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Sustaining Lifecycle Value: Valuable Changeability Analysis with Era Simulation

Matthew E Fitzgerald

Systems Engineering Advancement Research Initiative (SEARI)
Massachusetts Institute of Technology
Cambridge, MA 02139
mattfitz@mit.edu

Adam M Ross

Systems Engineering Advancement Research Initiative (SEARI)
Massachusetts Institute of Technology
Cambridge, MA 02139
adamross@mit.edu

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 era domain of Epoch-Era Analysis (EEA). A brief introduction to the necessary concepts of EEA is included, with references for further information. Examples are provided in the form of a partial case study of a potential orbit-realigning space tug system. The method is shown to effectively distinguish the lifecycle value of designs of interest, quantify the value and frequency of use for the various change mechanisms, and offer a value for the tradeoff between initial costs and lifetime returns associated with including change mechanisms.

Reference [8] is a companion paper (recommended to be read first), detailing additional metrics and methods used to value system changeability in the multi-epoch domain. 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; system lifecycle; simulation; strategy; tradespace exploration; valuation*

I. INTRODUCTION/MOTIVATION

Designing large engineering systems in the modern world more and more frequently involves a detailed analysis of complete lifecycle value rather than single-context performance optimization, driven by dramatic increases in budget sizes and required lifetime. *Changeability* has emerged as a popular means to achieve improved lifecycle value, allowing systems to avoid risk and seize opportunity by adjusting design or operational variables throughout all the phases of its life.

Changeability is a somewhat abstract concept, one that has been discussed in many ways, targeting possible solutions to the challenges of decades-long lifetimes with the rising cost of fielding a desirable system and the associated rising cost of failure. Terminology can prove to be a stumbling block here, and many similar terms such as *flexibility* are used to indicate the same concepts changeability is based upon. A survey of the usage of "flexibility" conducted by Saleh et al. [1] noted

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instances of flexibility literature in a wide variety of fields, including management, manufacturing, and engineering. It was determined that flexibility can apply both to the design *process* and the design *itself*, and can apply both to the customers' requirements and the designers' constraints. This paper will focus on flexibility/changeability in the design; however, even working with this subtype of changeability it is difficult to find a universally agreed upon definition. Most discussion of changeability for engineering systems revolves around the modification of design variables in anticipation of, or in response to, changes in exogenous variables, and the discussion in this paper will focus on this usage of the term.

A key difficulty in implementing changeability in design has been the justification of the extra cost of its inclusion, as it typically requires longer development and/or additional technology. The benefits changeability gives are extremely difficult to extract and value in a static context, which has led to a systematic favoring of systems employing passive robustness. The Epoch-Era Analysis (EEA) framework provides a means with which to intuitively explore system performance over time and across different contexts; it is the goal of this research to find and implement a method to investigate and quantify changeability value using EEA, allowing it to be compared effectively to passive robustness in the design process.

II. EPOCH-ERA ANALYSIS

Epoch-Era Analysis will be the method used to model the progression of time and context for the system being designed, in order to allow for proper valuation across the entire lifecycle [2]. Ross and Rhodes proposed EEA with the intent that it could be used to structure problems in which uncertain future contexts are a key factor impacting system value. An *epoch* is defined as one of these potential contexts: a period of time characterized by a fixed set of exogenous *epoch variables* such as weather, customers, or threats that have a significant impact on performance or perceived value. Then an *era* is defined as a sequence of epochs that, when placed in order, create a potential lifecycle of contexts that the system may face. The intermediate static conditions within epochs simplifies the analysis involved with calculated value, and constructing the epochs into eras creates an intuitive structure on which to consider full lifecycles.

The original application of Epoch-Era Analysis was to provide a temporal extension to Multi-Attribute Tradespace Exploration (MATE), and this paper's example will also be a MATE study. MATE allows for the investigation of an extremely large design space, rating designs with a utility function that is constructed from nonlinear functions of multiple performance attributes [3]. The design space is populated by a computer model that evaluates the performance of an enumerated design vector. The potential design space becomes combinatorially large as the number of design variables considered increases. However, large design spaces can be used to generate a more complete understanding of the breadth of options available than would be given by a point-design study. Each of the designs can then be investigated across the epochs in EEA to provide insight into their performance in different contexts, and eras can be constructed to check lifetime performance across changing contexts.

Epoch-Era Analysis is not limited to tradespace exploration applications, as it employs a conceptual framework for considering the progression of time. Thus, EEA is equally applicable as a means of exploring lifecycle value for point-design studies. As long as there are exogenous variables that change over time and affect the performance or perceived value of the system, EEA can be used to define epochs of static context and eras of stochastically sampled epochs, which gives a wide range of potential projects and studies for EEA to support.

III. USING STRATEGY TO VALUE CHANGEABILITY

Many previous studies have attempted to value changeability in engineering studies, generating metrics and methods with various levels of applicability [4,5,6,7]. The companion paper to this one [8] comments more extensively on these difficulties and previous methods, drawing particular attention to the dichotomy between the value obtained from the magnitude of the difference between the initial and final states of the system and the counting value created by having multiple options, presumably creating a larger space for the system to change in and generating value under a larger variety of future uncertainties.

With the understanding that value is derived only from executed changes, as opposed to potential changes, a logical next step then before valuing a design's changeability is determining *how* the design will change when faced with any particular context. A *strategy* encapsulates this decision into a simple statement of how a decision maker intends to utilize the system changeability during the lifecycle. 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). Multiple strategies should be considered for most studies, 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.

The use of strategies with EEA allows for 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 great insight about the total valuable changeability inherent in a design.

IV. ERA-LEVEL CHANGEABILITY ANALYSIS

The goal of era simulation is to uncover lifetime performance characteristics of the designs under consideration that are observable only when existing in time-ordered sequences of epochs. When changeability is implemented into the simulation, these time-dependent characteristics can have dramatic effects on lifecycle value. To illustrate this, consider a system and two epochs; the system has excellent utility in one epoch, and the ability to change its form to provide excellent utility in the other. This system has decent multi-epoch performance in its original form, which improves to superb when considering its changeability; however if the changed version of the design performs poorly in the first epoch and the system can't return to the original configuration, its lifetime value will be dramatically reduced. Alternatively, if the design *can* return to its original form but the epochs switch daily, the cost of maintaining that high utility by switching forms daily may outweigh the benefits. How then, can we create a method to uncover these effects systematically?

A. Era Construction Basics

An era simulator constructs a stochastic sequence of epochs over which designs will be valued. The simplest version of this can be achieved by using a random number generator to randomly select an epoch, either with equal probability or with predetermined likelihoods, and construct a sequence of constant-duration epochs this way [9,10]. However, the goal of era construction is to simulate the real world conditions faced by the system as accurately as possible. Thus, depending on the epoch variables used to define the epoch space, it is possible that much greater care can (and should) be taken. A few possible era constructor improvements are detailed in the paragraphs below.

Many epoch variables have a unidirectional, passage-of-time nature. For example, the technology readiness level (TRL) of the system's underlying components may have impacts on expected schedule time and cost to build or operate. It is reasonable to expect that the TRL will progress with time, so as the epochs are sequenced, they should be intelligently sampled so that the TRL epoch variable either remains the same or increases. Other epoch variables can continue to be randomized as appropriate, but the technology level should never decrease as that could create an unrealistic era.

Another potential improvement to a simple era constructor is the inclusion of varying epoch duration. In reality, not all contexts will last for the same amount of time, nor would it be reasonable to expect them to do so. Thus, a probability

distribution can be applied to sample the epoch duration at the time each epoch is selected for the era sequence. The durations can follow continuous or discrete distributions. Also note that it is frequently desirable to have different distributions associated with different epochs; for example, if there is an epoch variable associated with “peace” versus “war”, we might reasonably expect that wartime epochs will not last as long, driven by a rapidly increased rate of technology development or changes in operations requirements, and apply an appropriately shifted probability distribution shortening these epochs.

B. Data Collection and Processing

This paper assumes that a strategy as defined in the authors’ companion paper [8] and the previous section is available. The era simulation and analysis can be performed on the same system for multiple strategies, allowing system decision-makers to see the effects of their usage of change mechanisms. Change mechanisms are the means by which a design can change design variables and are the enablers of changeability, typically included in systems at extra costs in both money and development time.

With an era constructed, a design’s progression can be tracked through the different epochs. As each epoch begins, the strategy is checked to see if the current design will execute a change and, if so, the simulation is updated to reflect the new design while the total costs and utilized change mechanisms are recorded; then this is repeated for each epoch in the era sequentially. Any and all performance metrics of interest should also be recorded for the updated design in each epoch, including but not limited to: revenues, costs, accumulated utility, Pareto efficiency, and unviability. Each design under consideration should be tested as the initial design for a large number of simulated eras to ensure meaningful averages. This results in a massive quantity of data that can be difficult to process in an intuitive way to assist decision-making. The following sections explain techniques for visualizing the data that can aid the comparison of potential designs.

1) Best/Worst/Average FPN Plots

As described in Ref [8], Fuzzy Pareto Number (FPN) is a metric ranging from 0 to 100, describing a system’s percentage deviation from cost/utility Pareto efficiency. FPN is calculated for each design and epoch pair, and since it has a fixed scale between epochs (an FPN of 1 is 1% inefficient regardless of the level of performance defining efficiency) it can be tracked and compared effectively across epochs and eras. During era simulation, recording the FPN of the active design in each epoch allows for the output of the best, worst, and average FPNs at the completion of the era. These three values can be averaged between the different sample eras to get a good idea of the range and approximate center of value efficiency in each design. Then, potential designs can be compared effectively by showing these three numbers on the Y-axis of the same plot, demonstrating a likely efficiency performance “envelope.”

2) Rule Usage Tally – Per Lifetime likelihoods

Another statistic that should be recorded during era simulation is the count of each execution of a given change mechanism. By recording the frequency with which each is used, the mechanisms that are regularly employed to assist the

system’s performance and those that are unused or replaceable can be identified quickly. This potentially enables the design team to save development costs for unused mechanisms or can provide incentive to further refine a frequently used mechanism in order to reduce its execution cost. Both the average number of executions per lifetime (total rule usage across all sample eras divided by number of sample eras) and likelihood of rule usage in a lifetime (number of sample eras in which rule was used at least once divided by number of sample eras) can be calculated. Presented in heat map form, this can provide an easy to understand visual for change mechanism “hot spots” in the system [11].

3) Changeability “going rates”

A common piece of information desired by decision-makers is the tradeoff between including and not including changeability or change mechanisms in a system. This information is a valuable asset when making a final design selection and considering the addition or removal of changeability-enablers. Era simulation provides a means to compare these otherwise similar designs on their lifecycle value versus up-front or lifetime costs. This allows the establishment of a “going rate” for changeability: adding changeability will cost \$X but deliver an additional Y value measured by average FPN, revenue, and/or other performance metrics desired by the stakeholders.

4) Rule Removal

Some designs may prove to be dependent on a particular change mechanism for a large portion of their lifetime value. For example, a deep-space imaging satellite may depend heavily on thrusters to control its attitude in order to lock onto different regions of the sky; without this capability the satellite’s range of vision is crippled. This dependence may drive system designers to improve the change mechanism’s robustness through redundancy or design a substitute mechanism, and if that is impossible the decision-makers may settle on another design or scuttle the project. Mechanism dependence can be uncovered by reevaluating a strategy without considering any design transitions enabled by a particular mechanism (*removing* the associated design transition “rule”), and then performing era simulation again. The differences between the with- and without-mechanism performances quantify the dependence on that mechanism across all of the value metrics of interest.

V. APPLICATION TO A SPACE TUG EXAMPLE

The Space Tug is a small case study constructed to explore potential designs for a satellite intended to correct the orbit alignments of recently-launched or orbit-decaying satellites. The designs are enumerated using four design variables (propulsion type, fuel mass, manipulator capability, and Design for Changeability level) and evaluated across three attributes (delta V, speed, and mass capability). As the DFC level design variable increases, the space tug increases in weight, reducing delta V, but gains access to new and reduced cost change mechanisms, allowing more freedom to alter the design as context changes. This case study encompasses 384 design points over 16 epochs, which describe changes in technology and user preferences (in this case, modeling

TABLE I. 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 II. 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

potential missions). During the simulations, user preferences are changed at random, but the technology improvement variable switches from “present” to “future” technology and stays there, implementing the suggestion for one-way context variables. Additional detail on the tradespace is included in Ref 8.

Downselecting to a smaller set of designs for further analysis is desirable because it makes the results easier to understand and screens out designs that would be uninteresting regardless of their changeability. For reference, the list of designs of interest and available change mechanisms are included in Table I and Table II.

The era setup for Space Tug is meant to emulate the uncertainty of future needs for satellite tug services. The 16 epochs are differentiated by eight preference sets corresponding to different missions that could potentially be satisfied by the Space Tug, and two technology levels affecting the performance of the tug’s equipment. Each epoch in an era serves as a “contract” offered to the Space Tug by a commissioning party, with revenue to be made in the form of a small fixed amount and an additional amount proportional to both the duration of the epoch and the tug’s multi-attribute utility score for the preferences of the contract. The eight possible missions associated with the contracts include: (1) baseline mission, (2) technology demonstration, (3) GEO satellite rescue, (4) satellite deployment assistance, (5) in-orbit refueling and maintenance, (6) garbage collection, (7) all-purpose military mission, and (8) satellite saboteur.

To simulate the era, a changeability usage strategy is needed in order to determine whether or not the current space tug design will transition to a new design in each epoch, and if

TABLE III. ERA SIMULATION – PROFITS (UNITS OF \$10B)

Design	MAX UTILITY			MAX EFFICIENCY		
	Avg Rev	Avg Cost	Avg Profit	Avg Rev	Avg Cost	Avg Profit
A	3.3	1.7	1.6	2.4	0.1	2.3
B	4.0	2.6	1.4	4.4	0.4	4.0
C	4.3	2.3	2	4.4	0.6	3.8
D	6.9	4.6	2.3	7.9	3.6	4.3
E	6.6	5.7	0.9	6.7	3.7	3.0
F	5.7	2.7	3	3.0	0.8	2.2
G	6.5	0.4	6.1	2.2	0.9	1.3

Design	SURVIVE			MAX PROFIT		
	Avg Rev	Avg Cost	Avg Profit	Avg Rev	Avg Cost	Avg Profit
A	3.6	0.6	3.0	3.0	0.2	2.8
B	4.9	0.6	4.3	4.3	0.2	4.1
C	5.3	0.7	4.6	4.7	0.3	4.4
D	8.6	1.6	7.0	7.7	0.7	7.0
E	6.9	1.0	5.9	6.5	0.6	5.9
F	7.1	0.3	6.8	7.5	0.3	7.2
G	6.7	0.4	6.3	7.4	0.4	7.0

so, what end state will be chosen. Four strategies were tested in era simulation: maximize utility, maximize efficiency, survive (change only if invariable), and maximize single-epoch profit. Multiple strategies are tested because they will result in different total lifecycle costs and revenues. The relative desirability of different designs may be affected by the choice of strategy, and the strategies themselves may carry different appeal (for example, it may be desirable to have as few design changes as possible, for the sake of management simplicity, even at the sacrifice of potential revenue and profits).

To illustrate the dramatic effect that changeability usage strategy can have on a system, consider Table III, which shows the average revenues, costs, and profits of each of the designs of interest over a 10-year lifecycle. Significant fluctuations in both revenue and cost are apparent for every design across the different strategies, and the best and worst results under each strategy are highlighted in green and red, respectively. Very interestingly, three different designs have the highest average profit under the four different strategies.

Unsurprisingly, the highest value overall is achieved under the maximize profit strategy, but the reordering of the designs of interest according to the performance metric of profit across the different strategies demonstrates a key point: changeability usage can be just as important as initial design selection when it comes to determining lifecycle value.

Of course, not all engineering systems generate revenue or are intended to create profit. The lifetime FPN statistics for each design can serve as a valuable tool for understanding its cost-utility efficiency over time. For each era, we can record the best, worst, average, and average when viable FPN scores. Table IV then shows the average values for each of these statistics across 5000 eras, which provides a level of efficiency performance that can be expected for initially building each of the designs of interest. The lifecycle FPN data displays much more consistency across the various strategies, with significantly less reordering of the designs than the profit data. Some other interesting results visible in this data include:

- The lower DFC designs (A,B,C,D) have better *best FPN* but worse *worst FPN* scores. This suggests that changeability is avoiding worst case scenarios, but not finding extremely efficient design points.
- Design A always has the highest average FPN when ignoring epochs for which it is inviable, but these epochs are frequent enough that it never has the highest overall average FPN.
- Design G, despite high profits in the previous section, is consistently the least efficient design.
- Design E is highly efficient regardless of strategy selection.

Another interesting avenue of investigation is the relative usage rates of the various change mechanisms. Because the mechanisms are typically included in the system at some sort of development or carrying cost, usage rates can be powerful

justification for including or removing them from the system while still in development. Figure 1 shows the average number of mechanisms executions per era for each mechanism (also known as transition “rules” as in this figure) under each strategy. For this case study, we can see that the strategies maximizing utility and efficiency demand far more changes than the other two, suggesting that they will require more management during the lifecycle if employed. It is also apparent that mechanisms 1 and 3, the options to switch bipropellant and cryogenic engines, are very rarely used; therefore a potential cost-saving decision for the design team could be to scrap this option and not develop whatever common interfaces would be needed for the engine swap. This mechanism-usage data can also be presented as percent likelihoods of requiring each mechanism for a random epoch

TABLE IV. ERA SIMULATION – LIFECYCLE FPN

Design	MAX UTILITY				MAX EFFICIENCY			
	Best	Worst	Avg	Avg (no fail)	Best	Worst	Avg	Avg (no fail)
A	0.0	96.0	17.4	2.2	0.0	100.4	24.7	0.0
B	0.0	94.1	15.8	3.0	0.0	96.4	17.7	2.1
C	0.1	84.2	13.1	4.8	0.0	100.5	27.9	3.7
D	0.0	91.0	16.8	7.9	0.0	95.1	19.7	8.6
E	1.0	85.4	15.6	8.8	1.0	80.6	13.3	7.2
F	2.1	82.1	18.1	12.7	1.0	100.4	24.1	2.3
G	3.1	100.6	33.6	10.6	1.0	100.9	33.3	4.5

Design	SURVIVE				MAX PROFIT			
	Best	Worst	Avg	Avg (no fail)	Best	Worst	Avg	Avg (no fail)
A	0.0	99.3	20.1	1.4	0.0	100.5	25.6	0.3
B	0.0	97.5	19.3	2.9	0.1	97.9	20.1	3.2
C	0.0	93.8	16.5	4.3	0.0	99.9	25.5	4.1
D	0.1	96.1	26.8	16.2	0.7	100.4	38.5	19.9
E	1.0	87.3	14.4	5.5	1.4	97.0	22.9	8.5
F	3.2	100.8	38.2	16.9	3.2	100.7	38.3	17.3
G	3.7	100.9	44.0	21.2	2.9	100.7	38.2	15.5

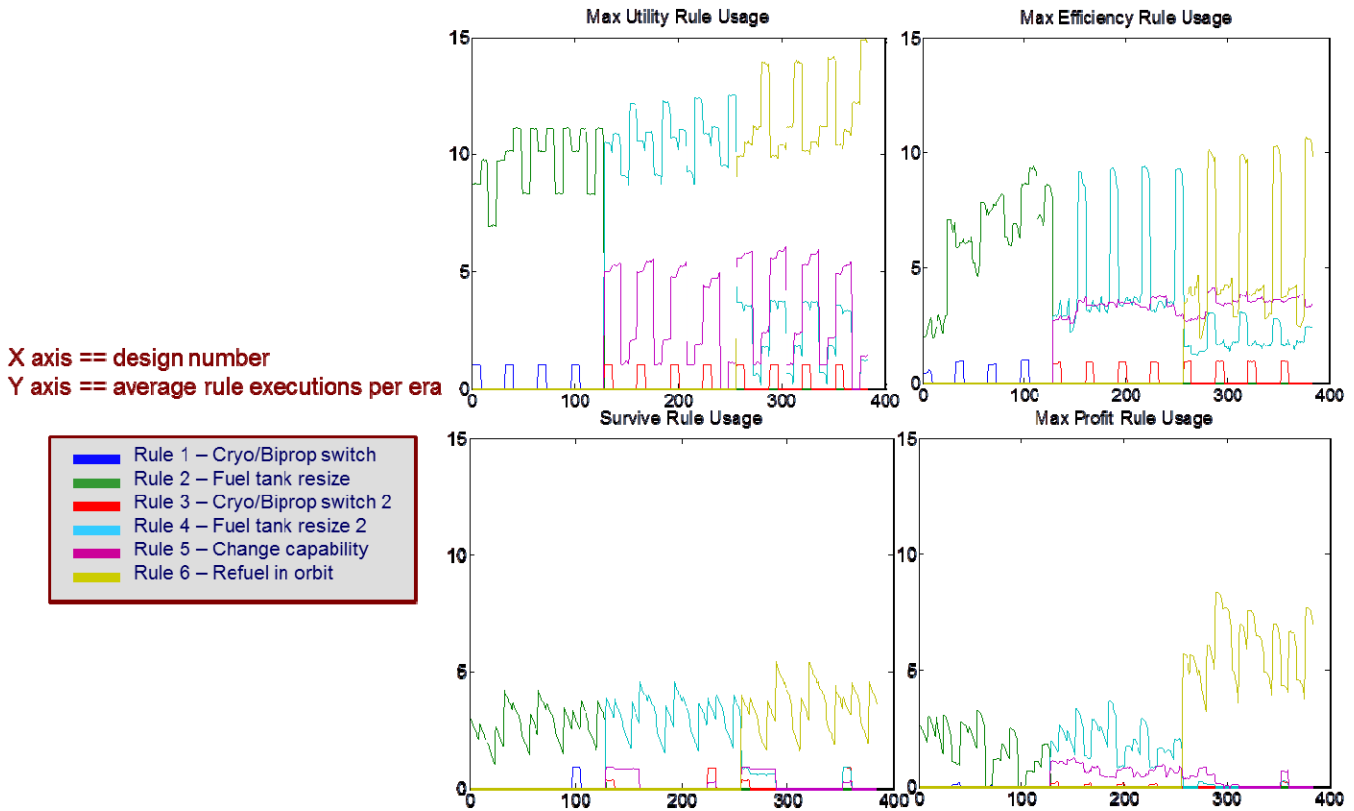


Figure 1. Space Tug – Change Mechanism Usage Rates

TABLE V. SPACE TUG DFC PERFORMANCE/COST TRADEOFFS

-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

switch or at any point in a complete era, but these plots are omitted here.

This sort of “under the hood” information can be extremely valuable to non-technical decision-makers, who may have difficulty differentiating between designs or conceptually understanding changeability development and usage. A quantification of the tradeoff between performance and cost inherent with the inclusion of change mechanisms is also useful for this reason. Table V illustrates the ability to clarify this “going rate” for changeability-enhanced performance in this case. The nature of the space tug dataset is such that it is possible to directly compare designs that are identical except for their DFC level, which is tied directly to the inclusion of change mechanisms. For example, if a stakeholder is interested in how well Design D, a DFC level 0 design, performs when changeability is added to the system, we need only look up and compare the initial cost and lifecycle profits of its corresponding DFC level 2 design, which costs an additional \$544M to build but results in an additional \$34B of profit over a ten year era (this number can be discounted using discounted cash flow analysis if desired). Both the increase and decrease of changeability from design of interest can be explored in this way, as shown for Design E.

Not all cases will be modeled with a design variable explicitly corresponding with the inclusion of change mechanisms. Performing a rule removal study can accomplish the same goal of establishing a performance tradeoff by clarifying the value of a design in the absence of one or more of its change mechanisms by recalculating the decisions made under each strategy using only a subset of the available options and then repeating the era simulation. Because the space tug data set *does* have the benefit of the DFC variable though, this would simply repeat the results of Table V, so this procedure is skipped here. Alternatively, for case studies in which there is some probability of the change mechanisms failing and becoming unavailable after deployment, rule removal can identify the performance decrease experienced by each design in the event of that circumstance. Again, the space tug case study is not well suited to this analysis, as the only change mechanism that is not a redesign is the in-flight refuel, and removing that simply turns a DFC level 2 design into a level 1 design, which is already enumerated and compared as above.

VI. SUMMARY AND CONCLUSIONS

Recently, changeability has been accepted as a valuable conceptual design feature, for its ability to improve lifecycle

value delivery. However, it can be difficult to compare the value of changeability to the older and better-understood design principle of passive robustness, particularly because much of the value of changeability is derived from uncertainties over the system’s lifetime and is not visible in a static context. Epoch-Era Analysis is a framework on which the time-dependent value derived from changeability can be explored, and this paper has suggested a number of ways to output useful information on valuable changeability with era simulation. The types of insights that can be gained from the use of these techniques were presented in a Space Tug case study.

Era analysis is a powerful technique, providing the means to explore designs and their changeability across a large number of potential futures while appropriately accounting for path-dependencies as the context the system is operated in evolves over time. However, era analysis can be limited by its resource-intensive nature, in terms of the manpower needed to set it up properly and the computational power and time necessary to run a significant sample size for a large number of designs, and also by its assumptions about the evolution of contexts contained in the era constructor. Multi-epoch analysis can generate many of the same insights at a lower cost and with fewer assumptions but with a reduced fidelity that does not include time-ordered effects of epochs or calculate expected lifetime performance characteristics. More information on multi-epoch analysis and further detail on some of the metrics in this paper (including FPN) can be found in Ref. [8], but a brief comparison of the results of the two analysis domains on Space Tug follows here.

Multi-epoch analysis alone could identify design D as a valuably passive robust design, with the highest Pareto Trace and a Fuzzy Pareto Shift (FPS) distribution with nearly all of its weight on zero, indicating few changes. Era analysis confirms this result, showing design D to have the most consistent performance across changeability strategies and to have the most accumulated utility across an average era among the designs of interest. Design E, which has the same parameters as D but for a lower capability level and a higher DFC level, was identified in multi-epoch analysis as a fuzzily passive robust design, but mostly dominated by D due to its lower utility and higher cost under each preference set. However, era analysis reveals design E to have one advantage over D, as its improved changeability allows it to satisfy slightly more contracts per era (albeit at a lower utility), which may be valuable if uninterrupted viability is of particular interest to system stakeholders. Meanwhile, design F was identified in multi-epoch analysis as valuably changeable using its FPS distribution showing a large number of efficiency-improving change options in the epoch space under most strategies. However, the magnitude of that value is only shown more quantitatively once era analysis is performed, with design F demonstrating the highest average lifecycle profits as it leverages its low-cost change mechanisms to great effect as contexts change over time.

Both multi-epoch and era analysis generate information that can be used by system designers to intuitively explore valuable changeability. Ideally, both domains of EEA should be explored in tandem, as the types of information that can be extracted from each are different, with multi-epoch analysis

focusing on the space of potential system performance in alternative static contexts and era analysis uncovering the path-dependent effects of changing context and stakeholder changeability usage on system performance over time. Multi-epoch analysis can identify and compare passively robust designs effectively, with era analysis frequently supporting its insights and expectations. Actively (and valuably) changeable designs can also be identified and compared effectively with multi-epoch analysis, however some value is obscured without considering path dependence and they cannot be compared directly with passive designs, as the metrics that identify passive and active robustness are not commensurate. Era analysis can demonstrate the lifecycle value of changeable designs both with path-dependence accounted for and on the same terms as passive designs, thus allowing direct comparison between the two types. Thus, while both domains are potentially valuable sources of information in their own right, their usefulness is maximized when used together, particularly when considering both passively and actively value robust designs.

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