Gaming the System: An Agent-Based Model of Estimation Strategies and their Effects on System Performance

John Meluso*

PhD Student
Global Design Laboratory
Design Science Program
University of Michigan
Ann Arbor, MI 48109
Email: jmeluso@umich.edu

Jesse Austin-Breneman
Assistant Professor of Mechanical Engineering
Global Design Laboratory
Department of Mechanical Engineering
University of Michigan
Ann Arbor, MI 48109
Email: jausbren@umich.edu

Parameter estimates in large-scale complex engineered systems affect system evolution yet can be difficult and expensive to test. Systems engineering uses analytical methods to reduce uncertainty, but a growing body of work from other disciplines indicates that cognitive heuristics also affect decision-making. Results from interviews with expert aerospace practitioners suggest that engineers bias estimation strategies. Practitioners reaffirmed known system features and posited that engineers may bias estimation methods as a negotiation and resource conservation strategy. Specifically, participants reported that some systems engineers "game the system" by biasing requirements to counteract subsystem estimation biases. An agent-based model simulation which recreates these characteristics is presented. Model results suggest that system-level estimate accuracy and uncertainty depend on subsystem behavior and are not significantly affected by systems engineers' "gaming" strategy.

1 Introduction

Large-scale complex engineered systems (LaCES) are engineering projects with significant cost and risk, extensive design cycles, protracted operational timelines, a significant degree of complexity, and dispersed supporting organizations. They span critical infrastructure and key resources from civil infrastructure (e.g. water supply, power grid, transportation systems) to national defense (e.g. cyber, aircraft, seacraft, spacecraft) [1–3]. Design teams necessarily work in parallel when designing LaCES, including during the early stages of design which shape the full life of a system [4, 5]. Early in the design process, systems architects characterize the design of a system or subsystem based on very little information [6]. But forming parameter estimates with low uncertainty early in the design process and testing them prior to product integration can be expensive and difficult, if not impossible [7]. The estimated values of design parameters affect both the evolution of a design and the eventual performance of the final system design [8].

A particularly important parameter for many LaCES is mass, which can be a key design driver of system performance. For example, in aerospace applications satellite mass has been shown to have a significant impact on statistical reliability [9]. The mass properties of a launch vehicle determine what orbital trajectory a specific payload can reach. If the mass of a launch vehicle is even slightly off, it can reduce the mass of the payload which can be delivered to orbit or place the existing payload in the wrong orbit altogether, thereby jeopardizing the system mission [10]. In 1994, a Pegasus XL failed in part due to uncertainty in mass properties [11]. The challenge becomes reducing uncertainty to ensure that the system's measured performance meets speci-

*Address all correspondence related to ASME style format and figures to this author.

fied requirements, despite the cost and difficulty.

To reduce parameter uncertainties, systems engineers methodically advance the design of a system using analytical tools [12, 13]. Techniques like the "Systems V" promote defining requirements, breaking a system down into subsystems, and then integrating them back into a final system [14–16]. More recently, design researchers have begun using economic methods to develop alternative frameworks such as Value-Driven Design (VDD) [17–20].

Even with these advances, systems engineering continues to have its shortfalls. Systems engineering assumes that subsystems act rationally in accordance with their requirements or objective functions. However, cognitive science literature on uncertainty suggests that decision making under uncertainty is not purely analytical but also involves heuristics and affect [21,22]. Heuristics, such as value-induced distortions and anchoring, may cause engineers to favor certain parameter values due to perceived desirability thereby biasing estimation methods and uncertainty determination [23]. When propagated throughout a system, inaccurate estimates may degrade system performance.

Given this context, this study seeks to answer the following research questions:

1. What strategies do practitioners currently use to estimate performance in complex system design?
2. How do practitioners currently allocate resources toward reducing uncertainty in complex system design?
3. What are the impacts of different estimation strategies on system performance?

To answer these questions, this study was divided into two phases. The first phase explored the strategies that engineers use to estimate parameters through a series of qualitative interviews with expert practitioners in the aerospace industry. The second phase then tested the impact of the identified strategies on system performance through a Monte Carlo simulation of an agent-based model (ABM) using the canonical test problem of FireSat [24].

2 Related Work

2.1 System Engineering Strategies

Systems engineering is "a methodical, disciplined approach for the design, realization, technical management, operations, and retirement of a system" and a quintessential method for working with LaCES [12]. The traditional approach follows the "Systems V" wherein a system's complexities are managed through a mission and high-level requirements, decomposition into subsystems, integration, and operation [14–16]. Breaking down a subsystem into constituent parts allows subsystem engineers to focus on the design of their subsystem while systems engineers manage the interfaces between subsystems [12].

Systems have grown larger and more complex over time, giving rise to the name LaCES [1–3,15]. At the highest level, design management methods become more sophisticated and flexible to accommodate the large number of design changes [13]. Nevertheless, traditional systems engineering methods may not design and manage LaCES effectively [25]. Time and cost overruns are common yet canceling programs may similarly not be an option [1].

Recently, an alternative suite of tools for managing LaCES has emerged including Value-Driven Design and Decision Analysis [17, 18, 25, 26]. These and similar frameworks use economic theories to optimize the systems engineering process by passing objective functions to subsystems instead of requirements [17]. Systems engineering research is in the process of stretching further into this domain [27–32].

2.2 Uncertainty in system engineering

Uncertainty is the error between the predicted value of a parameter and the actual value, typically expressed probabilistically as the variance of a population. In complex systems design, a common method for addressing uncertainty is to use margins, which are "probabilistic estimates of the uncertainty of design parameters relative to either worst-case estimates or performance goals" [33]. Margins are frequently added to estimated values in complex system design to account for future design changes as a risk management strategy [34], and can be the product of heuristics and intuition [33] or formally calculated as a replacement for heuristics [35]. A variety of formal strategies are used to implement and manage margins throughout complex system design [34–38].

2.3 Heuristics from the Behavioral Sciences

Studies in behavioral science on how people think about estimation and uncertainty date back to the 1960s. Primacy effects are those in which early information distorts subsequent information or which cause someone only to seek information which supports the original information [39–41]. Consequently, information becomes biased by previous experience or early estimations despite the introduction of new information.

The adjustment and anchoring heuristic further states that people tend to make estimates by starting from an initial value and then adjusting the estimate from that value. The initial value may come from a number of sources including historical data, a suggestion, or a partial calculation [21, 42]. Hence, people tend to adjust estimates by deviating from initial estimates as opposed to forming independently validated estimates.

A third influence is the affect heuristic, which describes how people "use their gut" when making decisions even about theoretically unaffective concepts [22, 43]. While the brain's ability to use affect empowers individuals to understand difficult concepts, it also allows people to be inadvertently manipulated or misguided based on their experiences and context [22]. This study uses these concepts to inform the qualitative interview analysis.

2.4 Strategies for Agent-Based Simulations

Various disciplines use agent-based models (ABMs) to study the evolutionary behavior of complex systems, from ecology to finance. An ABM is made up of independent decision makers ("agents") which follow simple rules and exchange information with one another during each iteration of a model [44, 45]. Implementation of an ABM varies depending on the application, but one method of note is heterogeneous simulated annealing teams (HSAT) agent-based modeling [46]. An HSAT ABM is a multiagent simulated annealing algorithm which uses Cauchy and Triki adaptive schedules [46, 47]. This study uses an HSAT ABM to model engineers' estimation strategies.

2.5 Research Gap

Current systems engineering tools assume that designers make rational decisions about uncertainty. However, as demonstrated by the extensive research in the behavioral science literature, people do not form estimations using purely rational strategies. This study seeks to build upon existing systems engineering frameworks by incorporating behaviors such as anchoring, primacy, and affect heuristics to deepen our understanding of how design estimations occur in teams.

3 Phase 1: Practitioner Interviews

3.1 Methodology

Interviews were conducted with seven aerospace practitioners with an average of 30 years experience in complex system design and management. Each 30 to 60 minute interview took place in the practitioner's office or over the phone. An interview protocol guided each interview through a series of open-ended questions structured to evoke stories of their experiences such as the following: "So I'm trying to understand how engineers spend resources to refine estimates. Related to [the last program you worked on], can you walk me through the process of updating the estimate of a parameter, such as mass?"

The interviews generated data on both the practitioners' beliefs about the estimation process and descriptions of the behaviors which reflect the behaviors which actually occur. The data resulted in criteria for designing the model described in Phase 2.

3.2 Results

According to the practitioners, historical data is critical on new programs. Engineers will "try to get whatever [they] can from previous experts" so as to "avoid first principle estimation," even if it means that they have to "extrapolate from what [they] know." They tend not to engage with projects without expertise.

After acquiring historical data, engineers begin initial estimations while developing a proposal by using "a little bit of paper and pencil, and maybe spreadsheets, hack together a little code. It's kind of a 'sandbox simulation'...once you've got something that makes sense, then you can iterate" the design by using "standard large-scale systems engineering."

If the team wins the proposal, systems engineering takes on a prominent role as the team takes on additional engineers and more detailed estimation begins in earnest. "[As a systems engineer,] you spend a lot of your time...worrying about the edges of [the design space], making sure you're not going to be too heavy, or making sure you're not going to need too much power, looking at all of the things that might go wrong which could put you out of your accommodation envelope." One practitioner characterized good systems engineers as "[B.S.] detectors." You need to "know your people" so you can assess the validity of estimates from the subsystems. In contrast, bad systems engineers tend to have the "green eyeshades on." They spend their time totaling and passing numbers along rather than challenging the credibility and reliability of an estimate.

If a subsystem's estimate falls outside of the requirements, subsystem engineers typically ask the systems engineers to accommodate the existing estimate. Systems engineers usually give the subsystem some fraction of the available system margin to accommodate the current estimates provided by the subsystem. Rarely do systems teams ask the subsystem to go back and refine their estimate to fall within the requirements. From the perspective of a systems engineer: "If it's really early on you might [ask for] a little bit more if there's a payoff in the science or in better margin or something...[but] if it's not in the early design phases...usually you don't do anything. You just move on and worry about some other fire that you have to put out today."

If the subsystem's estimate falls within the requirements—even if the subsystem knows that the requirements are too easy—subsystems tend not to refine the estimate due to higher-priority tasks and problems elsewhere. Again from the perspective of a systems engineer: "If I'm asking for something that's [too] easy to do, they usually won't tell you that...then they've got lots of margin in the requirements. If you can [meet your requirements] for that much power, mass, and volume, and it's actually pretty easy, they won't come back and say, 'I could've done twice as good.' They won't tell you that; they'll tell you, 'I can do that.' "

To counteract this, systems engineers "ask for a little more than you think everybody realistically can do and let them push back...You don't find out that [subsystems] could do twice as good if you ask everybody to do something that's easy." On the other hand, "If you try to force every single person to meet every single requirement, there's no room for anything to go wrong and your schedule blows up. That's what happens, so you always hold some [margin] so that when things go wrong, you can just say you're spending some margin and move forward." This strategy also engenders good-will and feelings of control in subsystem engineers.

Teams only focus on system performance "once you've nailed your design down, then things shift and you don't worry as much about the corner cases...you really focus on how well you think it's going to work."

3.3 Qualitative Analysis

First, note that historical information anchors new design estimates, as with the anchoring heuristic discussed in Section 2.3. In the interest of avoiding large uncertainties inherent to first-iteration science and engineering estimates, they instead "extrapolate from what [they] know," which is the adjustment portion of the same heuristic. They construct simple simulations to form initial estimates for the system based on what they *do* know. Nevertheless, "sandbox" estimates also have large uncertainties at the beginning of the design process because the focus is still on the "edges" of the design space until the design itself is cemented.

After expanding the size of the team, the subsystems form estimates based on the requirements and historical data. The practitioners indicated that subsystems tend to challenge existing requirements through their estimates if the subsystem can't or doesn't want to meet the requirement. On the other hand, if the subsystem easily meets a requirement, they *quietly* meet the requirement to preserve any additional margin they received as a consequence of receiving too lenient a requirement. Both cases indicate that subsystems prefer certain parameter values over other values—characteristic of value-induced distortions. A subsystem favors its existing estimate because it either reduces subsystem resource expenditure caused by estimate refinement or increases subsystem negotiating power later in the design process [33].

In both cases, subsystems provide estimates which favor the subsystem's interests over the interests of the system, thereby suggesting that subsystems do not follow the rational estimation strategies assumed by systems engineering practices. However, the practitioners recognize that engineers don't follow rational estimation strategies. Systems engineers attempt to counteract such irrational real-life strategies by pushing the subsystems harder than they "realistically can do." Hence, the systems engineers also favor certain values to support the interests of the system over the interests of the subsystems, as is certainly their responsibility.

This system-level strategy for mitigating the consequences of subsystem estimations is built into the requirements before the subsystems begin their own estimates. So when subsystem engineers return with their initial estimates, the systems engineers only push back if it's early enough in the design process and there is some mission-driven incentive to do so.

Based on the interview data, the estimation strategy model must embody the following design team characteristics:

C.1 Historical data serves as a reference point for estimates
C.2 Uncertainty is inversely proportional to resource use
C.3 Subsystem engineers favor their own interests over system-level interests
C.4 Systems engineers structure requirements to favor system-level outcomes over subsystem interests
C.5 Engineers only negotiate about parameter estimates if:

- **C.5.1** the design is still in an early enough phase, and
- **C.5.2** there is a mission-driven incentive to do so

Section 4 describes an ABM which simulates the impact of these characteristic estimation strategies on system performance.

4 Phase 2: Monte Carlo Simulation of an Agent-Based Model

The HSAT ABM simulated effects of the estimation strategies on system performance by modeling the internal mass estimate decision-making process for each of several independent agents, the agent dynamics, and system performance resulting from agent interactions. This produced mass estimates, accuracies, and uncertainties for each agent and the overall system.

The model consisted of a simplified version of a standard aerospace project breakdown on the canonical FireSat example [24]. The simplified system was made up of eight agents, shown in Figure 1 along with the agent interactions. Seven subsystem agents and one system-level agent, defined in Table 1, exchanged information during each iteration of the model, called "design cycles" to match the industry practice of applying the Shewhart and Deming Cycles [48]. During each design cycle, each subsystem made internal decisions about mass estimation. Their latest estimates were then passed to the system agent which similarly made decisions about the aggregate system mass before feeding information back to each subsystem for integration into their respective mass estimation strategies.

4.1 Model Assumptions

To address C.1, the model assumes that agents treat historical data as a reference point. Each agent knows its historical mass distribution—approximated as a normal distribution—for comparable subsystem final masses from spacecraft of the same class. Subsystems "update" their mass estimates by drawing samples from their historical data which they treat as normally distributed random variables with mean μ_{h_i} and variance ${\sigma_{h_i}}^2$. Each time a subsystem draws a new sample from the distribution, it expends resources as a real team would expend labor or capital to refine a mass estimate. The subsystem then calculates (or recalculates) its sample mean estimate $\overline{m_i}$ and sample variance estimate $\overline{\sigma_i}^2$:

$$\overline{m_i}(m_{i1}, m_{i2}, \ldots, m_{iq_i}) = \frac{1}{q_i} \sum_{j=1}^{q_i} m_{ij} \tag{1}$$

$$\overline{\sigma_i}^2 = {\sigma_{h_i}}^2 / q_i \tag{2}$$

where $m_{i1}, m_{i2}, \ldots, m_{iq_i}$ are mass samples and q_i the total number of samples taken for the i^{th} subsystem. Equation 2 satisfies C.2.

During each design cycle, each subsystem compares its mass estimate with the historical mean of the subsystem to determine whether the value of the current subsystem estimate is "good enough" or if it needs further refining.

Each subsystem has a utility function $u_i(\delta_i) \in [0,1]$ where δ_i is the difference between the current sample mean and the historical mean. The subsystem only chooses to draw a sample during the next design cycle if the utility of the current estimate $u_i(\delta_i) \leq T_i$ where T_i is the utility threshold set equal to the utility at $\delta_i = 0$ (also shown in Figure 1). By setting $u_i(\delta_i = 0) = T_i$, the model treats the historical mean as "good enough," so any estimate which yields $max(u_i(\delta_i \neq 0)) \geq u_i(\delta_i = 0)$ represents a biased preference function skewed from the mean. To test the biases captured by C.3 and C.4, the utility function for each subsystem is an adjustable normalized skew normal distribution [49]:

$$u_i(\delta_i, \alpha_i) = A_i * 2\psi_i(\delta_i)\Psi_i(\delta_i, \alpha_i) \tag{3}$$

where $\psi_i(\delta_i)$ is the PDF of a normal distribution centered at $\delta_i = 0$ with variance ${\sigma_{h_i}}^2$:

$$\psi_i(\delta_i|{\sigma_{h_i}}^2) = \frac{1}{\sqrt{2\pi{\sigma_{h_i}}^2}} e^{-\frac{{\delta_i}^2}{2{\sigma_{h_i}}^2}} \tag{4}$$

and $\Psi_i(\delta_i, \alpha_i)$ is the CDF of a normal distribution centered at $\delta_i = 0$ with variance ${\sigma_{h_i}}^2$ and skew parameter α_i:

$$\Psi_i(\delta_i, \alpha_i) = \frac{1}{2}\left[1 + erf\frac{\alpha_i\delta_i}{\sqrt{2}}\right] \tag{5}$$

and A_i is a normalizing constant:

$$A_i = \frac{1}{max(2\psi_i(\delta_i)\Psi_i(\delta_i, \alpha_i))} \tag{6}$$

Negative values of parameter α_i skew the distribution negatively, offsetting the mean of the distribution in the same direction, and vice versa with positive values of α_i. When $\alpha_i = 0$, the distribution becomes a normal distribution. However, when $\alpha_i < 0$ and $\delta_i = 0$, then $u_i(\delta_i = 0, \alpha_i < 0) = T_i < max(2\psi_i(\delta_i)\Psi_i(\delta_i, \alpha_i))$. Subsystems only update mass estimates which fall below the utility $u_i(\delta_i = 0) = T_i$ at the historical mean. Varying α_i across positive and negative values means that a subsystem favors positive and negative mass estimates respectively, thereby satisfying C.3 as the subsystem favors its own interests over those of the system. For example, positive values of α_i bias the subsystem to value slightly smaller-than-average estimates as "good," while estimates which are either below the mean or too far above the mean are "bad" and therefore require action.

The system agent then calculates the system mass estimate, approximated as a simple sum of the current subsystem estimates. Likewise, the system agent determines the utility of the estimate via the skew normal distribution about historical mean μ_{h_ξ} with variance ${\sigma_{h_\xi}}^2$ and parameter α_ξ, which satisfies C.4. The system updates the subsystems' thresholds for the next design cycle, according to the following function:

$$T_i = T_i + \frac{T_i - 1}{T_\xi} u_\xi * H(T_\xi - u_\xi) \tag{7}$$

where $H(x)$ is the Heaviside function. Equation 7 then represents the negotiation strategies of C.5. If the system utility u_ξ is below the system agent's similarly-determined threshold T_ξ, the system instructs each subsystem to increase it's threshold T_i so as to move the system estimate toward the desirable range. Otherwise, the system reaffirms the subsystem's current estimate.

Upon completion of this step, the ABM has completed one design cycle. The simulation iterates its procedures until the system mass estimate's standard deviation converges to within $\overline{\sigma_\xi} = \varepsilon\sigma_{h_\xi}$ on the nth design cycle, where parameter ε dictates the fraction of the historical standard deviation within which the sample standard deviation must converge.

4.2 Simulation Parameters

Each of the eight agents forms a historical normal distribution based on the values provided in Table 1. For example, the Structure Subsystem has a normal distribution with mean $\mu_{h_2} = 299.4$ kg and standard deviation $\sigma_{h_2} = 113.8$ kg, which represents the masses of structure subsystems on previous Low-Earth Orbit propulsionless spacecraft [24]. The Power Subsystem mean is $\mu_{h_4} = 284.5$ kg with standard deviation $\sigma_{h_4} = 80.8$ kg, and the overall system mean is $\mu_{h_\xi} = 1497.4$ kg with standard deviation $\sigma_{h_\xi} = 552.4$ kg. Note, however, that $\sum \mu_{h_i} = 1452.4$ kg < 1497.4 kg $= \mu_{h_\xi}$ due to ballast and launch hardware [24]. This discrepancy exists in the FireSat model because it is based on real-world data wherein systems engineers and subsystems each design to their own historical data which may not agree with one another.

The model examined system performance across a range of subsystem and system biases and uncertainty thresholds. A Monte Carlo simulation varied inputs to the ABM with 15 evenly-distributed values on each of the domains $\alpha_i \in [-0.01, 0.01]$ and $\alpha_\xi \in [-0.005, 0.005]$ with a consistent $\varepsilon = 0.2$. The Monte Carlo executed the ABM 1000 times for each combination of α_i and α_ξ before logging the initial and final mass estimates, the uncertainty, the number of mass samples required to reach convergence, and the utility of the final estimate for post-analysis. For simplicity, the Monte Carlo assumed that all seven subsystems exhibited the same behavior for each test, that is $\alpha_1 = \alpha_2 = ... = \alpha_7$ for every design cycle.

4.3 Results

Figures 2 and 3 show an example model run in which $\alpha_i = 0.01$, $\alpha_\xi = -0.005$, and $\varepsilon = 0.20$. Figure 2 shows the mass estimates mapped onto each agent's utility function. Figure 3 plots each agent's estimate uncertainty against the number of design cycles.

The control case in which $\alpha_i = 0$, $\alpha_\xi = 0$, and $\varepsilon = 0.20$ represents unbiased, or "rational," subsystem and system decision-makers. The utility thresholds are $T_i = u_i(\delta_i = 0) = 1$ and $T_\xi = u_\xi(\delta_\xi) = 1$, meaning that agents never surpass their thresholds and continue drawing samples until the system uncertainty converges, regardless of the estimated values.

The practitioners indicated that subsystems and systems tend to favor their own interests. From the authors' experiences, systems engineers typically favor masses which are low with respect to the mean ($\alpha_\xi = -0.005$) to incentivize the subsystems to decrease their masses. On the other hand, subsystems favor masses which are high with respect to the mean ($\alpha_i = 0.01$) to minimize resource expenditure and increase bargaining power [33].

Figure 4 shows the 1000-trial distributions for both the unbiased and the biased cases. Table 2 contains the mean and variance for the final state of each agent including δ, $\overline{\sigma}$, the number of samples for each agent q_n, and final solution utility $u(\delta)$.

The basic unbiased control and single biased cases represent a small subset of the possible combinations of α_i and α_ξ. Figure 5 expands the bias parameters to their full domains, $\alpha_i \in [-0.01, 0.01]$ and $\alpha_\xi \in [-0.005, 0.005]$, the implications of which will be discussed in the following section.

5 Discussion

The model supports the interview responses on "good" vs. "bad" systems engineering. With biased utility functions, subsystem estimates only converge if the subsystem updates its estimate every design cycle. Figure 3 shows that Subsystem 2 stops updating its estimate when it determines that the estimate is "good enough" without system-level influence. This embodies the practitioner's statement that "good" systems engineers are "[B.S.] detectors" who continually push subsystems to update their estimates to reduce uncertainty and increase accuracy. "Bad" systems engineers—with the "green eyeshades on"—just total the subsystem estimates and move onto the next problem, resulting in the greater uncertainty and reduced accuracy seen here with Subsystem 2.

The model also reflects the known inverse proportionality between resource expenditure and uncertainty as seen in Figure 4 and Table 2. The biased subsystem strategies may indicate a risk posture in which subsystems balance resource expenditure against estimate quality, the effects of which on overall system performance are twofold: (1) biased subsystem strategies may produce less-accurate system estimates with increased uncertainty for lower cost, and (2) biased system strategies may have little ability to counteract biased subsystem strategies. The model suggests that unbiased strategies may consume significantly more resources than biased strategies. Transitioning from a biased to an unbiased estimation strategy cost subsystems an average of 4.5-times more samples (and therefore resources) for a meager 6% increase in subsystem estimate utility. But the same transition yields a 156% increase in system estimate utility and hence system performance.

Note that employing bias indicates that subsystem and systems engineers use value-induced distortions. Engineering judgment may beneficially account for some of this distortion, but subsystem rationales differ from systems rationales for employing biased utility functions. The practitioners indicated that subsystem engineers tend to bias above the mean to increase negotiating power and reduce resource consumption. They further suggested both that systems engineers favor the historical mean and that an affective response to subsystem bias leads them to counter with their own biased strategy.

However, the ABM and Monte Carlo suggest that "gaming the system" may not improve system performance. Figure 5 indicates that as modeled, the mean and variance of δ_ξ primarily depend on subsystem biases and minimally on system biases which supports the practitioners' intuition that subsystem bias negatively affects system performance. It also suggests that Systems' biasing strategy may not counteract the subsystem strategy. Furthermore, the subsystems have little incentive to reduce their own biases given the sizable cost required for marginal estimate improvement. To improve system performance, systems engineers may need to reshape the incentive structures of subsystems to either reduce the cost or increase subsystem returns on expending resources to achieve increased accuracy and reduced uncertainty.

6 Conclusion

The first phase of this study used interviews with expert aerospace practitioners to identify the strategies that engineers use to estimate parameter values throughout the design process. The second phase implemented these cognitive estimation strategies through Monte Carlo simulation of an agent-based model.

The practitioners and the simulation suggested that system performance depends on the oft-overlooked behavioral strategies of engineers in addition to the technical design. When engineers anchor their estimates to historical data, unbiased estimation strategies may outperform biased strategies. Engineering judgments may cause beneficial value-induced distortions.

In turn, system estimate accuracy and uncertainty seem to strongly depend on value-distorting subsystem estimation strategies while the responsive systems engineering strategy of counteracting subsystem bias with their own opposite bias may not effectively improve system performance. The reduced costs inherent to biased subsystem estimation strategies may significantly reduce subsystem resource expenditure at the cost of system performance. But, the small potential gains in subsystem utility from reducing subsystem bias suggest that incentivizing subsystems to employ unbiased strategies requires a different system response strategy if systems engineers value increasing estimate accuracy, decreasing estimate uncertainty, and improving system performance.

1. What strategies do practitioners currently use to estimate performance?

Results from interviews suggest that both system and subsystem engineers may use value-induced distortions, anchoring, and adjustment heuristics to form estimates. Subsystem engineers may favor biased estimates to increase negotiating power and reduce resource expenditure. Systems engineers may attempt to counteract subsystem estimation strategies by using oppositely biased strategies.

2. How do practitioners currently allocate resources toward reducing uncertainty?

   Results from interviews suggest that practitioners may allocate resources based on the utility of an estimate. Subsystem engineers attempt to minimize the resource consumption due to workload constraints. Systems engineers attempt to minimize schedule delays and engender good-will by granting flexibility on estimate accuracy.

3. What are the impacts of different strategies on system performance?

   Unbiased utility functions may reduce estimate uncertainty and increase resource expenditure. Biased utility functions may decrease estimate accuracy and increase uncertainty while decreasing subsystem resource expenditure.

7 Future Work

Expanded use of social science analysis methods may reveal deeper insights into the behaviors of LaCES design teams. Grounded theory could distill common themes from current and future data to generate deeper theories with additional corroborating evidence [50, 51]. A laboratory experiment run with practitioners and/or students could test whether and how much engineers respond to different situations with both cognitive behaviors and social strategies. Theoretical mathematical analysis using evolutionary game theory and adaptive dynamics could explore how and why actors respond to these different situations. Finally, expanded agent-based modeling could test current strategies and hypothetical solutions by testing other objectives (uncertainty, financial), other constraints (uncertainty, financial, competition), and expanding the scale of the model to include multi-tiered teams and/or systems-of-systems.

Acknowledgements

The authors would like the thank the practitioners who participated in the interviews of this study, without whose insights the authors could not have characterized the estimation strategies of practicing engineers.

References

[1] Bloebaum, C. L., and McGowan, A.-M. R., 2012. "The Design of Large-Scale Complex Engineered Systems: Present Challenges and Future Promise". In AIAA Aviat. Technol. Integr. Oper. Conf. 14th AIAA/ISSM, no. September, American Institute of Aeronautics and Astronautics, pp. 1–19.

[2] McGowan, A.-M. R., Daly, S., Baker, W., Papalambros, P., and Seifert, C., 2013. "A Socio-Technical Perspective on Interdisciplinary Interactions During the Development of Complex Engineered Systems". *Procedia Comput. Sci.,* **16**, pp. 1142–1151.

[3] McGowan, A.-m. R., 2014. "Interdisciplinary Interactions During R & D and Early Design of Large Engineered Systems". PhD thesis.

[4] Yassine, A., and Braha, D., 2003. "Complex Concurrent Engineering and the Design Structure Matrix Method". *Concurr. Eng. Res. Appl.,* **11**(3), sep, pp. 165–176.

[5] Eppinger, S., 1991. "Model-based Approaches to Managing Concurrent Engineering". *J. Eng. Des.,* **2**(4), jan, pp. 283–290.

[6] Jankovic, M., and Centrale, E., 2015. "Understanding the Impact of Subjective Uncertainty on Architecture and Supplier Identification in Early Complex Systems Design". *ASCE-ASME J. Risk Uncert. Engrg. Sys., Part B Mech. Engrg.,* **1**(October), jul, p. 031005.

[7] de Weck, O. L., and Eckert, C. M., 2007. "A Classification of Uncertainty for Early Product and System Design". *Massachusetts Inst. Technol. Eng. Syst. Div. Work. Pap. Ser.*(February).

[8] Crossland, R., Williams, J. H. S., and McMahon, C. A., 2003. "An object-oriented modeling framework for representing uncertainty in early variant design". *Res. Eng. Des.,* **14**(3), nov, pp. 173–183.

[9] Dubos, G. F., Castet, J. F., and Saleh, J. H., 2010. "Statistical reliability analysis of satellites by mass category: Does spacecraft size matter?". *Acta Astronaut.,* **67**(5-6), pp. 584–595.

[10] Ryan, R. S., and Townsend, J. S., 1997. "Fundamentals and Issues in Launch Vehicle Design". *J. Spacecr. Rockets,* **34**(2), mar, pp. 192–198.

[11] Chang, I.-S., 1996. "Investigation of space launch vehicle catastrophic failures". *J. Spacecr. Rockets,* **33**(2), mar, pp. 198–205.

[12] Kapurch, S. J., 2007. "NASA Systems Engineering Handbook". *NASA Spec. Publ.*, p. 360.

[13] Cardin, M.-A., Nuttall, W. J., De Neufville, R., and Dahlgren, J., 2007. "Extracting value from uncertainty: A methodology for engineering systems design". *17th Symp. Int. Counc. Syst. Eng. San Diego, CA, United States,* **17**(1), jun, pp. 1–9.

[14] Forsberg, K., and Mooz, H., 1994. "The Relationship of System Engineering to the Project Cycle". *12th INTERNET World Congr. Proj. Manag.,* **1**(June 1994), oct, p. 12.

[15] Keating, C., Rogers, R., Unal, R., Dryer, D., Sousa-Poza, A., Safford, R., Peterson, W., and Rabadi, G.,

2008. *System of systems engineering*, Vol. 36.

[16] Clark, J. O., 2009. "System of Systems Engineering and Family of Systems Engineering from a standards, V-Model, and Dual-V Model perspective". *2009 3rd Annu. IEEE Syst. Conf.*, mar, pp. 381–387.

[17] Collopy, P. D., and Hollingsworth, P. M., 2011. "Value-Driven Design". *J. Aircr.,* **48**(3), may, pp. 749–759.

[18] Collopy, P. D., Bloebaum, C. L., and Mesmer, B. L., 2012. "The Distinct and Interrelated Roles of Value-Driven Design, Multidisciplinary Design Optimization, and Decision Analysis". In 12th AIAA Aviat. Technol. Integr. Oper. Conf. 14th AIAA/ISSMO Multidiscip. Anal. Optim. Conf. 2012, 12th AIAA Aviat. Technol. Integr. Oper. Conf. 14th AIAA/ISSMO, no. September, American Institute of Aeronautics and Astronautics, pp. 1–10.

[19] Mullan, C., Price, M., Soban, D., and Fanthorpe, C., 2012. "Development of Subsystem Relationships using a Value Driven Design Framework". In 12th AIAA Aviat. Technol. Oper. Conf., no. September, American Institute of Aeronautics and Astronautics.

[20] Bertoni, M., Bertoni, A., and Isaksson, O., 2016. "Evoke: A value-driven concept selection method for early system design". *J. Syst. Sci. Syst. Eng.*, dec, pp. 1–32.

[21] Kahneman, D., Slovic, P., and Tversky, A., 1982. *Judgment under uncertainty: heuristics and biases*. Cambridge University Press.[rNB].

[22] Slovic, P., Finucane, M., Peters, E., and MacGregor, D. G., 2002. "Rational actors or rational fools: Implications of the affect heuristic for behavioral economics". *J. Socio. Econ.,* **31**(4), pp. 329–342.

[23] Kahneman, D., and Tversky, A., 2001. *Judgment under uncertainty: heuristics and biases*. Cambridge University Press.

[24] Wertz, J. R., Everett, D. F., and Puschell, J. J., 2011. *Space mission engineering : the new SMAD*. Microcosm Press.

[25] Collopy, P. D., 2012. "A Research Agenda for the Coming Renaissance". In 50th AIAA Aerosp. Sci. Meet. Incl. New Horizons Forum Aerosp. Expo., no. January, American Institute of Aeronautics and Astronautics, pp. 1–10.

[26] Kim, H. M., Michelena, N. F., Papalambros, P. Y., and Jiang, T., 2003. "Target Cascading in Optimal System Design". *J. Mech. Des.,* **125**(3), p. 474.

[27] Tibor, E. B., Mesmer, B. L., Bloebaum, C. L., Miller, S. W., and Simpson, T. W., 2014. "Visualization of System Decomposition in a Value-Based Framework". In 15th AIAA/ISSMO Multidiscip. Anal. Optim. Conf., no. June, American Institute of Aeronautics and Astronautics, pp. 1–11.

[28] Kannan, H., Tibor, E., Mesmer, B., and Bloebaum, C. L., 2015. "Incorporation of Coupling Strength Models in a Value-based Systems Engineering framework for optimization". In 16th AIAA/ISSMO Multidiscip. Anal. Optim. Conf., American Institute of Aeronautics and Astronautics.

[29] Kwasa, B., Bloebaum, C. L., and Mesmer, B., 2015. "Value Impact of an Organization Structure in the Context of Value-Driven Design". In 56th AIAA/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf., no. January, American Institute of Aeronautics and Astronautics.

[30] Bhatia, G. V., Kannan, H., and Bloebaum, C. L., 2016. "A Game Theory approach to Bargaining over Attributes of Complex Systems in the context of Value-Driven Design". In 54th AIAA Aerosp. Sci. Meet., American Institute of Aeronautics and Astronautics.

[31] Kannan, H., Mesmer, B., and Bloebaum, C. L., 2016. "Incorporation of Risk Preferences in a Value-Based Systems Engineering Framework for a Satellite System". In *18th AIAA Non-Deterministic Approaches Conf.* American Institute of Aeronautics and Astronautics, Reston, Virginia, jan.

[32] Subramanian, T. R., Khol, A. R., Kannan, H., Winer, E. H., Bloebaum, C. L., and Mesmer, B., 2016. "Understanding the Impact of Uncertainty on the Fidelity of the Value Model". In 54th AIAA Aerosp. Sci. Meet., American Institute of Aeronautics and Astronautics.

[33] Austin-Breneman, J., Yu, B. Y., and Yang, M. C., 2015. "Biased Information Passing Between Subsystems Over Time in Complex System Design". *J. Mech. Des.,* **138**(1), p. 011101.

[34] Takamatsu, T., Hashimoto, I., and Ohno, H., 1970. "Optimal Design of a Large Complex System from the Viewpoint of Sensitivity Analysis". *Ind. Eng. Chem. Process Des. Dev.,* **9**(3), jul, pp. 368–379.

[35] Thunnisen, D. P., 2004. "Method for Determining Margins in Conceptual Design". *J. Spacecr. Rockets,* **41**(1), jan, pp. 85–92.

[36] Gu, X., Renaud, J., Batill, S., Brach, R., and Budhiraja, A., 2000. "Worst case propagated uncertainty of multidisciplinary systems in robust design optimization". *Struct. Multidiscip. Optim.,* **20**(3), nov, pp. 190–213.

[37] Helton, J. C., 2011. "Quantification of margins and uncertainties: Conceptual and computational basis". *Reliab. Eng. Syst. Saf.,* **96**(9), pp. 976–1013.

[38] Sentz, K., and Ferson, S., 2011. "Probabilistic bounding analysis in the Quantification of Margins and Uncertainties". *Reliab. Eng. Syst. Saf.,* **96**(9), pp. 1126–1136.

[39] Anderson, N. H., and Barrios, A. A., 1961. "Primacy effects in personality impression formation". *J. Abnorm. Soc. Psychol.,* **63**(2), pp. 346–350.

[40] Wallsten, T. S., 1981. "Physician and medical student bias in evaluating diagnostic information.". *Med. Decis. Making,* **1**(2), pp. 145–64.

[41] Wallsten, T. S. U. o. N. C., 1983. "The theoretical status of judgmental heuristics". In *Adv. Psychol.*, Vol. 16. pp. 21–37.

[42] Slovic, P., and Lichtenstein, S., 1971. "Comparison of Bayesian and regression approaches to the study of information processing in judgement". *Organ. Behav. Hum. Perform.,* **6**(?), pp. 649–744.

[43] Finucane, M. L., Alhakami, A., Slovic, P., and Johnson,

S. M., 2000. "The affect heuristic in judgments of risks and benefits". *J. Behav. Decis. Mak.,* **13**(1), jan, pp. 1–17.

[44] Macy, M. W., and Willer, R., 2002. "From Factors to Factors: Computational Sociology and Agent-Based Modeling". *Annu. Rev. Sociol.,* **28**(1), pp. 143–166.

[45] Macal, C., and North, M., 2009. "Agent-based modeling and simulation". In *Winter Simul. Conf. (WSC), Proc. 2009*. Springer Fachmedien Wiesbaden, Wiesbaden, pp. 86–98.

[46] McComb, C., Cagan, J., and Kotovsky, K., 2016. "Drawing Inspiration From Human Design Teams For Better Search And Optimization: The Heterogeneous Simulated Annealing Teams Algorithm". *Submitt. to J. Mech. Des.,* **138**(April), mar, pp. 1–6.

[47] Triki, E., Collette, Y., and Siarry, P., 2005. "A theoretical study on the behavior of simulated annealing leading to a new cooling schedule". *Eur. J. Oper. Res.,* **166**(1 SPEC. ISS.), pp. 77–92.

[48] Anderson, J. C., and Rungtusanatham, M., 1994. "A theory of quality management underlying the Deming Management Method". *Acad. Manag. Rev.,* **19**(3), jul, pp. 472–509.

[49] Azzalini, A., 1985. "A Class of Distributions Which Includes the Normal Ones". *Scand. J. Stat.,* **12**(2), pp. 171–178.

[50] Glaser, B. G., and Strauss, A. L., 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*, Vol. 1.

[51] Corbin, J. M., and Strauss, A., 2008. *Basics of qualitative research: Techniques and procedures for developing grounded theory*. SAGE.

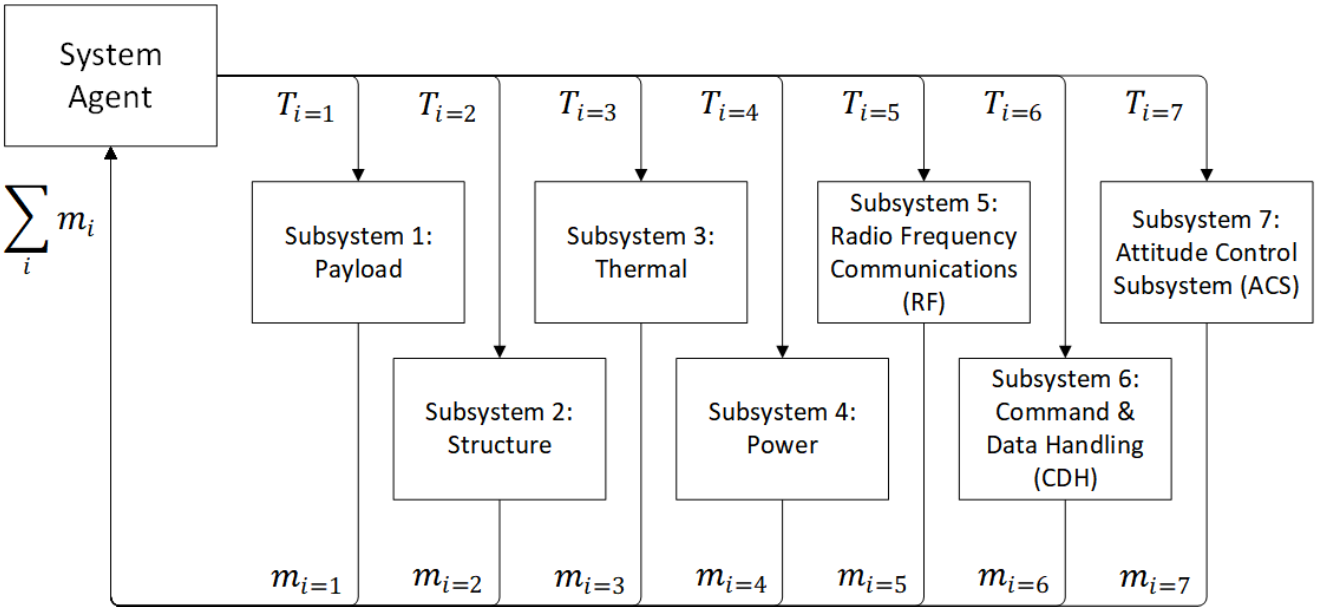

Fig. 1. The subsystem and system agents of the Agent Based Model, and the exchange of information between the agents during each design cycle

Agent	Agent Name	Mean (kg)	Standard Deviation (kg)
Subsystem 1	Mission Payload	613.8	140.7
Subsystem 2	Structure Subsystem	299.4	113.8
Subsystem 3	Thermal Subsystem	30.0	16.5
Subsystem 4	Power Subsystem	284.5	80.8
Subsystem 5	Radio Frequency Communications (RF)	30.0	21.0
Subsystem 6	Command & Data Handling (CDH)	74.9	34.4
Subsystem 7	Attitude Control Subsystem (ACS)	119.8	67.4
System	Propulsionless Low Earth Orbit Spacecraft	1497.4	552.4

Table 1. Nomenclature for the eight agents of the ABM including seven subsystem agents and one system agent. The table also shows the historical mean and standard deviation values used for each subsystem which were closely based on the FireSat documentation [24].

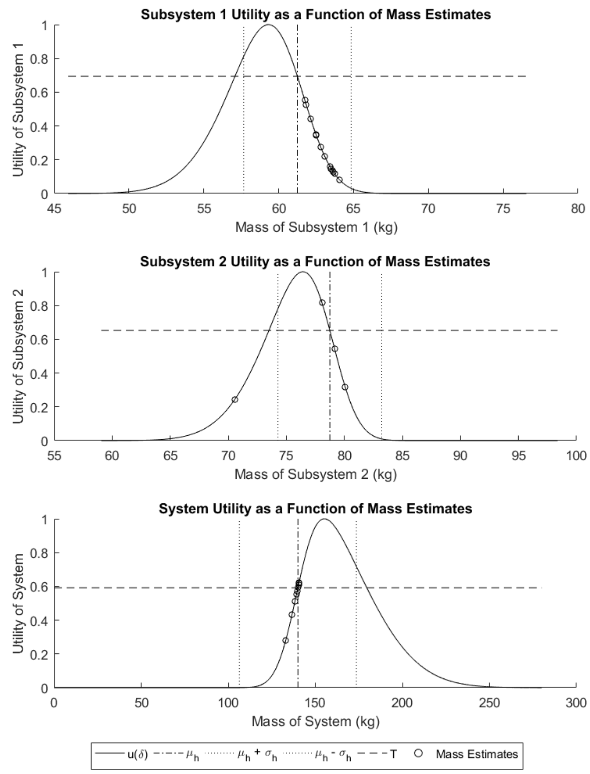

Fig. 2. Graphs showing the mass estimates for each agent and their respective utilities

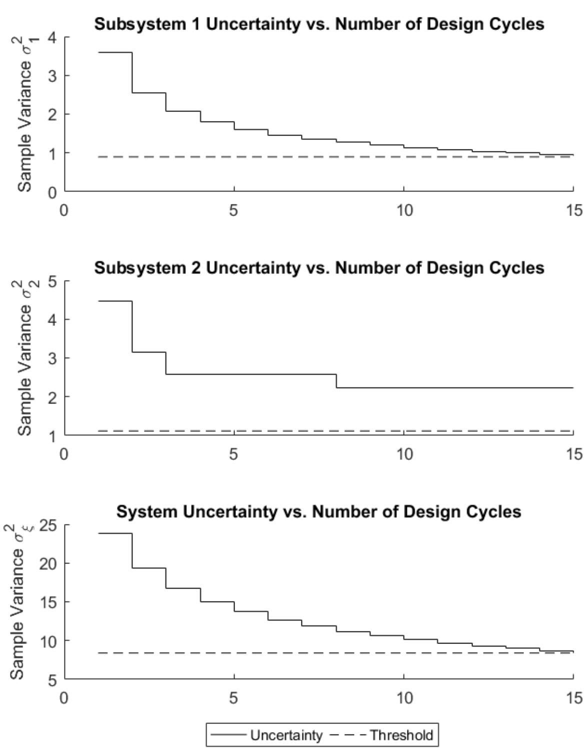

Fig. 3. Each agent's uncertainty as a function of number of design cycles

Test Case	Agent	Mean				Variance			
		Final δ	Final $\overline{\sigma}$	No. of Samples	Final $u(\delta)$	Final δ	Final $\overline{\sigma}$	No. of Samples	Final $u(\delta)$
Unbiased	Sub. 1	-0.74	28.72	25.00	0.979	842.92	3.87E-25	0.00	8.23E-04
	Sub. 2	1.27	23.23	25.00	0.981	507.80	2.84E-25	0.00	6.65E-04
	Sub. 3	1.25	3.37	25.00	0.979	10.07	2.89E-27	0.00	7.93E-04
$\alpha_i = 0$	Sub. 4	0.04	16.49	25.00	0.980	270.25	9.34E-26	0.00	8.27E-04
$\alpha_\xi = 0$	Sub. 5	3.31	4.29	25.00	0.974	12.90	8.38E-27	0.00	1.04E-03
$\varepsilon = 0.25$	Sub. 6	1.31	7.02	25.00	0.980	46.05	6.25E-27	0.00	7.86E-04
	Sub. 7	6.11	13.76	25.00	0.979	157.05	6.68E-27	0.00	8.24E-04
	Sys.	13.96	110.48	24.00	0.993	4028.89	6.57E-25	0.00	9.19E-05
Biased	Sub. 1	40.91	95.08	5.21	0.827	2958.45	1525.87	50.53	2.34E-02
	Sub. 2	32.58	76.96	5.11	0.859	1794.56	1020.70	46.74	1.55E-02
	Sub. 3	1.90	8.38	7.45	0.992	4.61	15.18	51.50	3.66E-04
$\alpha_i = 0.01$	Sub. 4	22.66	54.64	4.85	0.909	741.07	485.01	42.33	7.91E-03
$\alpha_\xi = -0.005$	Sub. 5	3.51	11.49	6.52	0.990	8.79	26.54	45.29	2.50E-04
$\varepsilon = 0.25$	Sub. 6	6.24	20.45	5.99	0.974	53.24	79.56	49.14	1.18E-03
	Sub. 7	20.51	45.96	4.25	0.938	414.85	295.61	31.60	3.40E-03
	Sys.	104.21	110.48	24.00	0.387	8583.02	6.57E-25	0.00	3.60E-02

Table 2. The mean and variance for each agent in the 7-subsystem Monte Carlo simulation in both the unbiased and biased cases.

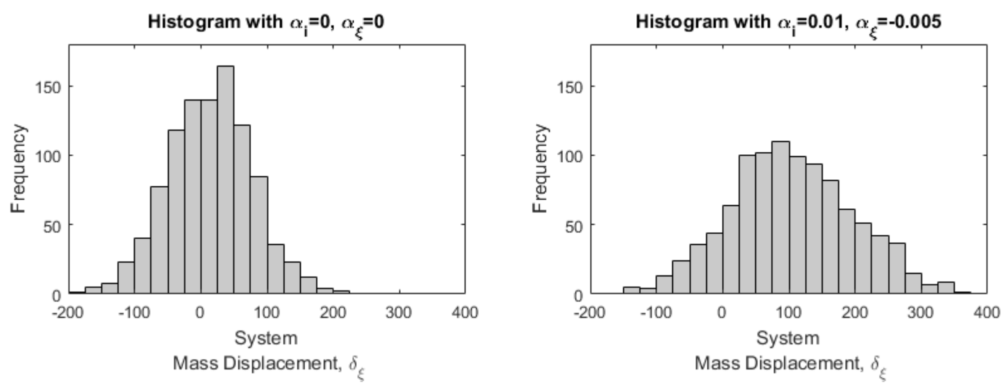

Fig. 4. Histograms of the 1000 trials for each of the unbiased and biased cases, respectively

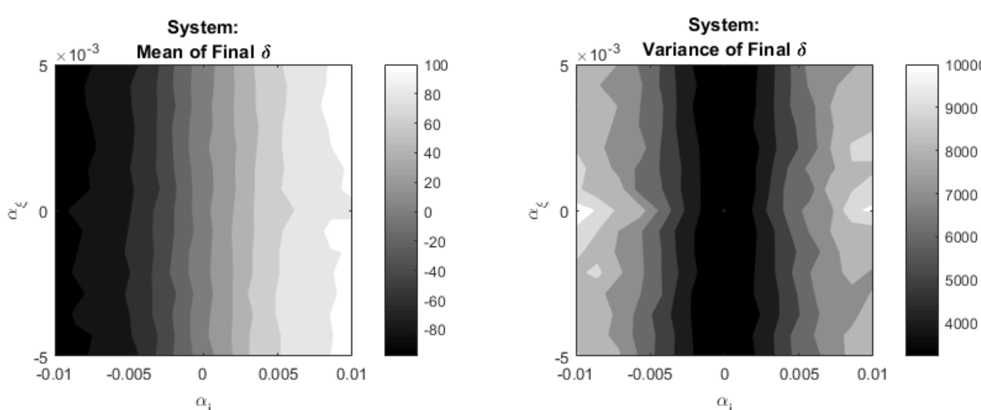

Fig. 5. Plots of the mean and variance for δ_ξ as a function of α_i and α_ξ