: Black-Scholes, binomial pricing, and simulation (Black and Scholes, 1973; Cox et al., 1979; Boyle 1977). All of these models have been used to value real options. However, the assumptions underlying the Black-Scholes model do not translate well to real options. The binomial pricing model and Monte Carlo simulation have been popular in valuing real options. Besides financial valuation models, decision analysis has been used to value real options. Decision analysis involves constructing a tree where the layers of nodes represent decision and chance outcomes alternatively. Uncertainties are modeled with probabilities of chance nodes. Decision analysis calculates the best decisions by maximizing the expected value of the outcomes. Real options valuation methods provide a means for quantitatively assessing decisions under uncertainty, but additional research is necessary to validate and evolve these methods, as real options differ significantly from financial options. For example, real options often have a high carrying cost, not typically incurred by financial options. Additionally, the execution of a real option may impact one's ability to exercise other real options. This coupling between real options introduces an additional cost for consideration during the analysis, which is not addressed in classical financial real options analytic methods.

Previous research at MIT's Systems Engineering Advancement Research Initiative (SEAri) has resulted in a metric for quantifying the degree of changeability in a system without using options theory: Filtered Outdegree (FOD). As previously mentioned, designs can have multiple associated change paths: the number of outgoing arcs from a particular design is called the *outdegree* for that design. The number of outgoing arcs from a particular design whose cost is less than a defined acceptability threshold, $\hat{C}$, is the *filtered outdegree* for that design (Ross, 2006). The nature of filtered outdegree captures the apparent relativity in perceived changeability of various designs: *what may be changeable to one decision maker may not be perceived changeable to another*. The subjective acceptability threshold differentiates the results per decision maker.

An attempt to modify filtered outdegree into a value (rather than quantity) metric was also pursued. The result was *value-weighted filtered outdegree*, which weights the outgoing arcs by the sign of their effect on utility, thus differentiating between positive- and negative-value changes (Viscito and Ross, 2009). However, this metric is unable to differentiate between changes resulting in large increases in value and small increases in value, nor is it clear that the behavior characterized by positive and negative changes cancelling each other out is desirable.

The Valuation Approach for Strategic Changeability (VASC)

The following sections will describe the challenges behind valuing changeability and how VASC is designed to meet these challenges with a general technique that can be applied to a broad spectrum of cases.

Magnitude and Counting Value. The value of changeability is characterized by two dimensions, which will be referred to in this paper as magnitude and counting value. The magnitude value relates to the level of performance improvement derived from a change; obviously, larger improvements in value are desirable over smaller ones. The counting value relates to the quantity of changeability, with the understanding that there is value in having multiple outgoing change paths, as this increases the likelihood that a desirable change is available regardless of the current context or potential breakages in the change mechanisms during operation. The previous methods for investigating changeability mentioned earlier approach the problem from only one of these two directions: real options generating a number associated with the value increase of a change option, and filtered outdegree simply counting up the number of potential changes originating at a given design. One of the key goals of VASC was to support the analysis of both of these dimensions of value at once, giving a more complete accounting of system changeability.

Strategies. In order to clarify the tension between magnitude and counting value explicitly in the changeability metrics, the concept of *rule execution strategy*, henceforth referred to as just *strategy*, was proposed. The concept of strategy encapsulates the idea that "value is derived from changeability only with executed changes." A strategy is a statement of how and when a stakeholder plans to execute any changeability options in the system. For example, "maximize utility," or "exercise for system survival only." Given a defined tradespace network and epoch, a strategy will select the "best" transition (if any) that should be utilized from each design point, as can be seen in Figure 2.

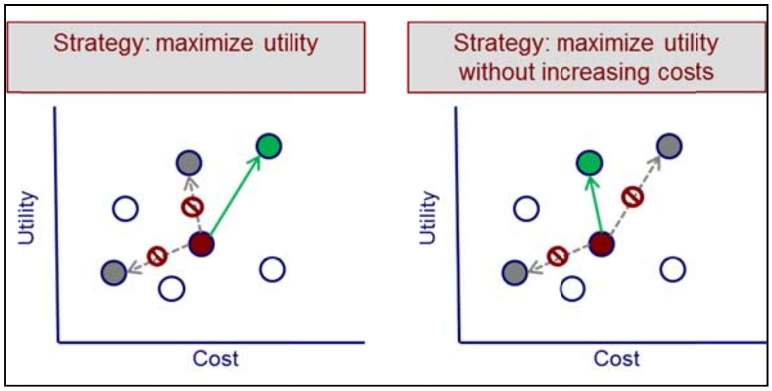

Figure 2. "Best" Path Selection Determined by Rule Execution Strategy

The concept of strategy reduces the burden of enumerating all possible end states. In practice, only "good enough" end states need to be enumerated in order for a strategy to show value in the changeability. Enumeration of better end states will result in higher value for the changeability given a strategy. In this way, confidence scales with effort and results can be gained without having to spend exhaustive effort to enumerate end states. In fact, numerical optimization and search methods can be used to generate target end states for a given strategy without having to enumerate full tradespace networks. This numerical search approach is recommended for future research.

In practice, the strategy designates the end state "targeted" by the stakeholder's anticipated use of changeability given both an initial design and an epoch. Then, the magnitude value will be derived from the value difference between that selected end state and the initial state for each epoch and the counting value is realized across the epoch space, where the increase in number of change paths gives more options and thus a better chance of a desirable option in each epoch. Evaluating multiple strategies is suggested, as knowledge of how changeability "should" be used is often requested by system stakeholders. While there is no "best" strategy, since each strategy defines its own value statement (such as "maximize utility") and is correspondingly the "best" at accomplishing that particular goal, the analysis of multiple strategies with VASC can clarify the effects of each strategy on *other* dimensions of value such as efficiency or expected lifetime, and the team performing the study can then compare the pros and cons of each strategy across all dimensions.

Desirable Metric Properties. In addition to the ability to capture both magnitude and counting value, two other features were also deemed desirable for any new metrics developed for use with VASC. The first was that the metrics should be independent of the considered alternatives; that is, a design's valuation by a metric should not change if designs are added or removed from the design space. This has two benefits, 1) metrics results have stability if designs of interest are added or removed in the middle of the study and 2) it removes the burden of proof from the team performing the analysis that a "good" result is not a misleading result only from comparison to other sub-optimal designs. The second desirable property was that the metrics should be universal in scale across contexts: a score of X in one context is equal to a score of X in another. This allows for much more powerful conclusions to be drawn for scores across the various epochs considered in an EEA study.

Useful Metrics. A set of metrics recommended for use with VASC is presented here. One of the goals of this research is the ability to properly compare and trade off between changeability and robustness; as such, the metrics here are designed to target both. While these metrics are recommended, one of the advantages of using VASC is that metrics can be inserted or removed as appropriate on a case-by-case basis, allowing for targeting of particular applications' metrics or stakeholders' desires.

- **Filtered Outdegree (FOD) –** As defined above, this metric scores designs on their number of outgoing change paths, which heuristically targets designs with the potential for high valuable changeability.

$$\mathrm{FOD}(\mathrm{d},\hat{\mathrm{C}}) = \sum_{\mathrm{j}}^{\mathrm{N}} \sum_{\mathrm{k}}^{\mathrm{num\_rules}} \mathrm{H}(\mathrm{T}_{\mathrm{d,j,k}}), \forall \mathrm{T}_{\mathrm{d,j,k}} < \hat{\mathrm{C}}$$

where $\hat{\boldsymbol{C}}$ is the acceptable change cost threshold, N is the number of designs, j is a given destination designs from d, k is a given transition rule, $\boldsymbol{T_{d,j,k}}$ is a matrix elements of cost for transition from d to j using rule k, and H(.) is the Heaviside function.

- **Fuzzy Pareto Number (FPN) –** Fuzzy Pareto Number is defined as the minimum required fuzziness for a design (*d*) to be included in the K% fuzzy Pareto set (P_K).

$$\mathrm{FPN(d)} = \min\{\, \mathrm{K} \mid \mathrm{d} \subset \mathrm{P}_K \,\}$$

FPN is defined for each design in each epoch. The "fuzzy" Pareto set allows for a margin of deviation from the true Pareto front, defined as a percent of the range of the data (Smaling, 2005). FPN is a measure of cost efficiency that is both independent and universal and thus is a key component of the valuation that takes place in VASC. It is independent because the Pareto front can be well-defined by a multi-variable optimization, and thus even if the Pareto front is only approximated by a tradespace, it is insensitive to the inclusion or exclusion of designs. FPN is universal because an FPN of 5 implies that the design is within 5% of total cost-efficiency in that epoch, regardless of the epoch. FPN varies from 0 (on the Pareto front) to 100. An index of 101 is used for invalid designs whose utility is therefore undefined.

- **(Fuzzy) Normalized Pareto Trace (NPT/fNPT) –** This metric targets passive robustness, scoring design on the fraction of epochs in the epoch space for which they are Pareto efficient: non-dominated in utility and cost.

$$\mathrm{NPT(d)} = \sum_{\mathrm{epochs}} 1\{\mathrm{FPN(d)} = 0\} \div \mathrm{N}_{\mathrm{epochs}}$$

$$\mathrm{fNPT(d,K)} = \sum_{\mathrm{epochs}} 1\{\mathrm{FPN(d)} \le \mathrm{K}\} \div \mathrm{N}_{\mathrm{epochs}}$$

- **Effective NPT / Effective fNPT (eNPT/efNPT) –** One of the new metrics, this measures changeability-enabled robustness by calculating NPT and fNPT for a design considering its end state (*d**) determined by a strategy, rather than its own position. This captures the "effective" robustness by accounting for the true value in any epoch in which the design would change.

$$\mathrm{eNPT(d)} = \sum_{\mathrm{epochs}} 1\{\mathrm{FPN(d^*)} = 0\} \div \mathrm{N}_{\mathrm{epochs}}$$

$$\mathrm{efNPT(d,K)} = \sum_{\mathrm{epochs}} 1\{\mathrm{FPN(d^*)} \le \mathrm{K}\} \div \mathrm{N}_{\mathrm{epochs}}$$

- **Fuzzy Pareto Shift (FPS) –** This metric is the basic choice for valuing the magnitude of the strategy-selected change path in each epoch, calculated as the difference in FPN of the start and end states. Thus it is measuring the efficiency improvement or decline caused by executed changes.

$$FPS(d) = FPN(d) - FPN(d^*)$$

- **Available Rank Improvement (ARI) –** Useful for comparing the relative value of different change mechanisms, ARI takes a defined epoch and scores each change mechanism (*r*) for each design in terms of how many other designs can be surpassed in rank-order utility via that change mechanism (where d^r is the set of designs reachable by *d* through *r*). This can be used effectively to identify mechanisms that in general deliver larger value increases across the design space.

$$ARI(r,d) = Rank(d) - \min\{Rank(d^r)\}$$

- **Lifecycle FPN statistics –** When simulating an era, the current FPN can be tracked at all times. This data can be processed at the end of each sample era to calculate best, worst, and average FPN across the lifecycle of the system. Average FPN in particular is useful for comparing the aggregate lifetime efficiency of different designs.

- **Rule Usage Likelihoods –** Another good statistic to track during era simulation is the number of usages of each change mechanism. In addition to then being able to compare the relative frequency of usage for each in a random lifetime, the likelihood of executing a given rule at any point during a lifetime can be calculated. This is a valuable piece of information that can justify the inclusion or exclusion of a change mechanism from a design.

- **"Going Rate" tradeoffs –** The tradeoff between cost and value for including a change mechanism is a frequently desired piece of information. By comparing designs that differ only by their inclusion of a given mechanism, the "going rate" for additional changeability can be calculated, comparing initial costs to any lifetime value metric. Alternatively, a removal weakness study can be performed, which recalculates the strategic end states while ignoring a specified mechanism or set of mechanisms, and the difference in value with the limited options describes the value created by the lost mechanisms and can identify designs which are dependent on a subset of their change mechanisms.

Procedure

There are five steps in the VASC process:

1. **Set Up Data for Epoch-Era Analysis** - Step 1 puts the case in question into the epoch-era framework, allowing for piecewise consideration of time in sequences of constant-context sections. Activities include identifying input data (design variables, change mechanisms, stakeholder preferences and desired attributes, and context variables). Outputs include design/epoch lists, transition matrices, and Fuzzy Pareto Number for each design/epoch pair.
2. **Identify Designs of Interest** - Step 2 is necessary to reduce both the computation time and the difficulty of synthesizing and grasping the results of the approach by reducing the scope of full attention. Activities include calculating robustness and changeability screening metrics (e.g. Normalized Pareto Trace and Fuzzy Normalized Pareto Trace for value robust designs, and Filtered Outdegree for highly changeable designs), and any other desired design identification techniques (such as picking favorite designs through reuse or high performance in other metrics). Outputs include a subset of

designs for further exploration. If concurrent visualization for comparison is desired, then the number of designs in this set should be on the order of 5-7 for clarity purposes.

3. **Define Rule Usage Strategies -** Defined in Step 3, the strategy is the unifying factor of the method, specifying the logic that interprets the system condition over time and identifies change mechanism options that should be executed. Activities include determining the set of possible rule usage strategies, defining strategies in terms of logic for change mechanism execution in each epoch, and for each design/epoch pair, determining the most desirable end state (defined by the strategy), which is reachable via transition rules. Outputs include the realized end states and transition costs for each combination of design/epoch/strategy.
4. **Conduct Multi-Epoch Changeability Analysis -** In Step 4, multi-epoch changeability analysis (Fitzgerald and Ross, 2012-A) considers possible contexts the system could be used in, but without the complication of time ordering or time dependence. Activities include calculating multi-epoch metrics, such as Effective NPT and Effective Fuzzy NPT, Fuzzy Pareto Shift, Removal Weakness, and Available Rank Increase. Outputs include information on when, why, and how designs of interest are changing within epochs and the value of those changes, as well as identification of particularly valuable change mechanisms and/or designs which rely on a single mechanism for a large portion of their value.
5. **Conduct Era Simulation and Analysis -** In step 5, era analysis (Fitzgerald and Ross, 2012-B) gives important lifecycle information on the designs as they perform, change, and age over time, as well as help identify valuable change mechanisms. Activities include simulation of many randomly generated potential eras for each design of interest. Outputs include change mechanism usage frequency and likelihood, era-level statistics on average/aggregate utility provided and design efficiency, and comparison of strategies and change mechanism usage for each design.

VASC is also well suited to an iterative design process. Since it is recommended that only a select set of designs are considered in detail at once, the process can be completed on different subsets of the design space in sequence, before eventually combining the designs deemed most desirable and comparing them to each other. For example, VASC could be applied to a surveillance mission that can be completed with either unmanned aircraft or new radar dishes by first iterating through aircraft designs of interest, then radar designs of interest, and finally through the best designs of each subtype.

The following section discusses a case study, demonstrating the steps of VASC and the types of insights that can be gained from its application. Example visualizations for the recommended metrics are included.

Case Study: Space Tug

The primary purpose of the application of the Space Tug case in this research investigation was to demonstrate the end-to-end process in a relatively simple case. In particular, the application to the Space Tug system demonstrates both evaluation of valuable changeability via strategies within epochs (short run value of changeability) as well as across eras (long run value of changeability).

Background. A space tug is a vehicle designed to rendezvous and dock with a space object; make an assessment of its current position, orientation, and operational status; and, then, either stabilize the object in its current orbit or move the object to a new location with subsequent release. A previous Multi-Attribute Tradespace Exploration (MATE) study explored the tradespace for a general-purpose servicing vehicle (McManus and Schuman, 2003). Three attributes formed the multi-attribute utility function: total ΔV capability, capability of the grappling system, and response time (slow or fast). To provide these attributes, three design variables were considered in subsequent modeling activities: manipulator mass, propulsion type, and fuel load. A 128-member design space was sampled and analyzed, by inputting each possible combination of the three design variables using a set of enumerated values into (1) a parametric cost estimation model and (2) a physics-based performance model.

Step 1: Set Up Data for Epoch-Era Analysis.

In order to apply the Space Tug dataset for this analysis, the original three design variables were expanded to four design variables, which, when enumerated, resulted in 384 designs. The design variables were propulsion type (biprop, cryo, electric, or nuclear), fuel mass, capability level, and design for changeability (DFC) level. The DFC level is a switch intended to model a conscious effort to design for ease of redesign/change. In the model, it varies from 0 to 1 to 2, with the reward of additional and/or cheaper change mechanisms, and the penalty of additional dry mass, resulting in higher costs and lower available ΔV.

In addition to the design-space, there were 16 epochs considered, generated from 2 contexts and 8 user preference sets. The 2 contexts corresponded to present or future technology level, which affects the transition costs, fuel efficiencies, and mass fractions.

In order to generate the tradespace network for Space Tug, six change mechanisms were defined and are listed in Table 1. Rules 1-5 are "redesign" rules, which require decommissioning and relaunching a space tug (with the associated costs) and rule 6 is an "operations" rule, and does not require a new space tug. The "effect" of each change mechanism is a modification of a single design variable to a different value.

Table 1. Space Tug Study Transition Rules (Change Mechanisms)

#	Rule	Effect	DFC level
1	Engine Swap	Biprop←→cryo	0
2	Fuel Tank Swap	Change propellant mass	0
3	Engine Swap (reduced cost)	Biprop←→cryo	1 or 2
4	Fuel Tank Swap (reduced cost)	Change propellant mass	1 or 2
5	Change capability	Change capability	1 or 2
6	Refuel in orbit (no redesign)	Change propellant mass	2

Once these rules were defined, an algorithm determined the accessible "end-states" available to each design via each of the 6 transition rules, as well as calculating the transition cost (dollars and time) for each allowed path between two designs. After these transition matrices were determined, a multi-arc calculation was performed to find the "non-dominated" paths linking any two designs in the tradespace via any combination of change mechanisms. The multi-arc transition matrix lists the most

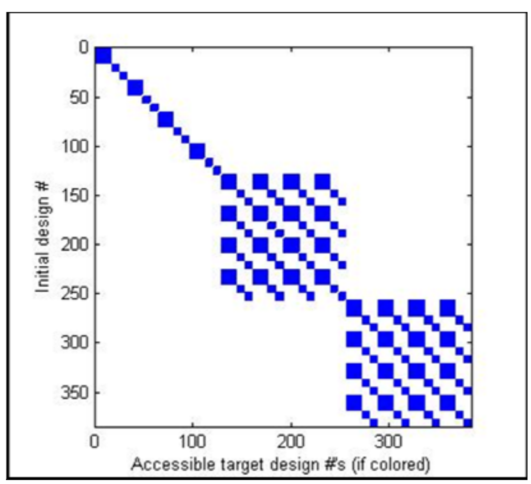

Figure 3. Space Tug Multi-arc Transition Matrix

efficient (in terms of cost and time) paths allowed between any two designs in the tradespace, and is illustrated with a "spyplot" in Figure 3, with each mark indicating allowable transition from the row design to the column design.

Step 2: Identify Designs of Interest

After setting up the data for epoch-era analysis, the next step is to identify designs of interest. For purposes of VASC, "interesting" designs are those that have a high likelihood of being valuable over a period of time, such as the intended lifecycle for a system. Two categories of potentially interesting designs include those that are "passively value robust" and those that are highly changeable. The former designs perform well across a number of epochs without needing to change. The latter designs have a large "degree" of change, but it is unknown if the accessible end states are of any value.

In order to identify the "passively value robust" designs, the Normalized Pareto Trace (NPT) and Fuzzy Normalized Pareto Trace (fNPT) can be used, with high scores indicating "interesting" designs for further consideration. NPT can be calculated by counting the fraction of epochs in which a given design appears in the utility-cost Pareto set (Figure 4). fNPT is calculated by allowing the definition of "Pareto set" to include designs within K% of the Pareto Frontier. For this study, the 1% and 15% fuzzy Pareto Frontiers were used (Figure 5). In order to identify the highly changeable designs, the Filtered Outdegree (FOD) can be calculated by counting the number of accessible end states available for a given starting design state. The filter is a constraint on the amount of dollars and time (transition cost) willing to be spent in executing a change. As the filter becomes more constraining, the FOD decreases differentially across design alternatives. No filter results in counting all accessible end states, regardless of transition costs, which is the Outdegree (OD) of a design in the tradespace network. For this study, both no filter, and a four-month transition time filter were applied (Figure 5).

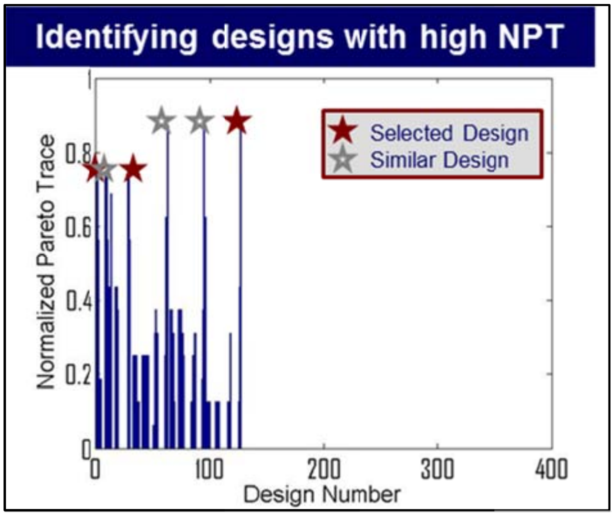

Figure 4. Space Tug Designs with High NPT

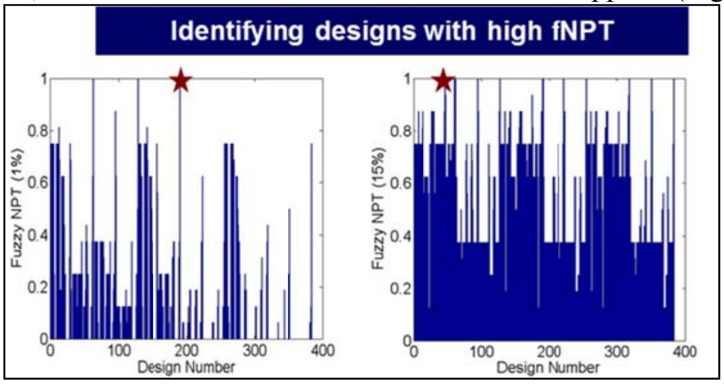

Figure 5. Space Tug Designs with High fNPT

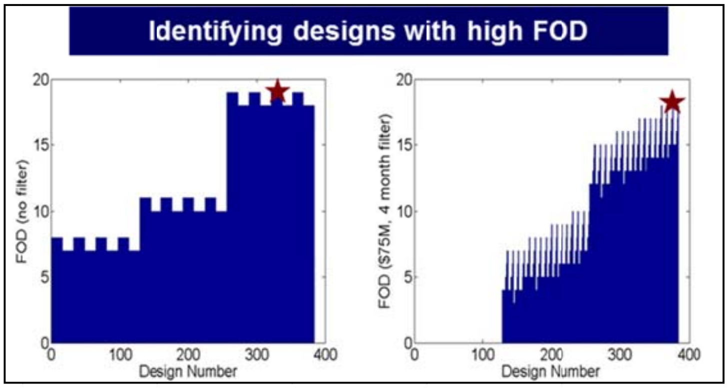

Figure 6. Space Tug Designs with High FOD

The three figures above illustrate the screening metrics across the design space and the indicated chosen designs of interest. Table 2 summarizes the selected designs of interest after applying the screening metrics. Note that the coverage of different levels for all three design variables is quite good (all propulsion types, DFC levels, and capabilities are represented); this is important as it means the screening metrics are not eliminating a subset of the tradespace before consideration. Also included are the attributes in the multi-attribute utility function for each design as output by the model, to give a sense of relative performance.

Table 2. Space Tug Designs of Interest

		Design Variables			*< Both >*	*Attributes (present context)*		
Design Number	**Ref**	**Prop Type**	**DFC Level**	**Fuel Mass (kg)**	**Capability (kg)**	**Fast?**	**DeltaV (m/s)**	**Base Cost ($M)**
1	**A**	Biprop	0	30	300	Y	143	97
29	**B**	Nuke	0	1200	300	Y	7381	306
47	**C**	Cryo	0	10000	1000	Y	6147	628
128	**D**	Nuke	0	30000	5000	Y	14949	3020
191	**E**	Nuke	1	10000	1000	Y	16150	980
328	**F**	Biprop	2	50000	3000	Y	4828	2804
376	**G**	Elec	2	30000	5000	N	27829	3952

Step 3: Define Rule Usage Strategies

Following the selection of designs of interest, the next step is to define the potential rule usage strategies, which will be used to select the “best” end states for each design/epoch pair. The four strategies used in the Space Tug analysis are described below.

Maximize Utility: Deliver best possible performance (highest reachable utility per epoch).

Maximize Efficiency: Desire to be as cost-utility efficient as possible (lowest FPN).

Survive: Execute change only if system risks becoming “invalid” (one or more attributes are unacceptable to stakeholders).

Maximize Profit: Use design changes to maximize revenues less costs in each epoch. A revenue model was created to implement this, however since it is dependent on the duration of each epoch, it is defined only at the era level. Therefore it will not be used in Step 4 but will be in Step 5.

After defining the strategies, a simple script was used to determine the selected change path (if any) from each design in each epoch, including the targeted end state, change mechanisms used, and transition cost accrued. This data is then analyzed in the next step.

Step 4: Conduct Multi-Epoch Changeability Analysis

The next step in the approach is to conduct multi-epoch analysis, that is, conduct analysis across the various potential epochs to see the distribution of valuable changeability across possible alternative future context-needs pairs. One of the activities in this step is the calculation of the Effective NPT (eNPT) and the Effective Fuzzy NPT (efNPT). These metrics are calculated in a similar to NPT and fNPT, however, instead of only considering the originating design state, this calculation looks at the selected end state in each epoch.

The “do nothing” strategy is included for comparison and is equivalent to the “robust” design approach, where no change mechanisms will be considered or executed. Figure 7 illustrates the impact of strategy on efNPT across the seven designs of interest. Insights that can be drawn from a figure like this are typically comparisons between either designs or strategies. For example, designs D and E have a 100% efNPT under each strategy, implying that they are highly passively robust and remain robust in efficiency when executing changeability for other goals (improved utility, etc). The level 2 DFC designs, F and G, are the least cost efficient due to the increased weight of their added change mechanisms. It is also apparent that the maximize efficiency strategy moves all the designs at least as close to the Pareto front as possible (as it should), and the survive strategy has the least regard for improving efficiency in the varying contexts.

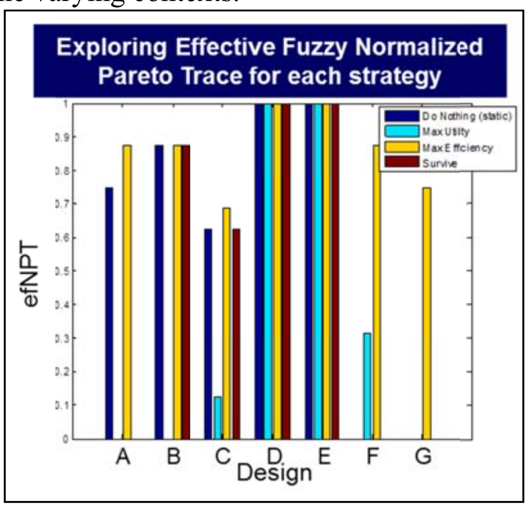

Figure 7. Space Tug efNPT by Strategy for Designs of Interest

Next, Fuzzy Pareto Shift (FPS) is considered in order to get a better idea of the changeability value independent of natural robustness. To do this, FPS distributions are displayed for each design of interest under a given strategy, where the distribution is a frequency plot across the different epochs. Using the “maximize utility” strategy (Figure 8), there is generally a slight negative effect on efficiency, with the exception of design F, which has the majority of its distribution’s weight on the positive side of zero. Designs D, E, and G do not execute changes in a majority of epochs, leading to a large spike at zero FPS. Designs A and F have the most effective improvements in efficiency.

Using the “maximize efficiency” strategy (Figure 9), one can see that it does not allow for negative FPS changes and that design G gains much more value from its changeability, however A and F are still the designs with the highest valuable changeability.

Using the "survive" strategy (Figure 10), one can see that there are many fewer changes, as most designs have a full peak (all 16 epochs) at zero. The exception to this is design A, which must always change, as it will run out of fuel if operated in consecutive epochs. Alternative ways to view FPS data include using a table of order statistics (a heat map coloring can assist in visualizing the numbers) or a stacked box and whisker plot for each design.

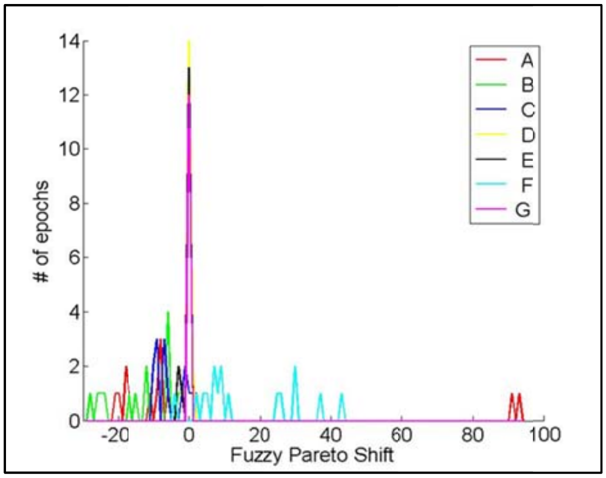

Figure 8. Maximize Utility FPS Distribution

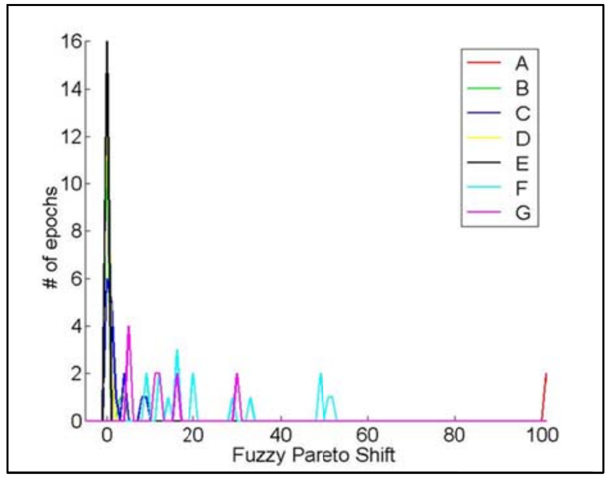

Figure 9. Maximize Efficiency FPS Distribution

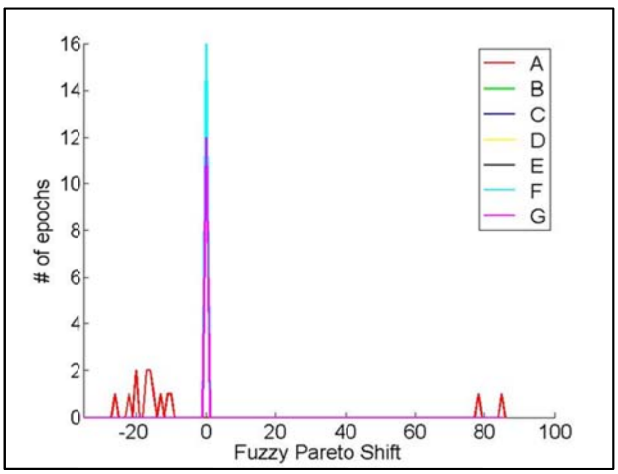

Figure 10. Survive FPS Distribution

After looking at the FPS results, we may be concerned that one change mechanism is driving all the value for some designs of interest. If so, we could perform a removal weakness study, taking that mechanism out of consideration and quantifying the decrement in FPS performance. This information is important for assessing the criticality of a change mechanism, showing how valuable a system would be if the mechanism failed. However for this system most of the change mechanisms are redesign types, which don't suffer from potential breakdowns, making the removal weakness study conceptually uninteresting. Removing the in-operation refuel just makes the DFC level 2 designs identical to DFC level 1 designs, but with an additional weight penalty, so that would simply result in redundant information.

One more analysis can be performed looking at the Available Rank Increase, which approximates value as the number of designs (ranks) a design can surpass in utility via change mechanisms. This is an imperfect metric (no accounting for costs and affected heavily by design enumeration), but can be an interesting basis for comparison of change mechanisms as utility enablers.

Figure 11 illustrates the ARI calculation across the design space, comparing potential rank gains with each change mechanism. The main take-away for this case study is that rules 2, 4, and 6 are the most effective at increasing utility; these three rules all relate to amount of fuel on-board. This highlights the important utility-enabling characteristic of having more fuel available to the Space Tug.

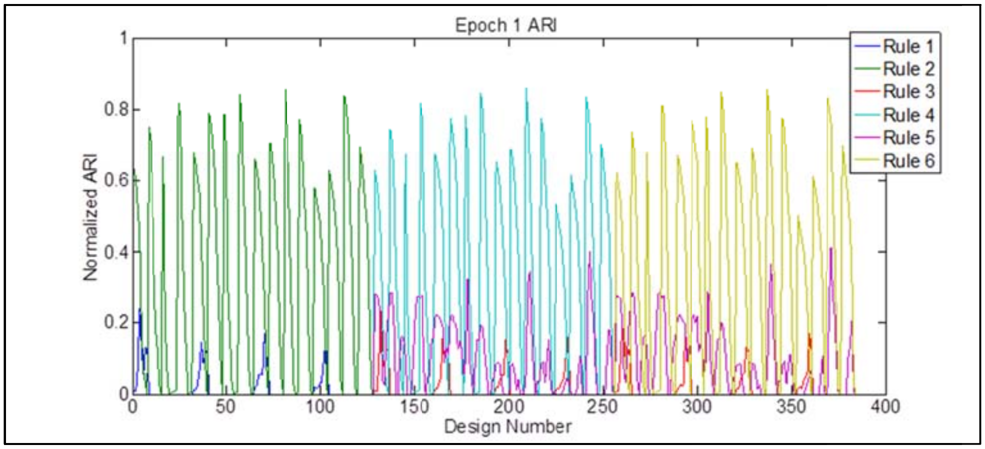

Figure 11. Space Tug ARI Comparison across Change Rules

Step 5: Conduct Era Simulation and Analysis

In Step 5, epochs are time sequenced to determine performance of systems across a lifecycle and can give insights into the path dependence of rule execution and likelihood of using change mechanisms given strategies. For the Space Tug study, 5000 sample epochs were run for each design of interest. As it turns out, time ordering has little effect on this case, so the lifecycle average FPN statistics for each design under each strategy are similarly ordered to what was found with the efNPT statistics, and thus the plots are omitted here.

Figure 12 illustrates a roll-up of the Era Analysis for Design E, investigating the usage of the different change mechanisms. For these eras, and across the four considered strategies, only rules 4 and 5 were executed. The probabilistic nature of the results is because the rule execution was dependent on the particular era (time-sequenced and duration-labeled epochs) that unfolded. This type of insight can be used to justify the inclusion of those change mechanisms. Alternatively, if a decision-maker believes the Survive or Maximize Profit strategies to be the logic by which he will make most changeability decisions, the exclusion of rule 5 can be argued since it goes relatively unused for those strategies; this can save development costs without sacrificing frequently desirable change paths.

Strategy	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6
MaxU	N/A	N/A	N/A	100.0%	89.2%	N/A
MaxEff	N/A	N/A	N/A	100.0%	97.1%	N/A
Survive	N/A	N/A	N/A	94.9%	0.0%	N/A
MaxP	N/A	N/A	N/A	96.8%	31.5%	N/A

Figure 12. Space Tug Design E Rule Usage by Strategy across a 10 Year Era

We may seek information about the "going rates" for the inclusion of changeability in the system. In this case, we can compare designs to their counterparts that are identical except for DFC level, and look at initial cost difference and average profit accrued over the lifetime of the system using the maximize profit strategy. This is illustrated in Table 3, by comparing designs with and without change mechanisms enabled, one can determine the costs and benefits of adding such changeability across the system lifecycle.

Table 3. Space Tug Changeability Lifecycle Cost/Benefit Tradeoff

-DFC tradeoff	Design	+DFC tradeoff
N/A	**D**	+$544M initial cost +$34B profit over 10 years
-$80M initial cost -$4B profit over 10 years	**E**	+$80M initial cost +$21B profit over 10 years
-$384M initial cost -$20B profit over 10 years	**F**	N/A

Conclusions and Future Research

The primary goal for the research was to uncover difficult to extract information on valuable changeability for a design space and present it in an accessible way to assist in decision making. Other important goals included identifying designs that deliver high amounts of value in different ways (e.g. robustness and changeability), and the operational strategies that maximize value. The research also enabled the assessment of what change mechanisms deliver the most value or are the most critical for some designs to continue to deliver value over time. Ultimately, in order to help to justify the investment in changeability, which has been difficult to do in the past due to asymmetry in ease of identifying costs over benefits, the research has demonstrated a first effort in being able to establish a cost versus benefit tradeoff for adding or removing changeability from a design (a.k.a. the "going rate" for changeability).

In order to organize and assist analysts and decision makers in capturing changeability tradeoffs within a study, the Valuation Approach for Strategic Changeability (VASC) was developed. VASC is a five-step approach that guides analysts through generation and organization of design data, as well as application of analysis to generate valuable changeability metrics and their interpretation. The main contributions of VASC include:

- Expanded set of screening and valuation metrics (eNPT, efNPT, FPN, FPS) in Table 4
- Explicit method for accounting for value of changeability over short and long time scales (strategy-interpreted)
- Linked explicit design decisions with changeability (change mechanism comparison)
- Incremental analysis approach that can scale with available information and effort
- An approach that is mostly automated, but also encourages focused value-elicitation and interpretation discussions between decision makers and analysts

Table 4. Working Set of Metrics for Use in VASC

Value Aspect	Acronym	Stands For	Definition
Robustness via "no change"	NPT	Normalized Pareto Trace	% epochs for which design is Pareto efficient in utility/cost
Robustness via "no change"	fNPT	Fuzzy Normalized Pareto Trace	Above, with margin from Pareto front allowed
Robustness via "change"	eNPT, efNPT	Effective (Fuzzy) Normalized Pareto Trace	Above, considering the design's end state after transitioning
"Value" gap	FPN	Fuzzy Pareto Number	% margin needed to include design in the fuzzy Pareto front
"Value" of a change	FPS	Fuzzy Pareto Shift	Difference in FPN before and after transition
"Value" of a change	ARI	Available Rank Increase	# of designs able to be passed in utility via best possible change
Degree of changeability	OD	Outdegree	# outgoing transition arcs from a design
Degree of changeability	FOD	Filtered Outdegree	Above, considering only arcs below a chosen cost threshold

Future research will apply VASC to larger case studies, featuring design spaces and epoch spaces orders of magnitude larger, in an effort to test the scalability of the process, which takes about one day to perform, including human interpretation, on a case the size of the Space Tug. Because most of the calculations that take place in VASC are independent between designs or epochs, it is expected that computation parallelization will be able to vastly speed up large case studies. Future case studies will also explicitly account for development phases, tracking the lifecycle of the system through design, build, test, and operations phases. The active phase will affect the available change mechanisms, and execution of changes will result in schedule delay or a reset to an earlier phase, which should greatly increase the number of insights that can be obtained from the time-ordering of epochs in era analysis.

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Biography

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