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Evaluating system change options and timing using the epoch syncopation framework

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Abstract

Complex engineering systems face many unknowns with respect to their operating contexts and time-varying stakeholder needs over their lifespan. A useful means for partitioning this problem is to consider a set of static snapshots of contexts with accompanying stakeholder needs over fixed periods of time, herein called "epochs." Designs can be optimized towards delivering stakeholder utility in a specific epoch or across a variety of epochs. In order to consider the uncertain sequence of epochs experienced by a system, the Epoch Syncopation Framework (ESF) is introduced in this paper. This framework, using Monte Carlo analysis and Markov probability matrices, analyzes the execution of potential system "change mechanisms," which alter a system over time to respond to epoch shifts. Through an analysis of design tradespaces, the ESF takes into account performance, schedule, cost, and uncertainty regarding experienced epoch shifts. The intended contributions of the ESF include a set of useful baseline designs, desirable change mechanisms, and strategies for executing change mechanisms across a system lifespan. The ESF is demonstrated through an application to an existing dataset containing designs for a "space tug" satellite including its set of potential epochs.
Keywords: Epoch-Era Analysis; Multi-Attribute Tradespace Exploration; evolvability

1. Introduction

Decisions early in the design process, especially in the conceptual design phase, require careful consideration as they will ultimately enable or limit the success of the system. Looking beyond traditional performance metrics, measuring a system's "ilities" such as changeability, adaptability, flexibility, and survivability gives stakeholders and decision makers an enhanced basis for differentiating between design alternatives [1, 2]. A set of contexts and needs that a system operates in, heretofore referred to as "epochs," can change over the lifecycle of the system [3]. If a system is not designed to robustly perform across shifting epochs, the system can be designed to change in response to these shifts in order to retain useful functionality and avoid suffering deficiencies or even failure. A system can incorporate changeability, the ability to change its form, function, or operations, including evolvability, the ability to change its architecture between generations with inheritance, as ways to dynamically react to changing epochs [4, 5]. Changeability looks at all change mechanisms (options that enable a transition to a new design state) available to a system and how they increase the number of states in the tradespace, or set of designs considered, available to the current design state [6]. One specific type of changeability is evolvability, which looks specifically at change mechanisms that involve redesigning a system with inheritance [5]. Evolutionary design starts from an existing design, rather than a blank slate, and is an increasingly common trend; for example, nearly 85% of GE's products are modifications of previous products [7]. Designing an evolvable system may reduce the long term cost of system upgrades or replacements in the presence of epoch shifts over its lifespan [5]. Executing change mechanisms, including redesigning a system, can be an expensive process. Additionally, if an epoch shift occurs shortly after or even during the execution of a change mechanism, the change can have less positive, or potentially negative consequences; deliberate and syncopated timing of change mechanism executions can potentially reduce cost and increase the benefit to system stakeholders. Choosing change strategies and time constants based on knowledge of epoch variables, the different variables that constitute an epoch, and how they change over time, can improve the timing of change mechanism executions. This paper introduces the Epoch Syncopation Framework (ESF) as a way of analyzing point designs, change mechanisms execution timing, and change strategies.

Nomenclature

DfE_C	current design evolvability level (zero or one)
DfE_T	target design evolvability level (zero or one)
EA	evolvability advantage (months)
EP	evolvability penalty (months)
S_B	baseline schedule (months)
S_{RD}	redesign schedule (months)

2. Epoch syncopation framework overview and application to space tug

The ESF is a framework designed to take in pertinent inputs for a system scenario, such as epoch variables (consisting of context variables and preference sets), point designs, possible design transitions, and change strategies, and to return information about lifecycle cost, utility, and design trajectories (aggregated over many sample lifecycles). Representing the path-dependent evolution of contexts and needs, the "era" construct is a time-ordered sequence of epochs [3]. The ESF is adapted from initial work done on the Technology Syncopation Framework (TSF) introduced in 2011 [5]. A similar framework is the Time-Expanded Decision Network (TDN) presented by Silver and de Weck [8]. The TDN method, along with the TSF, motivated and informed the creation of the ESF. The TSF lacked the ability to accurately track designs and epoch variables, the solution to which was well-defined design and epoch variables [5]. A shortcoming of the TDN that the ESF seeks to build on is the lack of non-preference epoch variables and only allowing decision nodes after uncertainty nodes [8]. The general structure of the ESF is shown in Figure 1. Text ovals represent functions whereas text boxes represent input or output data. Once implemented in software, the data flow shown in Figure 1 is executed many times for a given initial design and change strategy, and then averages are examined across the two input parameters. The simulation is run several times to account for the stochasticity built into the era constructor. The next sections will detail the specific components of the ESF as well as a detailed example implementation for a Space Tug satellite system data set.

The Space Tug data set contains designs for orbital transfer vehicles that can be used for a variety of on-orbit servicing missions such as observation of (potentially hostile) targets, assisting in orbit changes, and removing debris [9]. This data set has been used for studies in changeability and survivability [1, 4]. Recent work has added context variables to the existing preference curves used to define the epochs.

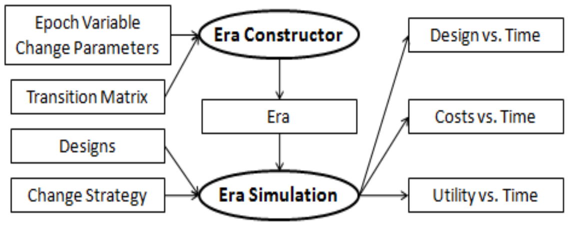

Figure 1. General ESF Structure

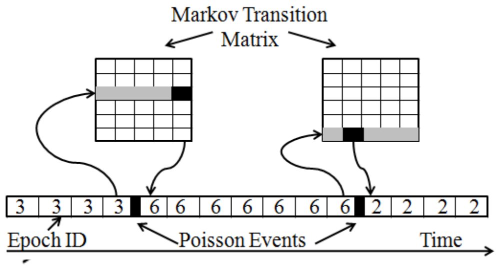

Figure 2. Era Constructor Mechanics

2.1. Era Constructor

Modeling the shifting of epochs is a very important step in the ESF. This particular constructor treats shifts in context variables and shifts in stakeholder preference as independent Poisson events. The ESF operator provides the average time between events for the missions and each context variable. The era is divided into time steps using a situationally-appropriate time scale (months for the Space Tug simulation). At each time step, the constructor generates a Poisson random value to determine whether or not a shift occurs in each context variable and mission. When a shift does occur, a Markov probability matrix is referenced to determine the destination epoch state. This process is illustrated in Figure 2. In accordance with Markov properties, this era constructor assumes that the next epoch state is a function only of the current epoch state.

Table 1. Mission Variable Markov Transition Matrix

Mission	To 1	To 2	To 3	To 4	To 5	To 6	To 7	To 8
From 1	0.300	0.400	0.050	0.050	0.050	0.050	0.050	0.050
From 2	0.050	0.150	0.133	0.133	0.133	0.133	0.133	0.133
From 3	0.150	0.050	0.500	0.060	0.060	0.060	0.060	0.060
From 4	0.150	0.050	0.060	0.500	0.060	0.060	0.060	0.060
From 5	0.150	0.050	0.060	0.060	0.500	0.060	0.060	0.060
From 6	0.150	0.050	0.060	0.060	0.060	0.500	0.060	0.060
From 7	0.150	0.050	0.038	0.038	0.038	0.038	0.500	0.150
From 8	0.150	0.050	0.038	0.038	0.038	0.038	0.150	0.500

The Space Tug data set, for the purposes of this paper, uses two epoch variables: mission and technology level (the only context variable). The missions are composed of three single attribute vs. utility curves as well as weightings for the different attributes. The weighted sum of the single attribute utilities forms the multi-attribute utility, which for the purposes of this paper is synonymous with “utility”. For this paper, a mission describes a potential set of needs and can be thought of as requirements for a specific contract that the system’s performance will be evaluated against. The eight ”missions” considered in this simulation are: (1) baseline, (2) technology demonstration, (3) GEO rescue, (4) deployment assistance, (5) refuelling and maintenance, (6) garbage collector, (7) all-purpose military, and (8) satellite saboteur. The transition matrix for preferences can be seen in Table 1. The specific values capture conditional probabilities and transition logic that may be available, representing that certain missions are more likely to follow other certain missions For example, the “baseline” mission has an equal probability of changing to any of the missions 3-8, but is more likely to switch to a technology demo or continue to exist in the current mission. As a technology demo, the system has an 80% chance of being used to satisfy a mission and changing preferences. It is possible, but less likely, that the preference will continue to be for a technology demo or revert to a baseline set of preferences. For the missions 3-6, all missions have an equal probability of switching to another mission (3-8 excluding the same mission) but slightly less likely to continue as the same mission (as compared to missions 1-2 probability of continuation). There is a possibility of reverting to a baseline mission or to a technology demo. Contracts 7 and 8 are slightly different in that they have a higher chance of switching between each other due to their similar nature. Technology is either “present level” or “future level” and affects the attribute levels associated with each design variable as well as the cost calculation. The attribute levels are then used to calculate utility. The context variable Markov transition matrix can be seen in Table 2. The future state is a sink; once the shift to “future level” technology occurs it cannot revert back to present technology.

Table 2. Context Variable Markov Transition Matrix

Technology Level	To 1	To 2
From 1	0	1
From 2	0	1

2.2. Tradespace generation and evaluation

The input set of designs for the ESF is organized such that each design has information corresponding to its design variables, attributes, initial cost, and initial schedule. For each sampled combination of epoch variables (mission and technology level for Space Tug) each design’s cost, schedule, attributes, and utility is calculated.

For Space Tug, the design variables originally introduced are manipulator size, propulsion type, and fuel mass [9]. An additional variable, design for evolvability (DfE), was added for the purposes of this simulation. The DfE variable represents the inclusion of design heuristics that make redesign simpler and is treated as a mass penalty [9]. The ranges of values for the design variables are seen in Table 3.

Table 3. Design Variable Levels [9]

Design Variables	Levels
Manipulator Mass (kg)	[300, 1000, 3000, 5000]
Propulsion System	Storable BiPropellant, Cryogenic, Electric, Nuclear
Fuel Mass (kg)	[30, 100, 300, 600, 1200, 3000, 10000, 30000]
DfE (% Mass Penalty)	[0, 20]

The three attributes calculated were capability, delta V, and response time. Capability is measured as the manipulator mass. Delta V is a function of all masses, specific impulse, and mass fraction. The latter two are properties of the propulsion system in use, as seen in Table 4. In cases where two values appear, the latter value is used in the future context. Response time is either fast or slow and is a function solely of the propulsion and is in the ‘Fast?’ column of Table 4.

Table 4. Propulsion System Values [9]

Propulsion System	I_{sp} (sec)	Base Mass (kg)	Mass Fract.	Fast?
Storable BiProp	300	0	0.12	Y
Cryo	450/550	0	0.13	Y
Electric	3000	25	.25/.3	N
Nuclear	1500	1000/600	0.20	Y

The cost of a design is a function of its dry and wet mass. The dry mass cost is $150,000/kg and the wet mass cost is $15,000/kg in the present context and $10,000/kg in the future context. The baseline schedule for this simulation is a function of the propulsion system: bipropellant (8 months), cryogenic (9 months), electric (10 months), nuclear (12 months). The schedule is increased by 2 months if DfE is included in the design. A representative tradespace showing how cost, utility, and schedule vary for different space tug designs is shown in Figure 3.

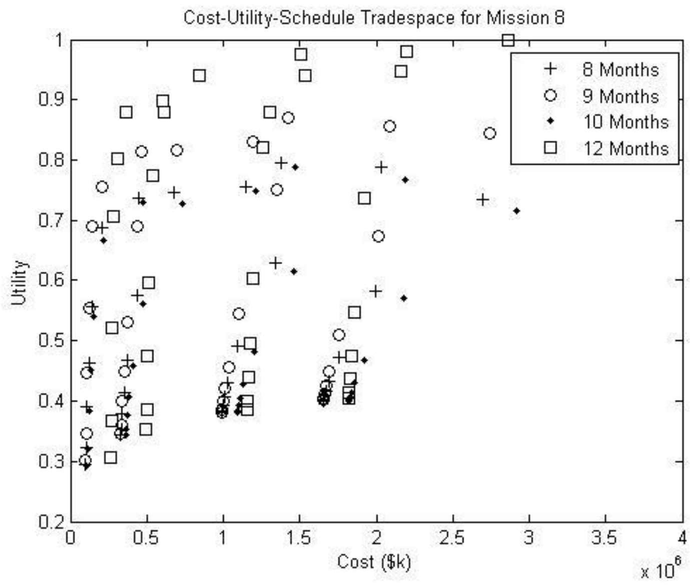

Figure 3. Cost-Utility-Schedule tradespace for all designs valid in mission 8.

2.3. Design transition matrix generation

The design transition matrices in the ESF determine what designs can be reached from the current state, how much it will cost, and how long it will take. Since change mechanisms can operate differently in different epochs, it is necessary to generate a transition matrix for each epoch. Additionally, a transition matrix is necessary for each specific change mechanism [4].

For Space Tug, the only epoch variable that affects transitions is context variable, technology level. The cost of transitioning is different in the future technology since some mass fractions and base masses change for the propulsion systems. For this study, the only change mechanism considered is "redesign." Redesign cost and schedule were calculated as a function of the similarity of the current and target designs.

To alter the clean-sheet cost of a design during redesign, a "reuse advantage" is applied. The reuse advantage lowers the cost of designing components that are already in use on the current design. Since cost is a function of mass in the Space Tug tradespace, reuse advantage is applied to mass. If a component, or design variable in the context of the Space Tug data set, is changed, the full component mass is used to calculate the cost. If a component does not change, its mass is reduced by the reuse advantage. If DfE is not included in the original design, the reuse advantage is zero. For this paper, if DfE is included, the reuse advantage is 50%. Identifying an appropriate reuse advantage is the subject of further research.

Redesign schedule (S_{RD}) is a function of the new propellant type, current DfE level (DfE_C), and target DfE level (DfE_T). The baseline schedule (S_B)is the same as in the original design, based on propellant type. If the previous design included DfE, an evolvability advantage (*EA*) is subtracted from the schedule. [Note all DfE variables are binary]

$$S_{RD} = S_B - DfE_C * EA + DfE_{added} * EP$$

Where

$$DfE_{added} = \begin{cases} 1 & if \quad DfE_T = 1 \quad and \quad DfE_C = 0 \\ 0 & else \end{cases}$$

In this simulation the evolvability advantage was 3 months, meaning the evolvable redesign process takes 3 months less time than that of a clean-sheet development of the same design. If DfE was not included in the original design but is to be included in the new design, the same 2 month evolvability penalty (*EP*) is applied. This penalty is not applied for continuing to have DfE (i.e., both the original and new design include DfE).

2.4. Change strategies

The change strategies are the algorithms inside the simulation that determine when change mechanisms will be executed, which change mechanisms will be executed, and what design will be transitioned to from a current design. These strategies attempt to capture the behavior of organizations in their decision-making. One of the goals of the ESF is to identify the best strategies for a given situation. An important part of making a decision to change or not change is the calculation of utility. Utility is a function of the current design and the current mission. Changing missions will change the perceived utility of a current design, hence the possible need to change designs in order to reach a satisfactory utility level.

For this simulation, three change strategies were examined: (1) always change to the best design possible, (2) change when utility falls below a certain threshold, and (3) change every *X* years. The first strategy looks at the current utility and the utility of all reachable designs (which is every design in which the only change mechanism is redesign); if a higher utility is reachable, then the least expensive transition to that design is initiated (with multiple change mechanisms, design transitions can occur at different costs). For change mechanisms like redesign, which do not affect the current system, utility will still be accumulated during the redesign by the current system. The second change strategy also begins by looking up the utility of the current design and the utility of all reachable designs. The decision to change or not is based on where the current utility ranks with other reachable utilities. An additional input to this strategy is the threshold percentile. For example, if the threshold percentile is 50, the change criterion is "change design if the current design is below the 50th percentile in utility". To decide which destination design to pursue, the algorithm finds the least expensive design above the threshold percentile. The third strategy mimics planned redesign. Every *X* years, the algorithm chooses a design to switch to, based on the current mission. The specific destination design is chosen based on the least expensive design above a threshold utility percentile (similar to strategy two). This strategy can also be looked at across several values for *X* to see if there is a natural change period which reduces costs while delivering acceptable utility.

2.5. Era simulation

Each trial of the ESF is characterized by the change strategy it uses and any parameters used in that strategy (e.g., Strategy 3 using 5 year redesign cycles and 70th percentile utility threshold). The trial will loop through 1,000 eras, using each design (of the full factorial, 256 design tradespace from Table 3) as a starting design in each era. For each simulation in the run (a single era, starting design, and strategy), the following are outputs: the lifecycle cost (initial design cost and cost of subsequent redesigns), the time-weighted average utility (TWAU), and the amount of time with unacceptable utility (a threshold utility is defined prior to the run). At the end of the run, the data are aggregated and compared on a design-by-design basis. After several runs for different strategies, analyses can be performed on design-by-design and strategy-by-design bases. The simulation was both executed and analyzed using MATLAB scripts and functions.

3. Results

The trials chosen for this simulation are shown in Table 5. The era lengths are 15 years, with the context shift (technology improvement) happening on average at year 8 and average mission duration of 4 years.

The selection of change strategy was designed to allow for meaningful comparison between strategies. The threshold percentiles used in strategy 3 are also used in strategy 2 so that the timing of the decision can be analyzed (i.e., is it better to look every time step or should decision opportunities occur on a predetermined schedule?). The choice of redesign periods (2, 4, and 6 years) was based on matching the average mission duration as well as being shorter and longer.

Table 5. Description of Trials

Trial	Strategy	Threshold Percentile	Years
1	1	-	-
2	2	20	-
3	2	40	-
4	2	60	-
5	2	80	-
6	3	40	2
7	3	40	4
8	3	40	6
9	3	80	2
10	3	80	4
11	3	80	6

The results of the 11 trials described in Table 5 are listed in Table 6. The figures given represent the aggregates over all 256 designs and 1000 eras, the highest/lowest average for a design across the 1000 eras, and the corresponding design. Strategy 3 had the lowest average lifecycle cost ($1.73B), followed by strategy 2 ($1.89B) and strategy 1 ($3.50B). In the strategy 2 trials, average lifecycle cost went down as the threshold percentile decreased. In strategy 3, the cost decreased as the generation length increased. For trials with the same generation length, the trial with the lowest threshold percentile always had a lower lifecycle cost, which is in agreement with the inverse correlation between lifecycle cost and threshold percentile seen in the strategy 2 trials.

The strategy with the lowest average time below acceptability was strategy 1 (13.8 months), followed by strategy 2 (31.2 months) and strategy 3 (38.5 months). In strategy 2, average time below acceptability decreased as the threshold percentile increased. This trend was also seen in the strategy 3 trials with generation length held constant. In strategy 3, the average time below acceptability increased as generation length increased.

The strategy with the highest average TWAU was strategy 1 (0.910), followed by strategy 2 (0.603) and strategy 3 (0.567). A positive correlation between average TWAU and threshold percentile was observed. The strategy 3 trials showed average TWAU increasing with generation length.

Table 6. Results of 11 ESF Trials

Trial	Average LC Cost ($M)	Lowest LC Cost ($M)	Design #	Average Time Below (months)	Lowest Time Below (months)	Design #	Average TWAU	Highest TWAU	Design #
1	3501	2403	145	13.76	8.00	72	0.910	0.937	112
2	1282	324	154	52.08	9.00	80	0.511	0.931	120
3	1491	518	154	34.07	9.67	80	0.547	0.931	120
4	2158	1056	155	20.60	9.13	72	0.623	0.931	120
5	2646	1442	153	18.20	9.88	112	0.732	0.931	120
6	1423	466	154	42.81	9.00	80	0.524	0.931	120
7	1340	395	154	45.23	9.00	80	0.500	0.931	120
8	1297	360	154	48.83	8.90	72	0.482	0.931	120
9	2379	1244	153	24.82	10.44	112	0.683	0.931	120
10	2056	992	153	31.56	10.33	112	0.627	0.931	120
11	1902	874	153	37.68	10.01	112	0.584	0.931	120

4. Discussion

Simulations using strategy 1 generally exhibited a redesign immediately after fielding the initial system. This redesign would be to the design with the highest utility in the current epoch, which was design 120 in 7 of the 8 missions and design 119 in the other mission. Design 120 has a nuclear propulsion system, a 5000kg payload, and 30,000kg of fuel; design 119 is the same except for having 10,000kg of fuel. The average LC cost seen in the Monte Carlo simulation is very similar to the average design price added to the average transition to designs 119 and 120 (this value is slightly lower because it does not account for eras that fluctuate between missions favouring 119 and those favouring 120). Not surprisingly, the average time below acceptability is very low as the majority of the era is spent in high performance designs. This is the same reason that the average TWAU is much higher than in trials using other strategies.

The average LC cost for trials using strategy 2 are understandably less than trials using strategy 1 since, even though more switching might occur, the target designs are less expensive than the ones targeted using strategy 1. The designs that had the lowest LC cost for strategy 2 were 153-155, as seen in Table 7, which interestingly are not very highly performing designs (average utility of 0.23 in 10 valid epochs and invalid in 6 epochs). However, these designs incorporated evolvability and were very inexpensive starting points, enabling less costly transitions to appropriate designs. The cost increases as threshold percentile increases since there are more situations where the change decision is triggered. The time below acceptability increased as threshold percentile decreased because the utility of the designs in use were more likely to be close to (just above) the threshold percentiles. The data showed a positive correlation between TWAU and threshold percentile for strategy 2.

The average LC cost decreases as generation length increases in strategy 3 because there are fewer opportunities for change costs to be incurred. As in strategy 2, designs 153-155 dominate the lowest LC cost category. The average time below acceptability decreases as generation length increases since it is related to the time between becoming unacceptable and triggering change, which is a function (among other variables) of generations length. Designs 72, 80, and 112, seen in Table 7, were the best performers in the time below acceptability criterion for all three strategies. This is due to the fact that they are high performing designs with short schedules; none of them incur a DfE penalty and use the propulsion systems that take the least amount time to build. In the set of trials using a threshold percentile of 40, there was approximately 5% decrease in TWAU with each 2 years of generation length added. More sensitivity analysis is required to see if this trend is meaningful or derived from the variance in the simulations. In the trials using 80 as a threshold there was approximately 5% decrease in TWAU with each 2 years of generation length added. Once again, more sensitivity analysis is required to validate or invalidate this relationship. Design 120, seen in Table 7, tended to dominate the TWAU column due to having the best performance in 7 of the 8 missions.

Table 7. Designs of Interest

Design #	DfE	Prop Type	Fuel Mass (kg)	Manipulator Mass (kg)	Category
72	0	BiProp	30000	3000	Time
80	0	Cryo	30000	3000	Time
112	0	Cryo	30000	5000	Time, Utility
120	0	Nuclear	30000	5000	Utility
145	1	Nuclear	30	300	Cost
153	1	Electric	30	300	Cost
154	1	Electric	100	300	Cost
155	1	Electric	300	300	Cost

5. Future Work

The ESF is a work in progress, at this time, and still an immature method for analyzing change strategies for complex systems and will need more development. The space tug data set is a suitable concept demonstration, but ideally ESF will be able to handle more complex data sets. Future research will include data sets related to more complex missions, such as a satellite radar-based ISR mission and a system of systems-based maritime security mission will test the ESF by incorporating additional epoch variables and additional change mechanisms, and will present the opportunity to test more change strategies. Some targeted enhancements to the ESF include: the incorporation of budgeting into change strategies, improvement of schedule modeling, and incorporation of other change mechanisms. Future work will also focus on using results to deduce effective design principles for changeability and evolvability.

6. Conclusion

The ESF shows promise as a valuable tool for exploring how a complex system traverses a tradespace in a multitude of eras by means of different change strategies. The framework seeks to combine temporal and cost aspects for simultaneous analysis. The era constructor presented in this paper is a new method for generating scenarios, based on the predicted properties of epoch variables, to test a systems performance in. The application to the space tug data set was a first step in demonstrating the use of the ESF to draw conclusions about the performance of system across changing contexts.

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