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Mitigating Contextual Uncertainties with Valuable Changeability Analysis in the Multi-Epoch Domain

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Abstract- **This paper details a method involving a series of metrics and visuals designed to assist in the determination of a single design or set of designs' valuable changeability in the multi-epoch domain of Epoch-Era Analysis (EEA). A brief introduction to the necessary concepts of EEA is included, with references for further information. Example application of these new metrics is provided in the form of a partial case study of a potential orbit-realigning space tug system. The metrics are demonstrated to give insight into the value added by changeability and the total value provided by changeability and robustness in tandem.**

Reference [12] is a companion paper, detailing additional metrics and methods used to value system changeability at the era level. Multi-epoch analysis is best suited for understanding the performance of systems across the space of potential future uncertainties when considering their ability to change design; era analysis uncovers additional time-dependent information related to lifetime value and applied change mechanism usage.

Keywords- changeability; flexibility; metrics; robustness; strategy; tradespace exploration; valuation

I. INTRODUCTION/MOTIVATION

Changeability (like many of the so-called "ilities") is a system property that provides a means to the end of lifetime value delivery. In particular, changeability corresponds with the ability to alter either the physical design parameters or operations of the system and can be leveraged in any of the lifecycle phases of common engineering systems: design, build, integration and test, and operate. For example, the ability to quickly redesign a particular subsystem of a rocket in the event of a requirements update would represent design-phase changeability, whereas the ability to burn fuel and adjust orbit altitude would correspond to operations-phase changeability.

Changeability is experiencing an increase in interest as engineering systems grow, both in budget size and system lifetime, demanding more emphasis on value delivery over time and under different contexts. The apparent potential performance advantages of changeable systems, the difficulty of designing a system fully robust to changes experienced over decades, and the increased cost of failure are driving the popularity of changeability and related concepts. For example, one concept with many similarities to changeability is *flexibility*; indeed, the words are often used interchangeably. Saleh et al. [1] performed a survey of the use of "flexibility" in the literature for different fields, mainly managerial, manufacturing, and engineering design, while cataloguing the different meanings of the usage. Focusing here on the meaning for engineering systems, Saleh finds two distinct uses: one for flexibility *in the design process* and another for flexibility *in the design*. Even those subtypes of flexibility have seen different usage of the word, such as design process flexibility being applied to both customers (flexibility in requirements specified) and designers (flexibility in constraints imposed). In-design flexibility is similarly split amongst various definitions, although most relate quite directly to the ability of the system to perform different functions, and it is this type of flexibility/changeability that this paper addresses.

This research seeks to utilize the Epoch-Era Analysis (EEA) framework as a platform on which to properly value the changeability of engineering systems. The end goal is that this will allow system designers to justify investment in changeability-enabling features and consider changeable designs on an equal footing with more traditional and conservative passively value robust designs.

II. EPOCH-ERA ANALYSIS

Epoch-Era Analysis is a system design approach, developed by Ross and Rhodes [2], designed to clarify the effects of time and context on the value of a system in a structured way. The base unit of time in the method is the *epoch*, which is a period of time defined by a fixed set of variables describing the context in which the system operates. These variables can encompass any exogenous circumstances that have an effect on the usage and value of the system: weather patterns, political scenarios, financial situations, operational plans, and the availability of other technologies are all potential *epoch variables*. The complete set of epochs, differentiated using these variables, can then be assembled into *eras*, ordered sets of epochs creating a description of a potential progression of contexts over time. This framework provides an intuitive base upon which to perform analysis of value delivery over time for systems under the effects of changing circumstances and operating conditions, an important step to take when evaluating large-scale engineering systems with long lifespans.

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Epoch-Era Analysis was created with the intent for it to be used in conjunction with Multi-Attribute Tradespace Exploration (MATE), which models large numbers of designs and compares their utilities, typically represented as combinations of nonlinear functions of performance attributes [3]. MATE is a powerful tool for conceptual system design, allowing for the evaluation and comparison of many different potential designs that could be chosen for building and fielding. A design vector enumeration is used to define many potential systems that are then modeled via a computer simulation, allowing for a more complete exploration of the entire design space than the traditional engineering practice of fleshing out a handful of potential designs and selecting from among them.

In addition to its function as a temporal extension of the typically static-context field of tradespace exploration, Epoch-Era Analysis can be used as a framework for considering value-over-time regardless of the underlying methodology. Treating the passage of time as a stochastic sequence of static conditions can be used to extend other common engineering practices, including the investigation of a single point design for which time-dependent performance variables are present. This allows for a broader application of Epoch-Era Analysis to different studies.

III. Complications in Valuing Changeability

Developing metrics for properly valuing changeability is a complicated task. There are a few criteria that are beneficial for metrics to possess in order to improve their ability to accurately rate and compare alternatives, but which many previously created changeability metrics do not satisfy. One of these is the *universality* criterion, which stipulates that a score of X for the metric is equally as good or bad as a score of X in a different context. Without this distinction, it is extremely difficult to effectively use the metric to address problems of uncertainty. In the case of EEA, scores in a non-universal metric become incomparable across different epochs. This is a key problem for any metrics that use multi-attribute utility as a value statement, as MAU is neither on a ratio scale nor ordinal between epochs under different preferences, making a score of 0.3 not equivalent to the same score in a different epoch. Previous valuable changeability metrics such as Value-Weighted Filtered Outdegree [4] suffer from this weakness.

Another useful quality for metrics to possess is for their scores to be *independent* of the set of designs being considered. If a design's score is a function of the other designs in the tradespace or in a point-design study, the use of that metric adds a very large burden of proof on the design team to show that any "good" design is good regardless of the other options under consideration. This is particularly important for metrics valuing changeability, as many stakeholders require concrete evidence of the added-value gains of changeability options in order to be convinced to fund them. Independence is also a useful property even for applications where value relative to alternatives *is* acceptable, as it allows the set of designs of interest to be modified during analysis while maintaining metric stability. As an example of a project where relative value is acceptable, think of a launch vehicle selection for a fully completed payload cleared for deployment: there is a fixed set of existing alternatives for launch vehicle and one *must* be selected (the project is not optional as the payload must be put into orbit). There is no need to prove a baseline "goodness" for the selected vehicle as long as it is superior to the others, because all alternatives are included in the decision and the decision to choose none is not an option. Under conditions like these, independent metrics are less critical but still superior to dependent metrics.

Changeability also has a fundamentally two-dimensional value. The value of changeability is derived from two distinct sources: (1) the increase in system value resulting from a change, as well as (2) the number of options available, generating robustness to perturbations via breadth of choice and redundancy. This dichotomy between *magnitude* and *counting* value is frequently in tension, resulting in metrics that account for only one of the two sources. For example, Filtered Outdegree [5] is explicitly designed to "count" option paths, and its extension Value-Weighted Filtered Outdegree does not resolve the magnitude value as previously referenced. Similarly, real options methods [6,7] frequently simplify the problem into a "dollarized" magnitude value for particular scenarios, which both ignores the counting value of multiple transition choices and is inappropriate for many large engineering systems that do not deliver value in the form of money. Simultaneously accounting for both sources of value will be critical in creating a broadly applicable valuable changeability metric.

Understanding all of these complications, it is important to make a statement about the nature of valuable changeability: value is only realized from changeability *through executed changes*. This is a simple statement, but one that is frequently ignored in favor of metrics that attempt to aggregate the value of all *potential* changes. A crucial step then before valuing a design's changeability is determining *how* the design will change when faced with any particular context. To this end, we define a *strategy* that specifies how the system stakeholder intends to utilize any available changeability. This strategy can range from the simple (maximize utility for any epoch at any cost) to the complex (execute change targeting the available design with highest predicted lifetime value, but only if utility falls below a certain threshold and design increases in cost efficiency, and in certain epochs changes are not allowed). Frequently, it will be of interest to consider multiple strategies, as the different strategies can be compared for their relative effectiveness at increasing system value. Employing a strategy thins out the multitude of *possible* options down to one *selected* option for a given design in each epoch, and it is this selected transition that we will use to value the system's changeability. This paper will refer to the selected option of design d as d^*, where d^* is defined separately for each epoch and can be equal to d if the design does not change. When multiple strategies are under consideration, different indicators should replace * to clarify what strategic end state is being referenced.

The use of strategies with EEA allows the reconciliation of the magnitude and counting values of changeability. The single selected path from each design in each epoch will be valued for its magnitude: the benefit gained from executing that design change. The counting value of the changeability options for a design comes out when considering the entire epoch space: when confronted with a full variety of changing contexts, designs with more options will tend to perform better in more of those contexts. By intelligently probing these two sources of information, a design team can extract insight about the total valuable changeability inherent in a design.

IV. Multi-Epoch Changeability Value Metrics

A set of metrics designed to identify the value contained in these strategically selected transitions is presented in the following sections.

A. Fuzzy Pareto Number (FPN)

Pareto efficiency is a common concept in tradespace exploration, where a system design is described as "Pareto efficient" or "on the Pareto front" if it is not dominated in *both* cost and utility by any other design. We can also consider designs to be "fuzzily" efficient, by allowing them to be within a certain distance of the true Pareto front [8]. This distance is calculated as a percentage of the range of the cost/utility data; for example, all 1% fuzzy Pareto efficient designs will be less than or equal to 1% of the range of costs more and 1% of the range of utilities less than a truly (0%) Pareto efficient design. The Fuzzy Pareto Number (FPN) of design d is the smallest percentage K for which the design is in the fuzzy Pareto set P_K.

$$FPN(d) = \min\{\, K \mid d \subset P_K \,\} \qquad (1)$$

FPN is a measure of cost/utility efficiency calculated for each design in each epoch and for which smaller is better, with a minimum of 0 and a maximum of 100. It will be used as an indicator of design value in other metrics. Note that, unlike many other measures of value such as multi-attribute utility, FPN is universal in scale (a design with an FPN of 3 in any epoch is within 3% of cost-efficiency). FPN is also largely independent of the enumerated design space: even though it is defined relative to the Pareto front, which in a tradespace study is determined by enumerated designs, multi-variable optimization can be used to mathematically explore the system dynamics and calculate a Pareto front for a point-design study, regardless of the point designs under consideration [9]. Similarly, an intelligent enumeration of designs in a tradespace will adequately approximate the exact Pareto front, making FPN insensitive to addition or removal of new design points.

B. Effective (fuzzy) Normalized Pareto Trace (eNPT/efNPT)

A common EEA metric for identifying passively robust system designs is the Normalized Pareto Trace (NPT), which is defined as the percentage of epochs in the epoch space for which a given system is Pareto efficient [10]. This can be calculated quite easily with FPN; it is simply the number of epochs in which a design has an FPN of zero, divided by the total number of epochs. Similarly, we can define a "fuzzy" corollary (fNPT) that counts all epochs with an FPN less than or equal to a certain fuzziness threshold. Both of these metrics describe the frequency with which a design achieves a high level of value across all potential future scenarios. Note that NPT is the same as fNPT with a fuzzy factor of 0%.

With the definition of a strategy, we now know that some designs will choose to change when confronted with particular epochs. Why then should we be judging designs based on their *own* FPN, given that they will change in response to an epoch shift? Thus, we define an *effective* version of the above two metrics (eNPT, efNPT) which considers not the FPN of the design d itself in each epoch, but the FPN of that design's strategically selected end state d^* for each epoch. This allows designs that frequently change in response to epoch shifts to be graded not on their baseline performance, but on their changeability-enhanced performance.

$$eNPT(d) = [\ \Sigma_{epochs}\ 1\{FPN(d^*)=0\}\ ] \div N_{epochs} \qquad (2)$$

$$efNPT(d,K) = [\ \Sigma_{epochs}\ 1\{FPN(d^*)\leq K\}\ ] \div N_{epochs} \qquad (3)$$

A design that scores high in eNPT or efNPT could be said to be "frequently cost efficient across the space of potential future scenarios *when considering its planned usage of changeability*". Note that these metrics consider passive robustness and changeability-enabled robustness simultaneously, as passively robust designs (which will not change very often due to naturally high cost efficiency) will be graded on their own FPN for most epochs.

C. Fuzzy Pareto Shift (FPS)

While the previous metrics attempt to quantify a measure of robustness across the uncertainty space that acknowledges changeability, we may wish to clarify the magnitude of the value of a design's selected changes. For example, two designs may score identically in eNPT but derive vastly different value from their respective change options because of differing amounts of passive robustness versus changeability. To do this, we analyze the Fuzzy Pareto Shift (FPS) distribution of each design.

$$FPS(d) = FPN(d) - FPN(d^*) \qquad (4)$$

FPS is defined as simply the difference in FPN of the pre- and post-change states (d and d^*) for a given design in a given epoch. Thus, a design with an FPN of 8 that transitions to a design with an FPN of 2 would have an FPS of 8-2 = +6. The "shift" in Fuzzy Pareto Shift represents an increase or decrease in cost efficiency as the result of executed changeability. An increase in FPN would result in a negative FPS; this is meant to signal a loss of efficiency, but does not necessarily signify that a mistake has been made, as the implementation of many strategies (for example, utility maximization) will sacrifice efficiency for gains in other objectives. An epoch in which no transition is made will have an FPS of zero, as the initial and final states are the same.

Because it is defined separately for each epoch, a design's FPS is best viewed as a distribution. This distribution curve can be compared against other designs for an intuitive understanding of the relative frequencies of different magnitudes of changeability value occurring in each design across the epoch space. When breaking down this distribution into representative statistics, preference should be given to order statistics (minimum, maximum, median, percentiles) over averages; the distributions are often heavily skewed by positive and/or negative outliers which makes the distribution mean ill-suited to summarizing the design performance.

D. Available Rank Improvement (ARI)

Unlike the previous metrics, Available Rank Improvement (ARI) does not depend on a strategy, but rather presupposes an attempt to maximize utility. Here, a change mechanism is defined as a single means for a design to change; for example, a modular payload bay to swap payloads and thrusters to alter orbit characteristics are two potential change mechanisms for a satellite system. ARI is calculated for each change mechanism (r) separately, as the maximum possible improvement in utility rank-ordering achievable using only that change mechanism. The term d^r represents all available designs from design d using only mechanism r.

$$ARI(r,d) = Rank(d) - \min\{Rank(d^r)\} \quad (5)$$

ARI is an imperfect metric, as it requires a tradespace and depends heavily on the chosen enumeration of designs, but serves adequately as an indicator of potential achievable value enabled by the inclusion of a particular change mechanism. A "strategic" version of ARI can be calculated by swapping out d^r with the strategic end state d^* used in the previous metrics and removing the min{} function, but this form is not recommended. ARI is best employed to represent what is made "available" by a change mechanism, and the other metrics are more appropriate for evaluating executed strategic transitions.

V. Application to a Space Tug Example

A. Introduction and Designs of Interest

To demonstrate some of the insights that can be gleaned from these metrics, a simple case study is now presented. The Space Tug data set is a conceptual tradespace study for a satellite designed to realign other satellites when their orbits begin to deviate from their planned trajectories. It is a small tradespace, with only 384 designs being considered across 16 epochs. Large studies can feature over 100,000 designs and 1,000 epochs, but a small study provides the opportunity to quickly assess the viability of changeability metrics. The designs are all graded on three attributes: available delta V, speed, and mass capability. This study is based on the work of McManus and Schuman [11].

There are only four design variables used to generate the Space Tug tradespace: propulsion type, fuel mass, manipulator capability, and Design for Changeability (DFC) level. In this case, DFC level is implemented as a mass penalty on the satellite and serves as an enabler of improved or additional change mechanisms. Think of DFC as the inclusion of extra design features or margin, at an additional cost, for example. DFC is implemented in three levels (0,1,2) and the associated change mechanisms are listed in Table I. As described, all designs with either a bipropellant or cryogenic engine can switch between the two options and all designs are capable of changing fuel tank size, and both of these options reduce in cost with any investment in DFC. Also gained from investment in levels 1 or 2 of DFC is the ability to switch manipulator capability; increasing capability improves utility, but decreasing capability reduces mass and thus cost. Finally, the DFC level 2 designs can also refuel in orbit, which extends lifetime while sparing the costs of redesigning and relaunching the satellite.

These change mechanisms specify which *other* designs are accessible via a change for each design. The combination of multiple change mechanisms can lead to even further designs, and considering these multi-arc transitions leads to a full accessibility matrix, which indicates *all* available end states via any combination of change mechanisms for each design. The Space Tug full accessibility matrix is shown in Figure 1, with design numbers on both axes. The plot is read by locating a design number on the vertical axis and reading across to find all available other designs on the horizontal axis as indicated by a mark in the appropriate column. This plot gives a fast understanding of how connected the tradespace is, and will also qualitatively allow for an assessment of designs with many change options and thus the potential for high valuable changeability, particularly in the counting value.

TABLE I. Space Tug Change Mechanisms

No.	Change Mechanism	Effect	DFC level
1	Engine Swap	Biprop/Cryo swap	0
2	Fuel Tank Swap	Change fuel mass	0
3	Engine Swap (reduced cost)	Biprop/Cryo swap	1 or 2
4	Fuel Tank Swap (reduced cost)	Change fuel mass	1 or 2
5	Change Capability	Change Capability	1 or 2
6	Refuel in Orbit	Change fuel mass (no redesign)	2

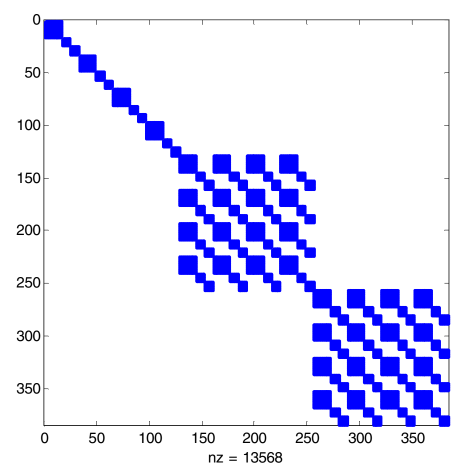

Figure 1. Space Tug Full Accessibility Matrix

This paper does not address the process of selecting designs of interest, but it is usually a good idea to narrow the field of consideration to a subset of the entire tradespace before considering valuable changeability, as there are likely to be many designs that are uninteresting to the stakeholders regardless of changeability. Any indicators of value or screening metrics can be used to downselect the designs. For this study, seven designs of interest were selected using a combination of Normalized Pareto Trace, fuzzy Normalized Pareto Trace, and Filtered Outdegree. The designs and their parameters are shown in Table II.

B. Comparing Designs with Multi-Epoch Analysis

Having selected designs of interest, the goal is now to use the new metrics to effectively compare their valuable changeability. In the Space Tug case study, there are 16 epochs under consideration, representing eight different "preference sets" (utility functions) corresponding to different

TABLE II. SPACE TUG DESIGNS OF INTEREST

Design No.	Ref	Prop Type	DFC Level	Fuel Mass (kg)	Capability (kg)	Speed	Delta V (m/s)	Base Cost ($M)
1	A	Biprop	0	30	300	Fast	143	97
29	B	Nuke	0	1200	300	Fast	7381	306
47	C	Cryo	0	10000	1000	Fast	6147	628
128	D	Nuke	0	30000	5000	Fast	14949	3020
191	E	Nuke	1	10000	1000	Fast	16150	980
328	F	Biprop	2	50000	3000	Fast	4828	2804
376	G	Elec	2	30000	5000	Slow	27829	3952

TABLE III. SPACE TUG ENPT/EFNPT RESULTS FOR DESIGNS OF INTEREST

Designs	eNPT				efNPT (5% fuzziness)			
	Do Nothing (NPT)	*Max U*	*Max Eff*	*Survive*	*Do Nothing (fNPT)*	*Max U*	*Max Eff*	*Survive*
A	0.75	0	0.875	0	0.75	0	0.875	0
B	0.75	0	0.813	0.75	0.875	0	0.875	0.875
C	0	0	0.25	0	0.625	0.125	0.688	0.675
D	0.875	1	1	0.875	1	1	1	1
E	0	0	0	0	1	1	1	1
F	0	0	0	0	0	0.313	0.875	0
G	0	0	0	0	0	0	0.75	0

missions, and two "technology levels", which affects the performance of different propulsion types. Three changeability usage strategies will be considered: *maximize utility*, *maximize efficiency*, and *survive* (transition only if design will fail otherwise). These are simple strategies but represent a broad range of potential ways to utilize changeability and will likely reflect different valuable changeability between the designs of interest.

First, eNPT and efNPT are used to scan the designs for their *changeability-enabled robustness*, the ability to remain valuable over variable contexts considering all planned design changes, which considers both passive robustness and changeability simultaneously. Table III displays the results of these metrics for the designs of interest with all of the strategies. A few results are immediately apparent. For one, considering changeability does not always increase Pareto Trace; as mentioned previously, some strategies, such as *maximize utility*, will frequently sacrifice cost efficiency in the name of another goal (here, increasing utility). On the other hand, the maximize efficiency strategy does always score at least as well as the "do nothing" NPT, because it will never sacrifice proximity to the Pareto front during a change. It is also apparent that the level 1 and 2 DFC designs (E,F,G) do not improve from NPT to eNPT, because they have a fixed cost increase associated with changeability that distances them from the Pareto front regardless of where they transition to. However, when allowing for a 5% fuzzy margin, these designs see a distinct improvement between fNPT and efNPT, particularly design E which has a perfect score of one in every strategy. This is capturing information as desired: the highly changeable designs, while never strictly (0%) efficient, can leverage their changeability to significantly improve value robustness across the epoch space. Looking at this metric, it appears that designs D and E are the most desirable options, with excellent scores across all strategies in efNPT. Figure 2 plots this data in bar chart form, which can provide a useful visual for seeing what designs perform well across which strategies and also what strategies lend themselves to more efficient administration of the system with which designs.

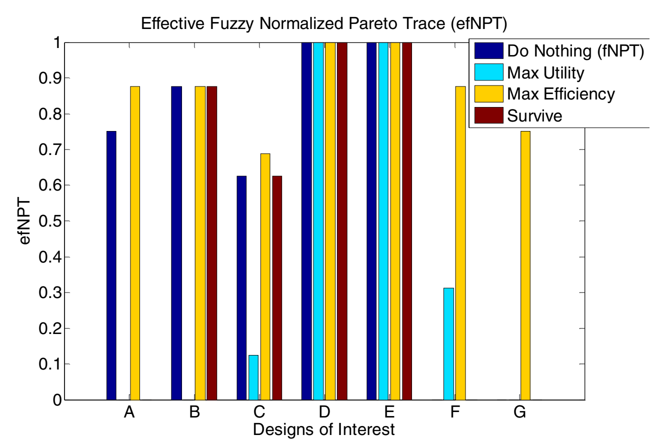

Figure 2. Space Tug efNPT Bar Chart

Using eNPT and efNPT has provided an understanding of the total performance, robustness and changeability influenced, of the designs. These statistics are followed up with an investigation of FPS, which isolates the value added by changeability. Remember, FPS is calculated for each design in each epoch, where the magnitude value of changeability is found in the score for each epoch, and the counting value is found in aggregate across the epochs.

Like eNPT, FPS is calculated for each strategy separately. The preferred way to view FPS data is with a distribution of the epoch scores, accompanied by a table of the order statistics of the distributions for each design. Order statistics are preferred to mean and standard deviation, because the distributions are frequently irregular and median is a vastly superior indicator of central tendency for them. Figure 3 shows the distributions for the *maximize utility* strategy: the distributions for the other strategies are not displayed for conciseness. However, the FPS order statistics for the designs of interest in each strategy are included in Table IV. If a design is invalid and cannot transition to a valid design, its score becomes -101 for that epoch: an index that is worse than the worst possible FPN. Similarly, if an invalid design becomes valid, its "initial FPN" (which is actually undefined, as it is not in the tradespace) for the purposes of calculating FPS is treated as 101.

The FPS data confirms a number of fundamental conjectures about the Space Tug system. For one, it is again clear that the *maximize efficiency* strategy does not allow for transitions leading to a worsening of FPN: these transitions would score negative FPS, and the only negative FPS scores reported for that strategy are -101 scores for invalid designs[1]. The *maximize utility* strategy tends to create small negative FPS transitions, with only the occasional large boost, in this case to designs A and F. The switch from the utility to the efficiency strategy swaps most of those negative FPS transitions for no-change decisions, as apparent from the large number of zeros. This is due in part to the selected designs being naturally passively efficient, as that was one of the selection criteria. Similarly, the *survive* strategy has even more no-change decisions, with the exception of design A, which is a bare-bones design with minimal fuel that must change to remain functional.

As an example of how to interpret an FPS distribution plot, Figure 3 displays that:

1. Design A derives very large value from a few changes (farthest right tail)
2. Design F most consistently generates positive value via changeability (most weight to the right of zero)
3. Designs D, E, and G are the most passively robust (largest spikes at zero indicating no transition)
4. Designs A, B, and C sacrifice small amounts of efficiency for more utility (significant weight slightly left of zero)

Overall, the plot can provide a quick-scan grasp of the difference in valuable changeability between the designs of

TABLE IV. SPACE TUG FPS ORDER STATISTICS

Maximize Utility FPS Order Statistics					
Design	**Min**	**1st Quart**	**Median**	**3rd Quart**	**Max**
A	-101	-19	-13	-8	93
B	-101	-25.5	-13.5	-6	-2
C	-10	-9	-6.5	-1	2
D	0	0	0	0	1
E	-3	0	0	0	0
F	-4	6	9	28	43
G	-101	-50.5	0	0	0
Maximize Efficiency FPS Order Statistics					
Design	**Min**	**1st Quart**	**Median**	**3rd Quart**	**Max**
A	-101	0	0	0	101
B	-101	0	0	0	4
C	0	0	1	3	9
D	0	0	0	0	1
E	0	0	0	0	0
F	9	13	18	41	52
G	-101	-48	8	14	30
Survive FPS Order Statistics					
Design	**Min**	**1st Quart**	**Median**	**3rd Quart**	**Max**
A	-101	-21	-16.5	-12	85
B	-101	0	0	0	0
C	0	0	0	0	0
D	0	0	0	0	0
E	0	0	0	0	0
F	0	0	0	0	0
G	-101	-50.5	0	0	0

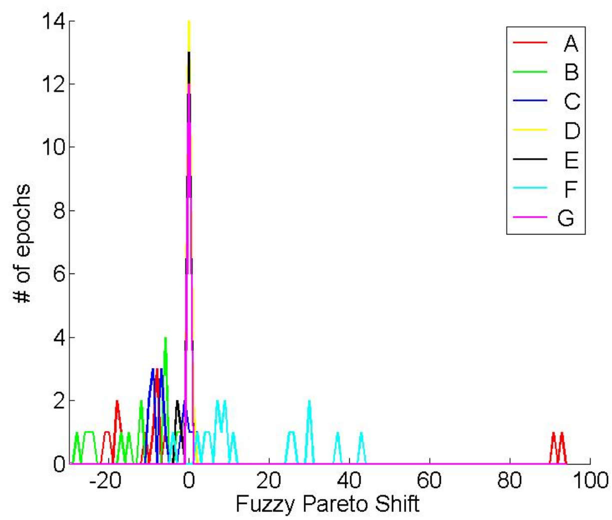

Figure 3. Space Tug Maximize Utility FPS Distribution

[1] The -48 score for design G's first quartile is a mathematical artifact created by averaging the fourth and fifth epochs' performances between -101 and 5, and does not represent an actual -48 FPS transition. The same applies for the -50.5 first quartile scores for design G in the other strategies: it is invalid in exactly one quarter of the epochs.

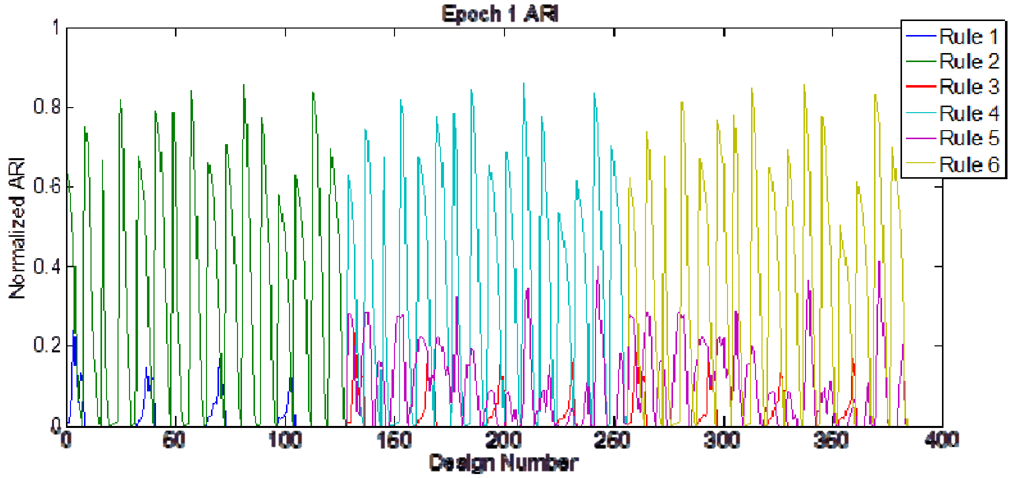

Figure 4. Space Tug Design ARI Plot

interest that is difficult to process out of the tables alone. In this case, similar insights can be had from the other distributions. There are other potential views with the ability to assist in the information absorption process. For example, coloring the tables like heat maps can provide a more distinct indicator of where positive (green) and negative (red) transitions occur. Also, the tables can alternatively be presented in plot form as a stacked box-and-whisker plot, displaying the minimum, median, maximum and quartiles visually for each design, separated on the on vertical axis.

Figure 4 is an example ARI plot for the entire tradespace. Recall that ARI is used to evaluate the effectiveness of the different change mechanisms in general, thus it is better to examine all designs rather than just a subset of the designs. Also, since the designs' rank order rearranges with the preference changes in the different epochs, ARI changes in each epoch; Figure 4 is an example for Epoch 1, with the vertical axis showing ARI normalized by the size of the design space. For this case study, it happens that this plot looks very similar across all epochs, so the conclusions drawn from this example will serve in general.

There is one main conclusion able to be drawn from the ARI plot. There is a different dominant change mechanism ("Rule") for each of the three DFC levels (which split the tradespace evenly in thirds): the fuel tank swap for level 0 (Rule 2), the reduced-cost version of the same rule for level 1 (Rule 4), and the refuel in orbit for level 2 (Rule 6), which all generate more than twice as high a rank increase as any other mechanisms. This suggests that the largest utility gains created by any mechanisms in the space are those that increase the fuel level of low-fuel designs. This is why the plot is jagged, as the high-fuel designs are unable to exploit those mechanisms for gain.

VI. Summary and Extensions

Changeability is a desirable trait in engineering systems, as it can allow them to avoid risk and seize opportunity. However, a number of mathematical challenges (dataset independence, universality, capturing magnitude and counting value of transitions) have hindered the development of metrics to justify investment in changeability, especially when compared to the older and better-understood design approach of passive robustness. Overcoming these challenges is likely to require a set of metrics designed to properly quantify the value of changeability together. This paper has discussed the aptness of Epoch-Era Analysis to structure this problem, and posited a new set of metrics (eNPT/efNPT, FPN, FPS, and ARI) designed to perform this task using a stakeholder-specified strategy. An example case using a Space Tug demonstrated the application of these metrics in the multi-epoch domain and the types of insights about valuable changeability in an engineering system can be gained from their use.

Among the most definitive results of multi-epoch analysis in this case study were the identification of designs D and E as extremely passively robust (with D slightly dominating E in cost and utility) and design F as extremely valuably changeable. However, it is difficult to directly compare these designs, as the means in which they are identified are on different scales, and because some of the changeability value of F is obscured without evaluating lifetime behavior. Multi-epoch analysis is limited in that it does not consider time-order effects of the system executing changes sequentially, nor does it calculate full system lifecycle properties such as lifetime cost or accumulated utility or expected number of change mechanism uses, which are typically much harder to predict for highly changeable designs. These performance metrics can be extracted by using the era domain of Epoch-Era Analysis, and thus it is recommended that multi-epoch and era analysis be performed together in order to generate as much information on the system as possible. Without evaluating these factors, from which changeable designs derive much of their potential advantages over passive designs, it is difficult to accurately compare the value of passively versus actively robust designs; era analysis allows this comparison. Despite this limitation, multi-epoch analysis has two advantages over era analysis: (1) reduced implementation time in manpower and computation, and (2) fewer assumptions, as the era constructor must make assumptions about the duration and ordering probabilities of each epoch, which may lead to unreliable results if not chosen carefully. For more detail on era analysis, consult this piece's companion paper [12].

VII. REFERENCES

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