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A Methodological Comparison of Monte Carlo Simulation and Epoch-Era Analysis for Tradespace Exploration in an Uncertain Environment

Andrew A. Rader, Adam M. Ross, and Donna H. Rhodes
Systems Engineering Advancement Research Initiative (SEAri), Engineering Systems Division
Massachusetts Institute of Technology
77 Massachusetts Avenue, Building E38-572
Cambridge, MA 02139
http://seari.mit.edu

Abstract – This paper examines uncertainty in design and traditional methods of accounting for it, while developing a methodological comparison of Monte Carlo Simulation (MCS) and Epoch-Era Analysis (EEA). Particular focus is placed on the way by which MCS and EEA handle uncertainty from both endogenous sources (i.e., those arising from modeling design and performance), and from exogenous sources such as requirements definition and the particularities of an uncertain future. The applicability of each approach is examined, along with the inherent assumptions, the information required for implementation, and the relative strengths and weaknesses. The contexts under which one method offers particular advantages in terms of quantifying, propagating, or visualizing uncertainty over the other are highlighted. Furthermore, we examine the potential for hybrid methods that combine the strengths of both MCS and EEA. Examples applications particularly suited to MCS, EEA, and a hybrid MCS/EEA method are presented.

Keywords – Monte Carlo Simulation, Epoch-Era Analysis, Risk, Uncertainty, Conceptual Design, Methodological Comparison

I. INTRODUCTION

Conceptual design is plagued by myriad sources of uncertainty arising from design requirements and constraints, the economic and political environment, and unknowns in the performance of the design itself. Despite this uncertain future environment, designers have traditionally assumed stable environments to frame their solutions and decisions. However, since the principal objective of design is to maximize value (a contextual, multi-dimensional, and dynamic concept including multi-stakeholder utility and cost), the quantification of uncertainty is essential to enable a comparison of alternative system concepts at an early stage.

This paper develops a methodological comparison of Monte Carlo Simulation (MCS) and Epoch-Era Analysis (EEA) as methods to quantify and propagate uncertainty. MCS was developed during the 1940s to harness computer simulation to examine probabilistic outcomes in uncertain environments, and has become one of the most widely used methods for finding computational solutions to problems that are difficult to solve analytically [1]. EEA is a relatively new approach that provides a structured way to consider the impact of context changes over a system's dynamic life cycle [2].

We examine MCS and EEA with particular emphasis on their scope, assumptions, strengths and weaknesses, and their applicability to tradespace exploration, in order to clarify these methods for designers familiar with one or the other. We highlight the conditions under which one method offers particular advantages over the other. Furthermore, we examine the potential for hybrid methods that incorporate the strengths of each approach. We also present example applications that are particularly suitable to MCS (landing distance on a contaminated runway), EEA (satellite radar), and a hybrid MCS/EEA approach (space tug).

A. *Types and Levels of Uncertainty*

Uncertainties arise from both endogenous and exogenous sources. An example of an endogenous source of uncertainty is our inability to quantify or predict a system's performance before it is actually built. Such "model uncertainties" or "design uncertainties" are inherent whenever we use imperfect mathematical models to describe a real-world system and often persist in spite of having historical performance data.

Exogenous sources of uncertainty include the political and economic environment (e.g., will the system still be viable and for how long?), competition, emergent technologies, and changes in the system operation environment. Exogenous uncertainties also include unknowns in design requirements and constraints (e.g., what will we actually need the system to do?). Panetta and Hastings suggest that failure to adequately identify user requirements may result in 60-80% of all system errors [3].

B. *Historical Methods for Dealing with Uncertainty*

Since the ballistic missile programs of the 1950s, systems engineers have developed qualitative, semi-quantitative, and quantitative methods in an attempt to account for uncertainty. Qualitative means of risk assessment can involve ranking or plotting the relative likelihood and cost of failure or sorting potential systems into buckets of "low risk", "medium risk", "high risk", and "uncertain risk" [4, 5]. Qualitative uncertainty management also includes "futures techniques" (e.g., Morphological Analysis, Delphi method, Scenario planning), which seek to forecast likely future events, or capture all possible futures.

Semi-quantitative methods include categorical scales, such as the technology readiness levels (TRLs) 1 to 9 used by NASA to quantify risk based on technological maturity and experience [6], and margins, the systematic estimation of parameters based on historical data. An example margin, developed by the American Institute of Aeronautics and Astronautics (AIAA), allows the designer to estimate the likely increase of spacecraft mass during the design process due to uncertainty [7]. Similar margins have been developed for estimates ranging from project cost to lines of computer code [8]. Semi-quantitative methods can also be used to generate estimates (initial conditions) to be carried forward in quantitative uncertainty propagation.

Quantitative engineering methods of categorizing uncertainty were originally adapted from economics research, where strategies had been developed so that investors could maximize returns given uncertain future trends [9, 10]. Most quantitative methods seek to generate statistical functions that correspond to a distribution of outcomes (i.e., probability density functions or PDFs) [11]. The decision maker can then isolate designs corresponding to confidence intervals depending on their risk aversion (e.g., 90%, 95%, or 99%).

Among the many quantitative methods for assessing uncertainty, some of the most commonly applied include Probabilistic Risk Assessment (PRA), Fault Tree Analysis (FTA), Extreme Conditions Analysis, Hazards Analysis (HA), and Failures Modes and Effects Analysis (FMEA). These quantitative methods can yield powerful insights, but they are highly sensitive to assumed probabilities and they are unlikely to account for all possible events. For example, PRA was favored by NASA until it was largely dropped after the Apollo 1 fire when it was discovered to be generating unreliable failure estimates [6]. Additionally, these methods generally seek to produce a single estimate of risk rather than a continuous probability distribution. This makes them more suitable for direct comparison than for visualizing uncertainty distributions across alternatives (e.g., using tradespace exploration).

II. OVERVIEW OF MONTE CARLO SIMULATION

Monte Carlo Simulation is a class of computational algorithms that relies on repeated (pseudo) random sampling from probability distributions to produce hundreds or thousands of possible outcomes instead of a few discrete scenarios. This allows it to approximate numerical solutions for problems that are difficult to solve analytically. Effectively, MCS seeks to answer the question: *what is the expected outcome distribution given known systematic uncertainties?*

MCS has been applied across a wide range of domains [5]. Indeed, so many variations of MCS exist that they defy a single condition for suitability [12].

The general MCS process is outlined in Fig. 1. First, M random samples of the N uncertain input variables are generated according to their specific probability distributions. Then, M sets of each output variable are deterministically calculated based on each set of randomly sampled input values. Finally, the resulting output probability density function(s) (PDF) or cumulative distribution function(s) (CDF) can be aggregated (or plotted as a tradespace), whereby the expected system performance can be assessed [11].

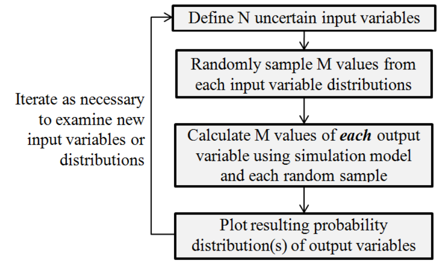

Fig. 1. Monte Carlo Simulation Process

Although a powerful tool, MCS does have some limitations. First, it is unlikely to capture all sources of uncertainty, and its results are highly sensitive to the input. Exogenous uncertainties are notoriously difficult to capture, particularly those with temporal qualities. While it would be theoretically possible to simulate all possible futures, this becomes both computationally and conceptually more difficult as the future becomes more uncertain, and future uncertainties are often better captured using a temporally structured approach like that offered by EEA.

Second, since a separate distribution is required for each uncertain input, accurate representation of the uncertainties in question can require a large number of samples [4]. The generation of many variables over a large tradespace can exacerbate this computational demand. For example, hundreds of physics-based equations are required for something approaching accurate spacecraft design [8]. This can be mitigated with Subset Simulation, a Markov Chain Monte Carlo (MCMC) method that focuses on the low probability tail regions where uncertainties are likely to have the largest impact [13].

A. Example MCS Application: Landing Distance on Contaminated Runways

Monte Carlo Simulation is especially well suited to problems involving many input uncertainties that can be categorized by known or estimable distributions. An illustrative example application is estimating the landing distance on runways contaminated with rain, snow, or ice.

Historically, pilot manuals have instructed that 15% should be added to the landing distance estimate for rain or 30% for snow or ice, without accounting for the actual measurable friction on the runway in question [14]. These margins, derived from expert opinion, fail to adequately account for the diverse variables involved. For example, the friction resulting from thick ice coverage can increase the required runway length by as much as an order of magnitude, whereas a thick covering of snow can potentially decrease landing distance by increasing drag on the landing gear [15]. Other uncertainties interact in a dynamic fashion to further complicate the problem (see Fig. 2 for a description of inputs and model of the problem).

The degree of information we have about each of these input variables determines how we choose to model their input probabilities for sampling (i.e., normal distribution, rectangular distribution, or other type). Note that although the terrain surrounding the runway has little impact on the landing distance *per se*, it is the primary driver of damage (i.e., the risk) should the actual landing distance exceed the runway available.

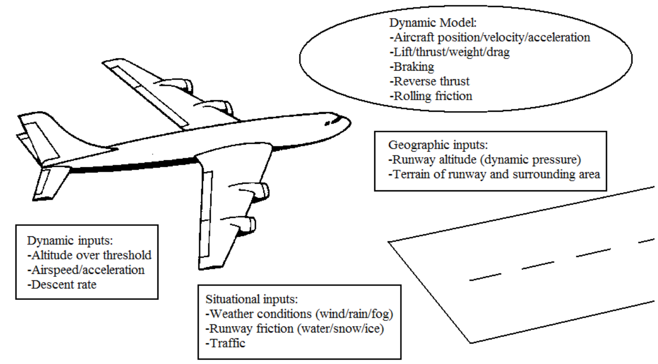

Fig. 2. Landing distance simulation includes a large number of unknowns

We can directly measure the situational inputs (including the local friction, if a runway friction cart is available [15]), although these are subject to spatial and temporal fluctuation and are better represented by a distribution. The dynamic inputs are theoretically measurable on a case-by-case basis. As a fallback, we can sample from a probability distribution of historic data, or specifically examine upper or lower limits.

Given distributions of the dynamic, geographic, and situational inputs, we can sample values and run the dynamic model for large number of trials to generate an estimated output probability distribution of landing distance. From these output distributions, we can estimate overshoot rates and safety margins for airports conducting operations for a given set of conditions, or for aircraft operators landing at specific airports. Alternatively, such a model could be used by pilots before an actual landing to estimate the length of runway required.

III. OVERVIEW OF EPOCH-ERA ANALYSIS

Epoch-Era Analysis (EEA) has been developed as a computational scenario planning method that provides a structured way to analyze the temporal system value environment [1]. EEA decomposes the lifecycle of a system (comprising an "era") into sequential epochs that each have fixed context and value expectations (see Fig. 3). Each epoch is parameterized by an epoch vector that defines its start time, duration, value expectation, and the key exogenous factors describing the epoch context. Effectively, EEA seeks to answer the question: *what is the expected value distribution given an uncertain future environment?*

The application of Epoch-Era Analysis consists of four steps:

1. Multi-stakeholder value definitions;

2. Epoch enumeration;

3. Era construction, comprising: (a) era duration specification, (b) epoch duration specification, (c) establishment of epoch transition logic, and (d) epoch sampling [16].

4. Value-based comparison of competing designs across eras (using a method such as tradespace exploration).

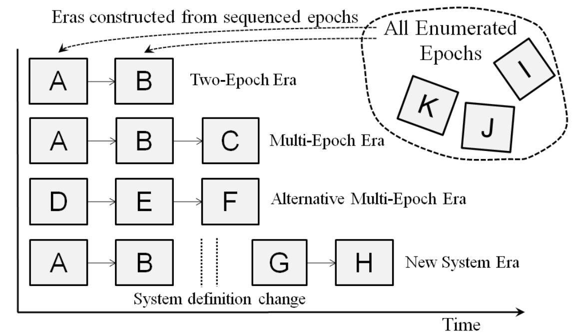

Fig. 3. An era spanning a system lifecycle is subdivided into epochs which define alternative future value expectations and contexts

EEA provides a structured framework that describes the value of a system over time given future uncertainties [2]. It can guide the analysis of utility-cost tradeoffs among alternatives by assisting in the evaluation of competing designs given alternative possible futures (eras) using existing methods, such as Multi-Attribute Tradespace Exploration (MATE) [10].

The epochs comprising a given era can either be pre-defined, "hand-picked" to fit imagined future scenarios of interest, or the process can be automated to construct eras from sets of possible epochs. An automatic selection can be random, based on a given set of conditions, or can be iterative, so that the selection of each subsequent epoch depends on the preceding one. The sequential ordering of the resulting epochs produces an emergent path dependence of value over time for each alternative (i.e., the optimal design strategy given an uncertain future may depend on the order of future events) [17].

EEA is particularly well suited to mental model building because it allows a designer to compare competing strategies in the face of uncertain future conditions (i.e., uncertainties of a temporal nature). For example, is higher value achieved by a strategy where a system can change to maintain value, or a passively value robust strategy that maintains satisfactory performance across diverse conditions?

A. Example EEA Application: Satellite Radar

Space systems, being expensive to design, implement, and operate, are especially vulnerable to economic, political, and operational uncertainties. This makes them particularly suitable for analysis using EEA, as demonstrated by the

Satellite Radar problem is presented in [16], [18], [19], and [20], and summarized below.

A model was developed to capture the key performance trades, while allowing the parametric exploration of a large set of designs within a large number of epochs. The endogenous system uncertainties were considered fixed (in contrast to the landing distance example), while exogenous variables such as user expectations, technology, communications infrastructure, collaborative assets, mission profiles, and threat of enemy jamming were varied in epoch enumeration.

In order to establish ranges for the exogenous variables, interviews were conducted with domain experts (steps 1 & 2 of EEA). The full factorial expansion of epoch variables yielded 3×3×2×2×9×2 = 648 potential epochs (Table 1). Of the 648 possible epochs, 224 were randomly selected, and 21 were handpicked to correspond with likely scenarios.

TABLE I. EPOCH VARIABLES FOR THE SATELLITE RADAR CASE (ADAPTED FROM [16])

Exogenous epoch variables (# enumerations)	Enumerations
Imaging vs. tracking utility priorities (3)	1. Imaging > Tracking 2. Imaging = Tracking 3. Imaging < Tracking
Radar technology (3)	1. Basic 2. Medium 3. Advanced
Communications Infrastructure (2)	1. Air Force satellite communications network (AFSCN) 2. Wideband global SATCOM (WGS) + AFSCN
Collaborative Assets (2)	Airborne intelligence, surveillance, and reconnaissance (AISR) available? (1. yes or 2. no)
Operational plans (9)	1 of 9 possible mission profiles
Threat environment (2)	1. Jamming present 2. No jamming

For era construction (step 3), overall era length was selected to be 20 years (a typical lifespan of a satellite program). Epoch length was specified based on the factors causing the epoch shifts. For example, whereas the satellite might be expected to confront new threat environments on short time scales, major infrastructure changes (e.g. fundamental mission changes requiring change in ground support) would take far longer.

Epoch transition logic (step 3c) was taken as random, with the sole exception that technology could never regress. Epochs were sampled (step 3d) using a computer-augmented morphological approach entailing direct assignment of epoch duration and ordering based on expert opinion in order to form seven eras [21]. Finally, these eras were analyzed (step 4) using MATE to facilitate a quantitative comparison of the designs with metrics such as Pareto Trace and Filtered Outdegree [22] [16]. The tradespace exploration allowed a visual comparison of the utility and cost tradeoffs of each design during any epoch individually, and also across each era, to identify the key designs that would maintain value under uncertain possible futures.

IV. DISCUSSION

While both MCS and EEA provide frameworks for propagating and evaluating uncertainty, they are nevertheless limited by assumptions made regarding the sources and nature of uncertainty (i.e., the model inputs derived from historical data, expert opinion, simulation, or some other method) [6].

Within these limitations, MCS and EEA provide different frameworks to allow designers to quantify and evaluate the effects of multiple sources of uncertainty. The suitability of each method depends on the nature of the expected uncertainties. Do they arise from endogenous or exogenous sources? Do we have any information beyond complete ignorance? Can we assign probability distributions? MCS and EEA each have inherent strengths and weaknesses, and carry assumptions and biases. Furthermore, since MCS and EEA analysis seek to answer fundamentally different questions, they are by no means mutually exclusive.

A. Strengths and Weaknesses of Each Method

MCS excels when uncertainty can be quantified using input probability distributions for problems with a large number of coupled degrees of freedom. This direct treatment of uncertainty is particularly suited to assess the overall effects of uncertainty arising from multiple endogenous sources, be they statistically characterized random variables, or known unknowns which may be bounded but have unknown values. MCS gives the designer more direct control over how uncertainties in system attributes and performance impact the system in a way that is easy to visualize.

In contrast, EEA does not directly account for these endogenous uncertainties. Instead, EEA's temporally ordered structure is designed to account primarily for exogenous sources of uncertainty, particularly those arising from future conditions over the dynamic lifecycle of a project. This makes EEA better suited to examine the effects of uncertainties that vary over *time*, particularly since the specific ordering of epochs results in an emergent property that would be difficult to capture with the direct treatment taken by MCS. For example, the economic environment in which a project resides might fluctuate; it can be highly relevant to establish exactly when during the lifecycle conditions are improving or worsening (and in what order).

In particular, whereas MCS typically needs a continuous variable (or at least a stably defined one) from which to sample, EEA is able to look at discontinuous changes in uncertain exogenous factors. While EEA may still fail to account for all potential uncertainties, its structure aids the designer in visualizing potential future scenarios and assessing their impact.

B. *Assumptions and Biases of Each Method*

MCS and EEA were each developed with specific types of applications in mind, and are therefore vulnerable to assumptions arising from their framework. For both methods, even exhaustive analyses will inevitably fail to account for all sources of uncertainty. Furthermore, both methods require the user to specify the nature of uncertainties as inputs to the model – only the effects of these uncertainties on the system as a whole are simulated.

Although MCS does not prohibit modeling of future uncertainty as a direct input, it is much more difficult to capture the temporal ordering represented in EEA: practically speaking, we are unlikely to capture all sources of uncertainty stemming from economic or political factors, let alone their order-dependent interactions across a project lifespan.

Conversely, Epoch-Era Analysis is specifically formulated to capture future contexts, but is less well suited to quantifying uncertainty from a large number of endogenous sources – especially model and design uncertainties. Though we can examine a large number of architectures whose associated value during any epoch is contextual, the performance of the system for a given context is generally considered fixed. The future stakeholder expectations and contextual factors are parameterized into discrete variables, allowing a more exhaustive enumeration of key uncertainties rather than a limited focus on the extremes. However, the analysis is utterly dependent on the epoch enumeration and era construction steps: handpicking epochs in order to correspond with scenarios that are deemed more likely is vulnerable to "wishful thinking", can fail to reflect the actual likelihood of future conditions, and can present a more favorable picture than ought to be expected.

C. *Combining MCS and EEA*

As previously noted, MCS and EEA seek answers to fundamentally different questions and are not mutually exclusive. EEA can benefit from Monte Carlo's direct treatment of uncertainty to estimate how endogenous or model uncertainties will affect the performance of competing systems. For example, architectural value in any epoch can be described by a combination of endogenous factors (sampled in a MCS sense) in addition to external unknowns described by the epoch vector. This suggests an approach whereby MCS is used to quantify a range of system performances, while EEA is used to examine the additional effects of exogenous uncertainties such as changing mission requirements (see example in the next section).

An alternative approach to combining MCS and EEA is to use MCS for epoch enumeration and era construction as part of an EEA. Specification of epoch durations, conditions, and transition logic is probabilistic in nature: a random sampling of epoch variables and epoch ordering can help prevent biases that could be introduced by hand-picking.

D. *Example Hybrid MCS/EEA Application: Space Tug*

This example is based on a space orbital transfer vehicle ("space tug") [23, 24]. Space tug concepts face serious challenges in orbital dynamics (energy-intensive maneuvers), environments (radiation, debris, and long shut-down periods), and economics (uncertain markets and payoff). Some missions require manipulation of heavy payloads (high thrust), while for others, efficiency (high delta-V) is the key. This tradeoff favors designs that are versatile enough to maintain value in the face of changing and uncertain future demands. Additionally, since the performance of any such vehicle is as yet unproven, space tug concepts also face endogenous uncertainties regarding their achievable performance and cost. This makes this problem particularly suitable for both EEA and MCS. EEA was first applied in order to select a number of designs of interest to carry forward. Following that, the impact of cost and performance uncertainties on these selected designs was examined using MCS.

Four classes of space tug were examined based on propulsion system: bipropellant fuel, cryogenic fuel, electric engine, and nuclear propulsion. Within each class, 32 designs were initially considered (4 payload capabilities × 8 propellant tank volumes), making a total of 128 designs (4 classes × 32 in each class). The expected performance of each design in terms of thrust, delta-V, and capability to perform orbital maneuvers, as well as the expected lifecycle cost was estimated using historical margins [23].

Utility was defined as a weighted combination of its mass manipulation capability, its delta-V, and its ability to access payloads across different orbits. Three handpicked epochs were enumerated by varying the weighting functions on these parameters (representing capability stressed, flexibility stressed, and balanced paradigms). From these 128 designs, the most value robust in each category (1 each of bipropellant, cryogenic, electric, and nuclear) across epoch shifts was retained for further examination using MCS.

Carrying forward the four designs identified by EEA, MCS was used to introduce endogenous performance and cost uncertainties. Specific impulse, mass fraction, and delta-V were sampled 40 times from rectangular distributions, and the historical margins were used to reassess cost and utility of each of the designs. The resulting tradespace highlights important tradeoffs inherent in the 4 classes of design (Fig. 4).

While the nuclear option is at the high end for both cost and utility, it carries much more cost uncertainty because it is a relatively unproven technology. However, the utility uncertainty of the nuclear option is relatively narrow because the expected capabilities are sufficient to perform any mission. The utility uncertainty is high for the electric option because it may or may not have sufficient thrust to meet the requirements for a given mission. For missions it is able to perform, it is an efficient choice; otherwise, it suffers severe utility penalties.

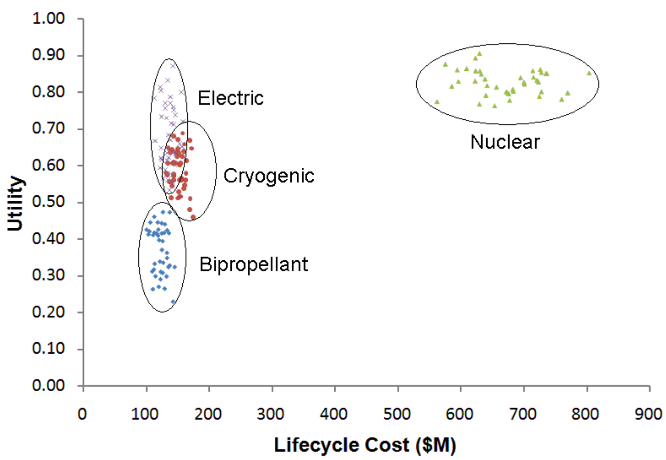

Fig. 4. Utility and cost distribution resulting from MCS of endogenous parameters on four designs selected by EEA

V. CONCLUSIONS

Monte Carlo Simulation and Epoch Era Analysis both empower the designer to examine the effects of uncertainties on a system design to maximize value. Each method has associated strengths and weaknesses and introduces its own biases. MCS excels at problems with large numbers of endogenous, probabilistically characterized uncertainties; EEA is better suited when a contextual framework can help highlight the effects of uncertain future contexts. MCS and EEA seek to answer fundamentally different questions, and they are by no means mutually exclusive. Indeed, since both endogenous and exogenous uncertainties pervade in most engineering problems, the application of each method will provide a different kind of information, and a combination of MCS and EEA in a hybrid method will foster the deepest insight. In the end, the choice of method must be directed by the nature of uncertainty specific to the problem.

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